A behavioral perspective on the commercialization of knowledge and technologies from research to industry

vorgelegt von
M. Sc.
Pia Anna Pohle
ORCID: 0000-0001-9943-0366

an der Fakultät VII – Wirtschaft und Management
der Technischen Universität Berlin
zur Erlangung des akademischen Grades

Doktor der Wirtschaftswissenschaften
- Dr. rer. oec. –

genehmigte Dissertation

Promotionsausschuss:

Vorsitzender: Prof. Dr. Sören Salomo
Gutachter: Prof. Dr. Knut Blind
Gutachter: Prof. Dr. Diemo Urbig

Tag der wissenschaftlichen Aussprache: 15. Dezember 2022

Berlin 2023

Abstract (English)

In a knowledge-based economy, scientists in research organizations play a key role as producers of new academic knowledge; however, they are also responsible for commercializing this knowledge. Thus, universities and public research organizations have experienced substantial organizational changes, which have come along with various managerial challenges. Unfortunately, the results of these reorganization efforts are far behind expectations: most patents never get licensed, the growth of spin-offs is far behind that of other start-ups, and scientists still view commercialization as a burden or something "nice to have," rather than essential. This dissertation argues that a change in behavior among scientists and executives will only occur if commercialization is successfully anchored as part of the organizational structure and hence new behavioral routines are stimulated. Therefore, this dissertation aims to expand and deepen the understanding of the behavior of individuals involved in the commercialization of academic knowledge. It uses insights on organizational behavior and human resource management to obtain a profound understanding of the individuals involved. In this dissertation, the topic is examined from four different angles.

First, this dissertation examines previous literature on commercialization to identify **determinants that have been proven to increase or decrease the commercialization of academic knowledge** in research organizations. This review reveals 97 determinants, which are categorized along six commercialization channels and the following five classes: environmental, individual, institutional, organizational, and technological. Second, this dissertation explores the **phenomenon of serial patentees**, providing insights into how commercial support infrastructure should be adopted according to the kind and timing of academic inventors' prior patent experiences. Third, this dissertation addresses how the bounded rationality of scientists hinders them from finding the best industry partner for their commercial activities; then, it develops a supervised learning approach to **support decision making in industry partner selection**. Finally, it empirically addresses the question of how **university knowledge transfer offices enable the intrinsic motivation** of their employees through satisfying their three psychological needs (for relatedness, competence, and autonomy), developing a framework of university- and organizational-level antecedents.

Depending on the research question, a variety of different methods and data are used. The chapters encompass a meta-analysis based on 99 published articles, a survival analysis based on recurrent patenting data, an explorative qualitative approach based on four case studies, and the testing of a supervised learning approach using cooperation and company data. The findings of this dissertation provide valuable insights for decision makers in research organizations, transfer professionals, and policy makers who seek a solid micro-foundation for the behavior of individuals involved in the commercialization of research results. These insights can be used to design organizational contexts and support that truly change their commercial behavior and routines

Abstract (Deutsch)

In einer wissensbasierten Ökonomie kommt Wissenschaftler*innen in Forschungseinrichtungen eine besondere Rolle, als Produzente*innen und Verwerter*innen von akademischem Wissen, zu. Daher haben Universitäten und öffentliche Forschungseinrichtungen in den letzten Jahren gravierende organisatorische Veränderungen durchlaufen, die mit verschiedensten Managementherausforderungen einhergehen. Jedoch sind die Ergebnisse dieser Reorganisationsbemühungen weit hinter den Erwartungen, beispielsweise wird der Großteil der Patente nie lizenziert, Spin-offs wachsen wesentlich langsamer als andere Start-Ups und viele Wissenschaftler*innen betrachten die Kommerzialisierung immer noch als zusätzliche Belastung oder als „nice-to-have“ anstatt als wesentliche Aufgabe.

Im Rahmen dieser Dissertation wird argumentiert, dass eine Verhaltensänderung bei Wissenschaftler*innen und anderen beteiligten Individuen nur dann eintreten wird, wenn Kommerzialisierung als Teil der Organisationsstruktur verankert wird und neue Verhaltensroutinen etabliert werden. Daher ist das Ziel dieser Arbeit das Verständnis für die Beweggründe und das Verhalten der an der Kommerzialisierung beteiligten Personen zu erweitern und zu vertiefen. Dazu werden die Erkenntnisse aus den Gebieten des Organisationsverhaltens und des Personalmanagements genutzt, um die beteiligten Individuen besser zu verstehen und Handlungsempfehlungen abzuleiten. Die vorliegende Dissertation untersucht die genannte Problematik in den folgenden Kapiteln aus vier verschiedenen Blickwinkeln.

Zunächst wird die bisherige Literatur zur Kommerzialisierung untersucht, um jene Erfolgsfaktoren zu ermitteln, die nachweislich die Kommerzialisierung von akademischem Wissen steigern. Dabei werden 97 Erfolgsfaktoren identifiziert, welche entlang von sechs Transferkanälen und fünf Dimensionen klassifiziert werden: externe, individuelle, institutionelle, organisatorische und technologische Faktoren. Daraufhin wird das Phänomen der seriellen Patentierer*innen untersucht und Empfehlungen für eine verbesserte Unterstützungsinfrastruktur abgeleitet, je nach Art und Zeitpunkt der früheren Patenterfahrungen der Patentierer*innen.

Als Nächstes befasst sich diese Dissertation mit der Frage, wie die begrenzte Rationalität von Wissenschaftler*innen sie daran hindert, den geeignetsten Industriepartner für ihre kommerziellen Aktivitäten zu finden. Dazu wird ein auf maschinellem Lernen beruhender Ansatz entwickelt und getestet. Dieser unterstützt die Entscheidungsfindung bei der Auswahl von Industriepartnern. Schließlich wird empirisch der Frage nachgegangen, wie die intrinsische Motivation Mitarbeitenden in Transferbüros gefördert werden kann. Im Ergebnisse stehen die notwendigen Vorläufer intrinsischer Motivation auf Universitäts- und Organisationsebene.

Je nach Fragestellung werden in dieser Dissertation unterschiedliche Methoden und Daten verwendet. Dies umfasst eine Meta-Analyse auf Basis von 99 veröffentlichten Artikeln sowie eine Ereigniszeitanalyse auf der Grundlage von Patent-, Publikations- und Personaldaten. Zudem verfolgt eine Studie einen qualitativen Ansatz auf der Grundlage von vier Fallstudien und es wird ein „Supervised learning approach“ auf Basis von Kooperations- und Unternehmensdaten entwickelt.

Die Ergebnisse dieser Dissertation liefern wertvolle Erkenntnisse für Entscheidungsträger in Forschungsorganisationen, Transferfachleute und politische Entscheidungsträger, die daran interessiert sind, organisatorische Kontexte und Unterstützungsprogramme, auf Basis von fundierten Erkenntnissen über die Mikro-Prozesse der an der Kommerzialisierung beteiligten Personen, zu gestalten.

Publication and submission record

The essay titled “Determinants of the commercialization of academic knowledge – A review of determinants and meta-analysis,” co-authored by Friedrich Dornbusch and Knut Blind, is a preprint and was presented at the TU Berlin Research Colloquium and the FG Inno Retreat in Berlin in 2021. It has been submitted for publication in Techno*vation.*

The essay titled “How to become a serial patentee? – A patent behavior analysis,” is a preprint and was presented at the TU Berlin Research Colloquium 2019, at the FG Inno Retreat in Berlin in 2020, and also in Florence, Italy, at the XXX ISPIM Innovation Conference “Celebrating Innovation: 500 Years Since Da Vinci” in 2019. It has been submitted for publication in *Science and Public Policy*.

The essay titled “How to Find New Industry Partners for Public Research: A Classification Approach,” co-authored by Karl Trela, Yuri Campbell, and Friedrich Dornbusch, won the IMW Best Paper Award 2020 and was published in *IEEE Transactions on Engineering Management*, 68 (5, 2020, p. 1214–1231, https://doi.org/10.1109/TEM.2020.2992060). A former version of the essay was presented at the 8th Global TechMining Conference 2018 in Leiden, the Netherlands, and won the Best Paper Award there as well.

The essay titled “Personnel motivation in knowledge transfer offices: The role of university-level and organizational-level antecedents,” co-authored by Elisa Villani and Rosa Grimaldi, was presented at the TU Berlin Research Colloquium 2020 and the FG Inno Retreat in Berlin in 2021. A former version of the essay was presented at the 81st Annual Meeting of the Academy of Management Conference 2021 “Bringing the manager back to management” as a virtual presentation and published in the conference proceedings. The essay was published in *Technological Forecasting and Social Change* (181, 2022, 121765; https://doi.org/10.1016/j.techfore.2022.121765).

Acknowledgements

To my grandparents Brigitte and Roland Pohle

I would like to take this opportunity to thank several people who have given me the support and motivation that I needed during my PhD studies. First, I would like to thank my supervisors. Professor Knut Blind, thank you for your scientific supervision, your patience, your ideas, your trust, and the amazing network that you have created around you. I would also like to sincerely thank Professor Diemo Urbig for taking over the second review. Many thanks also go to Professor Elisa Villani, Professor Rosa Grimaldi, Dr. Friedrich Dornbusch, Dr. Karl Trela, and Dr. Yuri Campbell for their great work as co-authors.

In addition, my thanks go to my colleagues at the Fraunhofer Center for International Management and Knowledge Economy, where I was allowed to write this thesis over the past years. I would like to thank Professor Thorsten Posselt and Dr. Steffen Preissler for giving me this chance. Friedrich Dornbusch, thank you for your support, feedback, and input on my ideas. Moreover, thanks to all "Innopolis" for their companionship on this journey.

Furthermore, I am truly lucky to have my beloved friends. Therefore, I would also like to take this opportunity to thank some of them. Sophia, Juliane, Mona, and Nora – thank you for accompanying me through all of the ups and downs, building me up, motivating me, or just being there – even when you were far away. I especially want to thank you, Cyrine, for your energy and motivation over the last months – and of course for our writing sessions. Philipp, thanks for being in my life.

Finally, I would like to thank my family – especially my grandparents, for always supporting me unconditionally, picking me up when I was down, and supporting all of my plans and ideas, no matter how absurd they seem to you. Thank you from the bottom of my heart for everything!

Anna Pohle
Leipzig, October, 2022

Table of contents

Acronyms

AMP	Academy of Management Perspectives
ASTP	Association of European Science and Technology Transfer Professionals
ATTP	Association of Technology Transfer Professionals
AUTM	Association of University Technology Managers
DUNS	Data Universal Numbering System
EC	European Commission
EPO	European Patent Office
EU	European Union
F	Patent received forward citations
$\overline{\mathrm{F}}$	Patent received no forward citations
FÖKAT	Förderkatalog
G	Patent was granted
$\overline{\mathrm{G}}$	Patent was not granted
IP	Intellectual property
KCA	Knowledge Commercialisation Australasia
KMU	Kleines- und mittleres Unternehmen
KTO	Knowledge and technology transfer office
KTT	Knowledge and technology transfer
LES International	Licensing Executives Society International
NACE	Nomenclature statistique des activités économiques dans la Communauté européenne
NASA	National Aeronautics and Space Administration
NETVAL	Network per la valorizzazione della Ricerca
NLP	Natural Language Processing
n.m.	Not mentioned
OBHRM	Organizational behaviour and human resource management
OECD	Organisation for Economic Co-operation and Development
PATSTAT	Worldwide Patent Statistical Database - European Patent Office
PhD	Doctor of Philosophy
PRO	Public research organization
PWP-GT	Prentice, Williams and Peterson model – Gap time
PWP-TT	Prentice, Williams and Peterson model – Total time
ROC AUC	Receiver-operating-curve, area under the curve metric
RQ	Research question
RTA staff	research, technical or administrative staff
RTO	Research and Technological Organization
R&D	Research and development

SDT	Self-Determination Theory
SME	Small and medium enterprise
TT	Technology transfer
TTO	Technology transfer office
UIIN	University Industry Innovation Network
UK	United Kingdom
US	United States
USA	United States of America
WZ	Wirtschaftszweig Klassifikation
ZEW	Leibniz-Zentrum für Europäische Wirtschaftsforschung

List of tables

List of figures

1

1 Introduction

"This [commercialization of academic knowledge] gives me satisfaction, this gives me a lot of satisfaction to know that I have contributed to bringing that thing […] on the market, and then it's also good for society" (interview #7, Manager, KTO 1, Chapter 5).

Over the past decades, universities and public research organizations (PROs) have experienced increasing pressure to maximize their social and economic return on public investment. Furthermore, growing international competition and global societal challenges urge research organizations to move beyond their core missions of research and teaching toward social and economic impact. The commercialization of academic knowledge is loosely defined as follows: the exploitation of academic knowledge and technologies with the objective of transferring them to industry and gaining industry income (based on Markman et al., 2008; Grimaldi et al., 2011; Perkmann et al., 2013). It is considered a prime example of generating economic impact, as it constitutes measurable, immediate industry acceptance for academic results (Grimaldi et al., 2011; Perkmann et al., 2013). Consequently, policymakers and research organizations have invested extensively in legislative reforms and initiatives to foster commercialization. This has led to substantial organizational changes within research organizations, in addition to various managerial challenges (Gibbons, 1998; Bercovitz & Feldman, 2008). Decision makers in universities and PROs have integrated commercialization into their strategies, established intermediary organizations, and invested in transfer networks and ecosystems. However, the commercial outcome of research organizations is far behind expectations: spin-offs exhibit low growth rates compared with other start-ups and most patents never enter the market; moreover, scientists see commercialization as a burden or something that is "nice to have," rather than as essential (Brown, 2016; Arvanitis et al., 2008).

Thus, I argue that a change in behavior among scientists and executives of research organizations will only occur if commercialization is successfully anchored as part of the organizational structure, thus stimulating new behavioral routines. Therefore, the aim of this dissertation is to expand and deepen the understanding of the behavior of individuals involved in the commercialization of academic knowledge. Even if this dissertation cannot offer a complete explanation, I wish to contribute to an enhanced understanding of the processes behind the commercialization of academic knowledge by applying various insights from organizational behavior to the field.

The following subsections of the introduction provide a comprehensive explanation of what is meant by the "commercialization of academic knowledge" and how it has changed research organizations. This is followed by a discussion of its benefits and challenges. Then, I derive the research gap and propose the research objectives. This chapter closes with an overview of the dissertation's structure.

1.1 What is the "commercialization of academic knowledge"?

1.1.1 From the Bayh–Dole Act to transfer ecosystems – A historical perspective on the commercialization of knowledge and technology

For nearly two centuries, universities followed the Humboldtian ideal of the freedom of science and the unity of teaching and research. A university's role was to provide higher education and produce knowledge to serve society (Gibbons, 1998). Yet, the knowledge produced was based on problems set and solved according to the interests of scientists and not to the context of application (Gibbons, 1998). Thus, the transfer of knowledge and technologies played a subordinate role. Furthermore, the commercialization of knowledge was seen as a threat that restricted the freedom of science.

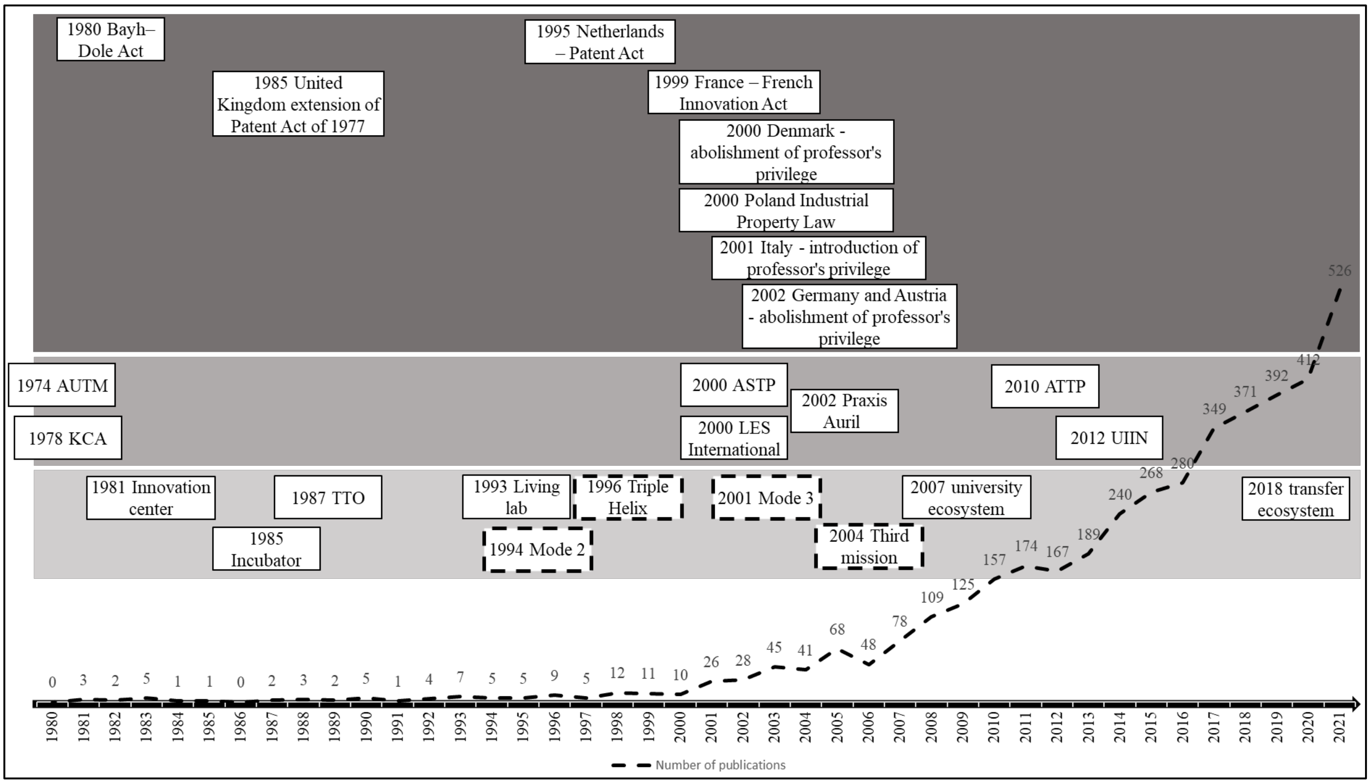
Yet, also back then, the academic knowledge produced by scientists in universities and PROs found its way into industry as well as society at large. The emergence and growth of knowledge-based industries, such as the pharma and electrical industries, were grounded in the transfer of academic knowledge to the economy (Szöllosi- Janse, 2004). Academic knowledge was transferred by teaching students who then entered the job market as qualified knowledge workers (Mowery & Sampat, 2005); furthermore, it was transferred by providing information through conferences and academic journals (Salter et al., 2000). In addition, new forms of universities were established that specialized in subject areas relevant to certain regional industries (Gibbons, 1998; Lam, 2010). Examples include colleges of technology such as the Royal College of Advanced Technology in the United Kingdom and polytechnics such as the École Polytechnique in France.

However, in the second half of the 20th century, the role of universities and PROs changed for various reasons. The rapidly increasing number of students, rise of the knowledge economy, and pressure due to international competition increased the importance of knowledge in the innovation process; as a result, the public grew to expect economic benefits from publicly funded research. Moreover, university–industry collaborations are seen as a tool for addressing economic and societal challenges (Skute et al., 2019). In their seminal work, Etzkowitz and Leydesdorff (2000) argued that a "university can play an enhanced role in innovation in increasingly knowledge-based societies" (the "triple helix model"; p. 109). Moreover, Etzkowitz et al. (2000) proposed that universities were undergoing an evolution from ivory tower to entrepreneurial paradigm. Universities are now expected to fulfill a "third mission," namely to contribute to the solving of societal and industrial challenges and to foster economic development (Etzkowitz & Leydesdorff, 2000; Etzkowitz et al., 2000). Gibbons (1998) described the change of universities' role as a transformation from mode 1 – where knowledge is produced based on academic interests, with homogenous skills, disciplinarily, and in hierarchical organizations – to mode 2 – where knowledge is produced based on the context of application, transdisciplinarily, with heterogenous skills, and in flat hierarchies. He stated that "this transformation is one of the most far reaching that we have described because it involves drawing the universities into the heart of the commercial process" (Gibbons, 1998, p. 30). Thus, the commercialization of academic knowledge was on the table, in turn leading to changes in law, public funding, as well as university and PRO practices.

The story of 'commercialization of academic knowledge' as it is discussed today, dates back to the Bayh–Dole Act of December 1980 (Grimaldi et al., 2011). The Bayh–Dole Act was aimed at enhancing the technology transfer activities of universities in the United States by allowing universities to patent publicly funded research (Decter, 2009). This resulted in an increase of US patents filed by universities, from 250 prior to 1980 to more than 2,000 by 2000 (AUTM, 2000). Additionally, estimations indicated that the commercialization of academic knowledge is responsible for approximately US$30 billion of economic activity and 250,000 jobs annually (Willey, 1999). The Bayh–Dole Act represented a key turning point as a multitude of countries then revised their laws of intellectual property ownership to enhance the technology transfer activities of research organizations. In 1985, the United Kingdom was the first European country to extend its patent act from 1977 to increase patenting (Bagley & Tvarnø, 2015). Many other European countries followed at the turn of the millennium (see Figure 1 for examples of legal acts in Europe). Furthermore, most European countries abolished the so-called "professor privilege," which granted scientists the rights to innovations instead of the university (e.g., Denmark in 2000 and Germany in 2002; Bagley & Tvarnø, 2015). Similar changes to laws occurred in Latin America, Asia, and Australia (Etzkowitz et al., 2000). Parallel to these changes, politicians established transfer-related funding. This included funding for research that broadly addresses industry needs or societal challenges (e.g., the Higher Education Reach Out to Business and Community [HEROBC] in the UK; 'GO-Bio initial' in Germany, or the 'PROOF OF CONCEPT' funding by the European Research Council) as well as funding for particular commercial activities of research organizations, such as funding for spin-off creations (e.g., the ‘EXIST’ scholarship for academic entrepreneurs in Germany or the Danish ‘Innoexplorer’; ERP-European Research Council, 2021; BMWI., n.d.; Innovation Fund Denmark., n.d.).

On the university practitioner side, new types of intermediary organizations emerged that aimed to enable university–industry links and support the commercial activities of scientists. These organizations include innovation centers, incubators, living labs, and knowledge and technology transfer offices (KTOs), the latter being arguably the best known. As of today, nearly all research organizations have established KTOs. In Germany alone, more than 150 KTOs exist (Kratzer et al., 2010). Depending on the type of organization, intermediaries can enable cognitive, social, and organizational proximity between academia and industry (Villani et al., 2017). Hence, unsurprisingly, intermediaries have also attracted academic interest; see Figure 1 for an illustration of the first appearance of the types of intermediaries in academic discourse. Moreover, research organizations and their technology transfer officers started to create networks to exchange good practices and foster the professionalization of technology transfer actors and activities. One of the oldest networks is the Association of University Technology Managers (AUTM). The AUTM was founded in 1974 as a national network in the USA (formerly called the Society of University Patent Administrators) and expanded into an international network with members in 65 countries (AUTM n.d.). Along with the changes in patent law in most European countries in the early 2000s, the Association of European Science and Technology Transfer Professionals (ATTP) was founded to connect European transfer professionals. Furthermore, transfer networks on the national level emerged, such as the Italian *Network per la valorizzazione della Ricerca* (Netval) in 2002 and the German *TransferAllianz – Deutscher Verband für Wissens- und Technologietransfer e. V.* in 2012.

Figure 1: *Historical overview of the commercialization of academic knowledge*



Examples of legal acts to change IP rights for research organizations (based on Bagley & Tvarno, 2015) Foundation year of international technology transfer networks; First appearance of a certain concept in the academic literature (dotted frame = theoretical concept; drawn through frame = type of organization); dotted line = number of publications on 'technology transfer' (based on Scopus)[1]

Once the path to technology transfer – as we know it today – had been created, scientists also began to analyze the conditions under which researchers were able to commercialize their knowledge and technologies most effectively (Teixeira & Mota, 2012). Over the last two decades, the number of studies on this issue has vastly increased (see Figure 1). By expanding our understanding of the mechanisms behind the commercialization of academic knowledge, the roles of universities and PROs continue to change. Recently, for example, scholars have coined the terms "university ecosystem" and "technology transfer ecosystem" to introduce a holistic approach to the discussion (Good et al., 2020; Hayter, 2016).

To sum up, under the Humboldtian ideal, the transfer of technologies from research to industry played a subordinate role. However, the rise of the knowledge economy as well as increasing international competition over the last century urged politicians, universities, and practitioners to foster the commercialization of academic knowledge professionally. Consequently, governments revised intellectual property rights and introduced transfer funding; university practitioners established intermediary organizations and transfer networks as well as trained transfer professionals; and scientists started to examine the mechanisms of the successful commercialization of academic knowledge. Over the past few decades, these actions have resulted in universities and PROs being transformed from "knowledge producers" to "engines of innovation systems" and "actors in transfer ecosystems."

[1] Search stream "TITLE-ABS-KEY ((universi* OR academic* OR research) AND (innovation OR "technology transfer")) AND (LIMIT-TO (PUBYEAR, 2008)) AND PUBYEAR > 1979" for dotted line, and in combination with additional keywords for the 'first appearance of the concept in academic literature' (accessed on February 17 2022).

1.1.2 Definition of commercialization of knowledge and technology and related concepts

Since 1980, various scholars have attempted to define the commercialization of academic knowledge. Consequently, many definitions and closely related terms have come to light. Accordingly, it is necessary to define what is meant by the "commercialization of academic knowledge" and to distinguish it from related terms. Such related terms include "knowledge and technology transfer" (KTT), "entrepreneurial university," "academic entrepreneurship," "academic engagement," and "third mission."[2] In this dissertation, the commercialization of academic knowledge is defined as *the exploitation of knowledge and technologies developed by academic scientists with the purpose of fulfilling an industry need and gaining industry income* (based on Grimaldi et al., 2011, Perkmann et al., 2013). This includes the commercialization of technology or knowledge in which *"*an academic invention is exploited with the objective to reap financial rewards*"* (Perkmann et al., 2013, p. 424). This covers commercialization through patenting, licensing, contract research, collaborative research projects, consulting, standardization, professional training, and spin-off creation (Grimaldi et al., 2013; OECD, 2013; Blind et al., 2018).[3]

The commercialization of academic knowledge is a process that involves a multitude of actors, including university/PRO governance, scientists, technology/knowledge transfer offices (TTOs/KTOs), industry partners, and often also additional intermediary organizations (e.g., incubators and patent attorneys). Figure 2 illustrates a simplified actor network for the commercialization of academic knowledge. However, it involves at least two actors: a scientist of a research organization and an industry employee of a firm.

[2] "Commercialization of academic knowledge" is used synonymous with the terms commercialization of knowledge and technologies, commercialization of research and commercialization of science / scientific results.

[3] Since patenting serves as a relevant precondition for licensing and spin-off creation in particular, it is often discussed as an additional channel.

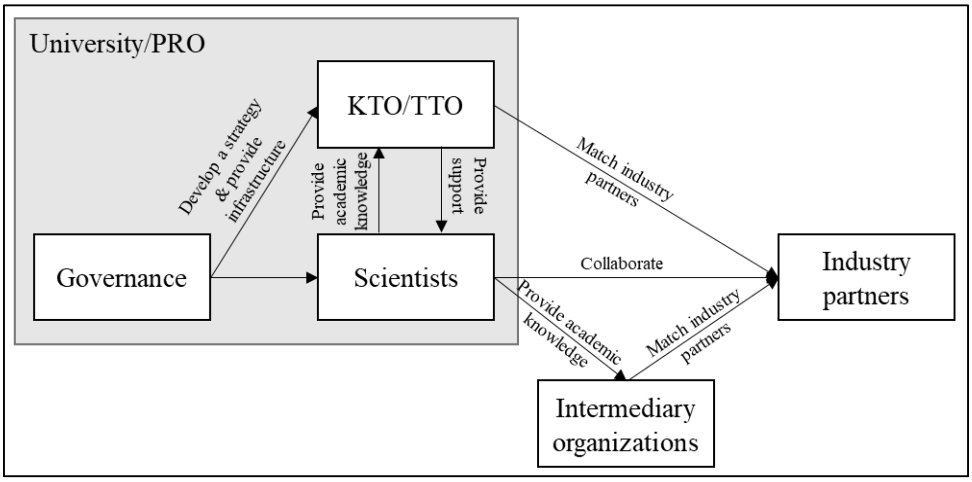
Table 1: *Related concepts*

	Commercialization of Academic Knowledge	Knowledge and Technology Transfer	Entrepreneurial University	Academic Entrepreneurship	Academic Engagement	Third Mission
Definition	Commercialization of Academic Knowledge refers to the exploitation of knowledge and technologies developed by academic scientists with the purpose of fulfilling an industry need and gaining industry income. (based on Grimaldi et al., 2011, Perkmann et al., 2013)	"[…] the movement of know-how, technical knowledge, or technology from one organizational setting to another" (Roessner, 2000, p. 1)	"[…] a university that has developed a comprehensive internal system for the commercialisation and commodification of its knowledge. This system includes not just structures such as liaison or technology transfer offices […] but also incentives for adjusting lines of study and the allocation of research budgets to the demand in the private and public sectors" (Jacob et al., 2003, p. 1556)	"[…] the objective of such [academic entrepreneurship] efforts is commercialization of innovations developed by academic scientists" (Grimaldi et al., 2011, p. 1045)	"[…] knowledge-related collaboration by academic researchers with non-academic organisations" (Perkmann et al., 2013, p. 424)	"[…] activities of a university which […] address actors outside the academic sphere, serve societal development interests that cannot be served by conventional teaching and research and research alone, use resources from research and/or teaching" (based on Henke et al., 2016, p. 21)
Included channels	Consulting; Contract research; Collaborative research; Intellectual property (IP); Licensing; Professional trainings; Spin-off creation; Standardization	Conference presentations/ proceedings; Consulting; Contract research; Collaborative research; IP; Licensing; Mobility programs; Networking/personal exchange; Open-source code/software/data; Professional trainings; Publications in industry journals and scientific journals; Spin-off creation; Standardization; informal meetings	Conference presentations/ proceedings; Consulting; Contract research; Collaborative research; IP; Licensing; Mobility programs; Networking/personal exchange; Open-source code/software/data; Professional trainings; Publications in industry journals and scientific journals; Spin-off creation; Standardization; Public events; establishment of intermediary organizations	Conference presentations/ proceedings; Consulting; Contract research; Collaborative research; IP; Licensing; Mobility programs; Networking/personal exchange; Open-source code/software/data; Professional trainings; Publications in industry journals and scientific journals; Spin-off creation; Standardization	Conference presentations/ proceedings; Consulting; Contract research; Collaborative research; IP; Licensing; Mobility programs; Networking/personal exchange; Open-source code/software/data; Professional trainings; Publications in industry journals and scientific journals; Standardization; Public events	Consulting; Contract research; Collaborative research; IP; Licensing; Mobility programs; Networking/ personal exchange; Open-source code/software/data; Professional trainings; Publications in industry journals; Spin-off creation; Standardization; Public events
Overlap with commer-cialization	-	- Process perspective - No focus on a particular type of research organization - Commercialization is a subgroup of KTT	- Commercialization is a task of an entrepreneurial university	- Commercialization is a part of academic entrepreneurship	- No focus on a particular type of research organization	- Commercialization is a part of the third mission

Differences to commer-cialization	-	- Much broader scope on channels - Not necessarily for reaping financial income - No focus on academic-industry exchange	- Focus on universities - Not necessarily for reaping financial income - Concept of how an organization should work	- Focus on universities - Not necessarily for reaping financial income - Concept of how an organization should work	- Not necessarily for reaping financial income	- Focus on universities - Not necessarily for reaping financial income - Broader scope of target group

I turn now to the differentiation of related terms, of which Table 1 provides an overview. Academic engagement is discussed as an umbrella term that describes the collaboration of academic researchers with a nonacademic partner organization, including formal (e.g., contract research or licensing) and informal modes of collaboration, such as industry exchange through conferences or networks (Perkmann et al., 2013). Likewise, knowledge and technology transfer also comprise various formal and informal channels. In addition, it includes the transfer of knowledge between organizations in general and is not limited to academia–industry transfer (Bozeman, 2000). The commercialization of academic knowledge overlaps with academic engagement and KTT as it addresses formal modes of engagement. Yet, it expands academic engagement by including the establishment of new firms in the form of spin-offs (Perkmann et al., 2013, Grimaldi et al., 2011). In contrast to KTT, the commercialization of academic knowledge focuses on the transfer of knowledge between academia and industry. Furthermore, this dissertation focuses on commercial activities in the direction from research to industry. However, it should be noted that this process is always also a bilateral exchange of knowledge and information.

Figure 2: *Key actors and relations of the commercialization of academic knowledge from research to industry (based on Rothaermel et al., 2007)*



University entrepreneurship refers to "entrepreneurial activities in which a university could be involved, including, but not limited to patenting, licensing, [and] creating new firms […]" (Rothaermel et al., 2007, p. 692). Like the terms entrepreneurial university and third mission, university entrepreneurship solely focuses on universities. These terms are too limited for the scope of this dissertation, as it aims to integrate the activities of PROs.

1.1.3 Commercialization channels

As indicated previously, the commercialization of academic knowledge occurs through various commercialization channels. Figure 3 provides an overview of the commercialization channels and their definitions. These channels differ in the following aspects: various characteristics of the transfer object (tacit vs. explicit knowledge, technology readiness level [TRL],[4] and knowledge finalization) and transfer recipient, relationship formalization, necessary relational intensity between sender and

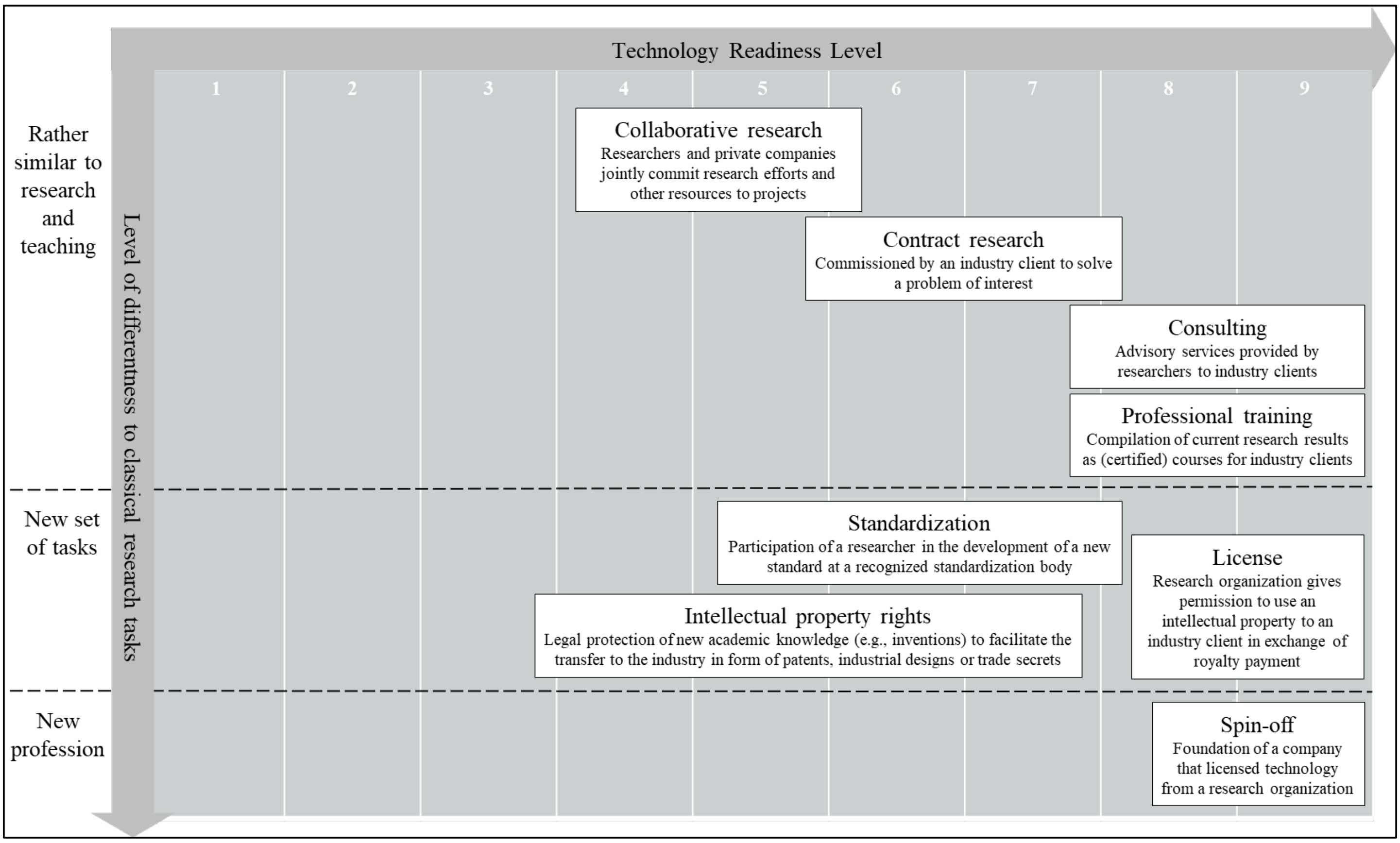
[4] Scale from 1-9 developed by the NASA: TRL1-Basic principles observed and reported, TRL2-Technology concept and/or application formulated, TRL3- Analytical and experimental critical function and/or characteristic proof-of-concept, TRL4-Component and/or breadboard validation in laboratory environment, TRL5-Component and/or breadboard validation in relevant environment, TRL6-System/subsystem model or prototype demonstration in a relevant environment (ground or space), TRL7-System prototype demonstration in space environment, TRL8-Actual system completed and „flight qualified" through test and demonstration (ground or space), TRL9-Actual system „flight proven" through successful mission operations (NASA, 2021).

recipient, motivation for faculty or researcher (e.g., high income potential or open access), complexity of the transfer process, and significance for industry (OECD, 2013; Bozeman et al., 2015; Rothaermel et al., 2007). Figure 3 differentiates the commercialization channels according to two dimensions. The first is the similarity of commercial tasks to classical research activities, which provides a first impression of the compatibility of research and commercial activities. The second dimension is the TRL, which indicates the required maturity of a research result for a certain commercialization channel (NASA, 2021).

From a researcher's perspective, it is crucial to understand the differences in channels to decide which are appropriate for commercializing knowledge and for allocating sufficient resources and skills. The skills required for collaborative research projects are highly similar to common research tasks. By contrast, patents require a new set of skills (e.g., how to write it) as well as legal advice. The creation of a spin-off goes beyond skill advancement as it represents a new profession – from scientist to entrepreneur. It should be noted that commercialization channels often complement each other or are conducted simultaneously. For example, IPRs are often seen as the "grammar" on which other channels are based. They may result in license agreements with an industry client or be used by researchers to start a business (OECD, 2013). In addition, IPR clauses in agreements also play a crucial role in collaborative projects (OECD, 2013). Standardization is another example of how commercialization channels relate to each other. Researchers build new industry relations and obtain new market insights while participating in standardization committees, which in turn can lead to follow-up collaborative or consulting projects (Blind et al., 2018).

Research organizations must understand the diversity, interplay, and impact of commercialization channels to align an appropriate transfer strategy. A research organization focused on basic research will prioritize other channels compared with an organization that specializes in applied research (see Figure 3, Moog et al., 2015, Sellenthin, 2009). Likewise, the scientific discipline determines to some degree the likelihood of certain channels. Natural and engineering sciences are prone to patenting, whereas social scientists rather start a business (Arvanitis et al., 2008). Consequently, the support infrastructure and incentivization differ depending on the prioritized commercialization channels. A university focused on spin-off creation would rather establish incubators and connect with the regional entrepreneurial ecosystem. By contrast, a research organization focused on patents would mainly set up a KTO in the form of a patent advisor and connect with patent attorneys.

***Figure 3:** Overview of commercialization channels*



Based on OECD (2013); Blind et al. (2018); Bozeman (2000); European Union (2021); Aguinis et al. (2021).

1.2 Benefits of commercialization of knowledge and technologies

Having defined what is meant by the commercialization of academic knowledge, I now move on to discussing its benefits for society, research organizations, scientists, and industry (see Figure 4).

Benefits of the commercialization of knowledge and technologies for society: The shift from an industrial economy to a knowledge economy during the last century increased society's expectations of research organizations. These expectations are reflected in descriptions of universities and PROs as "engines that contribute to the […] development of the regions" (Etzkowitz et al., 2000, p. 315), "key element[s] of the innovation system" (Compagnucci & Spigarelli, 2020, p.1), catalysts of economic growth, and seedbeds of new firms (Etzkowitz & Klofsten, 2005). According to the concepts of national and regional innovation systems, research organizations are producers of knowledge and technological advancements; through interactions with various (industry) actors, they circulate new technologies and enable an innovative industry (Lundvall, 1992; Gunasekara, 2006). Hence, a government that is interested in benefitting from its national competitiveness in industry will incentivize the transfer activities of research organizations. The examples of Sweden, the UK, and Austria demonstrate that governments influence the contributions of universities and PROs to the innovation system by aligning national funding streams (Trippl et al., 2015). Whereas the UK focuses on funding for the direct economic benefit of research organizations, Austria and Sweden employ a broader funding scope for the interorganizational interactions and community engagement of research organizations (Trippl et al., 2015).

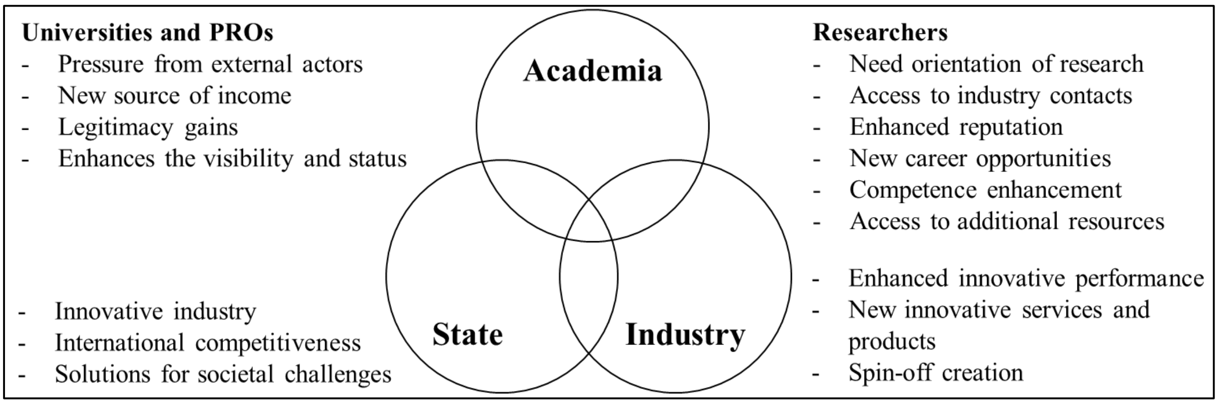
In addition, policy makers increasingly see the possibilities of using university–industry interactions to address economic, environmental, and societal challenges (Compagnucci & Spigarelli, 2020). Challenges such as global healthcare and affordable and clean energy require the joint efforts of multiple academic and industry partners (Purta-Sierra et al., 2021).

Benefits of the commercialization of knowledge and technologies for industry: With increased global competition, private companies are forced to continuously innovate their products and services to survive. This urges them to widen their knowledge base by sourcing cutting-edge external knowledge. Following the "open innovation" paradigm, firms open their innovation process (i.e., they involve internal as well as external ideas and R&D) to handle the challenges of the 21st century (Chesbourgh, 2003). Thus, firms that invest in co-operative R&D alliances with research organizations enhance their innovation performance. This has been proven in Germany, for example, where small and medium-sized enterprises (SMEs) that cooperate with the German PRO Fraunhofer-Gesellschaft are among the most innovation-active companies in the German SME sector (Dornbusch et al., 2016). Through a literature review, Piva and Rossi-Lamastra (2013) collected the following six reasons that private companies benefit from university–industry interactions: (1) access to basic knowledge; (2) improved problem-solving abilities; (3) access to new tools and techniques for the development of new technologies; (4) improved firm reputation; (5) access to the academic network; and (6) exploitation of opportunities for public funding. Hence, universities and PROs have become crucial strategic partners for firms (Perkmann et al., 2011). Yet, universities and PROs do not only support the innovativeness of existing firms; they also "build" new firms in the form of spin-offs.

Benefits of the commercialization of knowledge and technologies for universities and PROs: Over the last decades, research organizations have experienced various changes that pressured them to enhance their commercial activities. On the one hand, they experienced a structural decrease in basic public funding. Simultaneously, the competition for public funding has increased. Thus, universities and PROs have started to search for new funding sources. In particular, entrepreneurial activities are often undertaken with the objective of gaining a financial advantage for universities and faculties (Grimaldi et al., 2011). On the other hand, universities are expected to maximize their "social return on public investment," and thus, experience a greater pressure for greater accountability and transparency. Besides the external pressures, research organizations have realized the benefits that accompany the commercialization of academic knowledge. Universities gain legitimacy if they can demonstrate their impact on the local industry and community at large (Berghäuser, 2019). In addition, universities may attract more students and employees because of the enhanced visibility and status.

Benefits of the commercialization of knowledge and technologies for researchers: Researchers engage in the commercialization of academic knowledge for a multitude of reasons. Lam (2011) analyzed the motives of scientists (ribbon – reputational/career rewards; puzzle – intrinsic satisfaction and achievement; and gold – personal financial gain) related to commercial engagement. She found that personal income (gold) as well as intellectual curiosity and the desire for knowledge application (puzzle) have significantly positive effects on the commercial engagement of scientists. By contrast, reputation (ribbon) is equally critical for scientists who do and do not engage in commercialization. Other motives for commercialization include the following: access to additional resources, such as funding and infrastructure (Arvanitis et al., 2008; D'Este & Perkmann, 2011; Huang, 2018; Sellenthin, 2009); autonomy, meaning the "desire for independence" (D'Este & Perkmann, 2011; Sellenthin, 2009; Teixeira, 2017); competence enhancement, meaning the advancement of research and access to new information (e.g., the industry's needs; Arvanitis et al., 2008; D'Este & Perkmann, 2011; Huang, 2018); access to industry contacts (Huang, 2018; Teixeira, 2017); and contributions to grand societal challenges (Suominen et al., 2021). Despite the extent to which motivation differs depending on the commercialization channel, scientists participate in standardization activities mainly for intrinsic motives (gold) and in patenting mainly for financial rewards (gold; Blind et al., 2018). Often studied motives for spin-off creation are autonomy and financial income (D'Este & Perkmann, 2011; Sellenthin, 2009; Teixeira, 2017).

Figure 4: *Benefits for actors of the triple helix innovation model (based on Etzkowitz & Leydesdorff, 2000)*



Thus far, this dissertation has argued that the commercialization of academic knowledge is a new task for research organizations, which has led to major changes in law and university practices. This new task has numerous benefits for state, industry, and academia. However, such commercialization of academic knowledge has also been demonstrated to entail several serious challenges, which are discussed in the next section.

1.3 Challenges of commercialization

Even though the commercialization of academic knowledge is seen as beneficial for various actors, research organizations often fail to successfully commercialize their knowledge and technologies. Evidence suggests that university spin-offs' growth is far behind that of other start-ups (Brown, 2016). This means that spin-offs start small – in terms of number of employees and turnover rate – and stay small. Moreover, their contributions to the local environment are rather small (Corsi & Prencipe, 2018; Brown, 2016). Although firms view co-operative projects with external partners as an effective innovation strategy, universities are not the most relevant strategic partners for firms by far (Benneworth et al., 2017). Studies have demonstrated that the most relevant partners for firms are customers and suppliers (Miozzo et al., 2016; Fitjar & Rodríguez-Pose, 2013). Just some of the many reasons that firms report cooperation with universities and PROs to be problematic are as follows: different organizational cultures and incentive systems, different time horizons, a lack of information on available services and their benefits, high costs of academic research, as well as TRLs that are too low (e.g., results of basic research; Piva & Rossi-Lamastra, 2013; Dornbusch et al., 2016). In addition, most academic patents are never licensed; for example, the Netval Survey revealed that only 14% of all patents of over 60 Italian universities are licensed (Netval, 2021).

Within the commercial paradigm, "idle discoveries" are seen as "underutilized opportunities," and these issues broadly fall into two categories of failure: (1) research organizations and their scientists' miss the opportunity to exploit the full potential of academic knowledge, or even completely overlook the commercial potential; or (2) actors in research organizations conduct commercialization unsuccessfully, and therefore, an invention fails to become an innovation successfully introduced in the market. While failure is occasionally "part of the game," systematic failure is problematic.

Even worse, researchers can engage in commercialization only as a symbolic gesture, or even refuse to engage in commercial activities at all. Researchers oppose commercial activities for various reasons, including a hindering attitude toward KTT (e.g., considering it a threat to intellectual freedom; Arvanitis et al., 2008; Merchán-Hernández et al., 2015; Olaya Escobar et al., 2017); a lack of awareness of industry opportunities (Garcia et al., 2019; Govindaraju et al., 2009); excessive bureaucracy (Garcia et al., 2019; Huang et al., 2011); a lack of resources (financial, time, staff, and infrastructure; Blind et al., 2018; Swamidass & Vulasa, 2009); differences in motivation, attitudes, and interests between researchers and industry (Arvanitis et al., 2008; Garcia et al., 2019); as well as obstacles to publication due to commercialization in particular patenting (Blind et al., 2018; Cunningham & Link, 2015). Furthermore, professors are typically given substantial autonomy and authority over their work, and they are driven by Mertonian norms that foster the open dissemination of academic knowledge instead of direct commercial activity (Caruth & Caruth, 2013; Lam, 2011; Powell & Owen-Smith, 1998). Consequently, professors are more prone to considering commercialization as "an additional burden" or "nice to have" rather than as essential. Thus, convincing them to engage in commercial activities can be difficult (Benneworth et al., 2017; Caruth & Caruth, 2013).

Together, these problems represent crucial management challenges for research organizations. The governance of universities and PROs must provide the right incentives, resources, and infrastructure to motivate researchers and enable successful commercialization; as Benneworth et al. (2017) stated, "universities' specific organizational contexts as both structures and institutions (formal and informal rules) shape how university actors can exercise institutional entrepreneurship to improve their contribution to collective activities seeking to facilitate regional development and innovation" (p. 245). The following sections provide a more detailed account of how this issue relates to organizational change and the need for insights regarding organizational behavior and human resource management (OBHRM).

1.4 The need for behavioral insights

Gibbons (1998) stated that the commercialization of academic knowledge requires a substantial reorganization of universities. Thus, the introduction and pursuit of commercial activities represent a major organizational change process for research organizations (Bercovitz & Feldman, 2008). Successful changing research organizations toward commercialization depends on the willingness of the individuals involved (i.e., scientists and KTO personnel) to adopt behaviors, beliefs, and routines (Whelan-Berry et al., 2003). In the same vein, Choi (2011) found that "change efforts [in organizations] fail because change leaders often underestimate the central role individuals play in the change process" (p. 480). To activate scientists to commercialize their knowledge and technologies, an understanding is required of the extent and nature of scientists' mindset and behavior (OECD, 2012) as well as how organizational contexts shape their decision making and commercial behavior (Nelson, 2014). Thus, research on the commercialization of academic knowledge would benefit from insights into OBHRM. This is supported by previous research, which claimed that a solid micro-foundation of the individual behavior is required to coherently explain the factors that influence knowledge transfer (Broekel, 2006) and to offer valuable insights for improved policymaking (OECD, 2012). More recently, Balven et al. (2018) called for more research on the micro-processes of academic entrepreneurship (i.e., the human dimension of academic entrepreneurship). Similarly, Hmieleski and Powell (2018) demanded that future researchers should focus on the behaviors of individual academic scientists and how their organizational context shapes the overall success of commercial activities.

Nevertheless, the literature reveals very little about the individual characteristics and organizational processes that enable and increase the commercialization of academic knowledge; in turn, this leads to high uncertainty for decision makers in policy and research organizations in terms of sufficient commercial support (OECD, 2012; Bercovitz & Feldman, 2008). Thus far, research has focused on macro-level ideas regarding institutions and public policy, ignoring micro-level processes; specifically, research has focused on transfer outcomes rather than commercial behavior (Balven et al., 2018; Teixeira & Mota, 2012). For example, there has been increasing interest in intermediary organizations, such as KTOs and incubators (Villani et al., 2017; Siegel et al., 2003). Furthermore, researchers have highlighted the role of research organizations in (eco)systems (Skute et al., 2019; Gunasekara, 2006; Hayter, 2016) and studied the proximity and complementarity of academic–industry partners (Skute et al., 2019; Piva & Rossi-Lamastra, 2013).

Compared with studies on macro-level topics, only a relatively small body of literature has applied insights from OBHRM to better understand the commercial activities of research organizations and their scientists. Mainly, three OBHRM issues are currently addressed: the motivation of scientists (especially in the context on spin-off creation), rewards and incentives, and personality and individual differences (e.g., Lam, 2011; Lam, 2010; Arvanitis et al., 2008; D'Este & Perkmann, 2011; Huang, 2018; Sellenthin, 2009; Teixeira, 2017; see also the review of Skute et al., 2019). However, the insights offered by these studies have been severely lacking. First, most studies have examined either only single commercialization channels, such as licensing or collaboration (e.g., Abramo et al., 2011; Drivas et al., 2016), or treated all commercialization channels as one (e.g., Lam, 2011; Arvanitis et al., 2008). These studies have failed to consider how scientists' various motives are reflected by differences in commercial activities. Moreover, only very few studies have provided an integrative analysis on individual motives and the resulting preferences in commercial activities (D'Este & Perkmann, 2011; Blind et al., 2018; Arvanitis et al., 2008). Second, research explaining commercialization with the help of OBHRM has focused overwhelmingly on spin-off creation (i.e., the behavior of entrepreneurs and patenting; see Chapter 2). Third, individuals involved in commercialization other than scientists, such as KTO personnel and administrative staff, have been entirely neglected by previous studies. Fourth, most studies have focused on scientists in universities and ignored the specific contexts of other types of research organizations, such as federal labs and research and technology organizations (see Chapter 2). Finally, commercial behavior may be influenced by more than just motives, incentives, and personal interests. Thus, other OBHRM insights could also be of interest, such as career management or decision-making. According to the taxonomy of the Academy of Management Perspectives (AMP), OBHRM embraces 37 topics (see Table 2), which leads to the assumption that numerous white spots exist.

This dissertation addresses these gaps in its four chapters by applying insights from OBHRM to the topic of the commercialization of academic knowledge. The insights include the career management of serial patentees, motivation in hybrid contexts, and the decision making of individuals characterized by bounded rationality. Thus, I aim to expand and deepen the understanding of the behavior of individuals involved in the commercialization of academic knowledge, enabling practitioners to design organizational contexts and organizational infrastructures that foster commercial activities. Therefore, I empirically investigate the following research sub-questions:

(1) Which individual and organizational determinants have been proven to increase or decrease the commercialization of academic knowledge in research organizations?

(2) What causes one-time patentees to continue patenting and become serial patentees?

(3) Can a supervised learning approach, based on cooperation data, support decision making in industry partner selection?

(4) How do successful university KTOs enable the intrinsic motivation of their employees by satisfying their three psychological needs?

Table 2: *AMP's 37-category taxonomy of OBHRM topics (based on Aguinis et al., 2021)*

career development	citizenship behavior	coaching and development	conflict management
conflict styles	creativity	decision-making	deviance/counter-productive behavior
diversity and inclusion	empowerment	impression management	international human resource management
interpersonal communication	interpersonal trust	job designs, roles, and tasks	justice/fairness
labor relations	leadership	mood and emotions	motivation
negotiation	occupations, profession, and work	perception and attribution	performance management
personality and individual differences	person-situation fit	planning and succession	retention and separation
rewards and incentives	satisfaction and commitment	selection, staffing, and recruiting	spirituality and religion
strategic human resource management	stress and well-being	training and development	turnover, absenteeism, and withdrawal
work and family			

= topics that were already of interest within KTT literature; thick frame = topics of interest for this thesis.

1.5 Research objectives

As described in the previous section, research on the commercialization of academic knowledge would benefit from insights into OBHRM. This is because it would allow decision-makers and practitioners to design organizational contexts based on a profound understanding of the individuals involved in commercialization. This dissertation takes up this issue in the following chapters, examining the topic from four different angles.

Chapter 2 starts by consolidating and analyzing previous quantitative studies to identify and evaluate the determinants currently known to contribute to increased or decresed commercialization in research organizations. My co-authors and I address the difficulties in identifying relevant determinants due to the vastly growing number of academic studies on commercialization – characterized by fragmented and controversial findings. We argue that this oversight is a fundamental conceptual flaw. With the meta-analysis, we hope to help practitioners in KTOs, research organizations, and politics to make better decisions based on empirical evidence. We analyzed 99 published empirical studies, including 48 studies that have reported correlation data. We found a total of 97 determinants and categorized them into the following classes: (1) commercialization channels, namely patents, spin-offs, consulting services, licensing, contract research, and collaboration, which have correspondingly different characteristics, and (2) thematic classes of determinants, namely environmental, individual, institutional, organization, and technological.

The meta-analysis revealed that patenting, besides spin-off creation, is the most studied commercialization channel. Yet, while a vast amount of research has focused on the differences between inventors and non-inventors as well as the patent productivity of research organizations, we still lack an understanding of why some inventors continue patenting, while others stop after their first patent. Chapter 3 enlarges the existing discussion about academic patenting by targeting the phenomenon of serial patentees. It differentiates between one-time patentees and serial patentees and examines how certain factors differ regarding the timing of patent experiences; thus, it considers that the perception and motivation to patent can change over time. The study was based on employee data of a German research institute for applied science, patent data from Patstat, and publication data from Scopus. A survival analysis for recurrent event data was conducted to analyze the influence of the kind and timing of prior patent experiences on becoming a serial patentee. The results indicated that becoming a serial patentee is an active choice rather than a simple organizational duty.

Similar to Chapter 3, Chapter 4 also contributes to an enhanced understanding of how to support scientists' commercial activities. Finding new industry partners poses a challenge to many scientists in PROs. According to bounded rationality, scientists looking for industry partners deal only with a biased set of information, since the search for complete information is costly and time consuming. Thus, partner selection is often limited to existing networks, which carries the risk of finding no or poorly fitting industry partners. Therefore, we asked, "Can a supervised learning approach, based on cooperation data, support decision making in industry partner selection?" Thus, Chapter 4 explores how statistical classification can support partner selection with the example of the Fraunhofer-Gesellschaft in Germany. We used internal cooperation data and feature sets based on unstructured data, (i.e., text and industry codes), both of which describe firm's business activities. The chapter reports the performance of various classification techniques, such as logistic regression, support vector machines, and random forests in our dataset for diverse combinations of feature sets. Overall, our results demonstrated that the performance of most classifiers is high enough to support the decision process of finding new industry partners for public research.

Having discussed two specific issues of scientists' commercial behavior, Chapter 5 investigates KTO employees as another relevant group of individuals involved in commercialization. The meta-analysis revealed that many studies focus on the motives of scientists to engage in various commercial activities. Surprisingly, motivational aspects of KTO employees have been ignored thus far. Even though KTOs have become key actors in the commercialization of academic knowledge, KTO performance has mainly been addressed at the macro level of variables; insufficient attention has been paid to the effect that micro and behavioral dynamics have. By analyzing four Italian KTOs, chapter 5 aimed to obtain an enhanced understanding of the motivational aspects of KTO employees, with a particular focus on the antecedents of such motivation. Building on self-determination theory (SDT; Deci and Ryan, 2004), we linked the three basic psychological needs (relatedness, competence, and autonomy) that explain the intrinsic motivation of KTO employees to specific university-level institutional and KTO-level antecedents. We demonstrated that university management plays a key role in satisfying the need for autonomy among KTO personnel, while KTO organizational antecedents are more relevant in addressing the need for competence and relatedness. Table 3 presents an overview of the following four chapters, including the research questions, research approach, and main findings.

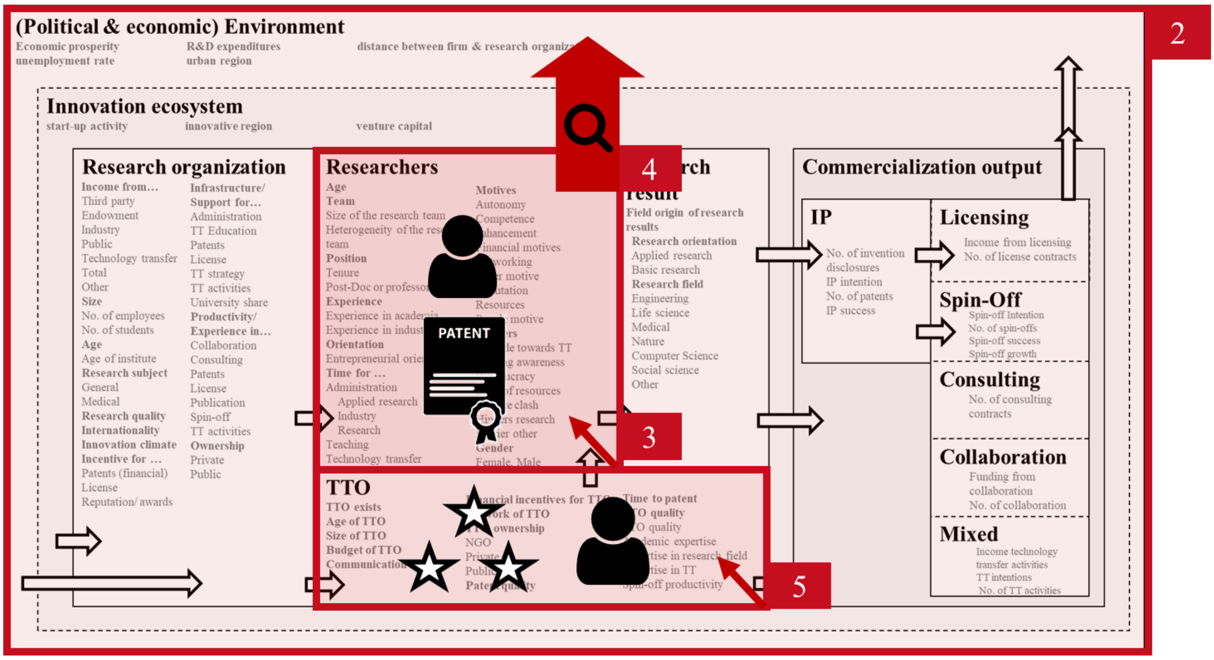
Table 3: *Overview of the research objectives*

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Title	Determinants of the commercialization of academic knowledge – A review of determinants and meta-analysis	How to become a serial patentee - A patent behavior analysis	How to Find New Industry Partners for Public Research: A Classification Approach	Personnel motivation in knowledge transfer offices: The role of university-level and organizational-level antecedents
Co-authors	Friedrich Dornbusch Knut Blind	-	Karl Trela Yuri Campbell Friedrich Dornbusch	Elisa Villani Rosa Grimaldi
Research aim(s)/ question(s)	• Increase the understanding of the construct of the "commercialization of academic knowledge" • Identify and categorize determinants • Perform a quantitative evaluation of the determinants	What causes one-time patentees to continue patenting and become serial patentees?	Can a supervised learning approach, based on cooperation data, support partner selection in public research? Is a combination of quantitative and qualitative information useful for supporting partner selection in public research?	How do contextual factors enable KTOs' employees to reach intrinsic motivation in a work context where satisfaction may be threatened?
Research approach and methodology & data	Review of determinants and meta-analysis (vote counting; effect size analysis) based on 99 published peer-reviewed research articles	Survival analysis for recurrent data, based on employee, patent, and publication data	Data-driven approach to support partner selection based on data from the Fraunhofer Gesellschaft, a company database, and data on public funding	Empirical case study (qualitative) based on four TTO cases with a total of 18 interviews
Data collection period	1980–2020	1990–2020	2012–2018	2020–2021
Contributions and main findings for theory	Offers a new comprehensive framework for studying determinants of commercialization and derives research gaps	Provides insights into the importance of the kind and timing of prior patent experiences; that is, a successful first patent experience and overall team size increases the likelihood of becoming a serial patentee	Provides evidence that a supervised learning approach is feasible for supporting industry-partner selection and highlights the importance of the combination of quantitative and qualitative information	Offers new insights on the micro processes of KTOs and develops a new framework for how university- and organizational-level antecedents enable the intrinsic motivation of KTO employees
Contributions and main findings for practitioners	Enables practitioners to better select and prioritize measures to foster their commercial activities	Helps university governments and KTO employees to develop better-fitting support infrastructures based on the previous experiences of scientists	Results were implemented in SME-Match, a web-applications for scientists in the Fraunhofer-Gesellschaft who are looking for new SME partners in Germany	Enables university governments and KTO managers to enable KTOs' employees to reach intrinsic motivation, in turn helping to increase the productivity of KTOs

1.6 Dissertation overview

The remainder of this dissertation proceeds as follows: Chapter 2 aims to expand the scientific understanding of the “commercialization of academic knowledge” through presenting a review of determinants and a meta-analysis; specifically, it consolidates and analyzes previous studies from a quantitative perspective. It ends by providing a comprehentive framework for studying the determinants of commercialization at research organizations. This chapter, co-authored by Friedrich Dornbusch and Knut Blind, has been submitted to a journal for publication. After providing this comprehensive overview of quantitative research on the commercialization of academic knowledge, I “zoom in” on two specific issues of scientists’ commercial behavior. Chapter 3 uses insights from academic patenting to investigate why some scientists continue to patent while others stop quickly. A logit regression is presented based on patent, publication, and employee data. This chapter describes a single-author study and has been submitted to a journal for publication. Chapter 4 examines how scientists’ ability to select fitting industry partners can be supported by testing a supervised learning approach based on cooperation data of the Fraunhofer-Gesellschaft. This chapter was co-authored by Karl Trela, Yuri Campbell, and Friedrich Dornbusch, and it has been published in *IEEE Transactions on Engineering Management*. Chapter 5 goes beyond scientists as study objects by focusing on another group of individuals involved in commercialization, namely KTO employees. Thus, it analyses which university- and KTO-level antecedents enable KTO employees to satisfy their three basic needs by using a multiple case study methodology. This chapter presents joint work conducted with Elisa Villani and Rosa Grimaldi. It has been published in *Technological Forecasting and Social Change*. Finally, Chapter 6 discusses the contribution of the dissertation and provides the limitations and future research ideas. Figure 5 illustrates the structure and relations of the following four chapters:

Figure 5: *Graphical overview of the chapters of this dissertation*



1.7 References

Abramo, G., D’Angelo, C. A., & Di Costa, F. (2011). University-industry research collaboration: a model to assess university capability. Higher Education, 62(2), 163-181.

Aguinis, H., Jensen, S. H., & Kraus, S. (2021). Policy implications of organizational behavior and human resource management research. Academy of Management Perspectives, (ja).

Arvanitis, S., Kubli, U., & Woerter, M. (2008). University-industry knowledge and technology transfer in Switzerland: What university scientists think about co-operation with private enterprises. Research Policy, 37(10), 1865-1883.

AUTM. (n.d.). Working in global membership - autm.net. Retrieved March 15, 2022, from https://www.autm.net/AUTMMain/media/Resources/Documents/AUTM_Tech_Transfer_Resources.pdf

AUTM (2000). Surveys – Bayh-Dole Act, Association of University Technology Managers, Retrieved May, 2002, from www. autm.net

Bagley, C. E., & Tvarno, C. D. (2015). Promoting Academic Entrepreneurship in Europe and the United States: Creating an Intellectual Property Regime to Facilitate the Efficient Transfer of Knowledge from the Lab to the Patient. Duke J. Comp. & Int'l L., 26, 1.

Balven, R., Fenters, V., Siegel, D. S., & Waldman, D. (2018). Academic entrepreneurship: The roles of identity, motivation, championing, education, work-life balance, and organizational justice. Academy of Management Perspectives, 32(1), 21-42.

Benneworth, P., Pinheiro, R., & Karlsen, J. (2017). Strategic agency and institutional change: Investigating the role of universities in regional innovation systems (RISs). Regional studies, 51(2), 235-248.

Bercovitz, J., & Feldman, M. (2008). Academic entrepreneurs: Organizational change at the individual level. Organization science, 19(1), 69-89.

Blind, K., Pohlisch, J., & Zi, A. (2018). Publishing, patenting, and standardization: Motives and barriers of scientists. Research Policy, 47(7), 1185-1197.

BMWI. (n.d.). Startseite. EXIST. Retrieved March 15, 2022, from https://www.exist.de/EXIST/Navigation/DE/Home/home.html

Bozeman, B. (2000). Technology transfer and public policy: a review of research and theory. Research policy, 29(4-5), 627-655.

Bozeman, B., Rimes, H., & Youtie, J. (2015). The evolving state-of-the-art in technology transfer research: Revisiting the contingent effectiveness model. Research Policy, 44(1), 34-49.

Broekel, T., & Binder, M. (2007). The regional dimension of knowledge transfers—a behavioral approach. Industry and Innovation, 14(2), 151-175.

Brown, R. (2016). Mission impossible? Entrepreneurial universities and peripheral regional innovation systems. Industry and innovation, 23(2), 189-205.

Caruth, G. D., & Caruth, D. L. (2013). NOTE FOR EDITOR: Understanding Resistance To Change: A Challenge For Universities. Turkish Online Journal of Distance Education, 14(2), 12-21.

Chesbrough, H. W. (2003). The era of open innovation. Managing innovation and change, 127(3), 34-41.

Choi, M. (2011). Employees' attitudes toward organizational change: A literature review. Human resource management, 50(4), 479-500.

Corsi, C., & Prencipe, A. (2018). The contribution of university spin-offs to the competitive advantage of regions. Journal of the Knowledge Economy, 9(2), 473-499.

Compagnucci, L., & Spigarelli, F. (2020). The Third Mission of the university: A systematic literature review on potentials and constraints. Technological Forecasting and Social Change, 161, 120284.

Cunningham, J. A., & Link, A. N. (2015). Fostering university-industry R&D collaborations in European Union countries. International Entrepreneurship and Management Journal, 11(4), 849-860.

D'Este, P., & Perkmann, M. (2011). Why do academics engage with industry? The entrepreneurial university and individual motivations.The Journal of Technology Transfer,36(3), 316-339.

Deci, E. L., & Ryan, R. M. (Eds.). (2004). Handbook of self-determination research. University Rochester Press.

Decter, M. H. (2009). Comparative review of UK-USA industry-university relationships. Education+ Training.

Dornbusch, F., Lehmann, H., Pohle, A., Radic, M. (2016). Die Bedeutung der Fraunhofer-Gesellschaft für den deutschen Mittelstand. Eine Bestandsaufnahme und Empfehlungen zur Intensivierung der Zusammenarbeit. Fraunhofer IMW. Leipzig.

Drivas, K., Economidou, C., Karamanis, D., & Zank, A. (2016). Academic patents and technology transfer. Journal of engineering and technology management, 40, 45-63.

ERP-European Research Council. (2021, November 17). Proof of concept. ERC. Retrieved March 15, 2022, from https://erc.europa.eu/funding/proof-concept

Etzkowitz, H., Webster, A., Gebhardt, C., & Terra, B. R. C. (2000). The future of the university and the university of the future: evolution of ivory tower to entrepreneurial paradigm. Research policy, 29(2), 313-330.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university–industry–government relations. Research policy, 29(2), 109-123.

Etzkowitz, H., & Klofsten, M. (2005). The innovating region: toward a theory of knowledge-based regional development. R&D Management, 35(3), 243-255.

European Union. (2021, October 21). Licensing and selling intellectual property in the EU. Your Europe. Retrieved March 31, 2022, from https://europa.eu/youreurope/business/running-business/intellectual-property/licensing-selling/index_en.htm

Fitjar, R. D., & Rodríguez-Pose, A. (2013). Firm collaboration and modes of innovation in Norway. Research policy, 42(1), 128-138.

Garcia, R., Araújo, V., Mascarini, S., Santos, E. G., & Costa, A. R. (2019). How the benefits, results and barriers of collaboration affect university engagement with industry. Science and Public Policy, 46(3), 347-357.

Gibbons, M. (1998). Higher education relevance in the 21st century. Good, M., Knockaert, M., Soppe, B., & Wright, M. (2019). The technology transfer ecosystem in academia. An organizational design perspective. Technovation, 82, 35-50.

Good, M., Knockaert, M., & Soppe, B. (2020). A typology of technology transfer ecosystems: how structure affects interactions at the science–market divide. The Journal of Technology Transfer, 45(5), 1405-1431.

Govindaraju, V. C., Ghapar, F. A., & Pandiyan, V. (2009). The role of collaboration, market and intellectual property rights awareness in university technology commercialization.International Journal of Innovation and Technology Management,6(04), 363-378.

Grimaldi, R., Kenney, M., Siegel, D. S., & Wright, M. (2011). 30 years after Bayh–Dole: Reassessing academic entrepreneurship. Research policy, 40(8), 1045-1057.

Gunasekara, C. (2006). Reframing the role of universities in the development of regional innovation systems. The Journal of technology transfer, 31(1), 101-113.

Hayter, C. S. (2016). A trajectory of early-stage spinoff success: the role of knowledge intermediaries within an entrepreneurial university ecosystem. Small Business Economics, 47(3), 633-656.

Henke, J., Pasternack, P., & Schmid, S. (2016). Third Mission von Hochschulen. Eine Definition. Das Hochschulwesen, 64(1/2), 16-22.

Huang, C. Y. (2018). How background, motivation, and the cooperation tie of faculty members affect their university–industry collaboration outputs: an empirical study based on Taiwan higher education environment. Asia Pacific Education Review, 19(3), 413-431.

Huang, W. L., Feeney, M. K., & Welch, E. W. (2011). Organizational and individual determinants of patent production of academic scientists and engineers in the United States. Science and Public Policy, 38(6), 463-479.

Innovation Fund Denmark. (n.d.). Innoexplorer. Innovationsfonden. Retrieved March 15, 2022, from https://innovationsfonden.dk/en/programmes/innoexplorer

Jacob, M., Lundqvist, M., & Hellsmark, H. (2003). Entrepreneurial transformations in the Swedish University system: the case of Chalmers University of Technology. Research policy, 32(9), 1555-1568.

Kratzer, J., Haase, H., & Lautenschläger, A. (2010). Benchmarking deutscher Transferstellen: Transferpotenzial, Transferkapazitäten, Transferaktivitäten im deutschlandweiten Vergleich; Bericht 2009/2010.

Lam, A. (2010). From 'ivory tower traditionalists' to 'entrepreneurial scientists'? Academic scientists in fuzzy university—industry boundaries. Social studies of science, 40(2), 307-340.

Lam, A. (2011). What motivates academic scientists to engage in research commercialization:'Gold','ribbon'or 'puzzle'?.Research policy, 40(10), 1354-1368.

Lundvall, Bengt-Åke (1992): National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning. London: Pinter Publishers.

Markman, G. D., Siegel, D. S., & Wright, M. (2008). Research and technology commercialization. Journal of Management Studies, 45(8), 1401-1423.

Merchán-Hernández, C., Valmaseda-Andia, O., & Fernández-Esquinas, M. (2015). The challenges of connecting science–industry in peripheral regions: researchers' attitudes and organizational and institutional features as determinants. European Planning Studies, 23(12), 2600-2620.

Miozzo, M., Desyllas, P., Lee, H. F., & Miles, I. (2016). Innovation collaboration and appropriability by knowledge-intensive business services firms. Research Policy, 45(7), 1337-1351.

Moog, P., Werner, A., Houweling, S., & Backes-Gellner, U. (2015). The impact of skills, working time allocation and peer effects on the entrepreneurial intentions of scientists. The Journal of Technology Transfer, 40(3), 493-511.

Mowery, David C.; Sampat, Bhaven N. (2005): Universities in National Innovation Systems. In: Jan Fagerberg, David C. Mowery und Richard D. Nelson (Hg.): The Oxford Handbook of Innovation. Oxford: Oxford University Press, S.209-239.

NASA (2021). https://www.nasa.gov/sites/default/files/trl.png (last access: 04.03.2022)

Netval - Network per la Valorizzazione della Ricerca. (2021). 17° RAPPORTO NETVAL Investire sulla valorizzazione della ricerca per una resilienza generativa. Pavia, Italy. Retrieved April 20, 2022, from https://netval.it/area-documenti-rapporti/.

OECD. Publishing. (2014). Commercialising public research: New trends and strategies. OECD publishing.

Olaya Escobar, E. S., Berbegal-Mirabent, J., Alegre, I., & Duarte Velasco, O. G. (2017). Researchers' willingness to engage in knowledge and technology transfer activities: an exploration of the underlying motivations. R&D Management, 47(5), 715-726.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'este, P., Fini, R., Geunael, A., Grimaldi, R., Hughesm, H., Krabelh, S., Kitsong, M., Llerenai, P., Lissonij, F., Saltera, S. & Sobrero, M. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. Research policy, 42(2), 423-442.

Piva, E., & Rossi-Lamastra, C. (2013). Systems of indicators to evaluate the performance of university-industry alliances: a review of the literature and directions for future research. Measuring Business Excellence.

Ponomariov, B., & Boardman, C. (2012). Organizational behavior and human resources management for public to private knowledge transfer: An analytic review of the literature.

Powell, W. W., & Owen-Smith, J. (1998). Universities and the market for intellectual property in the life sciences. Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management, 17(2), 253-277.

Puerta-Sierra, L., Montalvo, C., & Angeles, A. (2021). University-industry collective actions framework: societal challenges, entrepreneurial interactions and outcomes. Technology Analysis & Strategic Management, 33(12), 1377-1388.

Roessner, J. D. (2000). Technology transfer. Science and technology policy in the US. A time of change.

Rothaermel, F. T., Agung, S. D., & Jiang, L. (2007). University entrepreneurship: a taxonomy of the literature. Industrial and corporate change, 16(4), 691-791.

Salter, A., D'Este, P., Pavitt, K., Scott, A., Martin, B., Geuna, A., Nightingale, P. and Patel, P. (2000), Talent, Not Technology: The Impact of Publicly Funded Research on Innovation inthe UK, Science Policy Research Unit, University of Sussex, Brighton.

Sellenthin, M. O. (2009). Technology transfer offices and university patenting in Sweden and Germany. The Journal of Technology Transfer, 34(6), 603-620.

Siegel, D. S., Waldman, D., & Link, A. (2003). Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: an exploratory study. Research policy, 32(1), 27-48.

Skute, I., Zalewska-Kurek, K., Hatak, I., & de Weerd-Nederhof, P. (2019). Mapping the field: a bibliometric analysis of the literature on university–industry collaborations. The journal of technology transfer, 44(3), 916-947.

Suominen, A., Kauppinen, H., & Hyytinen, K. (2021). 'Gold','Ribbon'or 'Puzzle': What motivates researchers to work in Research and Technology Organizations. Technological Forecasting and Social Change, 170, 120882.

Swamidass, P. M., & Vulasa, V. (2009). Why university inventions rarely produce income? Bottlenecks in university technology transfer. The Journal of Technology Transfer, 34(4), 343-363.

Szöllosi-Janse, Margit (2004): Wissensgesellschaft in Deutschland: Überlegungen zur Neubestimmung der deutschen Zeitgeschichte über Verwissenschaftlichungsprozesse. In: Geschichte und Gesellschaft 30 (2), S.277-313.

Teixeira, A. A., & Mota, L. (2012). A bibliometric portrait of the evolution, scientific roots and influence of the literature on university–industry links. Scientometrics, 93(3), 719-743.

Teixeira, A. A. (2017). The Economic Performance of Portuguese Academic Spin-Offs—Do Science & Technology Infrastructures and Support Matter?. In THE WORLD SCIENTIFIC REFERENCE ON ENTREPRENEURSHIP: Volume 4: Process Approach to Academic Entrepreneurship—Evidence from the Globe (pp. 281-308).

Trippl, M., Sinozic, T., & Lawton Smith, H. (2015). The role of universities in regional development: Conceptual models and policy institutions in the UK, Sweden and Austria. European Planning Studies, 23(9), 1722-1740.

Villani, E., Rasmussen, E., & Grimaldi, R. (2017). How intermediary organizations facilitate university–industry technology transfer: A proximity approach. Technological forecasting and social change, 114, 86-102

Whelan-Berry, K. S., Gordon, J. R., & Hinings, C. R. (2003). Strengthening organizational change processes: Recommendations and implications from a multilevel analysis. The Journal of Applied Behavioral Science, 39(2), 186-207.

Willey, T.F. (1999), Technology Transfer and Licensing Activities of ARCH Development Corporation and the Impact of Federal R&D Technology Transfer Programs on Universities and Small Business, Hearing on Federal R&D Technology Transfer Programs, US Senate Committee on Commerce, Science and Transportation, Washington, DC, 15 April.

2

2 Determinants of the commercialization of academic knowledge – A review of determinants and meta-analysis

Anna Pohle, Friedrich Dornbusch, Knut Blind

Abstract: Over the last two decades, research on the successful commercialization of academic knowledge has attracted immense attention from scholars. Yet this growing number of academic studies on this issue – characterized by fragmented and controversial findings – have reported difficulties in identifying the relevant determinants that increase the quality and quantity of scientists' commercial activities. In addition, most studies have ignored how different commercialization channels – i.e., patents, spin-offs, consulting services, licensing, contract research, and collaboration – have correspondingly different characteristics. We argue that this oversight is a fundamental conceptual flaw. Hence, this paper is an attempt to provide a comprehensive overview of relevant determinants by conducting a review of determinants and meta-analysis. In doing so, we hope to help decision-makers in technology transfer offices, research organizations, and politics to draw conclusive recommendations based on empirical evidence.

In total, we analyzed 99 published empirical studies; all of them provided data on significance, and 48 provided correlation data. We identified a total of 97 determinants and categorized them in five classes: environmental determinants, individual determinants, organizational determinants, technology transfer office related determinants, and field determinants. The findings show that an innovative climate, transfer expertise of technology transfer offices, and collaboration experience are significant determinants for spin-off creation across studies. In contrast, public funding, a background in natural science, and organization size all foster patenting. Finally, we propose a comprehensive framework to further study the determinants contributing to commercialization of academic knowledge and derive future research gaps.

Keywords: Knowledge and technology transfer, academic entrepreneurship, patenting, licensing, third mission

This essay is a preprint and has been submitted for publication in Technovation.

2.1 Introduction

"Which determinants increase or decrease the commercialization of academic knowledge of research organizations?" has become an increasingly relevant question for politicians, university governance, public research organizations (PROs), and technology transfer offices (TTOs). For politicians, it is important to know how they can foster vibrant conditions for innovation and commercialization at research organizations and how to best design research funding. University governance and PROs have been experiencing increasing pressure to transfer academic knowledge to the non-academic world (OECD 2013), so this question affects them in their role as "engine of innovation systems". The decision-makers in such research organizations need to know, e.g., how different scientific fields offer different commercial potential, and how to set up successful TTOs. TTOs in turn support the commercial activities of academic scientists by raising awareness among scientists regarding market demand, advising them on intellectual property issues, and building bridges between these scientists and potential industry partners (Villani et al., 2017). For this reason, TTO managers are particularly interested in determinants that are based on motives and barriers of scientists to design more appropriate support, like incentives and trainings (Lam 2011; Beyhan & Rickne 2015; Blind et al., 2018). The increasing number of publications on the commercialization of academic knowledge highlights the need to better understand determinants that influence successful commercialization (Hamilton & Philbin 2020).

However, the existing research on determinants offers a severe lack of insights. First, determinants are often only discussed in actor-specific terms. For example, Comacchio et al. (2012) examined commercialization with a focus on TTOs, while Hue Kyung et al. (2016) studied universities as a whole. Academic debate would benefit from more comprehensive insights, because in practice, these different actors work together towards a common goal to commercialize knowledge. A TTO that ignores the strategy of the university governance or that fails to understand the needs of its researchers will be less successful. Second, the majority of previous studies examined single commercialization channels, such as licensing or collaboration (e.g., Abramo et al., 2011; Drivas et al., 2016). These studies fail to consider the differences between commercial activities. Only very few studies have provided a comparison of various commercial activities (Crespi et al., 2011; D'Este & Perkmann 2011; Meusburger & Antonites 2016; Arvanitis et al., 2008). However, results from these studies have been contradictory. For example, Crespi et al. (2011) found a significant positive relationship between consultation activities (as a form of commercialization) and research from the natural sciences, whereas D'Este & Perkmann (2011) found a significant negative relationship. There may be many reasons for those contradictions, such as differences in study designs, different variable operationalization, and non-comparable samples (Song et al., 2008). As such, these different study designs represent another hurdle to obtaining a comprehensive understanding of the determinants that lead to the successful commercialization of knowledge.

In conclusion, efforts to integrate the results of previous studies, to reveal what consistent and validated evidence already exists, and to identify blind spots for further research will require a review of determinants and meta-analysis. Previous attempts to integrate earlier research in this field have mainly been conceptual, combining research findings in a qualitative manner without integrating statistical measures (for an overview of reviews, see Hamilton & Philbin 2020). There is still no summary of quantitative results. To the best of our knowledge, only Hamilton & Philbin (2020) conducted a meta-analysis concerning the commercialization of academic knowledge. However, their focus relied on four determinants (knowledge management, knowledge investment, knowledge infrastructure, and external investment) that influenced TTO performance, and failed to provide an overall picture of determinants for the commercialization of academic knowledge.

Therefore, there is still a need to identify which determinants lead to an increase or decrease in commercial activities in research organizations. To address this gap, we conducted a meta-analysis that firstly reviewed 99 studies to identify relevant determinants and secondly statistically tests whether those determinates prove to significantly influence researcher's commercialization activities (especially patenting and spin-off creation) based on a subset of 48 studies. The purpose of this study is to expand the understanding of the concept of "the commercialization of academic knowledge" by incorporating a quantitative analysis. This analysis advances the knowledge on determinants of commercial activities in research organizations by synthesizing existing quantitative results and subsequently deriving a future research agenda. Moreover, the results will help practitioners to better select and prioritize measures that will foster their commercial activities. In sum, we aim to make the following contributions to literature on the commercialization of academic knowledge:

(1) The paper analyses previous reviews and derivates a new comprehensive framework for studying the determinants of commercialization at research organizations.

(2) This study provides a classification of determinants impacting the commercialization of academic knowledge – along various commercialization channels:

    1. To this end, the paper first reviews and identifies the commercialization output indicators, that are influenced by the determinants, for five commercialization channels;
    2. Second, it identifies quantitatively studied determinants that affect the commercialization of academic knowledge;
    3. Third, it categorizes those determinants into five classes (environmental determinants, organization (research institute) determinants, technology transfer office related determinants, individual determinants (researchers), and determinants related to the field of discipline).

(3) This study conducts a meta-analysis for the commercialization channels patenting and spin-off creation to identify the determinants in which empirical evidence proves to be consistent and valid. Moreover, in contrast to those determinants that are found to be well researched and consistently affect commercialization, the paper also identifies those determinants where the empirical evidence and its discussion must still be considered ambiguous.

(4) Finally, this paper transfers the determinants of commercialization at research organizations to the new comprehensive framework. In light of the accumulated data in the comprehensive framework, the paper points out research gaps for future exploration. As such, one goal of this study is to pinpoint those fields of research where there is still too little conclusive empirical evidence to develop a profound understanding of the "commercialization of academic knowledge" as a concept.

The remaining part of the paper is structured as follows: the next section is concerned with the delimitation of the concept of "the commercialization of academic knowledge" and proposes a new theory-based framework to study the commercialization of academic knowledge. Section three begins by describing the data collection and explains the methodology used for this study. The findings of the analysis are highlighted in section four. The key themes addressed in the findings section are: an overview of the publications included, an introduction of commercialization output indicators, a presentation of the determinants identified, and an analysis of the summary effect sizes. Section five concludes by revealing gaps to be filled by future research. Finally, section six critically discusses the implications of our findings for theory and practitioners and considers the limitations of this study.

2.2 Literature on commercialization of academic knowledge

2.2.1 Definitions of key concepts

This study sets out to complement the research on the commercialization of academic knowledge by defining, identifying, and discussing relevant determinants. To begin with, it is necessary to define what is meant by "the commercialization of academic knowledge" on the one hand, and "determinants" on the other hand. First, this paper defines the commercialization of academic knowledge as "the exploitation of knowledge and technologies developed by academic scientists with the purpose of fulfilling an industry need and gaining industry income" (based on Grimaldi et al., 2011, Perkmann et al., 2013). This includes commercialization via patenting, licensing, contract research, collaborative research projects, consulting, and spin-off creation (Grimaldi et al., 2013, OECD, 2013).[5] As such, our definition integrates the rather similar and overlapping concepts of "university entrepreneurship" and "academic engagement" (e.g., Perkmann et al., 2013; Grimaldi et al., 2011; Rothaermel et al., 2007; D'Este & Perkmann, 2011; Hamilton & Philbin, 2020). This allows us to include a comprehensive set of studies that all deal with the commercialization of technology or knowledge (D'Este & Perkmann, 2011, Hamilton & Philbin, 2020) in which "an academic invention is exploited with the objective to reap financial rewards" (Perkmann et al., 2013, p. 424) and include "entrepreneurial activities in which a university could be involved, including, but not limited to: patenting, licensing, creating new firms" (Rothaermel et al., 2007, p. 692). Some studies have also discussed standardization as commercialization channels (see Blind et al., 2018). Nevertheless, we decided to exclude this channel, because even though standardization represents an important transfer channel, it usually lacks the criterion of "reaping financial rewards."[6] Second, we understand determinants as "characteristics, conditions, or variables that when properly sustained, maintained, or managed can have a significant impact on [the achievement success of a certain goal]" (based on the definition of critical success factors from Leidecker & Bruno, 1984, p. 23).

2.2.2 Insights from former reviews - the need for a comprehensive framework

A large volume of literature has discussed determinants for the commercialization of academic knowledge. In particular, previous conceptual studies and literature reviews have already provided substantial contributions to the understanding of mechanisms and determinants influencing the commercialization of knowledge and technology (Rothaermel et al, 2007; Kochenkova & Grimaldi, 2016).

However, this research has some shortcomings when it comes to a comprehensive understanding of the determinants that influence the commercialization of academic knowledge. Although the commercialization of academic knowledge occurs through a variety of channels, it is often treated as a single activity (e.g., Skute et al., 2018; Compagnuccia & Spigarelli, 2020; D'Este & Patel, 2007). This overlooks the fact that different commercialization channels may require different forms of support to be successful. This is complicated further by the variety of sub-forms of channels and their respective combinations. For example, a scientist can create a spin-off using different legal forms and either start alone or with an internal or external team. An example for a combination of channels are patents: a

[5] Since patenting serves as a relevant precondition for licensing and spin-off creation in particular, it is often discussed as an additional channel.

[6] The aim of a formal standardization process is the development of an industry standard to facilitate work. Therefore, gaining direct financial income through the participation in standardization is not intended. The only possibility to generate direct income are standard essential patents. However, this is a very restricted option which is rather rarely used.

research organization can sell a patent or license it to an external company or a spin-off. It is likely that different determinants are relevant for each commercialization channel, since the channels themselves are very different. For TTO managers and decision-makers in research organizations, it is crucial to understand which determinants influence which channel, and which synergies exist.

Furthermore, it is essential to understand which actor is affected by a certain determinant, or which actor is responsible for properly setting up, managing, and maintaining a certain determinant. Hamilton & Philbin (2020) named the following actors: faculty researchers, TTOs, and the knowledge infrastructure (consisting of research labs, medical schools, and incubators). In contrast, the review of Perkmann et al. (2013) differentiated among individual, organization, and institutional determinants; Rothaermel et al. (2007) discussed various relevant internal actors for new-firm creation, including the university governance, faculties, TTOs, founders and teams, as well as external ones (such as investors). However, none of those reviews provided a comprehensive overall framework for commercialization determinants. This means that a new comprehensive framework is needed to consilidate relevant actor-related areas and different commercialization channels, classify determinants, and to explain the interrelations across these aspects.

Hence, in Figure 6 we propose a new comprehensive framework for the commercialization of academic knowledge which integrates the insights of previous reviews. The framework is based on the categories that were derived by existing reviews in related research fields (see Table 4). The authors of these reviews used the categories to organize and to discuss their research results and develop own models. We synthesized these categories into seven components (category groups): (political & economical) environment, innovation ecosystem, research organization, researchers, research result, technology transfer office (TTO), and commercialization output (see Figure 6).[7] The political and economic environment includes local and national policies, cultural aspects, and the characteristics of a research organization's stakeholders (e.g., Rothaermel et al. 2007; OECD, 2013; Sandström et al., 2018). The innovation ecosystem is a part of the environment and encompasses stakeholders and activities related to the innovation process (Compagnucci & Spigarelli, 2020; Hayter et al., 2018; Skute et al., 2017). Most reviews highlighted the importance of research organizations and researchers and provide various sub-categories to discuss their findings (like Hossinger et al., 2019; Miranda et al., 2018; Perkmann et al., 2021; Sandström et al., 2018; Skute et al., 2017). The research organization is embedded in its local environment. The management of research organizations sets the strategy and provides resources, incentives, and organizational culture. Thereby, it influences its researchers which in turn conduct research and hold research results. Research results can be described by scientific, technical and market characteristics (e.g., Hayter et al, 2018). Moreover, research organizations support commercial behavior through different interventions and entities, like support programs, incubators, and knowledge and technology transfer offices; here summarized as TTOs (Compagnucci & Spigarelli, 2020; Hayter et al., 2018; Maresova et al., 2019). The framework shows that the researchers and TTOs transform the research results to the commercialization output through certain commercialization channels. Lastly, the innovation ecosystem and boarder environment benefit from the commercialization output (e.g., Perkmann et al., 2021; Bozeman et al., 2015). To identify the connections between the components, we draw on the reviews which developed own models (e.g., Bozeman et al.,2015; Maresova et al., 2019; OECD, 2013; Perkmann et al., 2021; Rothaermel et al., 2007; Santström et al., 2018).

In summary, this section showed that a comprehensive picture of definitions, measurements, and classification of determinants, by commercialization channel and actor and within different contexts is

[7] Figure 10 in the supplementary files shows graphically how the categories, that are mentioned in the reviews, relate to the framework.

missing n previous reviews. This lacuna has led to confounding empirical evidence, made it difficult to compare results, and hampered the systemic understanding of ways in which to improve the success of transfer and commercialization activities. In consequence, we have proposed a new framework to study the commercialization of academic knowledge. This new framework builds the base for the following analysis of the determinants of commercialization at research organizations and the derivation of future research gaps.

Table 4: Overview of former literature reviews in the field of commercialization of academic research

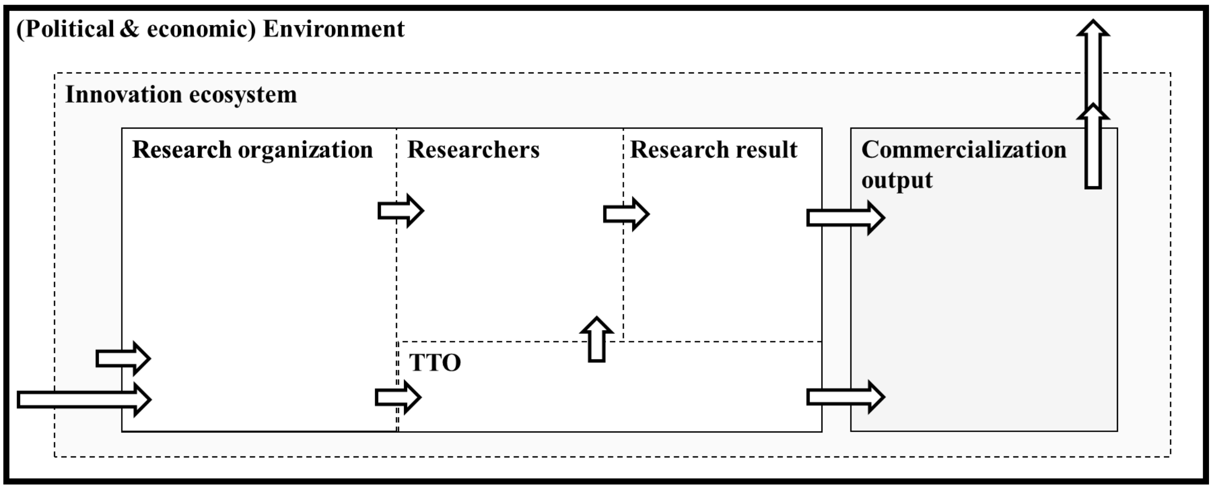
Author (Year)	Type of review	Reviewed database(s)	No. of studies	Time Period	Patents	License	Spin-Off	Collaboration	Consulting	Mixed	Relevant categories	Differentiation to current study
Bozeman et al. (2015)*	Update of a former literature review	Scholarly journals concerning technology, policy, and management	n.m.	n.m.						X	Transfer agent, transfer media, transfer object, demand environment, transfer recipient, transfer object use, effectiveness	• Focus on technology transfer effectiveness and technology transfer evaluation • has a US orientation, although not an exclusive one • No meta-analysis
Compagnuccia & Spigarelli (2020)	Systematic literature review	Thomson Reuters Web of Science, Elsevier's Scopus, and Google Scholar	134	2004 - May 2019						X	Design and the management of the entrepreneurial university, design, and the management of TTOs and related activities, engagement of university staff and stakeholders, development of third mission indicators, strategic orientation of the third mission	• Focus on the third mission of universities and measure to support this mission • Focusing especially on the engagement of non-academic stakeholders • No meta-analysis
Hayter et al. (2018)	Grounded-theory systematic approach	Journals of the Financial Times May 2016 ranking of the top 50 research journals	209	2000-January 2017	X	X	X				Characteristics of academic entrepreneurs, human capital, social networks, entrepreneurial environment, financial resources, scientific, technical, and product characteristics, Academic entrepreneurship support programs, university management and policy, spinoffs, university activity, university IP outputs, ecosystem elements and their connectivity	• Focus on academic entrepreneurship ecosystems • No meta-analysis
Hossinger et al. (2020)	Systematic literature review	Articles published in refereed journals on topics relating to academic spin-offs	193	1983-March 2019			X				Micro-level (individual academic), meso-level (university), macro-level (regional and national context)	• Focus on academic spin-offs and related drivers, barriers, and success factors • No meta-analysis
Maresova et al. (2019)	Systematic review	Web of Science, Scopus and ERIC databases	22	2012-April 2019						X	University-industry technology transfer, government, industry, TTO, researcher, society	• Focus in technology transfer management in universities • No meta-analysis
Mathisen & Rasmussen (2019)	Critical review	Prior literature reviews, special issues, ISI Web of Science	105	2000-2016			X				Individual and team, firm, institutional & ecosystem, spin-off development, spin-off growth, spin-off performance events	• Focus on university spin-offs • Text synthesis of key findings regarding the determinants of university spin-offs

												• No meta-analysis
Miranda et al. (2017)	Critical literature review	Web of Science Core Collection database	268	1997–2016			X				Individual level research, Firm-level research, Institutional context research	• Text synthesis of key findings regarding the characteristics, antecedents, and characteristics of university spin-offs • No meta-analysis
OECD (2013)	No specific review	n.m.	n.m.	n.m.	X	X	X	X	X		Public research results, IP protection, channel, local and national science and technology policies, industry characteristics, institutional characteristics, organizational resources, researcher incentives, market technology, benefits	• Provides common understanding of knowledge transfer channels and the commercialization of public research • No meta-analysis
Perkmann et al. (2021)*	Systematic review of the literature	Bibliographical database service EBSCO (including EconLit); Elsevier SCOPUS	58	2011-2019						X	Individual characteristics, institutional context, organizational and relational context, consequences	• Focus on academic engagement • Aim is to consolidate knowledge in the field • No meta-analysis
Rothaermel et al. (2007)		Proquest ABI/ Inform, Business Source Premier, EconLit	173	1981–2005			X				Environmental context including networks of innovation, new firm creation, (productivity of) TTOs, (entrepreneurial research) university, external factors, entrepreneurial activity	• Focus on university entrepreneurship • No meta-analysis
Sandström et al. (2018)	Systematic literature review	Papers included in earlier literature reviews; special issues, Web of Science, Google Scholar and EBSCOhost	166	2000-2014			X				Academic entrepreneurship policy, activating academic entrepreneurship, aligning capability, academic entrepreneurship initiative outcome, aligning interests, incentives and motives, goals of academic entrepreneurship initiatives, policy trade-offs, institutional and legislative context, regional and local context, university context, TTO and its capabilities	• Focus on academic entrepreneurship • Only aims to provide recommendations for public policy • No meta-analysis
Skute et al. (2017)	Biblio-metric analysis	Thomson Reuters Web of Science database	245	2011–2016						X	Individual level, organizational level, institutional level	• University–industry (U–I) collaborations • Derivation of topic clusters within the literature stream of university-industry collaborations: ecosystem, academic

			entrepreneurship, distance and partner complementarity, social relations perspective, interaction process and knowledge transfer, policy implications • No meta-analysis

* Article is an update of a former article, i.e., Bozeman et al. (2015) is an update of the article Bozeman et al. (2000) and Perkmann et al. (2021) is an update of Perkmann et al. (2013); n.m. not mentioned.

***Figure 6:** New theoretical framework to study the commercialization of academic knowledge based on former reviews*



Based on: Bozeman et al. (2015); Compagnuccia & Spigarelli (2020); Hayter et al. (2018); Hossinger et al. (2020); Maresova et al. (2019); Mathisen & Rasmussen (2019); Miranda et al. (2017); OECD (2013); Perkmann et al. (2021); Rothaermel et al. (2007); Sandström et al. (2018); Skute et al. (2017)

2.3 Methodology

To address the research goals two and three (i.e., to review the determinants impacting the commercialization of academic knowledge and to quantitatively analyze which determinants proves to influence patenting and spin-off creation) we conduct a meta-analysis. A meta-analysis is a special form of a systematic review that uses statistical techniques to integrate the results of the studies included on a given topic (Borenstein et al., 2009; Moher et al., 2009). In contrast to other forms of systematic reviews, a meta-analysis compares and combines quantitative studies by the use of specifically designed techniques that allow for the correction of different artifacts and sample sizes (Hunter & Schmidt, 2004). Meta-analyses are applied for multiple reasons, including to test the relationship between two variables across studies, to explain the variability of effect sizes using moderator variables, or to examine the influencing determinants of a focal concept (Eisend, 2014; Song et al., 2008). While the first two types are strongly guided by a specific theory, the third type of meta-analysis rests on heterogeneous theoretical grounds (Song et al., 2008). Since this study focuses on understanding the concept of "the commercialization of academic knowledge," we apply the third type of meta-analysis to identify and explore – rather than define – the relevant output indicators and determinants for the successful commercialization of academic knowledge.

2.3.1 Collection & selection of studies

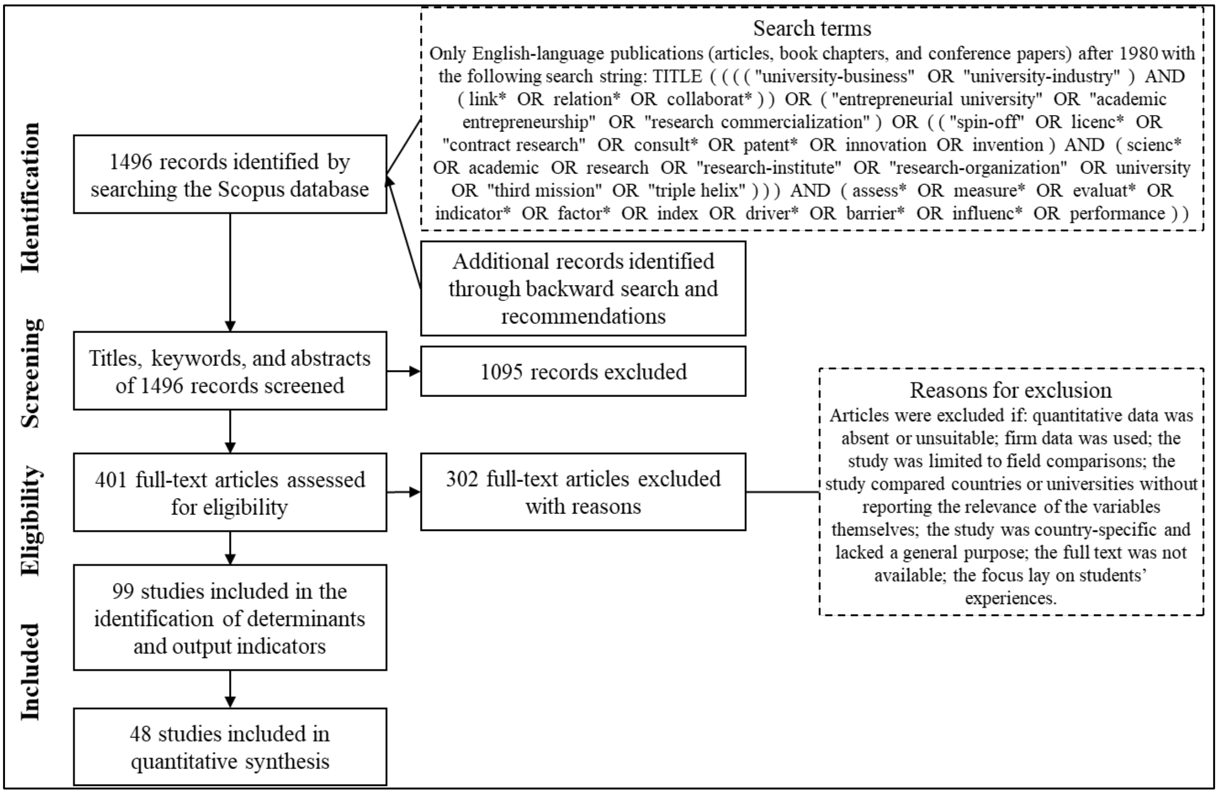
The database for this kind of a systematic review consists of comparable, earlier studies. To ensure the comparability of these earlier studies, we established a list of collection criteria. Studies that explicitly focused on the commercialization of academic knowledge were collected. The Scopus database[8] was used to identify peer-reviewed journal articles, conference papers, and book chapters written in English.[9] We chose a rather broad list of keywords, including combinations of "university-industry/business," "link," "collaboration," "triple helix," and "third mission," but also single commercialization channels such as "spin-offs," "licenses," or "contract research" (see Figure 7 for search strings). However, we excluded articles published before 1980, because the Bayh–Dole Act of

[8] https://www.scopus.com/; Many other previous reviews have used the Scopus database to identify relevant literature, like Compagnuccia & Spiagarelli (2020) and Maresova et al. (2019).
[9] Literature reviews, such as the reviews from Skute et al. (2017) and Miranda et al. (2017), have shown that a comprehensive literature search is feasible using only one literature database.

1980 has often been used as a starting point for research on technology transfer (Grimaldi et al., 2011), and constituted a new regulatory regime for transfer activities. In doing so, we identified 1496 initial studies.

In the initial screening of titles and abstracts, we excluded all articles that did not focus on the commercialization of academic knowledge. We only focused on one direction of the commercialization of academic knowledge, i.e., from research organization to industry. For this reason, articles that explored the company side only were excluded. The only exceptions were spin-offs from research organizations, because they represent a specific commercialization channel. We additionally excluded conceptual articles as well as articles that reported only qualitative data. This left us with 401 articles for full-text screening. According to our inclusion criteria, articles had to include variables designed to explain the success of a certain commercialization channel (patents, licenses, spin-off creation, collaboration, contract research, or consulting activities). Moreover, the articles had to report suitable data, i.e., correlation or regression tables (Borenstein et al., 2009). For an additional 20 articles, the full text was not available. This left us with 99 studies for the identification of influencing determinants (hereafter referred to only as determinants). Of these, only 48 of the 99 studies included data in the form of correlation tables.

Figure 7: The flow of information through the different phases of a systematic review



Adopted visualization based on Moher et al., 2009.

2.3.2 Data collection – identification of output indicators and determinants

Having identified a set of studies that matched our criteria for suitability, comparability, and validity, we coded each study's bibliographic attributes (e.g., author(s), year of publication, sample size), as well as their independent variables (determinants), dependent variables (commercialization output indicators), moderator variables, and effect sizes.

2.3.2.1 Coding variables

Initially, we defined what counted as *dependent variables*. These dependent variables represent commercialization channels, i.e., "licensing," "spin-off creation," "consulting," "patenting," and "collaboration." "Collaboration" includes collaborative research projects and contract research.[10] "Patenting" was integrated for two reasons. First, they represent an important throughput for spin-offs and licenses; second, patents are the most often used (dependent) variable in our set of studies (42 studies). In addition, we decided to add a "mixed" category, since some studies integrated several channels into one variable. We chose an open coding approach to code the operationalization of the commercialization channels, since this study aims to identify the output indicators of the commercialization channels. Table 10 provides an overview o all commercialization output indicators.

Independent variables were not predefined, since the goal of this study is to identify influencing determinants. Instead, all independent variables were gathered for each study, which initially resulted in 2841 variables. We then reduced the number of variables to 97 final determinants by stepwise grouping. Grouping relied on three criteria: 1) similar variable names, 2) similar variable

[10] If a study differentiated between collaborative research projects and contract research, only the results for collaborative research projects were used.

operationalization, and 3) similar overall essence of the variables.[11] Table 11 shows all 97 determinants. Moreover, we further grouped the determinants into five general classes and subsequently classified the determinants according to these classes: individual determinants, organization determinants, field determinants, TTO determinants, and environmental determinants. Individual determinants relate to all determinants concerning individual researchers (such as age, gender, position). Organization determinants describe determinants that concern the research organization as a whole, e.g., research quality, internationality, or innovation climate. Descriptions of the academic discipline of the commercialized knowledge constitute field determinants. All the determinants that described a characteristic of a technology transfer office were subsumed under TTO determinants. Environmental determinants describe the research organization's geographical location.

The final step involved coding *moderator variables*. Moderator variables are features of studies (content-related or methodological) that could affect the size of the relationship between the dependent and independent variables. These variables are crucial for conducting sub-group analyses and helping to explain heterogeneity (Eisend, 2014; Borenstein et al., 2009). For this study, three moderator variables were coded. The first was a binary variable representing the study's quality, based on the impact determinant of the journal in which the study was published (> 2 indicated "high" quality; otherwise "low" quality). Second, the type of the dataset used was coded as another binary variable (survey dataset vs. no survey dataset). Finally, the region of the dataset was represented by the third moderator variable (Europe, Asia, North America, South America).

2.3.2.2 Coding effect sizes

Revealing the relationship between particular influencing determinants (independent variables) and the output of commercialization activities (dependent variables) requires answering three questions: 1) Is there a significant effect? 2) What is the direction of the effect? 3) What is the size of the effect? To answer the first two questions, we used correlation and regression tables, and coded for each relationship to see if there was a significantly positive, positive, negative, or significantly negative effect (critical value equals 5%; see Tables 15-19 in supplementary files). Unfortunately, this kind of coding only allows the methods of "vote counting" and sign tests to analyze the significance of the effect (discussed in detail in Section 2.3.3. below). Additional coding of effect sizes is necessary to statistically integrate different effect sizes and to calculate the overall effect size. Therefore, this research used correlations to measure effect size. Correlations have the advantage of being standardized from -1 to 1, and can reduce the bias of different variable scales. In contrast to regression coefficients, correlations are independent of other model variables (Hunter & Schmidt, 2004). The coding of correlations as effect sizes reduced our sample from 99 to 48 studies.

[11] Coding examples:
1) similar variable names: "Gender_female" includes: "researcher is female = 1" (Miranda et al., 2017; Moog et al., 2015; Schuelke-Leech, 2013; Strong et al., 2018)
2) similar variable operationalization: "TTO size" includes: "Number of staff in industry-university cooperation foundation (IUCF)" (Han & Heshmati, 2016), "total number of full-time workers employed at TTO's" (Algieri et al., 2013), "the number of industry professionals employed by the university whose job is to identify and develop UIC partnerships" (Huang & Chen, 2017), "Three-year average of TLO employees" (Hue Kyung et al., 2016), "total number of full-time equivalent (FTE) employees for non-legal, technical evaluation of inventions and invention marketing" (Swamidass & Vulasa, 2009), etc.
3) similar overall meaning of variables: "innovation climate" includes: "positive climate regarding user - orientation in faculty" (Lee, 1998), "Universities' entrepreneurial culture" (Meusburger & Antonites, 2016), "Commercialization-Support Climate" (Hunter et al., 2011), etc.

2.3.3 Data analysis

The analysis followed four steps. To begin with, a descriptive publication analysis of the characteristics of the studies included provided us with an initial impression of the database. The second step involves preparation of the coded commercialization output indicators and the determinants. This step helped to form a more detailed image of the influencing determinants for the various commercialization channels: first, by describing all the indicators and determinants, and second by "vote counting." Vote counting is the simplest form of a meta-analysis. This method entails counting the number of studies that reported a statistically significant effect and comparing this to the number of studies that showed non-significant effects (Borenstein et al., 2009). However, interpreting the results of this process must be done with care. "Vote counting" ignores the sample sizes of studies, underestimates small or medium effect sizes, and provides no measure for the significance of the effect across all studies. It has been criticized in the literature for these shortcomings (see e.g., Borenstein et al. 2009, Bushman & Wang, 1994). Nevertheless, vote counting still provides an impression of the frequency and intensity with which a certain effect has been studied so far.

In the third step, the coded correlations were used to calculate the average effect sizes weighted by sample size (summary effect size) and the variances. The variance, however, depends heavily on the coefficient itself. Thus, we followed Borenstein et al.'s (2009) recommendation and transformed each correlation to Fisher's z scale, converted the result to a summary effect, and transformed it back to the summary effect sizes. We then calculated the summary effect sizes for all commercialization channels. In presenting the results, however, we focus on spin-off creation and patenting, because most of the studies covered those two channels.

Typically, a meta-analysis is either based on a fixed effects model or a random effects model. A fixed effects model assumes that an effect size measures the true population value and only varies because of random sample error (Eisend, 2014; Borenstein et al., 2009). In this case, the assumption underlying the fixed effects model could not be maintained, and thus, we applied a random effects model. In comparison to a fixed effects model, a random effects model assumes that effect sizes vary due to sampling errors as well as differences between studies. We then used confidence intervals to test the significance of the effect sizes at the 5% level. The hypothesis tests were two-tailed and verified by whether the confidence intervals for the z-value included the z-value.

In the final step, we conducted a subgroup analysis to explore sources of heterogeneity. Since correlations were only reported in 48 studies and this mostly for patents (25 studies), the subgroup analysis was necessarily limited to patents. Study quality and the type of dataset used served as moderator variables.[12] The subgroup analysis is presented in Section A1 and Tables 21-22 in the supplementary files.

2.4 Findings

This section presents the findings of the analysis. It starts with a descriptive overview of the studies that fulfilled the inclusion criteria. This is followed by an introduction of the output indicators and determinants for all commercialization channels.[13] The section closes with a detailed presentation of effect sizes for two of these channels: spin-offs and patents.

2.4.1 Findings from the publication analysis

We start with a wide-ranging descriptive presentation of the main characteristics of our study sample. Figure 8 depicts the distribution of publications over time. We gathered studies published after

[12] The third moderator variable, "country origin of the dataset," showed no significant results.

[13] The results of the vote counting are presented in the supplementary files.

the 1980 Bayh–Dole Act. Surprisingly, the first study in our sample was published in 1995 and the next in 1998. However, it seems reasonable that we found very few quantitative publications within the first two decades, since a new research field typically starts with conceptual and qualitative studies. Yet, a meta-analysis is based on quantitative studies. After 2003, the number of quantitative publications increased significantly. Table 5 adds information on all journals with at least two publications from our sample. The quantitatively most relevant journals were "Research Policy" and "The Journal of Technology Transfer."

Figure 8: *Publication years of studies included*

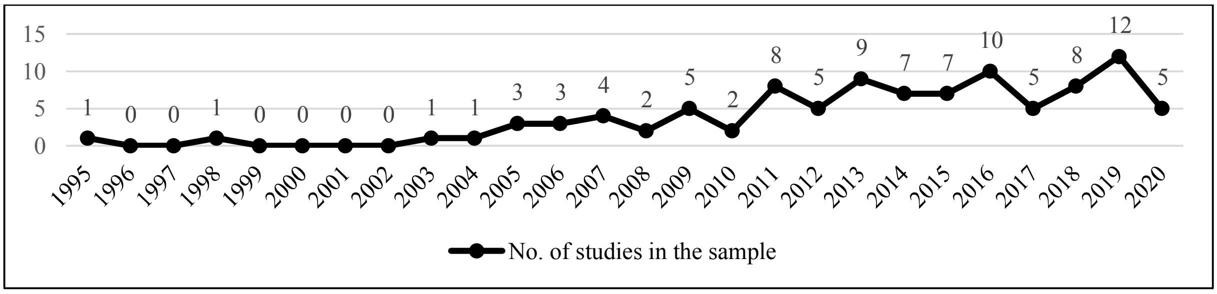


Table 6 shows that the most studied commercialization channel was patents, followed by spin-off creations. The least studied channel was consulting. This might already indicate a gap in the quantitative research in this field, at least in relation to the other channels. Tables 7-9 characterize the data samples used. A total of 40 out of the 99 studies relied on data gathered concerning the individual level of the researcher (or former researcher in the case of spin-offs; see Table 7). The second most frequently used level of analysis (study object) were universities, i.e., in comparisons of universities. Table 9 indicates the types of research organizations under investigation. Surprisingly, only two studies focused on public research organizations or a combination of universities and PROs. This result indicates that more quantitative research on PROs is needed. Table 8 shows that 24 studies collected data within the USA. There, annual surveys by the Association of University Technology Managers (AUTM) were often used and combined with other data sources to create new unique datasets. In addition, 14 studies gathered a cross-country dataset.

Table 5: *Number of publications per journal (at least two studies)*

	Journal name	**k**
1	Research Policy	14
2	The Journal of Technology Transfer	12
3	Technovation	5
4	Science and Public Policy	4
5	Technological Forecasting and Social Change	3
6	Scientometrics	3
7	International Entrepreneurship and Management Journal	3
8	International Journal of Technology Management	3
9	Small Business Economics	2
10	Higher Education	2
11	R&D Management	2
12	Journal of Business Venturing	2
13	International Journal of Entrepreneurship and Innovation Management	2
14	IEEE Transactions on Engineering Management	2
15	PICMET'09-2009 Portland International Conference on Management of Engineering & Technology	2
16	Technology Analysis & Strategic Management	2

Table 6: *Commercialization channels*

Commercial transfer channel	Patenting	License	Spin-off	Collab	Consulting	Mixed
No. of studies that reported correlations	25	10	24	6	1	5
Total no. of studies that reported on the	**42**	**15**	**40**	**24**	**8**	**14**

Table 7: *Study objects*

Study object	k
(Former) researcher	40
University	28
Spin-off	7
TTO	6
Patent	5
Inventor	5
University department/ team	4
Research project	2
PRO (& university)	2
Total	**99**

Table 8: *Country origins of the data set*

Country	k
USA	24
Italy	13
More than	11
UK	7
Spain	6
China	5
Germany	4
Taiwan	4
Europe	3
South Korea	2
Canada	2
Portugal	2
Korea	2
Malaysia	2
Iran	1
Japan	1
Austria	1
Brazil	1
Sweden	1
Nigeria	1
Switzerland	1
Turkey	1
France	1
Russia	1
Slovakia	1
South Africa	1
Total	**99**

Table 9: *Types of research organizations*

Research organization	k
University	87
PRO	6
University & PRO	5
University & company	1
Total	**99**

2.4.2 Findings from the review of output indicators for commercialization channels

To identify a broad range of commercialization output indicators, we have chosen an open coding approach, as previously mentioned. After reviewing the relevant literature, the output indicators are categorized according to the commercialization channels, i.e., “licensing,” “spin-off creation,” “consulting,” “collaboration,” “patenting,” and “mixed”, see Table 10.

Especially two findings are of relevance for this study. First, output indicators differ according to the stage in the commercial process: 1) before commercialization, and 2) after commercialization. The intention to commercialize knowledge through a certain channel is used as a measure before commercialization, i.e., the intention to patent (e.g., Calderini et al., 2007), to start a business (e.g., Davey et al., 2016), and the intention to transfer in general (e.g., Wen-ting & Yin-hui, 2013). The studies use these variables to examine the determinants that influence the commercialization intention or to study the commercialization potential of a research organization. Commercialization output indicators that consider the stage after the commercialization mainly include the number of specific commercial activities (like the number of invention disclosures or the number of consulting contracts; Hunter et al., 2011; Arvanitis et al., 2008) and the income generated by a certain commercialization channel, such as the income from licensing and technology transfer activities (Ken et al., 2009; Han & Heshmati, 2016). In addition, for patenting also patent success is used as a measure to describe that a patent was purchased, won an award, or reached a certain number of citations (Ardito, 2018; Owen-Smith & Powell, 2003). Similar, for spin-off creation, the indicators spin-off success (indicates the growth of a spin-off in terms of revenue, employees, or profitability; like Teixeira, 2017) and spin-off growth (indicates that the number of spin-offs of a research organization increased; Alegieri et al., 2013) are used by previous studies.

Second, the operationalization of the variables differs widely, including continues, categorical count, and binary variables. The income from a certain commercialization channel is most often measured as continues variable in a specific currency and the number of commercial activities is operationalized as count variable (like Crespi et al., 2011; Rossi & Rosli,2015; Rybnicek et al., 2019). The intention to commercialize is mostly measured on a Likert scale. Rather surprising is the high number of studies that use binary output variables. Often the output indicator describes only if a researcher uses a certain channel (such as the variable “knowledge and technology transfer activities in the period 2002–2004 (yes/no)” in Arvanitis et al., 2008). As possible reason serves that data on an individual level was incompatible with secondary databases or the necessary data was not collected and provided by a central office, such as a TTO.

Table 10: *Overview of dependent variables for commercialization channels*

Channel	Operationalization	Description	Relevant references
Collaboration	Funding from collaboration	Amount of funding (various currencies)	Rossi & Rosli (2015); Rybnicek et al. (2019)
	No. of collaborative projects	Count and binary variable for number of collaborative projects	Abramo et al. (2011); Arvanitis et al. (2008); Belkhodja & Landry (2007); Beyhan & Rickne (2015); Comacchio et al. (2012); Crespi et al. (2011); Cunningham & Link (2014); D'Este & Perkmann (2011); Franco et al. (2014); Garcia et al. (2019); Govindaraju et al. (2009); Huang (2018); Hue Kyung et al. (2016); Klasová et al. (2019); Merchán-Hernández et al. (2015); Meusburger & Antonites (2016); Muscio (2013); Olaya Escobar et al. (2017); Tartari & Breschi (2012); Van Looy et al. (2011)
Consulting	No. of consulting contracts	Count and binary variable for number of consulting contracts	Arvanitis et al. (2008); Beyhan & Rickne (2015); Crespi et al. (2011); D'Este & Perkmann (2011); Libaers (2014); Link et al. (2006); Meusburger & Antonites (2016)
Patent	No. of invention disclosures	Count variable for number of invention disclosures	Hunter et al. (2011); Swamidass & Vulasa (2009)
	IP intention	Categorical variable for the intention to apply for patents in the future	Calderini et al. (2007); Huyghe & Knockaert (2015); Varga & Horváth (2014)
	No. of patents	Count and binary variable for number of patents	Arvanitis et al. (2008); Balasubramanian et al. (2020); Baldini (2010); Blind et al. (2018); Bourelos et al. (2012); Chang et al. (2015); Chen et al. (2013a); Chen et al. (2019); D'Este & Perkmann (2011); Fadeyi et al. (2019); Huang & Chen (2017); Huang (2018); Huang et al. (2011); Hue Kyung et al. (2016); Hussler & Pénin (2012); Ken et al. (2009); Lee & Stuen (2016); Libaers (2014); Miranda et al. (2017); Riviezzo et al. (2019); Rizzo & Ramaciotti (2014); Rybnicek et al. (2019); Sellenthin (2009); Strong et al. (2018); Tartari & Breschi (2012); Thurner & Zaichenko (2014); Tijssen (2006); Tseng et al. (2020); Van Looy et al. (2011); Wong & Singh (2013); Xu et al. (2010); Yamaguchi et al. (2019); Ye et al. (2020); Zarghami et al. (2020)
	IP success	Binary variables for: patent was purchased; won an award; had a certain number of citations	Ardito (2018); Owen-Smith & Powell (2003)
License	Income from licensing	Amount of income from licenses	Hue Kyung et al. (2016); Ken et al. (2009)
	No. of license contracts	Count and binary variable for number of licenses	Arvanitis et al. (2008); Bozeman & Gaughan (2007); Buenstorf & Geissler (2013); Drivas et al. (2016); Fadeyi et al. (2019); Kim & Rhee (2018); Meusburger & Antonites (2016); Powers & McDougall (2005); Powers (2004); Son et al. (2019); Swamidass & Vulasa (2009); Tseng et al. (2020); Wong & Singh (2013); Wu et al. (2015); Yamaguchi et al. (2019)
Spin-off	Spin-off intention	Categorical variable for the intention to become an entrepreneur in the future	Clarysse et al. (2011); Davey et al. (2016); Diánez-González et al. (2020); Feola et al. (2019); Huyghe & Knockaert (2015); Miranda et al. (2017); Moog et al. (2015); Prodan & Slavec (2009)
	No. of spin-offs	Count and binary variable for number of spin-offs	Arvanitis et al. (2008); Balasubramanian et al. (2020); Bourelos et al. (2012); Crespi et al. (2011); Czarnitzki et al. (2016); D'Este & Perkmann (2011); Fadeyi et al. (2019); Fini et al. (2017); Gómez et al. (2008); Hayter (2013); Jung & Kim (2018); Lautenschläger et al. (2014); Markman et al. (2005); Meoli & Vismara (2016); Meusburger & Antonites (2016); O'Shea et al. (2005); Pitsakis & Giachetti (2020); Powers & McDougall (2005); Ramaciotti & Rizzo (2015);Riviezzo et al. (2019); Son et al. (2019); Tseng et al. (2020); Van Looy et al. (2011); Wong & Singh (2013)
	Spin-off success	Mix of binary, count, and categorical variables that measured the growth of the spin-off: No. of employees; sales/revenue; profitability; achievement of financial goals or quality	Civera & Meoli (2018); Epure et al. (2016); Niosi (2006); Soetanto & van Geenhuizen (2019); Teixeira (2017); Visintin & Pittino (2014)
	Spin-off growth	Binary variable taking the value of 1 if the total number of spin-offs rose compared to the previous year	Algieri et al. (2013)
Mixed	Income from technology transfer activities	Amount of income from all commercial technology transfer activities	Han & Heshmati (2016)
	TT intentions	Categorical variable for the intention to engage in various commercial transfer activities in the future	Lee (1998); Wen-ting & Xin-hui (2013)
	No. of TT activities	Count and binary variable for number of different technology transfer activities	Arvanitis et al. (2008); Beyhan & Rickne (2015); Chen et al. (2013b); D'Este & Patel (2007); Dill (1995); Govindaraju et al. (2009); Huyghe & Knockaert (2015); Lam (2011); Libaers (2012); Llopis et al. (2018); Merchán-Hernández et al. (2015); Schuelke-Leech (2013)

2.4.3 Findings from the review of determinants for the commercialization of academic knowledge

This study identified 97 determinants related to the commercialization of academic knowledge. Definitions for all these determinants are presented in Table 11. k_{Σ} represents the total number of studies that examined a certain determinant. In addition, the number of studies that examined the relationship between a determinant and a certain commercialization channel was represented as $k_{Patents}$, $k_{License}$, $k_{Spin\text{-}off}$, $k_{Collaborative\ research}$, $k_{Consulting}$, and k_{Mixed}.[14] In the supplementary files, Tables 15-19 report the results of the vote counting. Those tables also report the number of studies that found a negative ($k_{negative}$) or positive relationship ($k_{positive}$) between a commercialization channel and a determinant.[15] The following sub-sections of this paper present the main descriptive findings first by looking more deeply into the five classes of determinants, and second by comparing the results of previous studies between channels.

2.4.3.1 Describing the determinants using the classes

Taking a first descriptive look at the results, eight determinants are included in the environmental class, 30 are related to individual researchers, 33 to the research organization, 17 to the TTO, and another nine determinants to the scientific field. In other words, most determinants relate either to individuals or research organizations. For four classes (all except environmental determinants) we also defined "categories" as subclasses (see the second column).

Individual determinants: The categories identified in the individual class were age, position, gender, level of experience, team composition, entrepreneurial orientation, and division of time, as well as motives and barriers of researchers to commercialize. Determinants from the first four of these categories were used as control variables in most studies, and therefore appeared quite often. The categories entitled "division of time," "motives," and "barriers" comprise the greatest number of determinants. Many previous studies investigated how the commercial activities of researchers were influenced by how they divided up their working hours. Time spent on research and technology transfer seems to have had a positive effect; time for teaching seems rather counterproductive in this sense (Arvanitis et al., 2018; Libaers, 2012; Moog et al., 2015). A great deal of research focused on the motivation of researchers. By far, the most frequently discussed motives across all channels were "additional resources" and "financial rewards." In addition, for spin-off creation, the "autonomy" motive was examined in five studies. The most frequently analyzed barrier was the "attitude towards TT."

Organizational determinants: Moving on to consider determinants related to the organization, the dominant categories are size and age of the research organization, the research subject, and ownership of the organization. These again are often used as control variables (e.g., Fini et al., 2017; Balasubramanian et al., 2020; Lautenschläger et al., 2014). Moreover, research quality (as measured by awards, rankings, or citation counts) and research quantity (number of publications) have been frequently used in previous research on commercialization. Other categories were incentives, infrastructure for commercialization, and (diverse) sources of funding. Funding from "public" sources, "third parties" and "industry" funding have also been frequently discussed (for example, 5, 2, and 5 times with respect to licensing). Only a few studies, however, looked at funding from "endowments." The determinants of "internationality," "innovation climate," and "former experience in consulting"

---

[14] Some studies focus on two or more commercialization channels. Therefore, k_{Σ} may be lower than the sum of $k_{Patents}$, $k_{License}$, $k_{Spin\text{-}off}$, $k_{Collaborative\ research}$, $k_{Consulting}$, and k_{Mixed}.

[15] However, as described earlier, this could only be done for those studies that analyzed regression tables (β) and those that reported correlation tables (r).[15] Study results that reported significant positive or negative effects are indicated by an asterisk (β* and r*; critical value equals 5%).

have been largely overlooked. This indicates a need for further research. Previous experience of "productivity" in a certain commercialization channel is an often-used determinant to explain further commercial activities. Finally, our results indicate that cross-channel learning starts to emerge in organizations: An organization that has some experience with one channel may also be likelier to engage in another one, e.g., three studies analyzed spin-off creation as a determinant for subsequent collaboration.

TTO determinants: Like the organization class of determinants, age, size, and ownership were the most frequently analyzed determinants regarding technology transfer offices. The category of "TTO quality" is expressed in four determinants, yet only a few studies examined particular determinants of TTO quality; for example, the "expertise of the TTO in a certain academic field" was only addressed in two articles, and the "expertise in technology transfer" in four studies (see supplementary files). Moreover, the communication strategies of TTOs were only of interest for three publications, which seems far too few, since TTOs are intermediary organizations and one of their chief roles is to network and communicate with different stakeholders.

Field determinants: Field determinants describe the scientific discipline of the academic knowledge that is to be commercialized. These determinants are among the most often-used control variables. This class is often differentiated by the subject (e.g., engineering, social sciences, etc.) and its research orientation (basic vs. applied). "Engineering" and "natural" sciences are the most frequently used subjects (for example, regarding patenting 12 studies examined engineering and 12 the natural sciences; see Table 11). In contrast, "computer science" and "social sciences" have been analyzed less often (7 and 14 times). Depending on the study, various subdisciplines have also been investigated; Tartari & Breschi (2012) differentiated among civil engineering, process engineering, and systems engineering, for example.

Environmental determinants: Finally, environmental determinants are generally examined less frequently. This represents a weakness in that literature stream. Exceptions included the economic prosperity of the research organization's location and an organization's proximity to urban regions (Miranda et al., 2017; Ramaciotti & Rizzo, 2015).

2.4.3.2 Comparing determinants of the commercialization channels

A comparison of the commercialization channels reveals that research focuses not only on patenting and spin-off creation overall (see earlier section 2.4.1.), but even when broken down among the determinants of the five classes. Nevertheless, studies on spin-off creation have also examined a few particular determinants that were not studied or only rarely so in other channels. These determinants included "team heterogeneity," the barrier of "a lack of awareness," the "budget of the TTO" and the "unemployment" (2, 1, 3, and 2 studies, respectively). Moreover, the availability of "venture capital" is studied much more frequently for spin-off creation than for other channels. While the unemployment rate (as an indicator for potential employees) and the availability of venture capital are specifically relevant for spin-offs, it is worth asking why the other three determinants have been largely ignored in research on other channels. Team heterogeneity in particular may be extremely relevant, because the other channels also require team efforts similar to those of spin-off creation.

Turning to patenting and licensing, determinants for licensing were surprisingly far less investigated than for patenting, even though patenting is a prerequisite for licensing. The "individual" class (i.e., the researcher's individual characteristics) in particular reveal a lack of research on determinants for licensing. One possible explanation may be that researchers can outsource licensing to

TTOs in some research organizations. In addition, patents are a prerequisite for other commercialization channels as well, such as spin-off creation.

Another striking result is that consulting is so poorly studied as a commercialization channel, regardless of the class of determinants. For example, not even one study examines the relationship between environmental determinants and consulting. Similarly, regarding TTO determinants, only two relationships were analyzed. Consulting has been best covered by “individual” and “field” determinants as a result. The lack of research on determinants for consulting may be due to rules in some research organizations that forbid projects without a research aspect, such as consulting. In addition, consulting activities are generally not public, and are conducted via private contracts entered into by individual researchers; data availability is therefore restricted.

Table 11: *Overview of determinants*

Class	Category	Variables	k_{Σ}	Description (Operationalization)	$k_{Patents}$	$k_{License}$	$k_{Spin\text{-}off}$	$k_{Collaborative\ research}$	$k_{Consulting}$	k_{Mixed}	Relevant references
Environ-mental determinants		Economic prosperity	13	Includes indicators that express the economic prosperity of the region, e.g., number of companies, regional GDP, regional GDP growth, total sales and staff of local companies	3		10	1		1	Algieri et al. (2013); Civera & Meoli (2018); Fini et al. (2017); Han & Heshmati (2016); Meoli & Vismara (2016); Miranda et al. (2017); Muscio (2013); Ramaciotti & Rizzo (2015); Riviezzo et al. (2019); Soetanto & van Geenhuizen (2019); Son et al. (2019); Teixeira (2017); Varga & Horváth (2014)
		Unemployment rate	2	Unemployment rate at the regional or national level			2				Civera & Meoli (2018); Fini et al. (2017)
		Urban region	12	Research institute is located in or close to a metropolitan region or city; high population density	5	2	3	3		1	Belkhodja & Landry (2007); Civera & Meoli (2018); Fini et al. (2017); Han & Heshmati (2016); Hue Kyung et al. (2016); Jung & Kim (2018); Niosi (2006); Owen-Smith & Powell (2003); Rybnicek et al. (2019); Varga & Horváth (2014); Yamaguchi et al. (2019); Ye et al. (2020)
		R&D expenditure	5	R&D expenditure (as % of GDP) in region	1		4	1			Civera & Meoli (2018); Fini et al. (2017); Klasová et al. (2019); Meoli & Vismara (2016); Riviezzo et al. (2019)
		Innovative region	7	Innovative performance of the region measured by the number of patents or various innovation indices	3		4				Algieri et al. (2013); Civera & Meoli (2018); Meoli & Vismara (2016); Pitsakis & Giachetti (2020); Rizzo & Ramaciotti (2014); Varga & Horváth (2014); Ye et al. (2020)
		Start-up activity	3	Regional easiness to start a business and/or the presence of start-ups (self-employment rate)	2		3				Fini et al. (2017); Miranda et al. (2017); Riviezzo et al. (2019)
		Venture capital	12	Availability of venture capital; total venture capital received	2	2	9			1	Bourelos et al. (2012); Diánez-González et al. (2020); Feola et al. (2019); Fini et al. (2017); Han & Heshmati (2016); Hayter (2013); Hunter et al. (2011); Niosi (2006); Pitsakis & Giachetti (2020); Powers & McDougall (2005); Powers (2004); Teixeira (2017)
		Distance between firm & university	3	Geographical proximity or distance between the research institute and firm(s)	1		1	1		1	Chen et al. (2019); Merchán-Hernández et al. (2015); Soetanto & van Geenhuizen (2019)
Individual determinants	Age	Age	16	Age of researcher	7	1	5	7	4	4	Crespi et al. (2011); D'Este & Perkmann (2011); Davey et al. (2016); D'Este & Patel (2007); Dill (1995); Franco et al. (2014); Hussler & Pénin (2012); Lam (2011); Libaers (2014); Meusburger & Antonites (2016); Moog et al. (2015); Rybnicek et al. (2019); Strong et al. (2018); Tartari & Breschi (2012); Wen-ting & Xin-hui (2013); Zarghami et al. (2020)
	Team	Size of the research team	14	Number of researchers or inventors in a research team or department	6	2	3	6	2	3	Ardito (2018); Chen et al. (2019); Crespi et al. (2011); D'Este & Perkmann (2011); D''Este & Patel (2007); Drivas et al. (2016); Garcia et al. (2019); Kim & Rhee (2018); Llopis et al. (2018); Merchán-Hernández et al. (2015); Muscio (2013); Riviezzo et al. (2019); Rybnicek et al. (2019); Sellenthin (2009)
		Heterogeneity of the research team	2	Diversity in academic status, level of experience, and skills of the research team			2				Moog et al. (2015); Visintin & Pittino (2014)
	Position	Tenure	8	Researcher has a tenured position	3			2	2	3	Blind et al. (2018); Bozeman & Gaughan (2007); Lee & Stuen (2016); Libaers (2012); Libaers (2014); Link et al. (2006); Llopis et al. (2018); Schuelke-Leech (2013)
		Post-doc or professor	20	Researcher holds a PhD or higher; share of researchers who hold a PhD or higher	9	2	10	6	4	3	Algieri et al. (2013); Blind et al. (2018); Bourelos et al. (2012); Clarysse et al. (2011); Crespi et al. (2011); Czarnitzki et al. (2016); D'Este & Perkmann (2011); D'Este & Patel (2007); Epure et al. (2016); Huang et al. (2011); Huyghe & Knockaert (2015); Klasová et al. (2019); Lam (2011); Libaers (2014); Meusburger & Antonites (2016); Strong et al.

										(2018); Tartari & Breschi (2012); Visintin & Pittino (2014); Wu et al. (2015); Zarghami et al. (2020)
Experience	Experience in academia	10	Years in academia or in a specific academic position (professor, post-doc, tenured position)	6		3	4	3	3	Belkhodja & Landry (2007); Beyhan & Rickne (2015); Blind et al. (2018); Chang et al. (2015); Govindaraju et al. (2009); Huang (2018); Huyghe & Knockaert (2015); Link et al. (2006); Llopis et al. (2018); Miranda et al. (2017)
	Experience in industry	9	Previous industry experience as non-academic experience as a binary variable or in the number of years; share of faculty members with industry experience	5	1	2	3	2	3	Bourelos et al. (2012); Han & Heshmati (2016); Huang (2018); Lam (2011); Llopis et al. (2018); Meusburger & Antonites (2016); Rybnicek et al. (2019); Strong et al. (2018); Zarghami et al. (2020)
Gender	Female	6	Gender is female	3		3			2	Crespi et al. (2011); Huyghe & Knockaert (2015); Miranda et al. (2017); Moog et al. (2015); Schuelke-Leech (2013); Strong et al. (2018)
	Male	16	Gender is male	8	2	2	6	4	2	Blind et al. (2018); Bozeman & Gaughan (2007); Calderini et al. (2007); Clarysse et al. (2011); Franco et al. (2014); Huang (2018); Huang et al. (2011); Hussler & Pénin (2012); Libaers (2012); Libaers (2014); Link et al. (2006); Llopis et al. (2018); Meusburger & Antonites (2016); Tartari & Breschi (2012); Wu et al. (2015); Zarghami et al. (2020)
Orientation	Entrepreneurial orientation	11	Self-assessment of the entrepreneurial orientation	4	1	8	1		2	Balasubramanian et al. (2020); Belkhodja & Landry (2007); Clarysse et al. (2011); Diánez-González et al. (2020); Dill (1995); Feola et al. (2019); Hussler & Pénin (2012); Huyghe & Knockaert (2015); Miranda et al. (2017); Soetanto & van Geenhuizen (2019); Son et al. (2019)
Time for …	Administration	2	Self-assessment of the time spent on administrative tasks						2	Dill (1995); Libaers (2012)
	Applied research	1	Self-assessment of the time spent on applied research	1	1	1	1	1		Arvanitis et al. (2008)
	Industry	1	Self-assessment of the time spent on research with private firms	1		1				Bourelos et al. (2012)
	Research	9	Self-assessment of the time spent on administrative tasks	2		3	1	1	3	Arvanitis et al. (2008); Belkhodja & Landry (2007); Bourelos et al. (2012); Civera & Meoli (2018); Dill (1995); Hayter (2013); Libaers (2012); Link et al. (2006); Strong et al. (2018)
	Teaching	6	Self-assessment of the time spent on teaching	1	1	3	2	1	3	Arvanitis et al. (2008); Civera & Meoli (2018); Dill (1995); Klasová et al. (2019); Libaers (2012); Moog et al. (2015)
	Technology transfer	3	Self-assessment of the time spent on consulting or entrepreneurial activities	1		1			2	Bourelos et al. (2012); Dill (1995); Libaers (2012)
Motives	Autonomy	7	Desire for independence and enhanced career opportunities	3		5	2	1		D'Este & Perkmann (2011); Davey et al. (2016); Miranda et al. (2017); Olaya Escobar et al. (2017); Prodan & Slavec (2009); Sellenthin (2009); Tartari & Breschi (2012); Teixeira (2017)
	Competence enhancement	7	Advancing research and accessing new information (such as industry's needs)	4	1	3	5	4	2	Arvanitis et al. (2008); Beyhan & Rickne (2015); D'Este & Perkmann (2011); Garcia et al. (2019); Huang (2018); Lam (2011); Llopis et al. (2018)
	Financial motives	8	Financial incentives	5	1	3	1	1	2	Blind et al. (2018); D'Este & Perkmann (2011); Hussler & Pénin (2012); Lam (2011); Llopis et al. (2018); Prodan & Slavec (2009); Sellenthin (2009); Tseng et al. (2020)
	Networking	4	Access to industry contacts; expanding network	1		2	1	1	1	Davey et al. (2016); Huang (2018); Llopis et al. (2018); Teixeira (2017)
	Other motives	1	Dissatisfaction with academic environment			1				Prodan & Slavec (2009)
	Reputation	6	Technology transfer as a way to enhance reputation of researcher or institute	2		3			1	Blind et al. (2018); Davey et al. (2016); Feola et al. (2019); Huang et al. (2011); Lam (2011); Prodan & Slavec (2009)
	Resources	9	Access to additional resources (e.g., funding and infrastructure)	5		4	6	4		Arvanitis et al. (2008); Beyhan & Rickne (2015); D'Este & Perkmann (2011); Davey et al. (2016); Garcia et al. (2019); Huang (2018); Prodan & Slavec (2009); Sellenthin (2009); Tartari & Breschi (2012)
	Puzzle motive	8	Desire to bring research into practice; positive attitude towards technology transfer	1		4	3	1	2	Beyhan & Rickne (2015); Davey et al. (2016); Feola et al. (2019); Garcia et al. (2019); Lam (2011); Olaya Escobar et al. (2017); Prodan & Slavec (2009); Wen-ting & Xin-hui (2013)
Barriers	Attitude towards TT	8	Industry collaboration seen as threat to research (e.g., intellectual freedom)	2	1		3		4	Arvanitis et al. (2008); Hussler & Pénin (2012); Lee (1998); Merchán-Hernández et al. (2015); Olaya Escobar et al. (2017); Schuelke-Leech (2013); Tartari & Breschi (2012); Wu et al. (2015)

		Lack of awareness	3	Lack of awareness about industry opportunities and needs			1	2		1	Davey et al. (2016); Garcia et al. (2019); Govindaraju et al. (2009)
		Bureaucracy	2	Excessive bureaucracy hindering technology transfer	1			1			Garcia et al. (2019); Huang et al. (2011)
		Lack of resources	4	Lack of funding (or high costs), staff, infrastructure	2	1	1	1			Blind et al. (2018); Cunningham & Link (2014); Davey et al. (2016); Swamidass & Vulasa (2009)
		Culture clash	3	Differences in motivation, attitudes, and interests between researchers and industry	1	1	2	2	1		Arvanitis et al. (2008); Davey et al. (2016); Garcia et al. (2019)
		Obstacles to publication	5	Industry collaboration as a hinderance to publication (secrecy, non-disclosure)	3		1	2			Blind et al. (2018); Cunningham & Link (2014); Davey et al. (2016); Hussler & Pénin (2012); Tartari & Breschi (2012)
		Other barriers	4	Bad experiences with TTO, a lack of information on patents, etc.	1		2	1		1	Blind et al. (2018); Davey et al. (2016); Govindaraju et al. (2009); Hayter (2013)
Organiza-tional determinants	Size	No. of employees	27	Number of researchers or particular positions (professors, post-docs, full-time equivalents, etc.) at the research institute	10	4	14	4	1	3	Arvanitis et al. (2008); Balasubramanian et al. (2020); Belkhodja & Landry (2007); Chen et al. (2013a); Civera & Meoli (2018); Dill (1995); Epure et al. (2016); Fini et al. (2017); Gómez et al. (2008); Han & Heshmati (2016); Jung & Kim (2018); Lautenschläger et al. (2014); Meoli & Vismara (2016); Moog et al. (2015); O'Shea et al. (2005); Pitsakis & Giachetti (2020); Powers & McDougall (2005); Powers (2004); Ramaciotti & Rizzo (2015); Rizzo & Ramaciotti (2014); Rossi & Rosli (2015); Thurner & Zaichenko (2014); Van Looy et al. (2011); Varga & Horváth (2014); Xu et al. (2010); Yamaguchi et al. (2019); Ye et al. (2020)
		No. of students	10	Number of undergraduate or graduate students at the research institute; student enrollment	4	2	4	1		2	Algieri et al. (2013); Balasubramanian et al. (2020); Baldini (2010); Chen et al. (2013b); Civera & Meoli (2018); Han & Heshmati (2016); Hue Kyung et al. (2016); Lautenschläger et al. (2014); Meoli & Vismara (2016); Yamaguchi et al. (2019)
	Age	Age of institute	8	Founding year or age of the research institute/university/department	2		4	2		1	Fini et al. (2017); Han & Heshmati (2016); Klasová et al. (2019); Meoli & Vismara (2016); Pitsakis & Giachetti (2020); Riviezzo et al. (2019); Rossi & Rosli (2015); Varga & Horváth (2014)
	Research subject	General	4	Not a medical school	1	1	1	1		1	Balasubramanian et al. (2020); Davey et al. (2016); Han & Heshmati (2016); Hue Kyung et al. (2016)
		Medical	4	Medical school	2		1				Balasubramanian et al. (2020); O'Shea et al. (2005); Owen-Smith & Powell (2003); Xu et al. (2010)
	Ownership	Private	7	Private ownership of the university	2		3	2	1	1	Civera & Meoli (2018); Huang (2018); Libaers (2012); Meoli & Vismara (2016); O'Shea et al. (2005); Owen-Smith & Powell (2003); Rossi & Rosli (2015)
		Public	4	Governmental/public ownership of the university	2	1		2	1	1	Huang (2018); Lee (1998); Rossi & Rosli (2015); Yamaguchi et al. (2019)
	Research quality	Research quality	26	University rank in (inter-)national rankings; quality of department or faculty; average number of citations, or journal impact of researcher's publications	13	3	10	6	4	3	Abramo et al. (2011); Balasubramanian et al. (2020); Calderini et al. (2007); Chen et al. (2013a); Chen et al. (2019); Civera & Meoli (2018); Clarysse et al. (2011); Crespi et al. (2011); D'Este & Perkmann (2011); D'Este & Patel (2007); Fini et al. (2017); Huang (2018); Klasová et al. (2019); Lee & Stuen (2016); Libaers (2014); Llopis et al. (2018); O'Shea et al. (2005); Owen-Smith & Powell (2003); Pitsakis & Giachetti (2020); Powers & McDougall (2005); Powers (2004); Schuelke-Leech (2013); Varga & Horváth (2014); Wong & Singh (2013); Xu et al. (2010); Zarghami et al. (2020)
	Internation ality	Internationality	6	Internationality of researchers measured by experience outside the country in which the research institute is located, foreign-born status	4			2		1	Blind et al. (2018); Libaers (2012); Libaers (2014); Muscio (2013); Strong et al. (2018); Varga & Horváth (2014)
	Innovation climate	Innovation climate	11	Climate that supports commercialization; perceived entrepreneurial orientation of the university (e.g., innovativeness, proactiveness, and risk–taking propensity)	6	1	4	2	1	1	Chen et al. (2013a); Huang & Chen (2017); Hunter et al. (2011); Lee (1998); Meusburger & Antonites (2016); Miranda et al. (2017); Olaya Escobar et al. (2017); Riviezzo et al. (2019); Soetanto & van Geenhuizen (2019); Thurner & Zaichenko (2014)
	Incentive for …	Patents (financial)	8	Financial incentives for patents (royalty shares)	5	1	1			2	Baldini (2010); Chang et al. (2015); Han & Heshmati (2016); Huang et al. (2011); Lee & Stuen (2016); Libaers (2012); Son et al. (2019); Xu et al. (2010)
		License	1			1					Wu et al. (2015)

	Reputation/awards	1	Existence of entrepreneurial awards	1		1			1	Huyghe & Knockaert (2015)
Infrastructure/Support for…	Administration	1	Percentage of employees in administrative units			1				Meoli & Vismara (2016)
	TT education	3	Education, including business mentoring, training, and self-assessment of entrepreneurial education	1	1	3	1	1		Bourelos et al. (2012); Meusburger & Antonites (2016); Teixeira (2017)
	Patents	5	Existence of support (policies) for IP	3	1				1	Baldini (2010); Han & Heshmati (2016); Hussler & Pénin (2012); Sellenthin (2009); Wu et al. (2015)
	License	1	Existence of support (strategies) for licensing activities			1				Markman et al. (2005)
	TT strategy	7	Existence of explicit third mission (as strategy and policy)	2		4	1		2	Civera & Meoli (2018); Gómez et al. (2008); Huyghe & Knockaert (2015); Lautenschläger et al. (2014); Rizzo & Ramaciotti (2014); Rossi & Rosli (2015); Wen-ting & Xin-hui (2013)
	TT activities	15	Existing contacts / network memberships and support for technology transfer; existing infrastructure (labs etc.) for university-industry relations)	4	3	7	4	1	2	Belkhodja & Landry (2007); Comacchio et al. (2012); Cunningham & Link (2014); Feola et al. (2019); Gómez et al. (2008); Govindaraju et al. (2009); Han & Heshmati (2016); Huang & Chen (2017); Meusburger & Antonites (2016); Moog et al. (2015); Owen-Smith & Powell (2003); Son et al. (2019); Teixeira (2017); Thurner & Zaichenko (2014); Tseng et al. (2020)
	University share	2	Partial university ownership of spin-offs			2				Hayter (2013); Visintin & Pittino (2014)
Funding from…	Third party	17	Ratio or amount of funding from third parties, funding for application-oriented research	8	2	9	2	1	2	Balasubramanian et al. (2020); Bourelos et al. (2012); D'Este & Perkmann (2011); D'Este & Patel (2007); Fadeyi et al. (2019); Hayter (2013); Huang et al. (2011); Lautenschläger et al. (2014); Llopis et al. (2018); Niosi (2006); Pitsakis & Giachetti (2020); Rossi & Rosli (2015); Rybnicek et al. (2019); Teixeira (2017); Thurner & Zaichenko (2014); Tseng et al. (2020); Varga & Horváth (2014)
	Endowment	1	Amount of funding from endowment		1	1				Powers & McDougall (2005)
	Industry	22	Ratio or amount of funding from industry; number of contracts and grants from industry	7	5	9	4	2	6	Arvanitis et al. (2008); Balasubramanian et al. (2020); Beyhan & Rickne (2015); Bozeman & Gaughan (2007); Chen et al. (2013b); D'Este & Perkmann (2011); D'Este & Patel (2007); Fini et al. (2017); Garcia et al. (2019); Han & Heshmati (2016); Huang et al. (2011); Libaers (2012); O'Shea et al. (2005); Pitsakis & Giachetti (2020); Powers & McDougall (2005); Powers (2004); Rybnicek et al. (2019); Schuelke-Leech (2013); Son et al. (2019); Thurner & Zaichenko (2014); Tseng et al. (2020); Wu et al. (2015)
	Other	10	Scholarships or other unspecified funding sources	2	2	2	2			Balasubramanian et al. (2020); D'Este & Patel (2007); Drivas et al. (2016); Jung & Kim (2018); Klasová et al. (2019); Muscio (2013); Pitsakis & Giachetti (2020); Powers (2004); Thurner & Zaichenko (2014); Varga & Horváth (2014)
	Public	23	Ratio or amount of funding from federal/government/public/state organizations; number of contracts and grants	9	5	7	4	1	6	Algieri et al. (2013); Balasubramanian et al. (2020); Blind et al. (2018); Bozeman & Gaughan (2007); Chen et al. (2013b); D'Este & Perkmann (2011); D'Este & Patel (2007); Drivas et al. (2016); Han & Heshmati (2016); Jung & Kim (2018); Ken et al. (2009); Klasová et al. (2019); Libaers (2012); Merchán-Hernández et al. (2015); O'Shea et al. (2005); Powers (2004); Ramaciotti & Rizzo (2015); Rizzo & Ramaciotti (2014); Schuelke-Leech (2013); Thurner & Zaichenko (2014); Tseng et al. (2020); Xu et al. (2010); Yamaguchi et al. (2019)
	Total	2	Amount of total funding						1	Balasubramanian et al. (2020); Han & Heshmati (2016)
	Technology transfer	9	Funding directly from technology transfer activities (e.g., license revenue, commercial profits)	4	1	2	2	1	1	Han & Heshmati (2016); Libaers (2014); Pitsakis & Giachetti (2020); Ramaciotti & Rizzo (2015); Rizzo & Ramaciotti (2014); Rossi & Rosli (2015); Son et al. (2019); Thurner & Zaichenko (2014); Ye et al. (2020)
Productivity/Experience in…	Collaboration	18	Researcher has experience in collaborative or contract research; joint patents; share of public-private outputs; share or number of contracts	10	1	8	2	1	3	Bourelos et al. (2012); D'Este & Patel (2007); Gómez et al. (2008); Hayter (2013); Hunter et al. (2011); Huyghe & Knockaert (2015); Jung & Kim (2018); Lautenschläger et al. (2014); Libaers (2014); Moog et al. (2015); Muscio (2013); Sellenthin (2009); Tartari & Breschi (2012); Thurner & Zaichenko (2014); Tijssen (2006); Van Looy et al. (2011); Wen-ting & Xin-hui (2013); Yamaguchi et al. (2019)
	Consulting	3	Researcher has experience in consulting	1		2				Hayter (2013); Moog et al. (2015); Strong et al. (2018)

		Patents	45	Researcher has experience in patenting; number of patents or invention disclosures of the research institute; existence of IPR role models; patents per staff member	13	9	24	6	2	2	Balasubramanian et al. (2020); Baldini (2010); Bourelos et al. (2012); Buenstorf & Geissler (2013); Calderini et al. (2007); Chang et al. (2015); Civera & Meoli (2018); Clarysse et al. (2011); Crespi et al. (2011); Czarnitzki et al. (2016); Drivas et al. (2016); Epure et al. (2016); Fadeyi et al. (2019); Han & Heshmati (2016); Huang & Chen (2017); Huang et al. (2011); Hunter et al. (2011); Huyghe & Knockaert (2015); Jung & Kim (2018); Ken et al. (2009); Kim & Rhee (2018); Klasová et al. (2019); Lautenschläger et al. (2014); Meoli & Vismara (2016); Meusburger & Antonites (2016); Miranda et al. (2017); Moog et al. (2015); Niosi (2006); O'Shea et al. (2005); Owen-Smith & Powell (2003); Pitsakis & Giachetti (2020); Ramaciotti & Rizzo (2015); Riviezzo et al. (2019); Rizzo & Ramaciotti (2014); Sellenthin (2009); Son et al. (2019); Tartari & Breschi (2012); Teixeira (2017); Thurner & Zaichenko (2014); Tijssen (2006); Tseng et al. (2020); Van Looy et al. (2011); Wong & Singh (2013); Wu et al. (2015); Ye et al. (2020)
		License	7	Researcher has experience in (successful) licensing; number of license contracts of the research institute	1	2	2			1	Buenstorf & Geissler (2013); Fadeyi et al. (2019); Kim & Rhee (2018); Libaers (2012); Moog et al. (2015); Powers & McDougall (2005); Son et al. (2019)
		Publication	29	Researcher has experience in publishing; number of publications of the research institute	18	4	10	7	1	2	Belkhodja & Landry (2007); Bourelos et al. (2012); Calderini et al. (2007); Civera & Meoli (2018); Czarnitzki et al. (2016); D'Este & Patel (2007); Han & Heshmati (2016); Huang & Chen (2017); Huang (2018); Huang et al. (2011); Hue Kyung et al. (2016); Hussler & Pénin (2012); Jung & Kim (2018); Ken et al. (2009); Klasová et al. (2019); Lee & Stuen (2016); Libaers (2014); Meoli & Vismara (2016); Miranda et al. (2017); Moog et al. (2015); Owen-Smith & Powell (2003); Ramaciotti & Rizzo (2015); Rizzo & Ramaciotti (2014); Rybnicek et al. (2019); Schuelke-Leech (2013); Tartari & Breschi (2012); Tijssen (2006); Van Looy et al. (2011); Wong & Singh (2013); Yamaguchi et al. (2019)
		Spin-off	26	Researcher has experience in entrepreneurship; number of (successful) spin-off activities	7	4	18	3	2	2	Balasubramanian et al. (2020); Bourelos et al. (2012); Civera & Meoli (2018); Clarysse et al. (2011); Diánez-González et al. (2020); Epure et al. (2016); Fadeyi et al. (2019); Fini et al. (2017); Gómez et al. (2008); Hayter (2013); Huang (2018); Huyghe & Knockaert (2015); Jung & Kim (2018); Lautenschläger et al. (2014); Libaers (2012); Markman et al. (2005); Meoli & Vismara (2016); Meusburger & Antonites (2016); Moog et al. (2015); Niosi (2006); Pitsakis & Giachetti (2020); Powers & McDougall (2005); Ramaciotti & Rizzo (2015); Van Looy et al. (2011); Visintin & Pittino (2014); Yamaguchi et al. (2019)
		TT activities	15	Researcher has experience in technology transfer; number of commercialization projects; engagement in university-industry collaboration	3	1	6	5	1	4	Belkhodja & Landry (2007); Chen et al. (2013b); D'Este & Perkmann (2011); Gómez et al. (2008); Han & Heshmati (2016); Huang & Chen (2017); Hussler & Pénin (2012); Lautenschläger et al. (2014); Merchán-Hernández et al. (2015); Moog et al. (2015); Muscio (2013); Pitsakis & Giachetti (2020); Rossi & Rosli (2015); Wen-ting & Xin-hui (2013); Wong & Singh (2013)
TTO determinants	TTO exists	TTO exists	14	Affiliated TTO unit, TT center, or incubator	5		7	3	1	2	Balasubramanian et al. (2020); Baldini (2010); Bourelos et al. (2012); Bozeman & Gaughan (2007); Feola et al. (2019); Han & Heshmati (2016); Huang et al. (2011); Libaers (2014); Markman et al. (2005); Moog et al. (2015); Muscio (2013); O'Shea et al. (2005); Ramaciotti & Rizzo (2015); Schuelke-Leech (2013)
	Age of TTO	Age of TTO	8	Founding year or age of the TTO	3	2	5	1			Comacchio et al. (2012); Diánez-González et al. (2020); Fini et al. (2017); Owen-Smith & Powell (2003); Pitsakis & Giachetti (2020); Powers & McDougall (2005); Wong & Singh (2013); Xu et al. (2010)
	Size of TTO	Size of TTO	21	Number of employees or of certain positions (such as legal staff or full-time equivalents) at the TTO	8	6	11	3		2	Algieri et al. (2013); Civera & Meoli (2018); Comacchio et al. (2012); Diánez-González et al. (2020); Dill (1995); Gómez et al. (2008); Han & Heshmati (2016); Huang & Chen (2017); Hue Kyung et al. (2016); Jung & Kim (2018); Lautenschläger et al. (2014); Lee & Stuen (2016); Meoli & Vismara (2016); O'Shea et al. (2005); Powers (2004); Son et al. (2019); Swamidass & Vulasa (2009); Van Looy et al. (2011); Wong & Singh (2013); Xu et al. (2010); Yamaguchi et al. (2019)
	Budget of TTO	Budget of TTO	4	Budget and availability of financial support for the TTO			3			1	Algieri et al. (2013); Dill (1995); Gómez et al. (2008); Lautenschläger et al. (2014)

	Communication of TTO	Communication of TTO	3	Communication frequency, and no. of communication channels used		1	1			1	Dill (1995); Pitsakis & Giachetti (2020); Son et al. (2019)
	Financial incentives for TTO	Financial incentives for TTO	1	Existence of financial incentives for TTO employees		1	1				Son et al. (2019)
	Network of TTO	Network of TTO	1	Years of membership in a TTO network			1				Pitsakis & Giachetti (2020)
	TTO ownership	NGO	1	Independent non-profit unit or part of separately constituted research foundation			1				Markman et al. (2005)
		Private	3	TTO unit is independent/for-profit/autonomous	2		1				Huang et al. (2011); Pitsakis & Giachetti (2020); Xu et al. (2010)
		Public	1	TTO is an internal part of the research institute			1				Markman et al. (2005)
	TTO quality	TTO quality	7	Researcher’s perceptions that the TTO services are high-quality/adequate/important	2	3	3	3	2		Arvanitis et al. (2008); Hayter (2013); Huang et al. (2011); Meusburger & Antonites (2016); Olaya Escobar et al. (2017); Strong et al. (2018); Wu et al. (2015)
		Academic expertise	2	Years of academic experience among TTO staff as well as the number of employees with a PhD	1	1	1			1	Dill (1995); Fadeyi et al. (2019)
		Expertise in research field	2	Years of experience in a certain research field; diversity of field skills			1			1	Dill (1995); Lautenschläger et al. (2014)
		Expertise in TT	4	Professional expertise in technology transfer among employees	1	2	2	1			Comacchio et al. (2012); Fadeyi et al. (2019); Gómez et al. (2008); Kim & Rhee (2018)
		Spin-off productivity	2	Number of spin-offs created with the support of TTOs			2				Diánez-González et al. (2020); Gómez et al. (2008)
	Time to patent	Time to patent	3	Duration of the patent process (application, assessment, filing, etc.)	2	1					Ardito (2018); Baldini (2010); Drivas et al. (2016)
	Patent quality	Patent quality	8	(Backward, forward, or non-patent) citations of patents; number of patent classifications;	3	3	2				Ardito (2018); Buenstorf & Geissler (2013); Czarnitzki et al. (2016); Drivas et al. (2016); Hunter et al. (2011); Owen-Smith & Powell (2003); Powers & McDougall (2005); Tijssen (2006)
Field determinants	Research orientation	Applied research	8	Self-assessment of researchers of the extent to which their research, projects, and outcomes are application-oriented; papers in application-oriented journals	6	1	3	3	2		Beyhan & Rickne (2015); Blind et al. (2018); Meusburger & Antonites (2016); Moog et al. (2015); Sellenthin (2009); Strong et al. (2018); Tartari & Breschi (2012); Tijssen (2006)
		Basic research	6	PhDs as well as papers in basic research; self-descriptions of researchers as focusing on basic research	3		1			2	Calderini et al. (2007); Lam (2011); Lee (1998); Moog et al. (2015); Sellenthin (2009); Zarghami et al. (2020)
	Research field	Engineering	29	Disciplinary affiliation or self-description in an engineering field (e.g., general engineering; civil engineering; polytechnic affiliation; STEM)	12	2	12	11	4	8	Arvanitis et al. (2008); Balasubramanian et al. (2020); Baldini (2010); Bozeman & Gaughan (2007); Chen et al. (2013a); Civera & Meoli (2018); Crespi et al. (2011); D’Este & Perkmann (2011); Dill (1995); Epure et al. (2016); Fini et al. (2017); Govindaraju et al. (2009); Han & Heshmati (2016); Huang (2018); Huang et al. (2011); Huyghe & Knockaert (2015); Libaers (2012); Meoli & Vismara (2016); Merchán-Hernández et al. (2015); Muscio (2013); Riviezzo et al. (2019); Rossi & Rosli (2015); Schuelke-Leech (2013); Tartari & Breschi (2012); Teixeira (2017); Van Looy et al. (2011); Visintin & Pittino (2014); Yamaguchi et al. (2019); Zarghami et al. (2020)
		Life sciences	17	Disciplinary affiliation or self-description in a life science that is NOT medical (e.g., biology, chemistry)	9	2	7	6	5	4	Arvanitis et al. (2008); Baldini (2010); Beyhan & Rickne (2015); Crespi et al. (2011); D’Este & Perkmann (2011); Fini et al. (2017); Hayter (2013); Huang (2018); Huang et al. (2011); Huyghe & Knockaert (2015); Kim & Rhee (2018); Lam (2011); Libaers (2012); Muscio (2013); Owen-Smith & Powell (2003); Strong et al. (2018)

Medical	19	Disciplinary affiliation or self-description in a medical field (e.g., (bio)medical school, health, pharmacy)	10	3	4	7	1	3	Baldini (2010); Buenstorf & Geissler (2013); Chen et al. (2013a); Franco et al. (2014); Huang et al. (2011); Huyghe & Knockaert (2015); Lam (2011); Merchán-Hernández et al. (2015); Meusburger & Antonites (2016); Muscio (2013); Owen-Smith & Powell (2003); Riviezzo et al. (2019); Rossi & Rosli (2015); Strong et al. (2018); Tartari & Breschi (2012); Teixeira (2017); Van Looy et al. (2011); Yamaguchi et al. (2019)
Natural sciences	27	Disciplinary affiliation or self-description in a natural science that is NOT an engineering, medical, or life science (e.g., physics, mathematics, manufacturing, materials science, agriculture, etc.)	12	2	11	15	5	3	Arvanitis et al. (2008); Balasubramanian et al. (2020); Beyhan & Rickne (2015); Bozeman & Gaughan (2007); Chen et al. (2013a); Civera & Meoli (2018); Comacchio et al. (2012); Crespi et al. (2011); D'Este & Perkmann (2011); Fini et al. (2017); Franco et al. (2014); Garcia et al. (2019); Huang et al. (2011); Libaers (2012); Meoli & Vismara (2016); Merchán-Hernández et al. (2015); Meusburger & Antonites (2016); Muscio (2013); Riviezzo et al. (2019); Rossi & Rosli (2015); Rybnicek et al. (2019); Strong et al. (2018); Tartari & Breschi (2012); Teixeira (2017); Van Looy et al. (2011); Ye et al. (2020)
Computer science	8	Disciplinary affiliation or self-description in computer science	4		3	3	2	1	Crespi et al. (2011); D'Este & Perkmann (2011); Huang et al. (2011); Lam (2011); Strong et al. (2018); Tartari & Breschi (2012); Visintin & Pittino (2014); Zarghami et al. (2020)
Social sciences	14	Disciplinary affiliation or self-description in a social science (e.g., management, education, humanities, the arts, communication)	7	2	7	8	3	3	Arvanitis et al. (2008); Chen et al. (2013a); Fini et al. (2017); Franco et al. (2014); Huang (2018); Huyghe & Knockaert (2015); Klasová et al. (2019); Merchán-Hernández et al. (2015); Meusburger & Antonites (2016); Riviezzo et al. (2019); Rossi & Rosli (2015); Teixeira (2017); Van Looy et al. (2011); Zarghami et al. (2020)
Other	14	Various mixed or unclassified disciplines	7	1	6	1			Bourelos et al. (2012); Chen et al. (2019); Davey et al. (2016); D'Este & Patel (2007); Diánez-González et al. (2020); Fini et al. (2017); Huang et al. (2011); Hussler & Pénin (2012); Klasová et al. (2019); Niosi (2006); Riviezzo et al. (2019); Varga & Horváth (2014); Wu et al. (2015); Zarghami et al. (2020)

k_{Σ} = total number of studies; k_P = number of studies that investigated patents; k_L = number of studies that investigated licenses; k_{SO} = number of studies that investigated spin-offs; k_{CR} = number of studies that investigated collaborative research; k_C = number of studies that investigated consulting; k_M = number of studies that investigated mixed channels

Research on collaboration and mixed commercial activities displayed no determinants that were exclusively or significantly more often analyzed compared to the other commercialization channels. The following determinants were nonetheless studied for all channels: age of the researcher, size of the research team, position (post-doc/professor), experience in industry, gender, time dedicated to teaching, financial motives, the number of employees in the research organization, the research quality, the innovation climate, education concerning technology transfer, technology transfer support, funding (third-party, industry, public, technology transfer), various commercial experience, TTO quality, applied research, and various research fields. The next section discusses the size and direction of summary effect sizes, especially for patenting and spin-off creation.

2.4.4 Findings from the meta-analysis of determinants for patenting and spin-off creation

We calculated the summary effect sizes across studies to evaluate which determinants led to significant increases in the commercialization of academic knowledge. Table 20 presents the summary effect sizes of all determinants for all channels (see supplementary files). However, correlation tables were only published in 48 studies. This reduced the number of relationships that were possible to use for in-depth analysis, because the required amount of data (at least three studies reporting correlations) was only available for patenting and spin-off creation.

Tables 12 and 13 provide the summary effect sizes for all relationships (between a determinant and a commercialization channel) that were reported in at least three studies (for a complete overview, see Table 20). ES_r represents the summary effect size of all studies that examined the relationship between a determinant and a given channel. V_r is the variance of ES_r. The z-value is used to determine the significance of the ES_r (95% confidence interval: [-1.96, +1.96]). I^2 is the variance between studies divided by the total variance of effect sizes, and is used to indicate heterogeneity (Higgins et al., 2003; Eisend, 2014). It is standardized from 0 to 100% (100% indicates a high heterogeneity). N is defined as the total sample size of all studies included.

Table 12 illustrates that most determinants show a positive overall effect on patenting; only a few, however, are statistically significant. The only determinants that show a negative effect are the time a TTO needs to deal with legal patent issues (-0.02) and academic knowledge from fields of social science as well as engineering; however, these do not have a significant effect (-0.08 and -0.06). In addition, the sizes of the effects are very small. The few determinants that were proven to be statistically significant were the number of employees in the research organization (ES_r = 0.49, z = 2.06), public funding (ES_r = 0.61, z = 2.98), academic knowledge from the natural sciences (ES_r = 0.05, z = 2.16), and spin-off experience (ES_r = 0.20, z = 2.35). None of the other determinants showed a significant summary effect. Nonetheless, these results must be interpreted with caution, because heterogeneity is rather high for most relationships (I^2>80%). This indicates that other variables are necessary for explaining the relationship, such as differences in the study quality or study design.[16] This first means that our estimations tend to underestimate the significance of effects. Second, it shows that further empirical verification is needed for those determinants identified in this study, and/or that – from the perspective of journal editors – authors publishing quantitative research should be encouraged to provide their correlation tables in the future to allow for comprehensive meta-analytical approaches.

Table 12: *Effect size summary for patents (random effects model, only $k_\Sigma \geq 3$)*

Class	Category	Determinant	ES_r	v_r	z	I^2	N	k_Σ

[16] To check the robustness of our results and to increase their validity, we conducted a subgroup analysis (see Section A1 in the supplementary files).

Environmental determinants		Economic prosperity	0.0533	0.0014	1.42	25	2,028	**3**
		Urban region	0.1163	0.0138	0.99	82	2,641	**4**
		Innovative region	0.2213	0.0293	1.29	89	2,420	**3**
Individual determinants	Age	Age	0.0157	0.0160	0.12	87	4,658	**3**
	Team	Size of the research team	0.1269	0.0142	1.06	87	3,756	**4**
	Position	Post-doc or professor	0.0027	0.0248	0.02	94	7,806	**7**
	Experience	Experience in academia	0.2007	0.0207	1.39	92	20,648	**3**
		Experience in industry	0.0443	0.0096	0.45	74	2,316	**3**
	Gender	Male	0.0507	0.0072	0.60	82	4,307	**3**
	Orientation	Entrepreneurial orientation	0.2637	0.0473	1.21	96	2,034	**3**
Organizational determinants	Size	No. of employees	**0.4858**	0.0558	2.06	94	4,680	**8**
	Research quality	Research quality	0.2795	0.2216	0.59	99	75,622	**6**
	Innovation climate	Innovation climate	0.1148	0.0464	0.53	92	2,118	**3**
	Incentive for …	Patents (financial)	0.1138	0.0103	1.12	85	74,362	**4**
	Funding from…	Third party	0.0912	0.0278	0.55	91	4,657	**6**
		Industry	0.2611	0.1434	0.69	97	2,513	**4**
		Public	**0.6119**	0.0421	2.98	86	2,558	**6**
	Productivity	Collaboration	0.1992	0.0826	0.69	95	4,263	**6**
		Patents	0.3620	0.0913	1.20	97	25,573	**8**
		Publication	0.2760	0.0246	1.76	90	40,130	**12**
		Spin-off	**0.1977**	0.0071	2.35	53	1,605	**6**
Field determinants	Research field	Engineering	-0.0604	0.0443	-0.29	94	6,585	**8**
		Life sciences	0.1273	0.0239	0.82	90	4,936	**4**
		Medical	0.0592	0.0230	0.39	89	5,715	**8**
		Natural sciences	**0.0454**	0.0004	2.16	0	4,825	**6**
		Social sciences	-0.0750	0.0129	-0.66	67	2,419	**4**
TTO determinants	TTO exists	TTO exists	0.1387	0.0909	0.46	96	4,678	**4**
	Age of TTO	Age of TTO	0.3082	0.0276	1.86	62	2,077	**3**
	Size of TTO	No. of employees in TTO	0.5729	0.1261	1.61	85	34,087	**6**
	Time to patent	Time to patent	-0.0249	0.0025	-0.50	36	3,844	**3**
	Patent quality	Patent quality	0.0542	0.0326	0.30	96	8,167	**7**

ES_r = summary effect size (standardized from -1 to 1); v_r = variance of ES_r; z = z-value; I^2 = variance between studies divided by the total variance of effect sizes (standardized from 0 to 100%); k_Σ = total number of studies

***Table 13:** Effect size summary for spin-offs (random effects model, only k≥3)*

Class	Category	Determinant	ES_r	v_r	z	I^2	N	k_Σ
Environmental determinants		Economic prosperity	0.0762	0.0168	0.59	93	6,669	**6**
		Urban region	-0.0099	0.0031	-0.18	56	3,486	**3**
		R&D expenditure in region	0.0521	0.0078	0.59	87	4,990	**4**
		Innovative region	0.0417	0.0089	0.44	88	2,733	**3**
		Start-up activity in region	-0.0164	0.0186	-0.12	95	3,877	**3**
		Venture capital	0.0036	0.0220	0.02	90	4,645	6
Individual determinants	Position	Post-doc or professor	-0.0380	0.0251	-0.24	85	12,227	3
	Gender	Female	**-0.1226**	0.0005	-5.6	0	2,575	3
	Orientation	Entrepreneurial orientation	0.4863	0.0906	1.62	97	4,842	**4**
Organizational determinants	Size	No. of employees	0.1947	0.0256	1.22	93	8,615	**10**
	Age	Age of institute	-0.0840	0.0608	-0.34	99	4,866	**4**
	Research quality	Research quality	0.1578	0.0480	0.72	96	15,786	**8**
	Innovation climate	Innovation climate	**0.1211**	0.0024	2.48	35	1,970	**3**
	Infrastructure	License	0.0321	0.0901	0.11	92	384	**3**
		TT strategy	0.0993	0.0265	0.61	82	1,006	**4**
		TT activities	0.1313	0.0045	1.95	25	1,966	**3**
	Funding from…	Third party	0.0944	0.0648	0.37	91	2,941	**6**
		Industry	0.3609	0.0620	1.45	97	6,059	**4**
		Public	0.3240	0.0453	1.52	93	4,942	**3**
	Productivity	Collaboration	**0.1411**	0.0033	2.47	42	3,529	**8**
		Patents	0.2070	0.0227	1.37	90	19,876	**17**
		Publication	0.0378	0.0071	0.45	76	11,290	**7**
		Spin-off	0.1827	0.0394	0.92	93	14,395	**12**
		TT activities	0.0390	0.0289	0.23	85	2,959	**5**
Field determinants	Research field	Engineering	0.1246	0.0127	1.11	82	6,940	**6**
		Natural sciences	0.0700	0.0066	0.86	81	8,111	**6**
		Social sciences	-0.0633	0.0011	-1.87	27	3,900	**4**
TTO determinants	TTO exists	TTO exists	0.1570	0.0192	1.13	85	3,747	**5**
	Age of TTO	Age of TTO	0.1372	0.0144	1.14	86	3,606	**5**
	Size of TTO	No. of employees in TTO	0.1885	0.0141	1.59	76	4,208	**8**
	TTO quality	Expertise in TT	**0.5309**	0.0333	2.91	0	39	**3**

ES_r = summary effect size (standardized from -1 to 1); v_r = variance of ES_r; z = z-value; I^2 = variance between studies divided by the total variance of effect sizes (standardized from 0 to 100%); k_Σ = total number of studies

Like patenting, most determinants have a positive overall effect on spin-off creation (see Table 13), though again generally not statistically significant. Interestingly, female researchers are significantly less active in spin-off creations (ES_r = -0.12; z = -5.6). Academic knowledge from the social sciences is less likely to be commercialized as a spin-off (-0.06; not significant). Other non-significant, but negative effect sizes appear with post-doc or professor positions (-0.04) and the age of the institute (-0.08), as well as very small effect sizes from a location in an urban region (-0.01) and start-up activities in the region (-0.02). In contrast, we found the innovation climate in a research organization (ES_r = 0.12, z = 2.48), high number of collaborative activities of the research organization (ES_r = 0.14, z = 2.47), and the technology transfer expertise of TTOs (ES_r = 0.53, z = 2.91) to be significantly positive determinants. All other determinants showed no significant summary effect and relatively high heterogeneity.

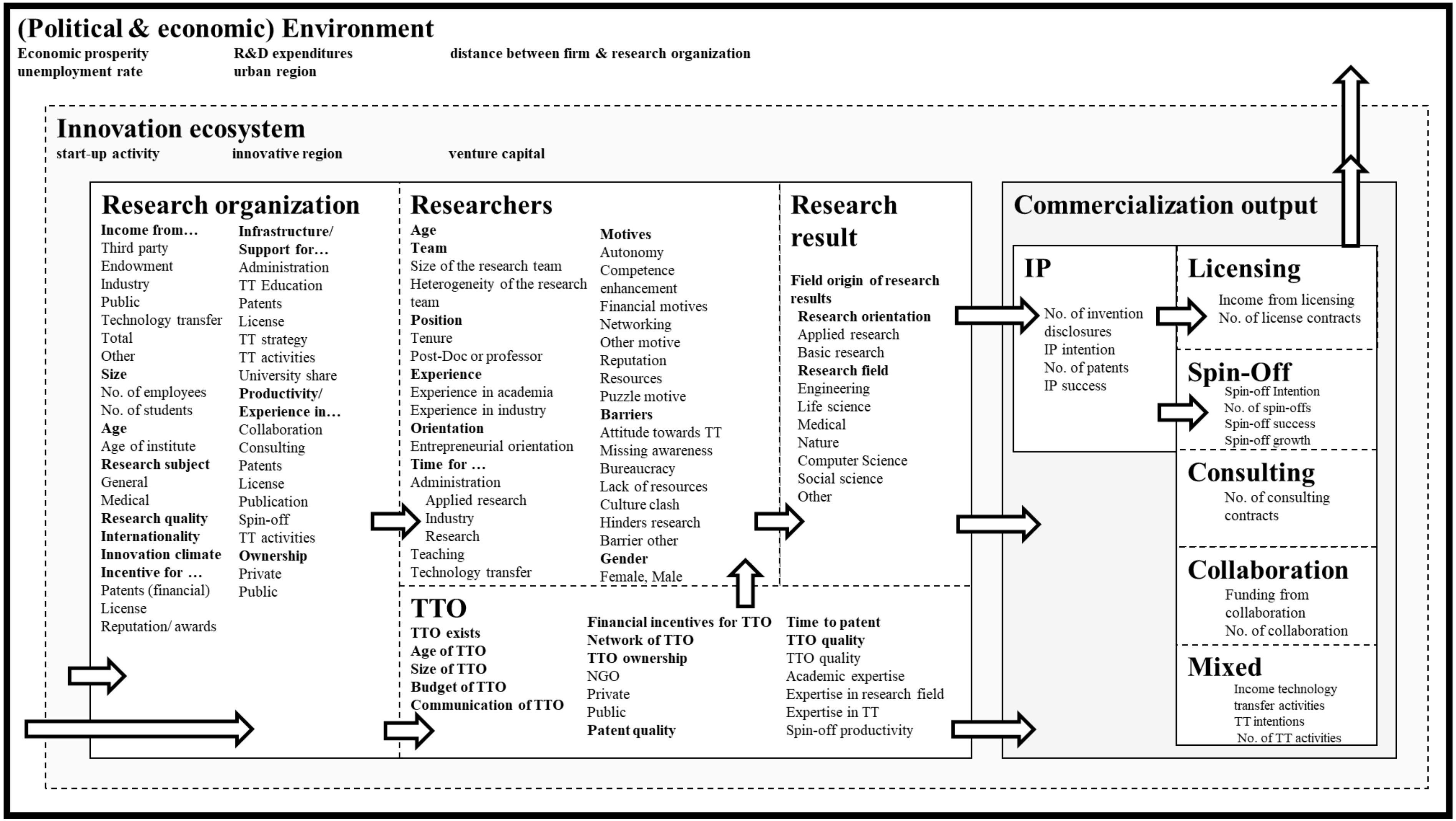
2.5 Towards a future research agenda

2.5.1 Merging theoretical components, determinants, and output indicators in the comprehensive framework

The first goal of this paper was to provide a comprehensive framework that integrates the findings of previous research and at the same time guides future studies that aim to examine the commercialization at research organizations. In consequence, the paper proposed a comprehensive framework based on previous literature reviews in the theory section (see Figure 6). Figure 9 presents how the identified determinants and output indicators relate to the seven main components of the framework. The organizational determinants belong to the research organization. Similarly, the individual determinants belong to the researchers. Obviously, the TTO determinants match with the component "TTO". Less obvious is the integration of the field determinants, since the scientific discipline is measured in different ways, i.e., as the scientific discipline of the research organization, the faculty, the scientist, or as the field that belongs to a certain patent code or spin-off company classification (e.g., Fini et al., 2017; Huang et al., 2011; Huyghe & Knockaert, 2015; Lam, 2011; Libaers, 2012; Owen-Smith & Powell, 2003). However, the determinants intend to provide in each case information about the characteristics of the research result or is at least serve as a proxy for the research result's characteristics. Therefore, the field determinants were integrated as filed origin of the research results to the related component. Considering environmental determinates, we integrated most determinants to the component named political and economic environment. Additionally, we set some determinants on the component innovation ecosystem as they better fit to this component. However, since the innovation ecosystem is embedded in the environment, the determinants blend in. Last, the output indicators related to the commercialization channels present the component named commercialization output.

Merging the identified determinants, and output indicators with the framework reveals the relations between the determinants. Even though the relations in the framework are rather rough and need more detailed insights by future researchers. In this way, this paper provides a comprehensive and straightforward framework to assess the determinants contributing to the successful commercialization of academic knowledge and allows for an initial systematic discussion on existing research gaps in the next section.

Figure 9: *Framework for studying the commercialization of academic knowledge*



2.5.2 Future research directions

The results of this meta-analysis showed that a large number of determinants have been subject to analysis over the years. However, several research gaps remain. Table 14 lists the research gaps we have identified. Regarding determinants, we showed that while team composition has been analyzed quite intensively for spin-offs, it remains largely ignored for other channels, even though team diversity is likely to play an important role in other channels, too. In addition, Bell (2007) performed a meta-analysis in which she found that agreeableness, conscientiousness, and openness to experience were predictors of team performance. Thus, these kinds of team characteristics could also be of interest for further researchers in the field of technology transfer.

Another lacuna in existing quantitative research concerns the lack of analysis of research fields in the social sciences and other types of nontechnical knowledge. Even though the social sciences are less relevant for patents and licensing, it could be interesting to see how social scientists commercialize their academic knowledge, in the form of training or consulting.

The characteristics of the regulatory environment and the innovation ecosystem have also been neglected, and therefore indicate research gaps. Here, cross-national studies analyzing different laws and regulations for intellectual property licensing conditions and university rights may be quite interesting. One aspect that did not appear at all is the effectiveness of various measures designed to incentivize commercialization among researchers, and when those incentives should be implemented, e.g., in light of different career goals over a career life cycle. Furthermore, the interplay between informal activities (such as discussions at conferences) and formal activities remains under-researched.

Table 14: *Summary of future research gaps*

Research-gap category	**Research gaps and examples of research questions**
Determinants	• Individual determinants o Team heterogeneity has proven to be relevant for spin-off creation, but has been ignored for the other channels so far; Does team heterogeneity increase the commercial success of licensing (or other channels)? o Additional team characteristics should be analyzed, such as agreeableness, conscientiousness, openness to experience, etc. What personality characteristics influence the commercial performance of a research team? • Field determinants o Previous research has provided little information on commercialization activities in social-science fields; What kind of support do social scientists need to commercialize their knowledge? Which role do social scientists play in the commercialization of technical knowledge? o Different types of knowledge should be investigated; How does the kind of knowledge (e.g.., explicit, implicit, and tacit) influence the commercialization process? • Environmental determinants o Data on the influence of policy interventions (except from grants), regulations, and laws is missing, especially on the international level; What impacts do TT interventions have on the commercial activities of research organizations in different European nations? • Determinants considering the innovation ecosystem are missing o Which innovation ecosystem elements influence the commercialization of academic knowledge? • Effectiveness of human resource measures

	o Forms of contract – "person-job fit" – are under-researched; How do recruitment decisions influence commercial activities? o Goal-setting/onboarding; How do multiple goals (according to the three missions of the university) affect the intrinsic motivation of scientists? • The timing and duration of various determinants (funding sources, industry contacts, TTO infrastructure, and incentives) may play an important role; o How does the timing of a success-determinant appearance within a scientist's career affect subsequent commercialization activities? • Linkages between informal and formal transfer activities (beyond effects of publication efforts on commercial activities) are understudied; o How do researchers use standardization activities to enhance commercialization? o What types of conferences enhance commercial activities (e.g., national or international conferences, science- or practitioner-oriented conferences, quality of conferences, etc.)?
Commer-cialization channels	• Research about the "consulting" channel is lacking; Which links, tradeoffs, and synergies exist between consulting and other channels? • Other forms of commercial transfer have been ignored so far, i.e., training programs and standardization; What is the role of professional training in the commercialization of academic knowledge? • Operationalization of commercialization channels has focused on quantitative indicators (such as "No. of consultancy contracts") and has failed to integrate qualitative indicators (e.g., customer satisfaction); How can the quality of commercialization be measured? What influences the quality of the commercialization of academic knowledge?
Processes & actors	• Current literature largely ignores the process perspective and activities between actors; How do actors' activities influence each other (university, TTO, researcher)? • Previous literature has focused on universities What influence do PRO structures have on commercial activities? Do the commercial activities of PROs differ from those of universities?
Data and methodo-logical issues	• Currently, most studies are based on surveys and/or have a strong focus on the US; o More panel data is necessary, such as the annual AUTM survey o The surveys are not standardized o Other data sources should be used, e.g., non-participant observations • Integration of a correlation matrix should become a mandatory condition for quantitative studies

We also showed that consulting activities as a commercialization channel appear to be a niche in quantitative research on the commercialization of academic knowledge, even though it is known to be crucial as an informal transfer channel.

In addition, none of the studies included took a process perspective to understand the determinants that influenced the commercialization of academic research. As a result, they ignored the sequence of timing of events that led to the successful commercialization of academic knowledge.

Since only two of the studies in our sample focus on PROs, we assert that more quantitative research on PROs is clearly needed. It would be of interest to see how PROs – federal laboratories, national laboratories, and research and technology organizations – differ from universities. Choi et al. (2022), for example, recently found that scientists working at federal labs differ from university scientists in their sense of public service as well as cognitive dissonance in pursuing technology transfer.

One of the most important aspects would be to improve data availability and rectify methodological issues. First, most studies rely on surveys. They usually vary in the way they operationalize their research questions, the definitions they apply, and the way samples are generated. For these reasons, it is difficult to compare results. The only survey providing a somewhat standardized result is the AUTM survey. Surveys that take a more similar approach, relying on the same definitions and operationalizations, could help to improve quantitative research on the commercialization of academic research, including the addition of more countries to the analysis. Another way to generate valid, more comparable data would be to exploit new and innovative sources of data generation such as web crawling and semantic analysis.

2.6 Conclusion

This paper analyzed 99 quantitative studies published since 1980 to 1) identify determinants and commercialization output indicators, 2) to identify determinants in which empirical evidence has proven influence spin off creation and patenting, and 3) to develop a new comprehensive framework for studying the determinants of commercialization at research organizations. The following section provides a summary of the major findings, and a discussion of theoretical and managerial implications.

2.6.1 Summary of major findings

Our initial descriptive analysis revealed that significant quantitative empirical verification started in the early 2000s. This means that over the last two decades, a number of studies have provided substantial empirical support for academic understandings of the commercialization of academic knowledge, and how to maximize its impact. By digging deeper into the data, the descriptive analysis showed major differences between channels of commercialization. It became obvious that the most studied commercial activity was patenting, followed by creating spin-offs. The least studied channel, on the other hand, was consulting. Thus, consulting activities, which qualitative research has shown to be an important channel for knowledge transfer, still seem to remain under-researched, at least in comparison to other channels (see Perkmann & Walsh, 2007). This may be because consulting activities are often “hidden”: they are conducted outside of academia, with private contracts with professors but not considered part of the academic mission. Furthermore, systematic data on consulting activities is missing because “consulting” is often difficult to define and measure with quantitative approaches. Moreover, more than one third of the studies were conducted in Italy or the US, which implies the threat of biased findings. Similar, the findings could be biased due to the vast number of studies that focus on the commercial activities of universities (88%).

Turning to the identified commercialization output indicators, the findings show that the indicators differ regarding the timing of commercialization activities (before and after commercialization) and the operationalization of indicators. Especially, the differences in the operationalization of indicators impede the comparability of the findings from different studies. Thus, future research would benefit from standardized approaches, like the AUTM survey.

The major contribution of this study depicts the identification of determinants that influence the commercialization of academic knowledge. The findings on determinants reveal that the most intensely studied determinants belong to the classes: individual determinants of the researchers and the organizational determinants of the research organization. When looking at TTOs, the most often analyzed determinants are again age, size, and ownership structure. Whereas the quality and the communication/networking strategies were only examined in a few studies. This is surprising, since these seem to be important determinants for successful technology transfer. The scientific field is one of the most often used variables and is subject to investigation in almost every study. However, “computer science” and “social sciences” are less often analyzed than the natural sciences. Moreover, other characteristics of research results are missing completely. Environmental determinants are generally examined less frequently, except from economic prosperity and the venture capital available to spin-offs. This is rather surprising, since previous literature reviews claim a wide range of environmental factors including industry characteristics, local and national policies, stakeholder engagement, and also cultural aspects (OECD, 2013; Maresova et al., 2019; Sandström et al., 2018).

Finally, the findings of the meta-analysis of determinants that influence patenting and spin-off creation reveals several insights. First, the generation of patents is significantly affected by the number of employees in the research organization (as a proxy for size), the volume of public funding, the share of academic knowledge from the natural sciences, and previous experience in spin-offs across all compared studies and coefficients. Thus, the sheer size of a research organization and the amount of public funding devoted to it pays off, at least in terms of the amount of academic knowledge patented. One possible explanation may be the principle of economies of scale. Larger research organizations are more likely to have specialized services for technology transfer, larger industry networks, and standardized administrative processes for patenting and exploitation strategies. Furthermore, our results support at least a correlation between previous experience that an organization has with spin-off creation and patenting. This finding has been shown in several studies before and still holds when analyzed from a meta-perspective (see Baldini, 2010; Son et al., 2019; Moog et al., 2015). Finally, the natural sciences proved to be significantly more prone to encourage patent filings.

Turning to spin-offs, our findings provide strong support for previous findings that female researchers are significantly less active in forming spin-offs than their male colleagues. These findings justify supplementary support activities for female entrepreneurship. Perkmann et al. (2021) reached a similar conclusion, discussing the relevance of university policy as well as government policy measures to increase female academic engagement. Once again, however, some moderator variables, such as field-specific effects, might also be in play here. In general, the results furthermore indicate that the innovation climate of a research organization is extremely relevant for spin-off creation. Similarly, the influence of technology transfer expertise from TTOs on spin-off creation is statistically significant. These findings are especially relevant for university governance and TTO managers because they are the ones responsible for measures and incentives that shape the innovation climate. Furthermore, a large number of collaboration activities of researchers with industry have also proven to be a significant determinant for spin-off creation. In accordance with previous research, our analysis indicates that researchers with industry experience are more likely to pursue a career in industry in the form of a spin-off (Rotharmel et al., 2007). In sum, all determinants underline the cultural and organizational aspects of entrepreneurship support from an organizational perspective.

2.6.2 Theoretical implications

This study contributes to the academic discourse in three ways. First, it provides a new comprehensive framework to further study the commercialization of academic knowledge. Second, it identifies 97 determinants that influence the commercialization of academic knowledge. The determinants are classified according to five classes and five commercialization channels. The transfer of these determinants to the comprehensive framework enables future researchers to better understand the complexity of commercialization activities in universities and PROs (see Table 9.). In conclusion, the findings serve as the base for future studies, that are interested in conducting a quantitative analysis. Moreover, this study revealed that no standardized questionnaire or survey exists to study the commercialization of academic research or even parts of the phenomenon. Hence, the identification of determinants can aid scientists that aim to develop a standardized survey. Similar, the research on commercialization of academic knowledge would benefit from standardized scales to measure the motives and barriers for commercial activities.

Last, this research provides various research gaps and examples of future research questions in the following fields: determinants for the commercialization of academic knowledge, commercialization channels, processes and actors, data and methodologies.

2.6.3 Managerial implications – commercialization of academic knowledge

This study holds a variety of implications for decision makers in research organizations, TTOs, and innovation policy. Specifically, university and PRO managers can use the findings to better align their knowledge transfer strategy and improve the support for commercial activities. The overview of determinants and commercialization channels will enable them to better understand the consequences of their interventions and thus to better prioritize the support programs. The findings indicate that the environmental conditions strengthen certain channels more than others; e.g., spin-of creation is facilitated in regions characterized by a high level of economic prosperity and the availability of venture capital. Thus, research organizations that aim to increase the commercialization of academic knowledge should align their TTO strategy depending on their environmental conditions. Depending on the prioritized commercialization channels, research organizations can connect more strategically with external organizations and networks. For example, a PRO that aims to strengthen its spin-off activities will rather connect with external incubators and investors. By contrast, a university seeking a higher income from international license contracts will rather participate in international company networks.

TTO managers can use the findings to improve their commercial support services, which more effectively address the motivation of researchers. The meta-analysis revealed that female scientists have founded significantly fewer spin-offs than male scientists. Therefore, TTOs should create services especially targeted at female researchers. Recent results from Perkmann et al. (2021) confirmed the importance of supporting female entrepreneurship.

Decision makers in innovation policy dealing with support mechanisms for commercial activities of scientists and research organizations can use our findings to create legal frameworks for knowledge and technology transfer that consider the needs of scientists and TTO professionals. Especially female scientists would benefit from customized entrepreneurship support for enhancing the number of spin-offs founded by women. In addition, the meta-analysis revealed the importance of public funding for commercial activities. Considering funding in general, additional third-party funding, for the advancement of research results to prototypes, would be valuable for improving commercial activities.

2.6.4 Limitations

The final and at the same time the biggest limitation of this study is that a large share of quantitative studies failed to provide the correlation matrix in their publication. This reduces the traceability of results and makes it hard for a meta-analysis to conduct a test for significance across all correlation coefficients beyond the regression results provided. For this study, the lack of correlation matrices meant that only two channels could be analyzed in depth and that even there – due to small sample size – heterogeneity in the database remained a challenge. Thus, the statistical validation of all previous research had – due to data restrictions – to remain rather hesitant and cursory. Nonetheless, this paper was able to, first, provide a systematic overview of commercialization channels and the determinants that influence them. Second, it was able to indicate which components have already been well-researched from a quantitative perspective for patenting and spin-off creation (and which have not). Third, it provided a comprehensive and easy-to-grasp framework for future research, and finally, it pointed out several future potential research streams.

2.7 Acknowledgements

We acknowledge the support of our student assistant, who helped us to code the variables and effect sizes.

2.8 Supplementary files

Tables 15-19 report the results of the vote counting (as explained in Section 2.3.). The total number of studies that investigated the relationship between a determinant and a commercialization channel is represented by k_{Σ}. In addition, the number of studies that found a negative ($k_{negative}$) or positive relation ($k_{positive}$) are reported and separated. However, this could only be done for those studies that analyzed regression tables (β) and those that reported correlation tables I.[17] Study results that reported significant positive or negative effects are noted with an asterisk (β* and *r**; critical value equals 5%).

[17] Some studies included both tables. Therefore, the sum of studies (k_{Σ}) may be lower than the sum of k_{positive} and k_{negative}.

Table 15: *Overview of individual determinants for each commercialization channel*

Individual factors		Patent					License					Spin-off					Collaboration					Consulting					Mixed				
		$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$		k_{Σ}
		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]	
Age	Age	**1 / .**	[1 / 2]	**2 / .**	[2 / .]	7				[1 / .]	1	**1 / .**	[2 / .]	**2 / .**	[4 / .]	5	**2 / .**	[. / 1]	**1 / .**	[4 / .]	7	**1 / .**			[3 / .]	4	**1 / .**			[2 / 1]	4
Team	Size of research team	**1 / .**	[. / 1]	**2 / 2**	[4 / 1]	6			**1 / 1**	[1 / .]	2			**1 / 1**	[2 / .]	3			**3 / 1**	[3 / .]	6		[1 / .]		[1 / .]	2			**2 / .**		3
	Team heterogeneity												[1 / .]		[1 / .]	2															
Position	Tenure		[1 / .]	**1 / .**	[1 / .]	3													**1 / .**	[1 / .]	2				[2 / .]	2			**2 / .**	[1 / .]	3
	Post-Doc or professor	**2 / .**	[1 / 1]	**2 / .**	[3 / 1]	9		[1 / .]		[1 / .]	2		[1 / 1]	**3 / .**	[4 / .]	10			**5 / .**	[2 / .]	6			**3 / .**	[1 / .]	4		[. / 1]		[2 / .]	3
Experience	Experience in academia		[1 / 1]	**2 / 2**	[2 / .]	6						**. / 1**	[2 / 1]			3	**1 / .**	[. / 1]	**1 / 1**	[1 / .]	4			**1 / 1**	[2 / 1]	3	**. / 1**	[2 / .]	**1 / .**		3
	Experience in industry		[2 / 1]	**1 / .**	[1 / 1]	5		[1 / .]			1				[2 / .]	2			**2 / 1**	[1 / .]	3			**1 / .**	[1 / .]	2				[3 / .]	3
Gender	Female	**1 / 2**	[1 / .]			3						**2 / 2**	[1 / .]			3											**. / 1**	[2 / .]			2
	Male		[1 / .]	**1 / .**	[4 / 1]	8				[2 / .]	2				[2 / .]	2		[1 / .]	**4 / .**		6				[3 / .]	4	**1 / .**		**1 / .**		2
Orientation	Entrepren. orientation			**1 / 3**	[1 / .]	4			**. / 1**	[1 / .]	1		[1 / 2]	**6 / 2**		8			**1 / .**		1								**1 / 1**	[1 / .]	2
Time for …	Administration																											[1 / .]		[1 / .]	2
	Applied research		[1 / .]			1	**1 / .**				1				[1 / .]	1	**1 / .**				1	**1 / .**				1					
	Industry				[1 / .]	1							[1 / .]			1															
	Research	**1 / .**	[1 / .]			2							[1 / 1]		[1 / .]	3		[1 / .]			1				[1 / .]	1		[1 / .]		[2 / .]	3
	Teaching		[1 / .]			1	**1 / .**				1		[1 / .]	**1 / .**	[. / 1]	3	**2 / .**				2		[1 / .]			1	**1 / .**			[2 / .]	3
	Technology transfer				[1 / .]	1									[1 / .]	1													**1 / .**	[1 / .]	2
Motives for TT	Autonomy	**1 / .**	[1 / .]		[1 / 1]	3						**1 / .**	[1 / .]	**6 / 1**	[2 / .]	5		[1 / .]		[1 / .]	2	**1 / .**				1					
	Competence enhancement		[1 / 1]		[3 / .]	4						**1 / .**			[1 / .]	3		[1 / .]	**3 / 1**	[1 / .]	5			**1 / 1**	[2 / 1]	4			**2 / .**		2
	Financial motives			**2 / 1**	[3 / .]	5			**. / 1**		1			**2 / 1**	[1 / .]	3				[1 / .]	1			**1 / .**		1			**2 / .**	[1 / .]	2
	Networking				[1 / 1]	1						**1 / .**	[3 / .]		[1 / .]	2				[1 / 1]	1		[1 / 1]			1			**1 / .**		1
	Motive other												[1 / .]	**1 / .**		1															
	Reputation			**1 / .**	[1 / .]	2							[3 / .]	**3 / .**	[2 / .]	3											**1 / .**				1
	Resources	**1 / .**	[2 / 1]		[2 / .]	5							[2 / .]	**3 / .**	[4 / .]	4	**1 / .**			[5 / 1]	6		[1 / .]	**1 / .**	[2 / 1]	4					
	Puzzle				[1 / .]	1							[1 / .]	**3 / .**	[1 / .]	4			**2 / .**	[1 / .]	3				[1 / .]	1			**1 / 1**	[1 / .]	2
Barriers	Attitude towards TT		[1 / .]			2	**1 / .**				1						**2 / .**			[1 / .]	3						**3 / .**			[1 / .]	4
	Missing awareness												[5 / .]			1				[1 / .]	1										
	Bureaucracy				[1 / .]	1											**1 / .**				1										
	Cost		[2 / .]		[1 / .]	2		[1 / .]		[1 / .]	1		[3 / .]	**1 / .**	[1 / .]	1		[2 / .]			1										
	Culture clash					1	**1 / .**				1	**1 / .**	[1 / .]	**1 / .**	[3 / .]	2		[1 / .]			2										
	Hinders research	**1 / .**	[1 / .]			3									[1 / .]	1	**1 / .**			[1 / .]	2										

Table 16: Overview of organization-based determinants for each commercialization channel

Organizational factors		Patent					Licence					Spin-off					Collaborative research					Consulting					Mixed				
		$k_{negative}$	k_n	$k_{positive}$	$k_{positiv}$		$k_{negative}$	k_n	$k_{positive}$	$k_{positiv}$		$k_{negative}$	k_n	$k_{positive}$	$k_{positiv}$		$k_{negative}$	k_n	$k_{positive}$	$k_{positiv}$		$k_{negative}$	k_n	$k_{positive}$	$k_{positiv}$		$k_{negative}$	k_n	$k_{positive}$	$k_{positiv}$	k_{Σ}
		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]	
Size	No. of employees		[. / 1]	**5 / 5**	[1 / .]	10		[1 / .]	**. / 3**	[3 / 1]	4	**1 / .**	[6 / 2]	**3 / 4**	[2 / 1]	14		[1 / .]	**1 / 1**	[2 / .]	4			**1 / .**		1			**2 / .**	[2 / .]	3
	No. of students		[. / 1]		[2 / .]	4		[1 / .]		[. / 1]	2		[2 / .]			4			**1 / .**		1							[1 / .]		[1 / .]	2
Age	Age of institute	**1 / .**	[. / 1]		[1 / .]	2						**1 / 1**	[2 / .]	**. / 2**	[. / 1]	4		[1 / .]	**1 / .**		2							[1 / .]			1
Research subject	General				[1 / .]	1		[1 / .]			1		[2 / .]		[3 / .]	1			**1 / .**		1									[1 / .]	1
	Medical		[1 / .]	**. / 1**		2							[1 / .]			1															
Ownership	Private			**1 / .**		2						**. / 1**	[1 / .]		[2 / 1]	3		[1 / .]			2									[1 / .]	1
	Public			**1 / 1**		2			**1 / 1**		1									[1 / .]	2								**1 / .**		1
Research	Research quality	**. / 1**	[1 / 1]	**8 / 3**	[3 / .]	13		[1 / .]	**3 / 4**		3	**. / 1**	[2 / 3]	**5 / 3**	[4 / 1]	10	**1 / .**	[2 / .]	**2 / .**	[1 / .]	6			**3 / .**	[2 / .]	4		[1 / .]	**1 / .**		3
Internat.	Internationality	**1 / .**	[1 / .]	**1 / .**	[1 / .]	3												[1 / .]	**1 / .**		2									[1 / .]	1
Climate	Innovation climate	**1 / 1**		**2 / 1**	[1 / 1]	6				[1 / .]	1			**. / 2**	[2 / 1]	4			**1 / .**	[1 / .]	2		[1 / .]			1			**1 / .**		1
Incentive	Patents (financial)	**. / 1**	[1 / .]	**4 / .**	[1 / .]	5		[1 / .]	**. / 1**		1				[1 / .]	1												[1 / .]		[1 / .]	2
	Reputation/ awards			**1 / 1**		1								**1 / 1**		1													**. / 1**	[1 / .]	1
Infrastructure/ Support for…	TT Education		[1 / .]	**1 / .**		1		[1 / .]			1				[3 / .]	3				[1 / .]	1			**1 / .**		1					
	Patents			**2 / .**	[2 / .]	3			**1 / .**		1																			[1 / .]	1
	TT strategy			**2 / 1**		2							[. / 1]	**1 / 1**	[. / 1]	4				[1 / .]	1							[1 / 1]	**. / 1**	[1 / .]	2
	TT activities		[1 / .]	**1 / 1**	[1 / .]	4		[1 / .]	**. / 2**		3	**1 / .**	[2 / .]	**1 / 1**	[1 / 1]	7	**1 / .**		**4 / 1**		4		[1 / .]			1		[1 / .]	**3 / .**		2
Income from…	Third party		[1 / .]	**1 / 3**	[3 / .]	8			**1 / 2**		2	**1 / .**	[. / 1]	**2 / 2**	[3 / 1]	9				[2 / .]	2				[1 / .]	1		[1 / .]			2
	Endowment								**1 / 1**		1			**. / 1**	[1 / .]	1															
	Industry		[. / 1]	**1 / 2**	[4 / .]	7		[1 / .]	**1 / 5**	[3 / .]	5	**1 / .**		**4 / 4**	[2 / .]	9			**3 / .**	[1 / .]	4		[1 / .]	**1 / .**		2			**1 / .**	[3 / .]	6
Other	Other		[1 / .]		[1 / .]	2	**1 / .**	[1 / .]	**1 / 2**		2			**. / 1**	[1 / .]	2		[1 / .]			2										
	Public		[1 / .]	**3 / 5**	[1 / .]	9		[1 / .]	**2 / 5**		5	**1 / .**	[2 / .]	**3 / 1**		7		[1 / .]	**3 / .**		4		[1 / .]			1	**1 / .**	[1 / .]	**1 / .**	[1 / .]	6
	Technology transfer		[1 / .]	**. / 1**	[3 / .]	4			**. / 1**		1	**. / 1**	[1 / .]	**1 / .**		2			**2 / .**		2				[1 / .]	1		[1 / .]			1
Productivity/ Experience in…	Collaboration	**1 / .**		**3 / 3**	[4 / 1]	10			**. / 1**		1		[3 / 1]	**1 / 1**	[1 / 1]	8			**2 / .**		2			**1 / .**		1		[. / 1]	**1 / 1**	[1 / .]	3
	Consulting				[1 / .]	1								**2 / .**		2															
	Patents		[1 / .]	**12 / 4**	[1 / .]	13			**6 / 5**	[3 / .]	9	**1 / .**	[2 / .]	**7 / 8**	[7 / 4]	24		[1 / .]	**2 / 3**	[2 / .]	6			**1 / .**	[1 / .]	2			**. / 1**	[1 / .]	2
	License			**. / 1**		1		[1 / 1]	**. / 1**		2		[1 / .]	**. / 1**		2														[1 / .]	1
	Publication		[1 / .]	**11 / 6**	[2 / 1]	18			**3 / 3**		4	**2 / .**		**2 / 1**	[5 / 3]	10			**5 / 3**	[1 / .]	7			**1 / 1**	[. / 1]	1	**1 / .**	[1 / .]			2
	Spin-off		[. / 1]	**1 / 3**	[1 / 1]	7		[. / 1]	**2 / 2**		4	**2 / 1**		**5 / 7**	[7 / .]	18			**2 / .**	[1 / 1]	3			**2 / .**		2			**. / 1**	[1 / .]	2
	TT activities		[1 / .]	**2 / 1**		3			**. / 1**	[1 / .]	1	**1 / .**	[1 / 1]	**2 / 1**	[. / 1]	6			**4 / .**	[2 / .]	5				[1 / .]	1	**1 / .**	[. / 1]	**3 / 1**	[1 / .]	4

Table 17: *Overview of field/discipline determinants for each commercialization channel*

Field factors		Patent					License					Spin-off					Collaboration					Consulting					Mixed					
		$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$		k_{Σ}
		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]	
Research orientation	Applied research		[1 / .]	**2 / .**	[1 / .]	6				[1 / .]	1		[1 / .]		[2 / .]	3		[1 / .]	**1 / .**	[1 / .]	3			**1 / .**	[1 / .]	2					
	Basic research				[2 / 1]	3						**1 / .**				1												[1 / .]	**1 / .**		2
Reseach field	Engeneering	**1 / .**	[2 / 2]	**5 / 2**	[2 / 1]	12		[1 / .]	**. / 1**		2	**. / 1**	[3 / .]	**3 / 3**	[3 / 1]	12	**1 / .**	[3 / 1]	**3 / 1**	[3 / .]	11			**2 / .**		4		[2 / .]	**4 / 1**	[2 / .]	8
	Life science			**2 / .**	[4 / 1]	9		[1 / .]	**1 / 1**		2	**1 / .**		**. / 1**	[5 / 1]	7		[2 / .]		[2 / .]	6	**1 / .**		**1 / .**	[2 / .]	5		[1 / 1]	**3 / .**	[1 / .]	4
	Medical	**1 / 2**	[3 / .]	**3 / 1**	[1 / 1]	10		[1 / 1]	**1 / .**		3	**. / 1**	[3 / 1]		[1 / .]	4		[3 / .]	**2 / .**	[2 / 1]	7		[1 / .]			1	**1 / 1**		**2 / .**		3
	Nature	**1 / .**	[3 / 1]	**2 / 1**	[3 / 2]	12		[2 / .]			2		[4 / 4]	**. / 2**	[5 / .]	11	**1 / .**	[4 / 1]	**4 / 1**	[6 / 1]	15	**1 / .**	[1 / .]	**1 / .**	[2 / .]	5		[1 / .]	**1 / .**	[1 / .]	3
	Computer Science	**1 / .**			[1 / .]	4								**1 / .**	[1 / .]	3		[1 / .]		[1 / .]	3	**1 / .**		**1 / .**		2			**1 / .**		1
	Social science	**1 / 1**	[4 / 2]		[. / 1]	7		[2 / .]			2	**1 / 2**	[4 / 1]	**1 / .**	[1 / 1]	7	**2 / .**	[3 / .]	**1 / .**	[2 / 1]	8		[1 / .]	**2 / .**		3	**2 / 1**		**1 / .**		3

Table 18: *Overview of TTO determinants for each commercialization channel*

TTO factors		Patent					License					Spin-off					Collaboration					Consulting					Mixed					
		$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$		k_{Σ}
		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]	
TTO exists	TTO existence		[1 / .]	**2 / 1**	[1 / .]	5							[2 / .]	**1 / 1**	[2 / 1]	7			**2 / .**	[1 / .]	3				[1 / .]	1		[1 / .]	**1 / .**		2
Age of TTO	Age of TTO	**1 / .**		**2 / 2**		3			**1 / 2**	[1 / .]	2		[2 / .]	**1 / 4**	[2 / 1]	5		[. / 1]		[1 / .]	1										
Size of TTO	No. of employees		[1 / .]	**5 / 4**	[2 / .]	8		[1 / .]	**3 / 4**	[3 / 1]	6		[1 / .]	**3 / 2**	[4 / 4]	11			**1 / .**	[2 / 2]	3								**1 / .**	[3 / .]	2
Budget	Budget of TTO													**1 / 1**		3														[1 / .]	1
Communication	Communication						**. / 1**			[1 / .]	1	**1 / .**	[. / 1]			1													**1 / .**		1
TTO incentives	Financial									[1 / 1]	1			**1 / .**		1															
TTO	Private			**. / 1**	[1 / .]	2						**1 / .**			[. / 1]	1															
TTO quality	TTO quality			**1 / .**	[1 / .]	2				[3 / .]	3	**1 / .**		**1 / .**	[1 / .]	3		[1 / .]		[2 / .]	3				[2 / .]	2					
	Academic expertise			**. / 1**		1			**1 / 1**		1			**. / 1**		1														[1 / .]	1
	Expertise in TT			**. / 1**		1		[1 / 1]	**1 / 1**		2			**. / 1**	[. / 2]	2			**1 / 2**	[1 / 1]	1										
	Spin-off productivity													**1 / 1**	[. / 1]	2															
Time to patent	Time to patent	**1 / 1**	[1 / 1]	**1 / .**		2		[1 / .]			1																				
Patent quality	Patent quality	**1 / 1**	[3 / 2]	**2 / 1**	[1 / 2]	3			**2 / .**	[1 / 1]	3			**1 / .**	[1 / 1]	2															

Table 19: *Overview of environmental determinants for each commercialization channel*

Environmental factors	Patent					License					Spin-off					Collaboration					Consulting					Mixed				
	$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$			$k_{negative}$		$k_{positive}$		k_{Σ}
	β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]		β* / r*	[β / r]	β* / r*	[β / r]	
Economic prosperity		[1 / .]	**. / 1**	[1 / 1]	3						**3 / .**	[. / 3]	**3 / 3**	[3 / .]	9		[1 / .]			1									[1 / .]	1
Unemployment											**. / 1**		**1 / .**	[1 / 1]	2															
Urban region		[3 / .]	**1 / .**	[1 / 2]	5				[1 / .]	1	**1 / .**	[. / 2]	**1 / .**	[. / 1]	3	**1 / 1**			[2 / .]	3							[1 / .]			1
R&D expenditures			**. / 1**	[1 / .]	1						**1 / .**	[. / 2]	**2 / 2**	[1 / .]	4			**1 / .**		1										
Innovative region	**1 / .**	[2 / .]	**1 / 1**		3							[. / 1]	**. / 1**	[3 / .]	4															
Start-up activity		[1 / 1]	**. / 1**		2						**1 / 1**	[1 / 1]	**. / 1**		3															
Venture capital		[1 / .]		[. / 1]	2		[1 / .]	**1 / 3**	[1 / .]	2	**. / 1**	[2 / 2]	**3 / 2**	[3 / .]	9														[1 / .]	1
Distance firm-university		[1 / .]		[. / 1]	1						**1 / .**		**1 / 1**		1		[1 / .]			1							[1 / .]			1

k_{Σ} = total number of studies; $k_{negative}$ = indicates the number of studies that found negative relationships; $k_{positive}$ = indicates the number of studies that found positive relationships; β = number of studies with regression tables; r = number of studies with correlation matrices; * = indicates studies with significant results (critical value = 5%); [number] = indicates studies with insignificant relationships.

Table 20: *Effect size summaries*

Environmental factors	Patent								License								Spin-off							
	ES_r	v_r	z	Q	I^2	C	N	k	ES_r	v_r	z	Q	I^2	C	N	k	ES_r	v_r	z	Q	I^2	C	N	k
Economic prosperity	0.0533	0.0014	1.42	2.6844	25	831	2,028	**3**	.	.	.	.	.	.	.	**0**	0.0762	0.0168	0.59	74.12	93	4154	6,669	**6**
Unemployment	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**-0.0635**	0.0003	-3.42	.	.	.	3,421	**2**
Urban region	0.1163	0.0138	0.99	17.1229	82	1,074	2,641	**4**	.	.	.	.	.	.	.	**0**	-0.0099	0.0031	-0.18	4.58	56	939	3,486	**3**
R&D expenditures region	**0.1400**	0.0034	2.39	.	.	.	294	**1**	.	.	.	.	.	.	.	**0**	0.0521	0.0078	0.59	23.84	87	2741	4,990	**4**
Innovative region	**0.2213**	0.0293	1.29	18.5127	89	584	2,420	**3**	.	.	.	.	.	.	.	**0**	0.0417	0.0089	0.44	16.16	88	1667	2,733	**3**
IP productivity in region	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Start-up activity in region	0.0399	0.0007	1.53	.	.	.	1,472	**2**	.	.	.	.	.	.	.	**0**	-0.0164	0.0186	-0.12	38.68	95	1998	3,877	**3**
Venture capital	0.0147	0.0033	0.26	.	.	.	745	**2**	0.3914	0.0508	1.74	11.89	83	208	322	**3**	0.0036	0.0220	0.02	51.41	90	2131	4,645	**6**
Distance between firm & univer	0.0050	0.0007	0.18	.	.	.	1,362	**2**	.	.	.	.	.	.	.	**0**	**0.4200**	0.0103	4.14	.	.	.	300	**1**

Environmental factors	Collaboration								Consulting								Mixed							
	ES_r	v_r	z	Q	I^2	C	N	k	ESr	vr	z	Q	I2	C	N	k	ES_r	v_r	z	Q	I^2	C	N	k
Economic prosperty	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Unemployment	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Urban region	**-0.1730**	0.0049	-2.47	.	.	.	1,502	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
R&D expenditures region	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Innovative_region	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
IP productivity in region	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Start-up activity in region	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Venture capital	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Distance between firm & univer	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**

TTO factors		Patent								License								Spin-off							
		ES_r	v_r	z	Q	I^2	C	N	k	ES_r	v_r	z	Q	I^2	C	N	k	r	v	z	Q	I	C	N	k
TTO exists	TTO exists	0.1387	0.0909	0.46	136.87	96.35	1,481	4,678	**4**	.	.	.	.	.	.	.	**0**	0.1570	0.0192	1.13	26.25	85	1200	3,747	**5**
Age of TTO	Age of TTO	0.3082	0.0276	1.86	10.56	62.10	325	2,077	**3**	0.4036	0.0051	5.65	.	.	.	202	**2**	0.1372	0.0144	1.14	28.82	86	1756	3,606	**5**
Size of TTO	No. of employees in TTO	0.5729	0.1261	1.61	48.10	85.45	348	34,087	**6**	0.5060	0.0512	2.24	28.89	79	463	731	**7**	0.1885	0.0141	1.59	29.77	76	1659	4,208	**8**
Budget of TTO	Budget of TTO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.3722**	0.0182	2.76	.	.	.	119	**2**
Communication of TTO	Communication of TTO	.	.	.	.	.	.	.	**0**	**-0.2630**	0.0068	-3.20	.	.	.	151	**1**	-0.0300	0.0011	-0.89	.	.	.	892	**1**
Financial incentives for TTO	Financial incentives for TTO	.	.	.	.	.	.	.	**0**	0.1180	0.0068	1.44	.	.	.	151	**1**	.	.	.	.	.	.	.	**0**
Network of TTO	Network of TTO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**-0.1200**	0.0011	-3.58	.	.	.	892	**1**
TTO ownership	NGO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.0100	0.0080	0.11	.	.	.	128	**1**
	Private	0.0170	0.0011	0.52	.	.	.	952	**2**	.	.	.	.	.	.	.	**0**	0.0200	0.0011	0.60	.	.	.	892	**1**
	Public	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**-0.8000**	0.0080	-8.94	.	.	.	128	**1**
TTO quality	TTO quality	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Academic expertise	**0.6900**	0.0455	3.24	.	.	.	25	**1**	**0.7200**	0.0455	3.38	.	.	.	50	**1**	**0.4400**	0.0455	2.06	.	.	.	25	**1**
	Expertise in research field	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.2600	0.0196	1.86	.	.	.	54	**1**
	Expertise in TT	0.3400	0.0455	1.59	.	.	.	25	**1**	0.0124	0.0003	0.78	.	.	.	3,949	**2**	**0.5309**	0.0333	2.91	0.50	-304	13	39	**3**
TTO	Spin-off productivity	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.2101**	0.0093	2.18	.	.	.	114	**2**
Time to patent	Time to patent	-0.0249	0.0025	-0.50	6.27	36.19	2,001	3,844	**3**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Patent quality	Patent quality	0.0542	0.0326	0.30	209.21	96.18	6,258	8,167	**7**	0.1000	0.0085	1.08	.	.	.	22,379	**1**	**0.1500**	0.0085	1.62	.	.	.	6,155	**1**

TTO factors		Collaboration								Consulting								Mixed							
		ES_r	v_r	z	Q	I^2	C	N	**k**	ESr	vr	z	Q	I2	C	N	**k**	ES_r	v_r	z	Q	I^2	C	N	**k**
TTO exists	TTO exists	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Age of TTO	Age of TTO	-0.1000	0.0167	-0.7746	.	.	.	128	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Size of TTO	No. of employees in TTO	0.0811	0.0062	1.0326	.	.	.	372	**2**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Budget of TTO	Budget of TTO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Communication of TTO	Communication of TTO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Financial incentives for TTO	Financial incentives for TTO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Network of TTO	Network of TTO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
TTO ownership	NGO	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Private	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Public	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
TTO quality	TTO quality	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Academic expertise	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Expertise in research field	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Expertise in TT	0.3850	0.0082	4.2522	.	.	.	256	**2**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Spin-off productivity	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Time to patent	Time to patent	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Patent quality	Patent quality	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**

Field factors		Patent								License								Spin-off							
		ES_r	v_r	z	Q	I^2	C	N	**k**	ES_r	v_r	z	Q	I^2	C	N	**k**	**Spin-off**	v	z	Q	I	C	N	**k**
Research orientation	Applied research	**0.1700**	0.0015	4.35	.	.	.	2,146	**1**	.	.	.	.	.	.	.	**0**	**0.1700**	0.0021	3.71	.	.	.	1,512	**1**
	Basic research	0.0700	0.0017	1.72	.	.	.	1,230	**1**	.	.	.	.	.	.	.	**0**	**-0.1700**	0.0021	-3.71	.	.	.	960	**1**
Research field	Engineering	-0.0604	0.0443	-0.29	147.67	93.91	3,197	6,585	**8**	**0.3000**	0.0085	3.26	.	.	.	290	**1**	0.1246	0.0127	1.11	27.91	82	1851	6,940	**6**
	Life science	0.1273	0.0239	0.82	49.43	89.88	1,972	4,936	**4**	**0.0400**	0.0003	2.50	.	.	.	4,068	**1**	**0.0554**	0.0004	2.95	.	.	.	5,699	**2**
	Medical	0.0592	0.0230	0.39	80.56	88.83	3,233	5,715	**8**	-0.1300	0.0085	-1.41	.	.	.	1,901	**1**	**-0.0915**	0.0019	-2.12	.	.	.	1,032	**2**
	Nature	**0.0454**	0.0004	2.16	3.63	-92.80	1,694	4,825	**6**	.	.	.	.	.	.	.	**0**	0.0700	0.0066	0.86	25.96	81	3254	8,111	**6**
	Computer science	-0.0379	0.0007	-1.46	.	.	.	3,033	**2**	.	.	.	.	.	.	.	**0**	-0.0900	0.0100	-0.90	.	.	.	2,623	**1**
	Social science	-0.0750	0.0129	-0.66	14.93	66.50	978	2,419	**4**	.	.	.	.	.	.	.	**0**	-0.0633	0.0011	-1.87	4.14	27	1354	3,900	**4**

Field factors		Collaboration								Consulting								Mixed							
		ES_r	v_r	z	Q	I^2	C	N	**k**	ESr	vr	z	Q	I2	C	N	**k**	ES_r	v_r	z	Q	I^2	C	N	**k**
Research orientation	Applied research	0.1500	0.0015	3.8360	.	.	.	1,209	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Basic research	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Reseach field	Engeneering	0.0623	0.0435	0.2990	20.33	90	432	6,695	**3**	.	.	.	.	.	.	.	**0**	**0.3000**	0.0023	6.25	.	.	.	4,513	**1**
	Life science	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	-0.0200	0.0023	-0.42	.	.	.	3,116	**1**
	Medical	**-0.0791**	0.0013	-2.1752	.	.	.	2,346	**2**	.	.	.	.	.	.	.	**0**	**-0.2200**	0.0023	-4.58	.	.	.	1,670	**1**
	Nature	**-0.0784**	0.0500	-0.3509	29.75	90	546	7,872	**4**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Computer science	**0.1300**	0.0015	3.3245	.	.	.	3,064	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Social science	0.1200	0.0098	1.2119	.	.	.	3,349	**1**	.	.	.	.	.	.	.	**0**	**-0.2100**	0.0023	-4.37	.	.	.	1,402	**1**

Individual factors		Patent								License								Spin-off							
		ES_r	v_r	z	Q	I^2	C	N	**k**	ES_r	v_r	z	Q	I^2	C	N	**k**	r	v	z	Q	I	C	N	**k**
Age	Age	0.0157	0.0160	0.12	15.7033	87	893	4,658	**3**	.	.	.	.	.	.	.	**0**	-0.0200	0.0021	-0.44	.	.	.	8,584	**1**
Team	Size of the research team	0.1269	0.0142	1.06	23.5375	87	1,491	3,756	**4**	0.0300	0.0003	1.87	.	.	.	24,776	**1**	**0.3200**	0.0034	5.46	.	.	.	2,711	**1**
	Heterogeneity of the research te	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.2330**	0.0017	5.60	.	.	.	1,166	**2**
Position	Tenure	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Post-Doc or professor	0.0027	0.0248	0.02	98.40	94	3,764	7,806	**7**	.	.	.	.	.	.	.	**0**	-0.0380	0.0251	-0.24	13.53	85	483	12,227	**3**
Experience	Experience in academia	0.2007	0.0207	1.39	24.67	92	1,120	20,648	**3**	.	.	.	.	.	.	.	**0**	**-0.1405**	0.0006	-5.64	.	.	.	1,769	**2**
	Experience in industry	0.0443	0.0096	0.45	7.7093	74	654	2,316	**3**	.	.	.	.	.	.	.	**0**	0.1000	0.0034	1.71	.	.	.	921	**1**
Gender	Female	**-0.1341**	0.0006	-5.38	.	.	.	2,203	**2**	.	.	.	.	.	.	.	**0**	**-0.1226**	0.0005	-5.60	1.35	-48	1225	2,575	**3**
	Male	0.0507	0.0072	0.60	11.31	82	1,376	4,307	**3**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Orientation	Entrepreneurial orientation	0.2637	0.0473	1.21	47.50	96	973	2,034	**3**	**0.4730**	0.0068	5.75	.	.	.	151	**1**	0.4863	0.0906	1.62	86.93	97	932	4,842	**4**
Time for …	Administration	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Time for…	Applied research	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Industry	0.0200	0.0034	0.34	.	.	.	537	**1**	.	.	.	.	.	.	.	**0**	0.0150	0.0034	0.26	.	.	.	523	**1**
	Research	-0.0600	0.0034	-1.03	.	.	.	1,125	**1**	.	.	.	.	.	.	.	**0**	-0.0265	0.0013	-0.75	.	.	.	1,148	**2**
	Teaching	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	-0.0164	0.0010	-0.51	.	.	.	1,637	**2**
	Technology transfer	0.1000	0.0034	1.71	.	.	.	537	**1**	.	.	.	.	.	.	.	**0**	**0.2000**	0.0034	3.42	.	.	.	523	**1**
Motives for TT	Autonomy	0.0460	0.0009	1.58	.	.	.	2,629	**1**	.	.	.	.	.	.	.	**0**	**0.3520**	0.0009	12.07	.	.	.	7,590	**1**
	Competence enhancement	-0.0020	0.0027	-0.04	.	.	.	1,658	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Financial motives	**0.2890**	0.0070	3.44	.	.	.	1,837	**1**	**0.2320**	0.0070	2.76	.	.	.	145	**1**	**0.2590**	0.0070	3.09	.	.	.	1,656	**1**
	Learning	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Networking	0.0002	0.0027	0.00	.	.	.	376	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Motive other	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Reputation	0.0400	0.0012	1.15	.	.	.	897	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Resources	**0.0834**	0.0010	2.67	.	.	.	2,638	**2**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Puzzle motive	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Barriers	Attitude towards TT	0.0300	0.0015	0.77	.	.	.	830	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Missing awareness	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Bureaucracy	**-0.0800**	0.0012	-2.30	.	.	.	829	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Cost	-0.1759	0.0333	-0.96	.	.	.	104	**2**	-0.1900	0.0333	-1.04	.	.	.	36	**2**	.	.	.	.	.	.	.	**0**
	Culture clash	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Hinders research	**-0.1100**	0.0015	-2.81	.	.	.	898	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**

Individual factors		**Collaboration**								**Consulting**								**Mixed**							
		ES_r	v_r	z	Q	I^2	C	N	**k**	ESr	vr	z	Q	I2	C	N	**k**	ES_r	v_r	z	Q	I^2	C	N	**k**
Age	Age	-0.0390	0.0012	-1.14	.	.	.	5,258	**2**	.	.	.	.	.	.	.	**0**	**0.1089**	0.0006	4.49	.	.	.	2,253	**2**
Team	Size of the research team	**0.2400**	0.0049	3.43	.	.	.	4,313	**1**	.	.	.	.	.	.	.	**0**	**0.1100**	0.0007	4.27	.	.	.	3,041	**1**
	Heterogeneity of the team	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Position	Tenure	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Post-Doc or professor	**0.0800**	0.0015	2.05	.	.	.	7,244	**1**	.	.	.	.	.	.	.	**0**	**0.1829**	0.0005	8.06	.	.	.	2,417	**2**
Experience	Experience in academia	**0.1981**	0.0018	4.65	.	.	.	1,868	**2**	**0.3030**	0.0027	5.8519	.	.	.	1277	**1**	-0.0800	0.0023	-1.67	.	.	.	1,383	**1**
	Experience in industry	**0.2530**	0.0049	3.61	.	.	.	981	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Gender	Female	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**-0.1900**	0.0023	-3.96	.	.	.	1,604	**1**
	Male	**0.2200**	0.0015	5.63	.	.	.	4,584	**1**	.	.	.	.	.	.	.	**0**	**.**	.	.	.	.	.	.	**0**
Orientation	Entrepreneurial orientation	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.3700**	0.0023	7.71	.	.	.	517	**1**
Time for …	Administration	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Time for…	Applied research	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Industry	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Research	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Teaching	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Technology transfer	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Motives for TT	Autonomy	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Competence enhancement	**0.1410**	0.0027	2.72	.	.	.	2,427	**1**	0.1070	0.0027	2.06651	.	.	.	1668	**1**	.	.	.	.	.	.	.	**0**
	Financial motives	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Learning	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Networking	0.0670	0.0027	1.29	.	.	.	376	**1**	-0.0390	0.0027	-0.7532	.	.	.	376	**1**	.	.	.	.	.	.	.	**0**
	Motive_other	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Reputation	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Resources	**0.1144**	0.0010	3.67	.	.	.	3,084	**2**	0.0250	0.0027	0.48283	.	.	.	1668	**1**	.	.	.	.	.	.	.	**0**
	Puzzle motive	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.2900**	0.0053	4.00	.	.	.	661	**1**
Barriers	Attitude towards TT	**-0.3200**	0.0015	-8.18	.	.	.	1,671	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Missing awareness	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Bureaucracy	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Cost	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Culture clash	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Hinders research	0.0200	0.0015	0.51	.	.	.	671	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**

Organizational factors		**Patent**								**Licence**								**Spin-off**							
		ES_r	v_r	z	Q	I^2	C	N	**k**	ES_r	v_r	z	Q	I^2	C	N	**k**	r	v	z	Q	I	C	N	**k**
Size	No. of employees	**0.4858**	0.0558	2.06	108.10	94	1,823	4,680	**8**	**0.2445**	0.0081	2.72	4.86	38	322	612	**4**	0.1947	0.0256	1.22	131.90	93	4834	8,615	**10**
	No. of students	**0.1244**	0.0011	3.76	.	.	.	2,106	**2**	0.0200	0.0085	0.22	.	.	.	260	**1**	**0.3200**	0.0196	2.29	.	.	.	861	**1**
Age	Age of institute	**0.2725**	0.0006	10.97	.	.	.	2,500	**2**	.	.	.	.	.	.	.	**0**	-0.0840	0.0608	-0.34	273.81	99	4472	4,866	**4**
Research subject	General	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Medical	**0.1221**	0.0013	3.32	.	.	.	1,371	**2**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Ownership	Private	**0.1200**	0.0016	2.99	.	.	.	1,624	**1**	.	.	.	.	.	.	.	**0**	**-0.1158**	0.0006	-4.88	.	.	.	3,278	**2**
	Public	**0.3500**	0.0085	3.80	.	.	.	497	**1**	**0.3300**	0.0085	3.58	.	.	.	121	**1**	.	.	.	.	.	.	.	**0**
Research quality	Research quality	0.2795	0.2216	0.59	489.84	99	2,191	75,622	**6**	**0.5814**	0.0867	1.97	27.59	89	292	404	**4**	0.1578	0.0480	0.72	190.10	96	3827	15,786	**8**
Internationality	Internationality	**0.3700**	0.0008	13.01	.	.	.	5,021	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Innovation climate	Innovation climate	0.1148	0.0464	0.53	24.07	92	483	2,118	**3**	.	.	.	.	.	.	.	**0**	**0.1211**	0.0024	2.48	3.09	35	619	1,970	**3**
Incentive for …	Patents (financial)	0.1138	0.0103	1.12	20.48	85	1,766	74,362	**4**	**0.2640**	0.0068	3.21	.	.	.	151	**1**	.	.	.	.	.	.	.	**0**
	License	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
		.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Reputation/ awards	**0.3000**	0.0023	6.25	.	.	.	437	**1**	.	.	.	.	.	.	.	**0**	**0.2700**	0.0023	5.62	.	.	.	437	**1**
		.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Infrastructure/ Support for…	Administration	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.0010	0.0008	0.04	.	.	.	1,275	**1**
	TT Education	**0.1002**	0.0017	2.42	.	.	.	1,074	**2**	.	.	.	.	.	.	.	**0**	**0.1550**	0.0017	3.75	.	.	.	1,308	**2**
	Patents	**-0.0700**	0.0013	-1.98	.	.	.	2,265	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
		.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.0321	0.0901	0.11	23.87	92	250	384	**3**
	TT strategy	**0.2508**	0.0014	6.70	.	.	.	1,015	**2**	.	.	.	.	.	.	.	**0**	0.0993	0.0265	0.61	16.91	82	545	1,006	**4**
	TT activities	**0.4318**	0.0013	11.93	.	.	.	1,595	**2**	**0.4407**	0.0034	7.51	.	.	.	694	**2**	0.1313	0.0045	1.95	2.66	25	225	1,966	**3**
	Universityshare	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.1300	0.0100	1.30	.	.	.	323	**1**
Income from…	Third party	0.0912	0.0278	0.55	53.01	91	1,750	4,657	**6**	**0.4497**	0.0061	5.76	.	.	.	195	**2**	0.0944	0.0648	0.37	58.77	91	839	2,941	**6**
	Endowment	.	.	.	.	.	.	.	**0**	**0.5500**	0.0085	5.95	.	.	.	120	**1**	**0.4000**	0.0085	4.33	.	.	.	120	**1**
	Industry	0.2611	0.1434	0.69	109.68	97	748	2,513	**4**	**0.5391**	0.0194	3.87	12.50	68	479	1,151	**5**	0.3609	0.0620	1.45	107.44	97	1693	6,059	**4**
		-0.1300	0.0010	-4.06	.	.	.	1,932	**1**	**0.2676**	0.0051	3.75	.	.	.	21,079	**2**	**0.1323**	0.0008	4.68	.	.	.	1,258	**2**
	Public	**0.6119**	0.0421	2.98	35.15	86	735	2,558	**6**	**0.5992**	0.0066	7.39	6.10	34	440	21,445	**5**	0.3240	0.0453	1.52	27.51	93	577	4,942	**3**
	Total	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Technology transfer	0.3943	0.0022	8.47	.	.	.	2,290	**2**	**0.8620**	0.0068	10.49	.	.	.	151	**1**	**-0.0558**	0.0008	-2.03	.	.	.	1,587	**2**
Productivity/ Experience in…	Collaboration	0.1992	0.0826	0.69	100.07	95	1,159	4,263	**6**	**0.5700**	0.0085	6.19	.	.	.	121	**1**	**0.1411**	0.0033	2.47	12.05	42	1803	3,529	**8**
	Consulting	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.2400**	0.0021	5.24	.	.	.	1,077	**1**
	Patents	0.3620	0.0913	1.20	260.59	97	2,785	25,573	**8**	0.4089	0.1276	1.14	114.71	97	869	29,818	**5**	0.2070	0.0227	1.37	152.75	90	6053	19,876	**17**
	License	**0.6500**	0.0455	3.05	.	.	.	25	**1**	-0.0076	0.0003	-0.48	.	.	.	3,924	**2**	**0.3087**	0.0017	7.52	.	.	.	1,080	**2**
	Publication	0.2760	0.0246	1.76	111.95	90	4,146	40,130	**12**	**0.4467**	0.0333	2.45	7.79	74	193	442	**3**	0.0378	0.0071	0.45	25.36	76	2840	11,290	**7**
	Spin-off	**0.1977**	0.0071	2.35	10.7366	53	916	1,605	**6**	0.4613	0.4262	0.71	64.37	97	148	664	**3**	0.1827	0.0394	0.92	159.60	93	3786	14,395	**12**
	TT activities	**0.4070**	0.0127	3.62	.	.	.	1,214	**1**	**0.3010**	0.0127	2.68	.	.	.	82	**1**	0.0390	0.0289	0.23	27.05	85	816	2,959	**5**

Organizational factors		**Collaboration**								**Consulting**								**Mixed**							
		ES_r	v_r	z	Q	I^2	C	N	**k**	ESr	vr	z	Q	I2	C	N	**k**	ES_r	v_r	z	Q	I^2	C	N	**k**
Size	No. of employees	**0.2300**	0.0098	2.32	.	.	.	1,562	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	No. of students	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.6800**	0.0204	4.76	.	.	.	330	**1**
Age	Age of institute	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Research subject	General	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Medical	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Ownership	Private	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Public	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Research quality	Research quality	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.0700**	0.0007	2.72	.	.	.	3,443	**1**
Internationality	Internationality	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Innovation climate	Innovation climate	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Incentive for …	Patents (financial)	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	License	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
		.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Reputation/ awards	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.2000	0.0023	4.17	.	.	.	437	**1**
		.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Infrastructure/ Support for…	Administration	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	TT Education	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Patents	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
		.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	TT strategy	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.1027**	0.0016	2.57	.	.	.	630	**2**
	TT activities	0.3600	0.0167	2.7885	.	.	.	2,851	**1**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Universityshare	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Income from…	Third party	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.3500**	0.0007	13.60	.	.	.	2,276	**1**
	Endowment	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Industry	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.2434	0.0541	1.05	51.33	96	917	6,125	**3**
		.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Public	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.0603	0.0175	0.46	52.80	96	2956	6,690	**3**
	Total	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Technology transfer	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
Productivity/ Experience in…	Collaboration	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	**0.4821**	0.1414	1.28	483.14	99	3402	3,654	**4**
	Consulting	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Patents	**0.1959**	0.0049	2.7875	5.73	48	674	4,139	**4**	.	.	.	.	.	.	.	**0**	**0.2100**	0.0023	4.37	.	.	.	576	**1**
	License	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**
	Publication	0.1492	0.0319	0.8357	30.05	90	869	3,798	**4**	**0.2820**	0.0027	5.44632	.	.	.	376	**1**	.	.	.	.	.	.	.	**0**
	Spin-off	0.1200	0.0098	1.2119	.	.	.	879	**1**	.	.	.	.	.	.	.	**0**	**0.1500**	0.0023	3.12	.	.	.	1,980	**1**
	TT activities	.	.	.	.	.	.	.	**0**	.	.	.	.	.	.	.	**0**	0.1742	0.0023	3.61	30.12	93	-1964	1,481	**3**

Section A1: Description of the subgroup analysis

The goal of a subgroup analysis is to explain the variation of effect sizes and therefore also a certain amount of the heterogeneity. To explain the variation, we tested two moderator variables, i.e., the study object of the data samples used in the studies, and study quality. Since the dataset of studies had to be split into subgroups and analyzed separately, the number of relationships to analyze in depth was further reduced. For this reason, we only conducted the subgroup analysis for patenting. For the subgroup analysis, we applied the same statistical model (random effects model).

Table 21 shows the results of the subgroup analysis for the "study object" moderator variable. The right-hand subgroup only includes studies that collected data on individuals (e.g., via a survey), whereas the left-hand subgroup only consists of studies with datasets that had a non-individual study object (e.g., on the organization level or patents). It shows that for seven determinants, significant differences exist between the summary effect sizes of the two subgroups. Interestingly, six of those determinants show a higher absolute value of the summary effect size. This implies on the one hand a methodological problem; one the other hand, it seems as if individuals perceive their patenting activities differently than they are. However, due to the small sample sizes (k_{Σ}) of the studies included in the subgroups, these results should be interpreted with caution.

Table 21: *Subgroup analysis for publications with individuals as the study object vs. no individual (patents; only significant differences shown; higher absolute value is highlighted in gray)*

			Study object is not an individual			**Study object are individuals**				
Class	**Category**	**Variable**	ES_r	v_r	$\mathbf{k_{\Sigma}}$	ES_r	v_r	$\mathbf{k_{\Sigma}}$	Diff.	SE_{diff}
Environ-mental		Start-up activity in region	-0.0900	0.0034	**1**	0.0720	0.0009	**1**	**-0.1620**	0.0655
Organization	Size	No. of employees	0.5077	0.0347	**7**	-0.0700	0.0085	**1**	**0.5777**	0.2078
		No. of students	0.1600	0.0013	**1**	-0.1200	0.0085	**1**	**0.2800**	0.0986
	Innovation climate	Innovation climate	-0.1400	0.0034	**1**	0.1764	0.0008	**2**	**-0.3164**	0.0654
TTO	TTO exists	TTO exists	0.2498	0.0010	**2**	0.0321	0.0009	**2**	**0.2177**	0.0431
	Ownership	Private	0.2000	0.0083	**1**	-0.0100	0.0012	**1**	**0.2100**	0.0977
Field	Research field	Life sciences	0.2476	0.0007	**2**	-0.0125	0.0008	**2**	**0.2601**	0.0387

ES_r = summary effect size (standardized from -1 to 1); v_r = variance of ES_r; k_{Σ} = total number of studies, Diff. = difference between ES_r of the subgroups; SE_{diff} = standard error of diff.

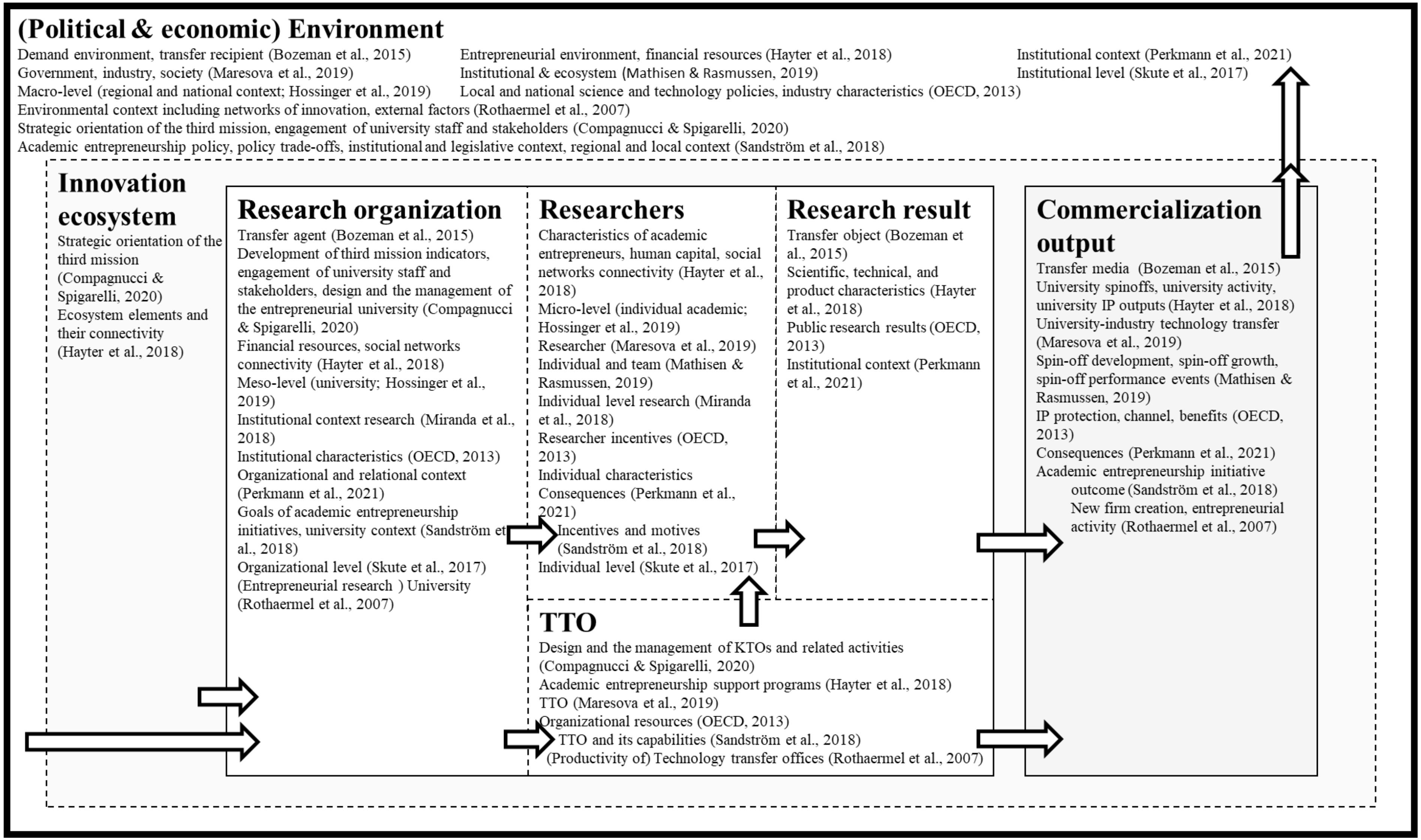
The second subgroup analysis addressed the quality of the studies included, measured by the impact determinants of the journals in which they were published. Table 22 shows that the summary effect size of 15 determinants differed significantly between studies published in low-quality journals (left side) vs. high-quality journals (right side). However, no clear trend is visible in the table. In addition, the subgroups often only consisted of a single study. Therefore, any interpretation of the influence of the "study quality" moderator variable based on the results reported in Table 22 is very limited.

Table 22: *Subgroup analysis for publications in high-quality and low-quality journals (patents; only significant differences shown; higher absolute value is highlighted in gray)*

			Low journal quality			**High journal quality**				
Class	**Category**	**Determinant**	ES_r	v_r	$\mathbf{k_\Sigma}$	ES_r	v_r	$\mathbf{k_\Sigma}$	Diff.	SE_{diff}
Environmental		Urban region	0.0247	0.0013	**2**	0.1968	0.0012	**2**	**-0.1722**	0.0506
		Start-up activity in region	0.0720	0.0009	**1**	-0.0900	0.0034	**1**	**0.1620**	0.0655
Individual	Experience	Experience in academia	0.2551	0.0006	**2**	-0.0010	0.0023	**1**	**0.2561**	0.0543
	Gender	Female	-0.0940	0.0009	**1**	-0.2400	0.0023	**1**	**0.1460**	0.0562
	Orientation	Entrepreneurial orientation	0.1510	0.0009	**1**	0.4420	0.0015	**2**	**-0.2910**	0.0483
Organization	Size	No. of students	-0.1200	0.0085	**1**	0.1600	0.0013	**1**	**-0.2800**	0.0986
	Age	Age of institute	0.3300	0.0008	**1**	-0.0100	0.0034	**1**	**0.3400**	0.0647
	Research subject	Medical	0.3300	0.0083	**1**	0.0800	0.0016	**1**	**0.2500**	0.0997
	Innovation climate	Innovation climate	0.1750	0.0009	**1**	-0.1242	0.0033	**2**	**0.2992**	0.0646
	Funding from…	Third party	0.0513	0.0044	**4**	0.3263	0.0029	**2**	**-0.2749**	0.0854
TTO	TTO exists	TTO exists	0.0321	0.0009	**2**	0.2498	0.0010	**2**	**-0.2177**	0.0431
	Age of TTO	Age of TTO	0.5000	0.0083	**1**	0.2720	0.0014	**2**	**0.2280**	0.0988
	Time to patent	Time to patent	-0.0515	0.0004	**2**	0.0500	0.0013	**1**	**-0.1015**	0.0412
	Patent quality	Patent quality	0.0047	0.0018	**6**	0.5300	0.0016	**1**	**-0.5253**	0.0586
Field	Research field	Life sciences	-0.0400	0.0012	**1**	0.2003	0.0120	**3**	**-0.2403**	0.1148

ES_r = summary effect size (standardized from -1 to 1); v_r = variance of ES_r; $\mathbf{k_\Sigma}$ = total number of studies, Diff. = difference between ES_r of the subgroups; SE_{diff} = standard error of diff.

Figure 10: *New framework of the commercialization of academic knowledge based on the categories of former reviews*



Based on: Bozeman et al. (2015); Compagnuccia & Spigarelli (2020); Hayter et al. (2018); Hossinger et al. (2020); Maresova et al. (2019); Mathisen & Rasmussen (2019); Miranda et al. (2017); OECD (2013); Perkmann et al. (2021); Rothaermel et al. (2007); Sandström et al. (2018); Skute et al. (2017)

2.9 References

Abramo, G., D'Angelo, C. A., & Di Costa, F. (2011). University-industry research collaboration: a model to assess university capability. Higher Education, 62(2), 163-181.

Algieri, B., Aquino, A., & Succurro, M. (2013). Technology transfer offices and academic spin-off creation: the case of Italy. The Journal of Technology Transfer, 38(4), 382-400.

Ardito, L. (2018). Markets for university inventions: the role of pate'ts' underlying knowledge in university-to-industry technolo78ommercializationion. International Journal of Technology Management, 78(1-2), 9-27.

Arvanitis, S., Kubli, U., & Woerter, M. (2008). University-industry knowledge and technology transfer in Switzerland: What university scientists think about co-operation with private enterprises. Research Policy, 37(10), 1865-1883.

Balasubramanian, S., Yang, Y., & Tello, S. (2020). Does University entrepreneurial orientation matter? Evidence from university performance. Strategic Entrepreneurship Journal.

Baldini, N. (2010). Do royalties really foster university patenting activity? An answer from Italy. Technovation, 30(2), 109-116.

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: a meta-analysis. Journal of applied psychology, 92(3), 595.

Belkhodja, O., & Landry, R. (2007). The Triple-Helix collaboration: Why do researchers collaborate with industry and the government? What are the factors that influence the perceived barriers?. Scientometrics, 70(2), 301-332.

Beyhan, B., & Rickne, A. (2015). Motivations of academics to interact with industry: the case of nanoscience. International Journal of Technology Management, 68(3-4), 159-175.

Blind, K., Pohlisch, J., & Zi, A. (2018). Publishing, patenting, and standardization: Motives and barriers of scientists. Research Policy, 47(7), 1185-1197.

Boehm, D. N., & Hogan, T. (2014). 'A jack of all trades': the role of PIs in the establishment and management of collaborative networks in scientific knowledge commercialization. The Journal of Technology Transfer, 39(1), 134-149.

Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2009). Introduction to meta-analysis. John Wiley & Sons.

Bourelos, E., Magnusson, M., & McKelvey, M. (2012). Investigating the complexity facing academic entrepreneurs in science and engineering: the complementarities of research performance, networks and support structures in commercialisation. Cambridge Journal of Economics, 36(3), 751-780.

Bozeman, B. (2000). Technology transfer and public policy: a review of research and theory. Research policy, 29(4-5), 627-655.

Bozeman, B., & Gaughan, M. (2007). Impacts of grants and contracts on academic researchers' interactions with industry. Research policy, 36(5), 694-707.

Bozeman, B., Rimes, H., & Youtie, J. (2015). The evolving state-of-the-art in technology transfer research: Revisiting the contingent effectiveness model. Research Policy, 44(1), 34-49.

Buenstorf, G., & Geissler, M. (2013). Not invented here: technology licensing, knowledge transfer and innovation based on public research. In The Two Sides of Innovation (pp. 77-107). Springer, Cham.

Bushman, B. J., & Wang, M. C. (1994). Vote-counting procedures in meta-analysis. The handbook of research synthesis, 236, 193-213.

Calderini, M., Franzoni, C., & Vezzulli, A. (2007). If star scientists do not patent: The effect of productivity, basicness and impact on the decision to patent in the academic world. Research Policy, 36(3), 303-319.
Chang, X., Chen, Q., & Fong, P. S. (2015). Scientific disclosure and commercialization mode selection for university technology transfer. Science and Public Policy, 43(1), 85-101.
Chen, C., Ma, W., & Zhu, G. (2013). Influencing factors of collaboration with industry of Chinese Universities. Information Technology Journal, 12(16), 3875.
Chen, G., Yang, G., He, F., & Chen, K. (2019). Exploring the effect of political borders on university-industry collaborative research performance: Evidence from China's Guangdong province. Technovation, 82, 58-69.
Chen, S. H., Huang, M. H., & Chen, D. Z. (2013). Driving factors of external funding and funding effects on academic innovation performance in university–industry–government linkages. Scientometrics, 94(3), 1077-1098.
Choi, H., Yoon, H., Siegel, D., Waldman, D. A., & Mitchell, M. S. (2022). Assessing differences between university and federal laboratory postdoctoral scientists in technology transfer. Research Policy, 51(3), 104456.
Civera, A., & Meoli, M. (2018). Does university prestige foster the initial growth of academic spin-offs?. Economia e Politica Industriale, 45(2), 111-142.
Clarysse, B., Tartari, V., & Salter, A. (2011). The impact of entrepreneurial capacity, experience and organizational support on academic entrepreneurship. Research policy, 40(8), 1084-1093.
Comacchio, A., Bonesso, S., & Pizzi, C. (2012). Boundary spanning between industry and university: the role of Technology Transfer Centres. The Journal of Technology Transfer, 37(6), 943-966.
Compagnucci, L., & Spigarelli, F. (2020). The Third Mission of the university: A systematic literature review on potentials and constraints. Technological Forecasting and Social Change, 161, 120284.
Crespi, G., D'Este, P., Fontana, R., & Geuna, A. (2011). The impact of academic patenting on university research and its transfer. Research policy, 40(1), 55-68.
Cunningham, J. A., & Link, A. N. (2015). Fostering university-industry R&D collaborations in European Union countries. International Entrepreneurship and Management Journal, 11(4), 849-860.
Czarnitzki, D., Doherr, T., Hussinger, K., Schliessler, P., & Toole, A. A. (2016). Knowledge creates markets: The influence of entrepreneurial support and patent rights on academic entrepreneurship. European Economic Review, 86, 131-146.
D'Este, P., & Perkmann, M. (2011). Why do academics engage with industry? The entrepreneurial university and individual motivations. The Journal of Technology Transfer, 36(3), 316-339.
D'Este, P., & Patel, P. (2007). University–industry linkages in the UK: What are the factors underlying the variety of interactions with industry?. Research policy, 36(9), 1295-1313.
Davey, T., Rossano, S., & Van der Sijde, P. (2016). Does context matter in academic entrepreneurship? The role of barriers and drivers in the regional and national context. The Journal of Technology Transfer, 41(6), 1457-1482.
Diánez-González, J. P., Camelo-Ordaz, C., & Fernández-Alles, M. (2021). Drivers and implications of entrepreneurial orientation for academic spin-offs. International Entrepreneurship and Management Journal, 17(2), 1007-1035.
Dill, D. D. (1995). University-industry entrepreneurship: the organization and management of American university technology transfer units. Higher education, 29(4), 369-384.

Drivas, K., Economidou, C., Karamanis, D., & Zank, A. (2016). Academic patents and technology transfer. Journal of engineering and technology management, 40, 45-63.

Eisend, M. (2014). Metaanalyse. Rainer Hampp Verlag.

Epure, M., Prior, D., & Serarols, C. (2016). Assessing technology-based spin-offs from university support units. Regional Studies, 50(3), 411-428.

Fadeyi, O., Maresova, P., Stemberkova, R., Afolayan, M., & Adeoye, F. (2019). Perspectives of University-Industry technology transfer in African emerging economies: Evaluating the Nigerian scenario via a data envelopment approach. Social sciences, 8(10), 286.

Feola, R., Vesci, M., Botti, A., & Parente, R. (2019). The determinants of entrepreneurial intention of young researchers: Combining the theory of planned behavior with the triple Helix model. Journal of Small Business Management, 57(4), 1424-1443.

Fini, R., Fu, K., Mathisen, M. T., Rasmussen, E., & Wright, M. (2017). Institutional determinants of university spin-off quantity and quality: a longitudinal, multilevel, cross-country study. Small Business Economics, 48(2), 361-391.

Franco, M., Haase, H., & Fernandes, A. (2014). The influence of academic staff's personal and professional characteristics on the decision to cooperate with industry. European Journal of International Management, 8(3), 293-309.

Garcia, R., Araújo, V., Mascarini, S., Santos, E. G., & Costa, A. R. (2019). How the benefits, results and barriers of collaboration affect university engagement with industry. Science and Public Policy, 46(3), 347-357.

Gómez Gras, J. M., Galiana Lapera, D. R., Mira Solves, I., Verdú Jover, A. J., & Sancho Azuar, J. (2008). An empirical approach to the organisational determinants of spin-off creation in European universities. International Entrepreneurship and Management Journal, 4(2), 187-198.

Govindaraju, V. C., Ghapar, F. A., & Pandiyan, V. (2009). The role of collaboration, market and intellectual property rights awareness in university technology commercialization. International Journal of Innovation and Technology Management, 6(04), 363-378.

Grimaldi, R., Kenney, M., Siegel, D. S., & Wright, M. (2011). 30 years after Bayh–Dole: Reassessing academic entrepreneurship. Research policy, 40(8), 1045-1057.

Hamilton, C., & Philbin, S. P. (2020). Knowledge Based View of University Tech Transfer—A Systematic Literature Review and Meta-Analysis. Administrative Sciences, 10(3), 62.

Han, J., & Heshmati, A. (2016). Determinants of financial rewards from industry-university collaboration in South Korea. International Journal of Entrepreneurship and Innovation Management, 20(3-4), 235-257.

Hayter, C. S. (2013). Harnessing university entrepreneurship for economic growth: Factors of success among university spin-offs. Economic Development Quarterly, 27(1), 18-28.

Hayter, C. S., Nelson, A. J., Zayed, S., & O'Connor, A. C. (2018). Conceptualizing academic entrepreneurship ecosystems: A review, analysis and extension of the literature. The Journal of Technology Transfer, 43(4), 1039-1082.

Hossinger, S. M., Chen, X., & Werner, A. (2020). Drivers, barriers and success factors of academic spin-offs: a systematic literature review. Management Review Quarterly, 70(1), 97-134.

Huang, C. Y. (2018). How background, motivation, and the cooperation tie of faculty members affect their university–industry collaboration outputs: an empirical study based on Taiwan higher education environment. Asia Pacific Education Review, 19(3), 413-431.

Huang, M. H., & Chen, D. Z. (2017). How can academic innovation performance in university–industry collaboration be improved?. Technological Forecasting and Social Change, 123, 210-215.
Huang, W. L., Feeney, M. K., & Welch, E. W. (2011). Organizational and individual determinants of patent production of academic scientists and engineers in the United States. Science and Public Policy, 38(6), 463-479.
Hue Kyung, L.; Hyun Duk, Y.; Si Jeoung, K.; Yoon Kyo, S. (2016). Factors affecting university–industry cooperation performance: Study of the mediating effects of government and enterprise support
Hunter, E. M., Perry, S. J., & Currall, S. C. (2011). Inside multi-disciplinary science and engineering research centers: The impact of organizational climate on invention disclosures and patents. Research Policy, 40(9), 1226-1239.
Hussler, C., & Pénin, J. (2012). Proactive versus reactive motivations for patenting and their impact on patent production at universities. International Journal of Technology Management 21, 58(3/4), 213-235.
Huyghe, A., & Knockaert, M. (2015). The influence of organizational culture and climate on entrepreneurial intentions among research scientists. The Journal of Technology Transfer, 40(1), 138-160.
Jung, H., & Kim, B. K. (2018). Determinant factors of university spin-off: the case of Korea. The Journal of Technology Transfer, 43(6), 1631-1646.
Ken, Y., Hsu, W. L., & Tsai, T. Y. (2009, August). A study on the factors influencing license income of technology commercialization in United States Universities. In PICMET'09-2009 Portland International Conference on Management of Engineering & Technology (pp. 2834-2841). IEEE.
Kim, Y. C., & Rhee, M. (2018). Professional collaboration in technological innovation: a case of technology licensing of university inventions. Technology Analysis & Strategic Management, 30(11), 1351-1363.
Klasová, S., Korobaničová, I., & Hudec, O. (2019). University-industry links in slovakia: What are the factors underlying the number of interactions with industry?. Quality Innovation Prosperity, 23(1), 102-118.
Kochenkova, A., and Grimaldi R. 2016. Public policy measures in support of knowledge transfer activities: A review of academic literature. Journal of Technology Transfer 41: 407–29.
Lam, A. (2011). What motivates academic scientists to engage in research commercialization:‘Gold’,‘ribbon’or ‘puzzle’?. Research policy, 40(10), 1354-1368.
Lautenschläger, A., Haase, H., & Kratzer, J. (2014). Contingency factors on university spin-off formation: an empirical study in Germany. Journal of Entrepreneurship and Public Policy.
Lee, J., & Stuen, E. (2016). University reputation and technology commercialization: evidence from nanoscale science. The Journal of Technology Transfer, 41(3), 586-609.
Lee, Y. S. (1998). University-Industry Collaboration on Technology Transfer: Views from the Ivory Tower. Policy Studies Journal, 26(1), 69-84.
Leidecker, J. K., & Bruno, A. V. (1984). Identifying and using critical success factors. Long range planning, 17(1), 23-32.
Libaers, D. (2014). Foreign-Born Academic Scientists and Their Interactions with Industry: Implications for University Technology Commercialization and Corporate Innovation Management. Journal of Product Innovation Management, 31(2), 346-360.
Libaers, D. P. (2012). Time allocation decisions of academic scientists and their impact on technology commercialization. IEEE Transactions on Engineering Management, 59(4), 705-716.

Link, A. N., Siegel, D. S., & Bozeman, B. (2006). An empirical analysis of the propensity of academics to engage in formal university technology transfer. In Working Papers in Economics.

Llopis, O., Sánchez-Barrioluengo, M., Olmos-Peñuela, J., & Castro-Martínez, E. (2018). Scientists' engagement in knowledge transfer and exchange: Individual factors, variety of mechanisms and users. Science and Public Policy, 45(6), 790-803.

Maresova, P., Stemberkova, R., & Fadeyi, O. (2019). Models, processes, and roles of universities in technology transfer management: A systematic review. Administrative Sciences, 9(3), 67.

Markman, G. D., Phan, P. H., Balkin, D. B., & Gianiodis, P. T. (2005). Entrepreneurship and university-based technology transfer. Journal of business venturing, 20(2), 241-263.

Mathisen, M. T., & Rasmussen, E. (2019). The development, growth, and performance of university spin-offs: A critical review. The Journal of Technology Transfer, 44(6), 1891-1938.

Meoli, M., & Vismara, S. (2016). University support and the creation of technology and non-technology academic spin-offs. Small Business Economics, 47(2), 345-362.

Merchán-Hernández, C., Valmaseda-Andia, O., & Fernández-Esquinas, M. (2015). The challenges of connecting science–industry in peripheral regions: researchers' attitudes and organizational and institutional features as determinants. European Planning Studies, 23(12), 2600-2620.

Meusburger, M., & Antonites, A. J. (2016). Assessing antecedents of entrepreneurial activities of academics at South African universities. International Journal of Innovation Management, 20(06), 1650058.

Miranda, F. J., Chamorro, A., & Rubio, S. (2017). Determinants of the intention to create a spin-off in Spanish universities. International Journal of Entrepreneurship and Innovation Management, 21(4-5), 299-317.

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Int J Surg, 8(5), 336-341.

Moog, P., Werner, A., Houweling, S., & Backes-Gellner, U. (2015). The impact of skills, working time allocation and peer effects on the entrepreneurial intentions of scientists. The Journal of Technology Transfer, 40(3), 493-511.

Muscio, A. (2013). University-industry linkages: What are the determinants of distance in collaborations?. Papers in Regional Science, 92(4), 715-739.

Niosi, J. (2006). Success factors in Canadian academic spin-offs. The Journal of Technology Transfer, 31(4), 451-457.

OECD (2013), Commercialising Public Research: New Trends and Strategies, OECD Publishing. http://dx.doi.org/10.1787/9789264193321-en

Olaya Escobar, E. S., Berbegal-Mirabent, J., Alegre, I., & Duarte Velasco, O. G. (2017). Researchers' willingness to engage in knowledge and technology transfer activities: an exploration of the underlying motivations. R&D Management, 47(5), 715-726.

O'Shea, R. P., Allen, T. J., Chevalier, A., & Roche, F. (2005). Entrepreneurial orientation, technology transfer and spinoff performance of US universities. Research Policy, 34(7), 994-1009.

Owen-Smith, J., & Powell, W. W. (2003). The expanding role of university patenting in the life sciences: assessing the importance of experience and connectivity. Research Policy, 32(9), 1695-1711.

Perkmann, M., Salandra, R., Tartari, V., McKelvey, M., & Hughes, A. (2021). Academic engagement: A review of the literature 2011-2019. Research Policy, 50(1), 104114.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., ... & Sobrero, M. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. Research policy, 42(2), 423-442.

Perkmann, M., & Walsh, K. (2007). University–industry relationships and open innovation: Towards a research agenda. International journal of management reviews, 9(4), 259-280.

Pitsakis, K., & Giachetti, C. (2020). Information-based imitation of university commercialization strategies: The role of technology transfer office autonomy, age, and membership into an association. Strategic Organization, 18(4), 573-616.

Powers, J. B. (2004). R&D funding sources and university technology transfer: What is stimulating universities to be more entrepreneurial?. Research in Higher Education, 45(1), 1-23.

Powers, J. B., & McDougall, P. P. (2005). University start-up formation and technology licensing with firms that go public: a resource-based view of academic entrepreneurship. Journal of business venturing, 20(3), 291-311.

Prodan, I., & Slavec, A. (2009, August). The influence of ten different motivational factors on academic entrepreneurial intentions. In PICMET'09-2009 Portland International Conference on Management of Engineering & Technology (pp. 1909-1914). IEEE.

Ramaciotti, L., & Rizzo, U. (2015). The determinants of academic spin-off creation by I talian universities. R&D Management, 45(5), 501-514.

Riviezzo, A., Santos, S. C., Liñán, F., Napolitano, M. R., & Fusco, F. (2019). European universities seeking entrepreneurial paths: the moderating effect of contextual variables on the entrepreneurial orientation-performance relationship. Technological Forecasting and Social Change, 141, 232-248.

Rizzo, U., & Ramaciotti, L. (2014). The determinants of academic patenting by Italian universities. Technology Analysis & Strategic Management, 26(4), 469-483.

Rossi, F., & Rosli, A. (2015). Indicators of university–industry knowledge transfer performance and their implications for universities: evidence from the United Kingdom. Studies in Higher Education, 40(10), 1970-1991.

Rothaermel, F. T., Agung, S. D., & Jiang, L. (2007). University entrepreneurship: a taxonomy of the literature. Industrial and corporate change, 16(4), 691-791.

Rybnicek, R., Leitner, K. H., Baumgartner, L., & Plakolm, J. (2019). Industry and leadership experiences of the heads of departments and their impact on the performance of public universities. Management Decision.

Sandström, C., Wennberg, K., Wallin, M. W., & Zherlygina, Y. (2018). Public policy for academic entrepreneurship initiatives: A review and critical discussion. The Journal of Technology Transfer, 43(5), 1232-1256.

Schuelke-Leech, B. A. (2013). Resources and research: An empirical study of the influence of departmental research resources on individual STEM researchers involvement with industry. Research Policy, 42(9), 1667-1678.

Sellenthin, M. O. (2009). Technology transfer offices and university patenting in Sweden and Germany. The Journal of Technology Transfer, 34(6), 603-620.

Skute, I., Zalewska-Kurek, K., Hatak, I., & de Weerd-Nederhof, P. (2019). Mapping the field: a bibliometric analysis of the literature on university–industry collaborations. The journal of technology transfer, 44(3), 916-947.

Soetanto, D., & van Geenhuizen, M. (2019). Life after incubation: The impact of entrepreneurial universities on the long-term performance of their spin-offs. Technological Forecasting and Social Change, 141, 263-276.

Son, H., Chung, Y., & Hwang, H. (2019). Do technology entrepreneurship and external relationships always promote technology transfer? Evidence from Korean public research organizations. Technovation, 82, 1-15.

Song, M., Podoynitsyna, K., Van Der Bij, H., & Halman, J. I. (2008). Success factors in new ventures: A meta-analysis. Journal of product innovation management, 25(1), 7-27.

Strong, D. R., Chandran, V. G. R., & Hayter, C. S. (2018). Great expectations: assessing the impact of commercialization-focused policies among Malaysia's public research institutes. Economics of Innovation and New Technology, 27(5-6), 438-453.

Swamidass, P. M., & Vulasa, V. (2009). Why university inventions rarely produce income? Bottlenecks in university technology transfer. The Journal of Technology Transfer, 34(4), 343-363.

Tartari, V., & Breschi, S. (2012). Set them free: scientists' evaluations of the benefits and costs of university–industry research collaboration. Industrial and Corporate Change, 21(5), 1117-1147.

Teixeira, A. A. (2017). The Economic Performance of Portuguese Academic Spin-Offs—Do Science & Technology Infrastructures and Support Matter?. In THE WORLD SCIENTIFIC REFERENCE ON ENTREPRENEURSHIP: Volume 4: Process Approach to Academic Entrepreneurship—Evidence from the Globe (pp. 281-308).

Thurner, T. W., & Zaichenko, S. (2014). Research and Technology Organizations (RTOs) in the primary sector: Providing innovation to Russia's mines and corn fields. European Journal of Innovation Management.

Tijssen, R. J. (2006). Universities and industrially relevant science: Towards measurement models and indicators of entrepreneurial orientation. Research Policy, 35(10), 1569-1585.

Tseng, F. C., Huang, M. H., & Chen, D. Z. (2020). Factors of university–industry collaboration affecting university innovation performance. The Journal of Technology Transfer, 45(2), 560-577.

Van Looy, B., Landoni, P., Callaert, J., Van Pottelsberghe, B., Sapsalis, E., & Debackere, K. (2011). Entrepreneurial effectiveness of European universities: An empirical assessment of antecedents and trade-offs. Research Policy, 40(4), 553-564.

Varga, A., & Horváth, M. (2014). Institutional and regional factors behind university patenting in Europe: An exploratory spatial analysis using EUMIDA data. In Knowledge, diversity and performance in European higher education. Edward Elgar Publishing.

Villani, E., Rasmussen, E., & Grimaldi, R. (2017). How intermediary organizations facilitate university–industry technology transfer: A proximity approach. Technological forecasting and social change, 114, 86-102.

Visintin, F., & Pittino, D. (2014). Founding team composition and early performance of university—Based spin-off companies. Technovation, 34(1), 31-43.

Wen-ting, D., & Xin-hui, J. (2013, July). Why researchers engaged in technology transfer collaborations: A self-determination theory perspective. In 2013 International Conference on Management Science and Engineering 20th Annual Conference Proceedings (pp. 1906-1914). IEEE.

Wong, P. K., & Singh, A. (2013). Do co-publications with industry lead to higher levels of university technology commercialization activity?. Scientometrics, 97(2), 245-265.

Wu, Y., Welch, E. W., & Huang, W. L. (2015). Commercialization of university inventions: Individual and institutional factors affecting licensing of university patents. Technovation, 36, 12-25.

Xu, Z., Parry, M. E., & Song, M. (2010). The impact of technology transfer office characteristics on university invention disclosure. IEEE Transactions on Engineering Management, 58(2), 212-227.

Yamaguchi, Y., Fujimoto, J., Yamazaki, A., & Koshiyama, T. (2019, August). Analysis of the Factors Influencing Patent Creation and Patent-Based Technology Transfer in Universities. In 2019 Portland International Conference on Management of Engineering and Technology (PICMET) (pp. 1-10). IEEE.

Ye, L., Zeng, G., & Cao, X. (2020). Open innovation and innovative performance of universities: Evidence from China. Growth and Change.

Zarghami, Hamid Reza, Alireza Amrollahi, and Mostafa Jafari. "Research commercialisation and academic performance: A study of doctoral projects in Iran." Higher Education Quarterly (2020).

3

3 How to become a serial patentee - A patent behavior analysis

Anna Pohle

Abstract: Serial patentees contribute to economic growth by inventing new technologies that serve as the basis for innovations. Surprisingly, there has been no discussion about why some inventors stop their patent activities after their first patent while others continue patenting time and time again. This study focuses on the nature of high-performing inventors through an analysis of serial patentees. In doing so, it aims to explain what causes one-time patentees to continue patenting and become serial patentees. The dataset, consisting of 475 inventors, was collected by matching employee, patent, and publication data of five German research institutes. Using a survival analysis for recurrent event data, the results reveal that the kind and timing of prior patent experiences influence serial patenting. Notably, first-time patent experiences related to reputational benefits increase the likelihood of becoming a serial patentee, while overall the inventor's team size matters. The study concludes that becoming a serial patentee is a career choice, rather than a simple duty to achieve technology transfer objectives. Serial patentees would therefore benefit from strategic career support.

Keywords: Academic patenting, inventor behavior, timing of experiences, academic career

This essay is a preprint and has been submitted for publication in Science and Public Policy.

3.1 Introduction

By inventing and commercializing new technologies, academic inventors play a vivid role within innovation systems (OECD, 2013). They contribute to economic growth, because the resulting patents represent technological opportunities for innovative firms (D'Este et al., 2012). High-performing academic inventors in particular are of great value for universities and research organizations since they enhance the potential transfer income from patent licensing or from high-tech spinoffs. In line with the literature on high-performing "star scientists" (e.g., Zucker & Darby, 1996), high-performing inventors contribute not only directly, but also indirectly to the enhancement of research commercialization (Lawson & Sterzi, 2014). Indirect contributions may include spillover effects, e.g., serial patentees may positively influence their peers and act as role models (Bercovitz & Feldman, 2008; Lawson & Sterzi, 2014). Nonetheless, the patenting behavior of scientists varies widely. While most academic inventors stop patenting after the first patent, others continue patenting and become "serial patentees" (Narin & Breitzman, 1995).

The importance of serial patentees for the advancement of research commercialization has raised questions as to how best to motivate and support inventors in continuing to patent. Decision makers in research and policy have a great interest in factors that increase the patent output of scientists. As a consequence, a considerable amount of literature has examined various individual and institutional factors to explain variation in patent activities (D'Este et al., 2012; Wu et al., 2015; Baldini et al., 2007; Azoulay et al., 2007; Lam, 2011). These studies have focused on the motives of inventors for commercialization as well as the effects of organizational regulations, incentives, and strategy on the patent propensity of researchers (Lam, 2011; Baldini et al., 2007; Blind et al., 2009).

However, most of those studies examined either how non-inventors differed from inventors or merely how inventors operate (e.g., van Looy, 2006). It is surprising that there has been no discussion about why some inventors discontinue their patent activities and others proceed with more patenting. In addition, previous studies have almost completely neglected the fact that inventors' motives and behavior can change over time depending on the kind and timing of the experiences they have had. Research on "serial entrepreneurs" clearly shows that the motives and methods used by a first-time entrepreneur differ markedly from a person who founded already many startups (Wright, 1997). The dominant stream of this research has examined what determines the phenomenon of serial entrepreneurs (persons who engage in multiple startups) (Wright, 1997; Lafontaine & Shaw, 2016; Hyytinen & Ilmakunnas, 2007; Amaral et al., 2011). So far, however, a comparable discussion on high-performing inventors is still missing – even though the same arguments can be applied to serial patentees (Lawson & Sterzi, 2014). Prior patenting experience may help develop the skills required for commercialization (Shane & Venkataraman, 2000).

As a consequence, it remains unknown why some scientists stay one-time patentees and others continue patenting. However, knowledge about the differences in the timing of experiences related to the factors influencing this phenomenon is crucial for university managers and decision makers in research organizations. This knowledge would enable them to develop a support infrastructure that would be tailored to the scientists' previous individual experiences and career phases – especially considering the growing importance of the commercialization of academic knowledge.

Based on these premises, this study focuses on the phenomenon of serial patentees. This paper aims to explain how the kind and timing of prior patenting experiences related to reputational benefits, patent support infrastructure, the inventor's team size, and industry relationships influence whether a scientist continues patenting. It sheds light on what research organizations and employees of knowledge transfer offices (KTOs) can do to "breed" more serial patentees. Inspired by the term "serial entrepreneur," the term "serial patentee" is used in this study to describe a scientist who holds multiple inventions (Wright et al., 1997). This is the first study to address the question "What causes one-time patentees to continue patenting and become serial patentees?" It explores this research question by analyzing 475 inventors of the "Light and Surfaces" group of the Fraunhofer-Gesellschaft. The matching of information on employees with patent data from the European Patent Office (EPO Patstat) and bibliographic data from Scopus constitutes a unique dataset.

I contribute to the literature on academic patenting and commercial behavior in two complementary ways. First, while most of the existing research focused on inventors vs. non-inventors, or treated all inventors as a single group, this study deepens our understanding about high-performing inventors by differentiating between one-time and serial patentees. Second, the findings enlarge the solution space for debates on how prior patent experiences within an organization change the inventor's perception and decision on continuing to patent. Overall, this research contributes to the literature on academic inventor behavior by analyzing the conditions that enhance the likelihood of scientists becoming serial patentees. Understanding the conditions under which scientists proceed with patenting will help heads of research groups, transfer offices, and policymakers to enhance patent productivity and thus foster technological advancement.

The following section reviews the previous literature on academic patenting, focusing on influencing factors and addressing the timing of experiences in depth. The literature review closes with a formulation of hypotheses. Subsequently, Section 3.3. describes the dataset and the methodology. This is followed by a presentation of the results, a discussion of the findings, and the conclusion of the study.

3.2 Academic patenting

Since the Bayh–Dole Act of 1980, a large body of literature has investigated how scientists deal with the new "third mission", i.e., technology transfer. The third mission changed academic career paths and brought along new tasks that required new competences in areas such as market knowledge and legal knowledge about transfer channels (Jones, 2009). Academic patenting attracted a great deal of research interest because it enabled research organizations to generate transfer income from licensing or spinoffs. In addition, patents signal transfer potential (Freitas & Nuvolari, 2012; Lawson & Sterzi, 2014). Nonetheless, the patenting behavior of scientists varies widely. While most academic patentees stop patenting after the first or second patent, others continue patenting. For this reason, a great amount of literature deals with how decision makers in research organizations can increase the number and the quality of patents applied for by their scientists (e.g., Arvanitis et al., 2008; Blind et al., 2018; Lam, 2011).

However, the majority of studies have examined academic patenting at a single point in time and fail to differentiate between the factors that cause scientists to start patenting and those that motivate scientists to continue patenting. Motives can change with the experiences individuals had and the feedback they obtained (Shane, 2000; Shane & Venkataraman, 2000). Scientists who become (serial) patentees acquire specific technological and legal knowledge, enabling them to gain unique experiences within the research organization they work for (Jones, 2009). These kinds of career event(s) can change individual perceptions of the benefits and obstacles related to academic patenting. Depending on the kind of previous experience, scientists may be annoyed by the effort or delighted by the success, and then integrate this experience into future decisions about if and when they will continue patenting. Moreover, depending on the timing, some experiences may be more influential than others, such as the first experience or the most recent experience.

In sum, I propose that the factors that influence academic patenting change over time, or, in other words, the timing of patent experiences related to the factors matters. Knowledge about the differences in the timing of experiences related to the influencing factors is crucial for university managers and decision makers in public research organizations (PROs). After all, this insight enables them to develop a support infrastructure that is tailored to scientists' previous individual experiences and career phases. Consequently, this could enhance the patenting behavior of scientists.

Since academic patenting is a very broad field of research, I first provide a brief review of the factors that influence academic patenting and highlight those that are relevant for this study. Second, I discuss the role of the timing of patenting experiences in the two subsequent subsections. Based on those insights, I break down the research questions into testable hypotheses.

3.2.1 Factors that influence academic patenting

Up to now, the literature on academic patenting and technology transfer has pointed out three main categories of influencing factors: 1) individual characteristics and motives (e.g., Lam, 2011; Blind et al., 2018; D'Este & Perkmann, 2011); 2) the organizational setting (Baldini, 2010; D'Este & Patel, 2007; D'Este & Perkmann, 2011); and 3) relational and team characteristics (Chen et al., 2019; Lam, 2011; Huang, 2018). Moreover, a number of previous studies have also discussed the particular field of technology and the legal regulations as influencing factors (Arvantis et al., 2008; Drivas et al., 2016; Baldini, 2010). However, this study focuses on factors that lie within the spectrum of influence of managers of research organizations and KTOs.

3.2.1.1 Reputational benefits

The factors most often discussed in the literature are those related to the individual characteristics and motives of scientists (e.g., Lam, 2011; Blind et al., 2018; Blind et al., 2022; Giuri et al., 2007; Baldini et al., 2007; Freitas & Nuvolari, 2012; Vick & Robertson, 2018). There, individual motivation plays a dominant role in the academic discourse on academic patenting, whereas individual characteristics such as age, education, research field, and gender tend to be used as control variables.

Results from several studies report that the opportunity for personal benefits associated with patenting (including monetary benefits, enhanced reputation, and in turn career advancement) is a key motive for scientists to patent their research results (Lam, 2011; Blind et al., 2018; Blind et al., 2022; Baldini et al., 2007). Monetary benefits are seen as the traditional motivation for patent application (Freitas & Nuvolari, 2012). In line with this strand of literature, Blind et al. (2022) found that applicants in industry who had many patenting experiences were significantly motivated by monetary rewards. However, research related to applicants in science shows that, for them, reputation is a greater motivator than monetary rewards (Baldini et al., 2007; Lawson & Sterzi, 2014; Giuri et al., 2007). Baldini et al. (2007) found that the Italian scientists surveyed in their study ranked “prestige/visibility/reputation” as the most important motive. Also, Lawson & Sterzi (2014) discussed the signaling effect of patents and the resulting increase of the scientist’s visibility. Results by Giuri et al. (2007) implied that social and personal motivations were on average more important than monetary benefits and/or career opportunities. In addition, the results of a study by Göktepe-Hulten and Mahagaonkar (2010), who analyzed the responses of 2,500 Max Planck scientists in Germany, showed that scientists were motivated by a potential reputational gain rather than by direct monetary gains. These differences in the priority of the kind of personal benefits may be explained by the different mindsets of scientists and their organizational socialization (Owen-Smith & Powell, 2003; Lam, 2011), i.e., socialization in industry versus science. I therefore argue that the achievement of reputational benefits through patenting enhances the likelihood of becoming a serial patentee.

3.2.1.2 Patent support infrastructure

Considering organizational characteristics, several studies have reported that some of the most relevant obstacles to academic patenting are a lack of knowledge about the commercial potential, a lack of support during patenting activity, and the nonexistence of a KTO, as well as excessive bureaucracy (Baldini et al., 2007; Arvanitis et al., 2008; Huang et al., 2011). To conclude, an insufficient support infrastructure hinders academic patenting. The converse argument claims that a supportive infrastructure would foster academic patenting. Such an infrastructure is generally provided by KTO employees. Following this thought, a high level of KTO expertise fosters the amount of patenting activity (Fadeyi et al., 2019; Kim & Rhee, 2018). Baldini et al. (2007) found that the existence of internal patent regulations in organizations fostered academic patenting activity. Moreover, research organizations and KTOs that invested in the “pro-commercial socialization” of their scientists and established a “commercial culture” also increased pro-patenting attitudes in their organization (Lawson & Sterzi, 2014; Chen et al., 2013; Bercovitz & Feldman, 2008).

To sum up, the existence of a helpful patent support infrastructure provides sufficient incentives, supports the identification and selection of patentable research results, and facilitates the legal patenting process to ensure patents are granted. Thus, I state that the existence of a supporting infrastructure enhances the likelihood of becoming a serial patentee.

3.2.1.3 Team size

Inventions and innovations are mostly team efforts, as innovations benefit from different perspectives, e.g., cross-innovation (Jones, 2009). Jones (2009) argued that a growing knowledge base leads to highly specialized individual inventors, which in turn spurs inventors to rely on greater teamwork (“educational burden”). This idea is supported by the increasing share of co-invented patents in recent decades, from 60% in 1980 to 75% in 2010 (Crescenzi et al., 2017). In addition, academic inventors typically have larger networks, are better connected, and are more central in patent networks than non-academic inventors (Balconi et al., 2004).

Academic patenting behavior benefits from inventor team efforts for several reasons. A team of peers and colleagues who have a positive attitude towards commercialization and patenting enhance scientists’ patenting activities (Azoulay et al., 2007; Bercovitz & Feldman, 2008). Singh and Fleming (2010) found that patents from inventor teams were less likely to generate a poor outcome and more likely to create breakthroughs, and that ultimately the diversity of inventor teams prevented patents with poor outcomes. Agiakloglou et al. (2016) analyzed nearly 200,000 US patents and found that inventor teams with more than two inventors were more likely to become commercialized. Several studies have shown that the size of the faculty, the department, or the research team correlates with patent productivity within universities (D’Este & Perkmann, 2011; D’Este & Patel, 2007; Drivas et al., 2016). Furthermore, the number of inventors who work on a patent reduces the period of time before a patent gets licensed (Singh & Fleming, 2010). On the contrary, lone inventors are less likely to achieve breakthroughs, and are instead more likely to invent patents with a poor outcome (Singh & Fleming, 2010). In sum, working in large inventor teams fosters patenting activities. I therefore postulate that the inventor’s team size enhances the likelihood of that person becoming a serial patentee.

3.2.1.4 Industry relationships

Not only does team size matter, but the kind of relationships may as well. Numerous studies have highlighted in particular the role of industry relationships for commercial activities (e.g., Crescenzi et al., 2017; Chen et al., 2013; Powers, 2004; Wu et al., 2015; Kalar & Antoncic, 2016). Moreover, Hottenrott and Lawson (2017) found that the research group’s industry network increases the likelihood of young scientists to move to the industry. Considering academic patenting, research projects that are financed at least in part by industry partners result more often in patents (Chen et al., 2013; Powers, 2004; Wu et al., 2015), and commercially oriented collaboration partners have a positive effect on academic inventorship (Lawson & Sterzi, 2014; Kalar & Antoncic, 2016). Likewise, scientists with experience outside of research organizations – especially in private industry – are more likely to transfer knowledge (Huang, 2018; Lam, 2011). Industry relationships among scientists also increase the likelihood of a patent getting licensed in the future; in other words, industry relationships foster the success of academic patenting (Wu et al., 2015). In the same vein, Crescenzi et al. (2017) found that patents co-invented by industry and academic partners attracted more forward citations than patents assigned by a single organization.

Together, these results imply that industry relationships among scientists are beneficial for their patenting activities. The existence of an industry relationship therefore represents the final influencing factor considered in this study. I argue that the existence of industry relationships increases a scientist’s likelihood of becoming a serial patentee.

3.2.2 The role of timing of experiences

As previously indicated, the pure existence of influencing factors is not sufficient to exhaustively explain why some inventors stop after the first patent(s) and others continue patenting time and time again. It is therefore necessary to take a deeper look at the kind and timing of prior patent experiences related to influencing factors. Various former studies proved that the ability and willingness to continue patenting are affected by the kind of prior experiences an academic has (Shane & Venkataraman, 2000; Shane, 2000). It is plausible that a scientist who receives personal benefits from patenting will be more motivated to continue patenting than a scientist who failed to receive personal benefits. Amaral et al. (2011) showed that entrepreneurs who were able to sell off their prior startup were more likely to become serial entrepreneurs than those who had to dissolve it. Drivas et al. (2016) published results that showed that the number of inventors, as well as the amount of their patenting activity, along with other factors, such as the scope of the patent, increase the likelihood of concluding a licensing contract, and reducing the time it takes to do so.

In addition, previous studies argued that early experiences are more influential than later experiences and, in turn, later experiences have less effect because individuals already got stuck in the path (Piersen, 2000). Likewise, the "Matthew Effect" states that initial success entails increasing productivity in the future, and vice versa (Perc, 2014). Many organizations try to strategically shape the kind of first experiences of employees in ways that establish favorable routines and behaviors through onboarding programs. Following this argument, the most productive scientists start early in their career and continue producing until the end of their career, with a slightly decreasing trend (Mariani & Romanelli, 2007). In their study of academic patenting, Lawson & Sterzi (2014) focused on early-career factors to analyze serial inventorship. They argued that especially failure and success in early inventions had a lasting effect on subsequent perceptions and competence regarding patenting (Lawson & Sterzi, 2014). A successful patent experience due to the patent support infrastructure during the first patent application may motivate a scientist to continue patenting, while a negative experience may cause such a high level of frustration that the scientist stops after the first patent.

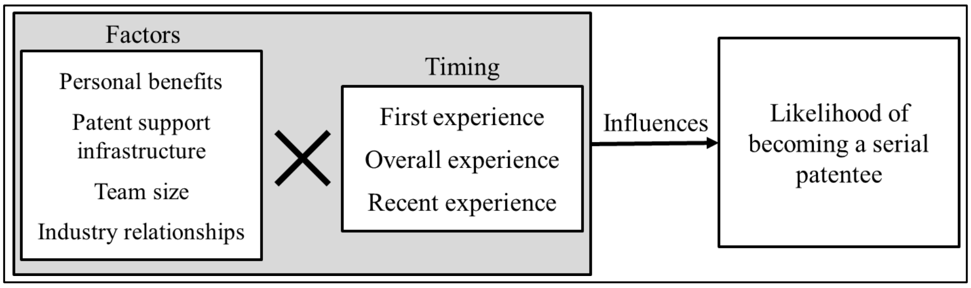
Despite these findings about the role of first experiences, some studies highlight the role of the patentee's most recent experiences. The "freshest" memories are related to the most recent experience, and new memories may redraw over old perceptions. Crescenzi et al. (2017) studied 1,297 Italian inventors and discovered that having co-invented in the recent period increased the likelihood of collaborations in the following patent. Thus, a recent patent experience that is related to a great number of personal benefits may compensate for previous, less successful patenting experiences. Besides the first experiences and the most recent experiences, overall experience at a certain point in time may also influence the later patenting behavior of scientists. For example, Blind et al. (2022) studied 277 company employees with a strong overall track record in patenting and found that they were more motivated by financial incentives than those without a strong overall track record. It follows that the overall patent experience with industry partners could be more relevant than the first experience, since a network with trusted relationships requires time to grow.

To sum up, I argue that the timing of prior patent experiences related to influencing factors matter. Hence, this study aims to analyze three different timings of experiences a scientist has in a research organization, i.e., first experiences, recent experiences, and overall experiences (Figure 17 in the supplementary files illustrates these three different time horizons).

3.2.3 Formulation of hypotheses

So far, this study has introduced four main factors that foster academic patenting: personal benefits, patent support infrastructure, team size, and industry relationships. I have argued that the timing of prior patenting experiences related to these factors matters. This study aims to examine the relevance of three different timings (first experiences, recent experiences, and overall experiences) on the likelihood of becoming a serial patentee (see Figure 11: Visualization of different timing of experiences). In other words, it is worth discovering if the timing(s) are relevant, as well as which timing(s) are relevant.

Figure 11: *Visualization of different timing of experiences*



Based on the four factors and the three aforementioned timings, I derive the hypotheses presented in Table 23. All hypotheses address the research questions about what causes one-time patentees to continue patenting and become serial patentees; rows two to four differentiate between the three time-horizons under investigation.

***Table 23:** Overview of hypotheses*

	Serial patentee (recurrent patenting)
First experience	H1a: The higher the reputational benefits due to the first patent application, the higher the likelihood that the scientist will become a serial patentee. H1b: A successfully granted first patent application increases the likelihood that the scientist will become a serial patentee. H1c: An industry co-applicant in the first patent application increases the likelihood that the scientist will become a serial patentee. H1d: The larger the inventor team in the first patent application, the greater the likelihood that the scientist will become a serial patentee.
Overall experience	H2a: The higher the average reputational benefits due to the patent applications of a patentee, the greater the likelihood that the scientist will become a serial patentee. H2b: The higher the share of successfully granted patent applications of a patentee, the greater the likelihood that the scientist will become a serial patentee. H2c: The higher the share of patent applications with industry co-applicants of a patentee, the greater the likelihood that the scientist will become a serial patentee. H2d: The larger the inventor team, the greater the likelihood that the scientist will become a serial patentee.
Recent experience	H3a: The higher the reputational benefits due to the most recent patent application, the greater the likelihood that the scientist will become a serial patentee. H3b: A successfully granted recent patent application increases the likelihood that the scientist will become a serial patentee. H3c: An industry co-applicant in the most recent patent application increases the likelihood that the scientist will become a serial patentee. H3d: The larger the inventor team in the recent patent application, the greater the likelihood that the scientist will become a serial patentee.

3.3 Data collection and methodology

3.3.1 Situating the data: the Fraunhofer-Gesellschaft

This research studies the case of the Fraunhofer-Gesellschaft. Fraunhofer is the largest organization for applied science in Europe. It comprises 74 decentralized institutes, plus various administration centers and branch offices. In 2019, its approximately 28,000 employees applied for 733 invention disclosures (Fraunhofer-Gesellschaft e.V., 2019a). According to the 2019 annual report, the organization holds a total number of 2,654 intellectual property exploitation agreements and generates annual license fee revenue of €107 million. Moreover, the Fraunhofer-Gesellschaft is among the top 20 patent applicants in Germany (DPMA, 2019). These factors make Fraunhofer a prime location for studying the patenting behavior of scientists.

71% of Fraunhofer employees are research, technical, or administrative staff (RTA staff), 27% are students, and 2% are trainees. The research staff in turn can be grouped into 38.2% postdoctoral researchers, 22.4% doctoral candidates, and 39.4% other students (Fraunhofer-Gesellschaft e.V., 2019b). The human resources policy for scientists states that "a career with Fraunhofer prepares scientists for future roles in industry or business, unless they choose to remain in research" (Fraunhofer-Gesellschaft e.V., 2019a, p. 28). Consequently, the Fraunhofer-Gesellschaft presents itself as a starting point for a (scientific) career, which is insofar relevant as the timing of experiences is of interest for this study.

3.3.2 Data collection

This study focuses on one specific Fraunhofer group – the "Light and Surfaces" group – to prevent a bias in patenting behavior due to differences in the particular field of technology (e.g., Azoulay et al., 2007; Blind et al., 2018; Baldini et al., 2007). The Fraunhofer "Light & Surfaces" group has five members: the Fraunhofer Institute for Organic Electronics, Electron Beam and Plasma Technology (FEP), the Fraunhofer Institute for Laser Technology (ILT), the Fraunhofer Institute for Applied Optics and Precision Engineering (IOF), the Fraunhofer Institute for Physical Measurement Techniques (IPM), and the Fraunhofer Institute for Material and Beam Technology (IWS). This group is characterized by its strong transfer orientation not only in patenting and licensing, but also in spinoff creation.[18]

For the data collection, a list of Fraunhofer employees was used that was available to all internal employees. This list includes information on the employee's institute and group affiliation as well as their academic status and job title. All non-scientists, such as employees from the accounting, marketing, and maintenance departments, were excluded.[19] This resulted in a remainder of 2,139 employees for the subsequent identification of patentees. The database of Patstat, the European Patent Office, was used to identify employees who held at least one patent family (PF).[20] For this identification, I applied a fuzzy string matching of employee names with inventor names mentioned in patent data. The fuzzy string matching allows for spelling mistakes and abbreviations, and is based on the Levenshtein distance similarity. The search for patent families was restricted to the time from 1989 until 2019. Since the interest of this paper is to analyze employees within a single organizational context, only patents with Fraunhofer as an applicant were included. Additional matching criteria were the following: Patstat-standardized name ID, less than 100-kilometer distance between the institute's address and the inventor addresses, and at least one of the addresses of the inventors had to be in Germany. An additional manual quality check of all patentees with more than 20 patents allowed for the correction of false matches, especially outliers due to common German surnames. As a result, it was possible to identify 475 patentees and 1,664 non-patentees. The 475 patentees held a total of 1,789 patent families. The number of patent families is used instead of the number of patents because in a simple patent family, all patents are based on the same invention.[21] This happens, for example, when a patent is applied in different countries. Moreover, I included granted patents as well as patent applications, since not-granted patent applications are also of interest. I retrieved information on the application procedure for every patent application in each patent family, including the filing date, number of claims, number of citations, granted status, inventors, applicants, and pendency time. This ultimately yielded a rich source of data on every single patent family.

The last step involved obtaining information about the publication behavior of the patentees. To do so, I used the "author search" function of the Scopus database.[22] Authors were identified as patentees using the following criteria: exact name matching, affiliation, and a match of the author affiliation's city and the institute. This allowed me to obtain the number of publications for all employees.

[18] For more information on the "Fraunhofer Group for Light & Surfaces," see https://www.light-and-surfaces.fraunhofer.de/en.html (last accessed on June 4, 2022).
[19] The dataset includes only employees who were employed at the time of the collection, i.e., at the beginning of 2019. The employee data also includes student assistants of scientific staff.
[20] For more information on the "Patstat" database, see https://www.epo.org/searching-for-patents/business/patstat.html (last accessed on December 21, 2020).
[21] I used the DOCDB simple patent family; see https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patent-families/docdb.html.
[22] Official description: "Scopus is the largest abstract and citation database of peer-reviewed literature: scientific journals, books and conference proceedings." Elsevier (2019).

3.3.3 Description of the model variables

This study aims to understand the phenomenon of serial patentees, which are defined as patentees who hold more than one patent family. In their study about serial entrepreneurs, Hyytinen and Ilmakunnas (2007) framed serial entrepreneurs in a similar way. Since I conducted a survival model to analyze the data (see method section), the dependent variable is a combination of whether the event (patent family application) occurred (binary), and when it occurred (continuous) (Schober & Vetter, 2018). In addition, the order of each patentee's patent family application is denoted by the variable episode (Amorim & Cai, 2015). Table 24 provides an overview of the model variables.

3.3.3.1 Covariates – characteristics of patent family applications

Reputational benefits: As discussed earlier, gaining reputational benefits is a main motive for inventors to patent. By the definition of this study, reputational benefits relate to the wish to enhance a patentee's own reputation.[23] Hence, the amount of reputational benefit was measured by the number of forward citations a certain patent family received.

The number of forward citations signals the importance of the patent for further research (Mariani & Romanelli, 2007). Similar to forward citations of a scientific publication, forward citations of patent families represent the reputational gains of the patent. However, since older patents tend to have more citations than more recent ones, there is a risk of biased results. To reduce this time bias, I constructed a variable to represent the number of forward citations a patent family had four years after the first patent in the patent family was filed. To generate the overall experience related to reputational benefits, I used the average number of forward citations across all patent families that an inventor held at a certain point in time.

Patent support infrastructure: To measure the influence of patent support infrastructure on serial patenting, I used the granted status of patents as a proxy, i.e., if at least one patent within a patent family was granted. As stated before, a helpful support infrastructure provides sufficient incentives, beneficial assistance, and facilitation of the legal patenting process to ensure patents get granted (see Section 3.2.1.2.). The converse argument implies that a patent that got granted indicates a helpful support infrastructure. To generate the overall experience with the patent support infrastructure, I used the share of all granted patent families with at least one granted patent across all patent families an inventor held at a certain point in time.

Team size: To codify the team size, I used the number of inventors reported in the patent. Most of the time, all patents within a single patent family have the same number of inventors. However, if the number of inventors within a patent family varied, the maximum number of inventors was used. To generate the overall experience, I used the average of the inventor team size across all patent families an inventor held at a certain point in time.

Industry relationships: To test the influence of the existence of industry relationships, I used the co-applicants reported in the patents. If at least one co-applicant was a private company, the patent was marked as industry-related. To generate the overall experience with industry relationships, I used the share of all patent families with industry co-applicants an inventor held at a certain point in time.

[23] In the case of the Fraunhofer-Gesellschaft, various kinds of financial incentives exist (Fraunhofer-Gesellschaft e.V. 2006). First, depending on the number of inventors, a fixed payment called "incentive program" of between €150 and €510 is paid to each inventor for a granted patent if the inventor transfers his/her patent rights to the Fraunhofer-Gesellschaft. In addition, an inventor receives a performance-related payment if the patent is exploited. This is a maximum of 30% of the profit for all inventors. If the patent is not exploited, but the Fraunhofer-Gesellschaft continues to hold the patent for more than seven years, the inventors get a fixed payment totaling €600.

3.3.3.2 Covariates – characteristics of patentees

Turning to control variables, I made use of earlier works on patent behavior (e.g., Blind et al., 2018; Azoulay et al., 2007; Baldini et al., 2007). The ability to conduct scientific work is the basis for high-technology inventions. Blind et al. (2018) showed that academic status positively affected researchers' patent activity. Academic status was therefore introduced as a dummy variable equal to one if the researcher holds a PhD title. Likewise, patenting is based on a knowledge stock (Azoulay et al., 2007). Researchers who are able to generate high-quality research are also more likely to patent (Owen-Smith & Powell, 2003). This issue is considered by integrating the number of scientific publications as a control variable. In addition to academic status, the hierarchical status within the research organization may also be important. A researcher who is the head of a research group has access to additional resources, which in turn is beneficial for patenting. The dummy variable "group lead" indicates if the inventor is the head of a research group or a department. Nevertheless, causality should be considered with caution because scientists with high levels of patent activity may be more likely to be promoted at work. Finally, previous research has shown that male scientists tend to patent more often than female researchers (Mariani & Romanelli, 2007). For this reason, a dummy variable for gender was included in the dataset. In sum, the control variables are academic status, number of publications, leadership position, and gender of researchers.

3.3.4 Data analysis

The empirical analysis was performed in two steps. The first step was to derive descriptive statistics of the variables collected. This made it possible to obtain an impression of the patentees and patent families in the dataset. Moreover, various figures provide initial insights into the relationships between the independent variables and the patent behavior of the inventors (Figures 13-16 and Figures 18-20 in the supplementary files).

In the second step, I applied a survival model for recurrent event data to examine my hypotheses. Following Amorim and Cai (2015), I used the Prentice, Williams, and Peterson (PWP) model to study the association between recurrent patenting behavior and multiple covariates (reputational benefits, patent support infrastructure, team size, and industry relationships). The PWP model is an extension of the semiparametric Cox proportional hazards model – one of the most-used models to analyze survival data (Schober & Vettel, 2018; Prentice et al., 1981). In general, survival models analyze the time until an event of interest occurs – such as the first patent application since employment. Survival models for recurrent event data, such as the PWP model, incorporate the fact that specific events can happen multiple times –in this study, recurrent patent applications. The PWP model is a semiparametric technique that analyzes ordered multiple events by stratification, i.e., a separate model is fitted for each event. This model is preferable to other models when the effects of covariates are different in subsequent events, which is likely to be the case for patent applications because of learning effects. Incomplete observations of survival times of individuals are another special use for survival models (censored data). The dataset is right-censored, which means that the observation of patentees could be terminated before the next recurrent event occurs (Schober & Vetter, 2018).[24] The final dataset includes 475 inventors, with 30% one-time patentees; 70% of the inventors became serial patentees. The analysis thus also includes 475 first-time events out of a total of 2,800 recurrent events (recurrent patenting).

To test Hypotheses H1a – H3d, I used the gap time (GT) as the risk interval. The coefficients of the PWP-GT model represent the effect of an independent variable since the time from the previous

[24] The patentees could have theoretically applied for a patent before their employment at the Fraunhofer-Gesellschaft. However, this study focuses on the experiences patentees had in the context of a single organization. The dataset is therefore not left-censored.

event, meaning that the starting time is reset to zero after each recurrence (Kelly & Lim, 2000; Amorim & Cai, 2015). The coefficients are interpreted as the risk of recurrence of events. I used the Huber–White (robust) Sandwich Estimator for covariance matrix to achieve a robust standard error for the parameter estimates (Amorim & Cai, 2015). The analysis was conducted in Stata 16.

3.3.5 Robustness checks

In the supplementary files, I present additional estimations to confirm the robustness of the estimations and to strengthen the link between the covariates and patent behavior. First, I used the total time (TT) as alternative risk interval to gap time. The results are reported in Tables 28-34 in the supplementary files.

Next, I applied a conservative estimation of the PWP model. The PWP model assumes that individuals can only be at risk for one event at a time, and not for multiple events at the same point in time. However, a patentee can apply more than one patent in one year, e.g., when one project offers two patent opportunities. Although the dataset includes a distinct order for all patent applications within each year, it cannot show if one or more patents belonged to the same project. This issue increases the risk of biased results. To dampen this effect, I generated a new variable which is 1 if a patentee applied for at least one patent in a certain year, and 0 if not. The patent application's characteristics were calculated as the average of all patent applications within one year. I then ran the PWP model as described in earlier with gap time and total time as risk interval (see Tables 31-32 in the supplementary files). Again, the results of the PWP-GT model were interpreted as the effect of an independent variable on the risk of recurrence, since the time from the previous year with at least one patent application. The results of the PWP-TT model are interpreted as the risk of recurrence of a year with at least one patent application since the beginning.

As a third robustness check, an additional statistical model was conducted with a binary dependent variable (1 equals "being a serial patentee/more than one patent," 0 equals "not being a serial patentee/one patent application" (see Tables 33-34 in the supplementary files). This procedure was based on the analysis of several studies on serial entrepreneurs (e.g., Hyytinen & Ilmakunnas, 2007). This means that the unit of observation was the individual patentee. Since the dependent variable is a binary variable, a logistic regression was applied to reveal which independent variables significantly influenced patent behavior. A probit model would be appropriate as well (Long & Freese, 2006). All results also hold for a probit regression.

.

Table 24: *Description and descriptive statistics of the covariates*

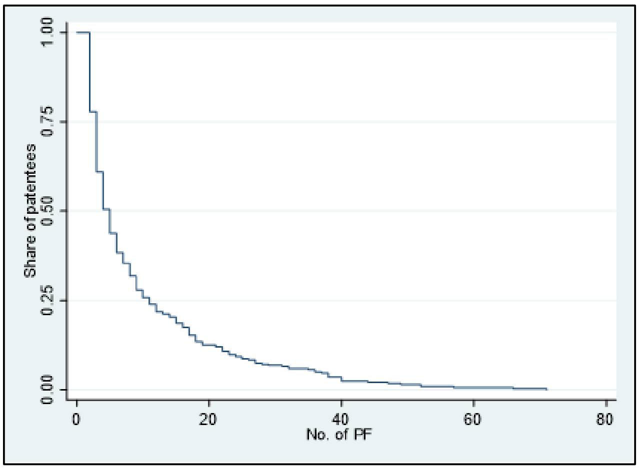
	Title	Description	Timing	Variable type	Share	Mean	SD	Min.	Max.	N
PF characteristics	Proxy for patent support infrastructure	Granted PF; 1=yes	First	Binary variable	66.53%	-	0.4724	0	1	475
			Average	Continuous variable [0;1]	-	0.7213	0.2594	0	1	3275
			Recent	Binary variable	64.82%	-	0.4776	0	1	3275
	Proxy for reputational benefits	No. of citations	First	Discrete variable	-	1.9	2.8	0	19	475
			Average	Continuous variable	-	2.56	2.28	0	19	3275
			Recent	Discrete variable	-	2.45	5.47	0	78	3275
	PF with industry applicant	1=yes	First	Binary variable	15.16%	-	0.359	0	1	475
			Average	Continuous variable [0;1]	-	0.1739	0.2477	0	1	3275
			Recent	Binary variable	17.35%	-	0.3787	0	1	3275
	Inventor team size	No. of inventors	First	Discrete variable	-	4.16	1.94	1	21	475
			Average	Continuous variable	-	4.16	1.35	1	21	3275
			Recent	Discrete variable	-	4.23	1.96	1	21	3275
Patentee characteristics	No. of publications	No. of publications based on Scopus	-	Discrete variable	-	36.65	117.4	0	1936	475
	PhD	PhD degree; 1=yes	-	Binary variable	46.12%	-	0.499	0	1	475
	Group lead	Head of a research group; 1=yes	-	Binary variable	25.68%	-	0.4374	0	1	475
	Gender	1=male	-	Binary variable	88%	-	0.3253	0	1	475
	Proxy for age	2020 – year of patent application	-	Discrete variable	-	11.17	6.37	3	31	475

3.4 Results

3.4.1 Descriptive results: first impressions of factors and timing

First, Figure 12 illustrates the distribution of inventors according to the number of patent families they held. The majority of inventors – 70% of the patentees – continued patenting after their first patent. However, the graph shows a sharp drop until three patent families, after which the graph stabilizes slowly. After the third patent, only 43% of the inventors continued patenting.

Figure 12: *Distribution of inventors according to the number of patent families (PF) they hold*



Figures 13-16 depict the kind and timing of experiences related to the four influencing factors for the first five patents of inventors. For the visual representation, I used decision trees and integrated the "survival rate," i.e., each branch depicts the number of scientists who had patented that far, and the rate of inventors who continue patenting. Only the first five patents are illustrated to reduce the complexity of the figures.

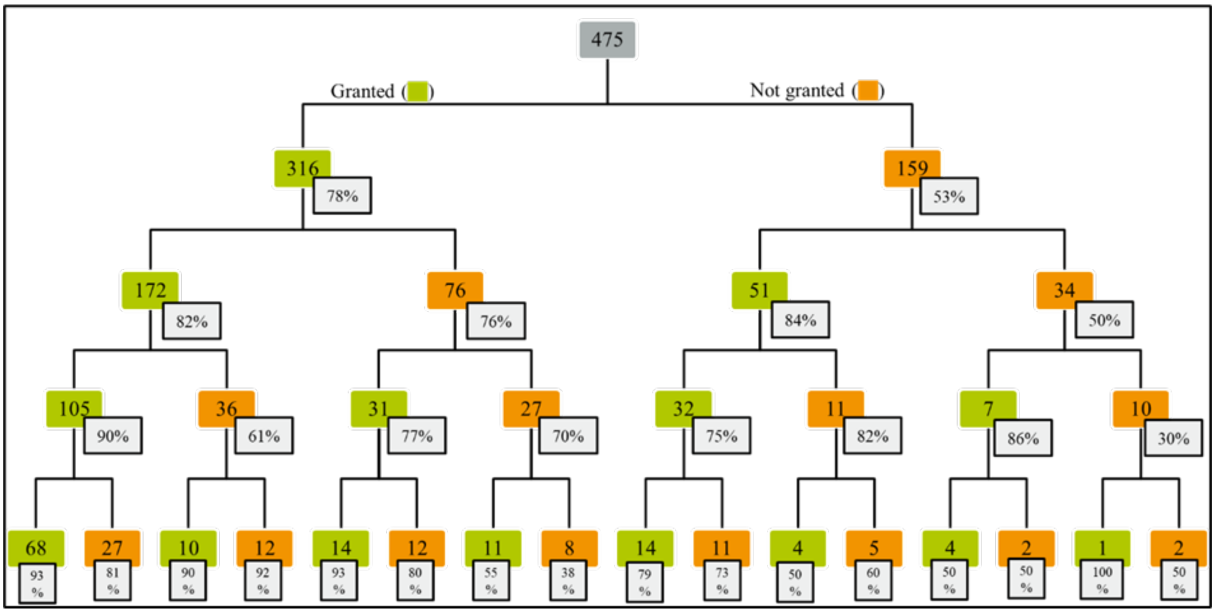
Figure 13 shows how the granted status – as a proxy for patent support infrastructure – influences subsequent patenting behavior. For 316 inventors, their first patent was granted; for 159 inventors, their first patent application was rejected. Out of the 316 inventors with a positive experience (patent granted), 78% continued patenting. In contrast, only 33% of the inventors with a negative first patent experience (patent not granted) continued patenting. This indicates that if an inventor's first patent application was granted, (s)he is more likely to continue patenting and thus Hypothesis H1b is supported (also presented in Figure 18 in the supplementary files). When looking at patentees' most recent experience, the results are mixed. For example, a positive most recent experience in the branch "G-G-G" leads to a survival rate of 90%, which is higher than the neighboring branch "G-G-$\overline{G}$" where the recent experience is negative (61%).[25] However, in the case of the branches "$\overline{G}$-G-G" and "$\overline{G}$-G-$\overline{G}$," the opposite is the case, i.e., a recent positive experience leads to a lower survival rate (75%) than a recent negative experience (82%). Last, to obtain a first impression of the influence of overall experiences, similar branches can be compared, e.g., branches with two granted and two not granted patents. As with the most recent experience, mixed results exist for the overall experience. The following three branches lead to survival rates of around 50%: "$\overline{G}$-$\overline{G}$-G-G," "$\overline{G}$-G-$\overline{G}$-G," and "G-$\overline{G}$-$\overline{G}$-G." In contrast, branches "G-G-$\overline{G}$-$\overline{G}$," "G-$\overline{G}$-G-$\overline{G}$," and "$\overline{G}$-G-G-$\overline{G}$" entail a survival rate of between 73 and 92%.

A similar observation relates to the occurrence of forward citations within the first patent (see Figure 14). The tree shows that the survival rate for inventors whose first patent received a forward

[25] G = patent was granted; $\overline{G}$ = patent was not granted; F = patent received forward citations; $\overline{F}$ = patent received no forward citations.

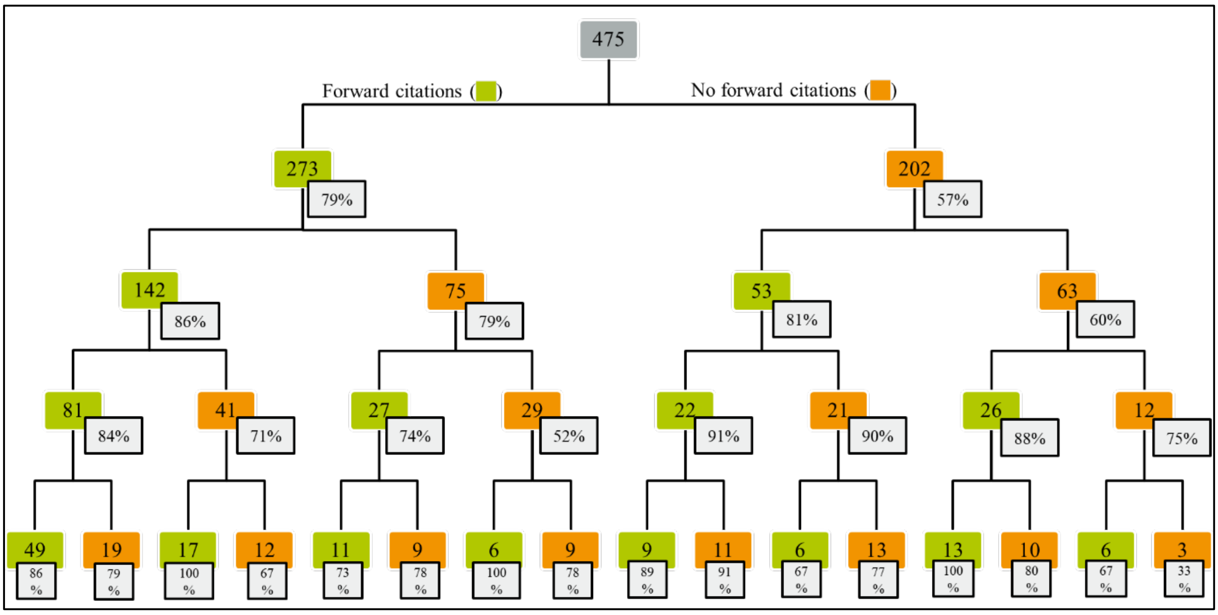
citation is 79%. In contrast, the survival rate of inventors without a cited first patent is only 57%. This is a first indication that inventors who receive positive feedback for their first patent are more likely to continue patenting. Likewise, the tree indicates that the most recent experience matters as well (supporting Hypotheses H1a and H2a). The majority of nodes with a recent patent that was cited have higher survival rates than their neighboring nodes in the same branch with a recent patent without citations (e.g., branch “F-$\bar{F}$-F” compared to “F-$\bar{F}$-$\bar{F}$”). Considering the overall experience, the evidence is less clear. Whereas 75% of the inventors with only positive experiences (four patents with forward citations) continue patenting, only 33% of the inventors with exclusively negative experiences (four patents without forward citations) do so. However, the survival rates of branches with the same overall experiences vary widely (e.g., branch “F-$\bar{F}$-F-$\bar{F}$” and “F-F-$\bar{F}$-$\bar{F}$”).

Figure 13: *Distribution of patentees and survival rates for the first 5 PF, differentiated according to the granted status of PF*



XX% = survival rate, i.e., the number of scientists in each branch who continued patenting

Figure 14: *Distribution of patentees and survival rate for the first five patent families (PF), differentiated by the appearance of forward citations**

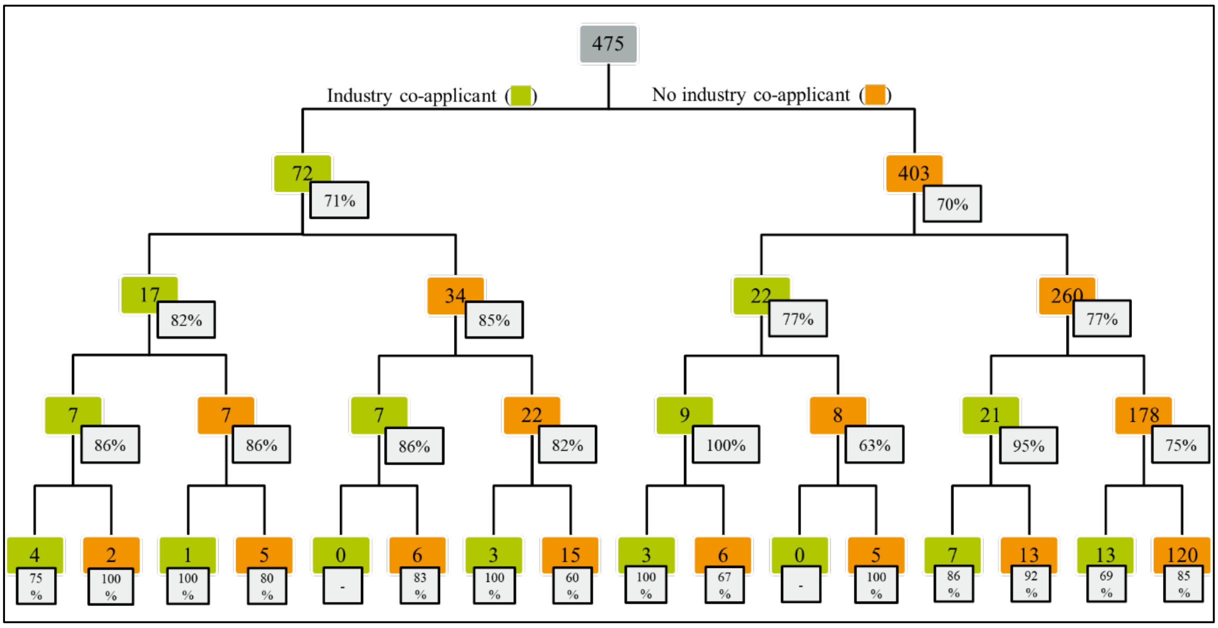


*For a better graphical visualization, the figure only differentiates between a patent family (PF) with forward citations or without forward citations; XX% this equals the survival rate, i.e., the number of scientists who continued patenting in each branch.

Turning to the influence of industry relationships and team size on patenting behavior, Figures 15 and 6 provide a first impression. To begin with, only 72 inventors had an industry co-applicant in their first patent. When looking at timing, neither the first nor the most recent nor the overall experience seem to matter. For example, in the case of the first patent experience, the survival rate for inventors who hold their first patent with an industry co-applicant is 71%, while a first patent without an industry co-applicant leads to a survival rate of 70%. It follows that the tree indicates that industry relationships fail to make an impact on a given researcher becoming a serial patentee.

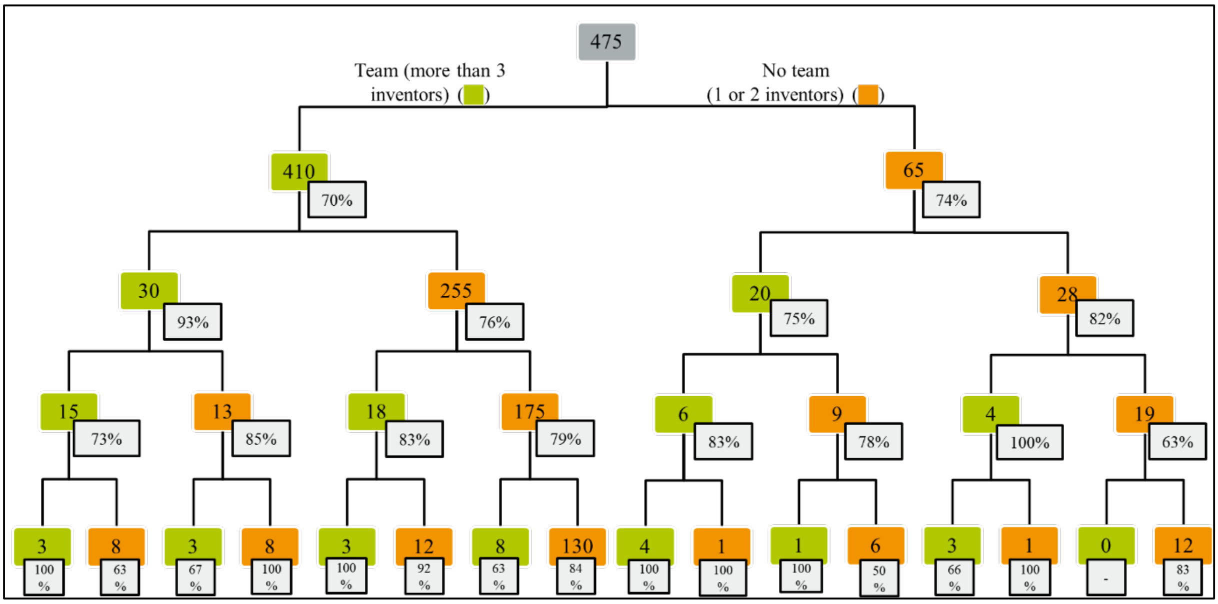
The last tree (Figure 16) reveals that most inventors applied for their first patent in a team of three or more members (86%). As with the influence of industry relationships, team size also seems to have no impact on subsequent patenting behavior. 70% of the inventors whose first patent was a team effort continued patenting; 74% of first-time lone inventors or inventor pairs continued patenting. When looking at most recent and overall experiences, evidence is mixed. Yet, the validity of the results on team size is limited due to the complexity reduction for a better visualization, i.e., an inventor team is defined as 3 or more people. This skews the impact of differences in teams as it ignores larges teams.

__Figure 15:__ Distribution of patentees and survival rate for the first five patent families (PF), differentiated by the presence of industry applicants



XX% = survival rate, i.e., the number of scientists in each branch who continued patenting

*__Figure 16:__ Distribution of patentees and survival rate for the first five patent families (PF), differentiated according to the inventor team size**



*For better graphical visualization, an inventor team is defined as three or more inventors;

XX% = survival rate, i.e., the number of scientists in each branch who continued patenting

3.4.2 Results of the survival analysis for recurrent events

So far, the hypotheses relating to the impact of reputational benefits and patent support infrastructure on becoming a serial patentee have been supported by the descriptive statistics presented above, especially for the first and most recent experiences. Next, I take a deeper look at the significance of these results. This section tests the hypotheses using a survival model for recurrent event data.

First-time patenting experiences: Table 25 illustrates the results of the survival analysis for recurrent event data to verify the significance of the influences indicated in the previous section. To elaborate on the role of first experiences in determining recurrent patenting, I constructed five different (semi-)parametric survival models (see Columns A-E). The models in Columns A-D examine each influencing factor separately, and the last column integrates all factors into one model. Table 25 reports the coefficients, which can be interpreted as the effect on the risk of recurrence of the event of interest (patenting) due to an increase in the corresponding covariate.

The results of the first model (Column A) show that inventors who hold a successfully granted first patent have a significantly higher "risk" of becoming a serial patentee (at the 1% level). This result also holds for the complete model. This implies that inventors who receive patent support for their first patent are more likely to become serial patentees. Likewise, higher reputational benefits related to the first patent experiences also tend to facilitate serial patenting compared to those who did not receive reputational benefits; this is apparent from the positive effect of forward citations on the risk of recurrent patenting (coefficient 0.03, at a significance of 0.01%). This finding supports Hypotheses H1a and H1b. Turning to the influence of industry relationships, the results reveal no significant effect. Hence, H1c is not confirmed. Moreover, even though the team size seems to increase the risk of recurrent patenting according to Model D, the factor loses statistical significance if tested for the complete model E. Therefore, I find somewhat ambiguous evidence on the relationship between the team size of the first patent and the relevance of recurrent patenting. As a result, H1d is only partly supported.

Lastly, a look at the control variables, i.e., the covariates describing the characteristics of patentees, reveals that inventors who publish a lot are more likely to become serial patentees than those with a low publication record. Another important factor is the patentees' level of education. A PhD degree significantly increases the likelihood of recurrent patenting. Both findings are in line with previous findings. However, organizational role as a group leader and gender have no significant influence on becoming a serial patentee. [26]

[26] As expected, older inventors are more likely to have recurrent episodes than their younger counterparts. One possible reason is that I used right-censored data.

Table 25: PWP-GT model, first-time, coefficients (standard error)

	(A)	(B)	(C)	(D)	(E)
Proxy for patent support infrastructure	0.147***				0.104**
(Granted; 1=yes)	(0.0485)				(0.0496)
Proxy for reputational benefits due to the first PF		0.0314***			0.0264***
(No. of citations)		(0.00646)			(0.00682)
Industry applicant in the first PF (1=yes)			-0.00227		-0.0371
			(0.0477)		(0.0510)
Inventor team size in the first PF				0.0262***	0.0175
				(0.00984)	(0.0108)
No. of publications	0.000446***	0.000477***	0.000458***	0.000473***	0.000470***
	(6.61e-05)	(6.64e-05)	(6.65e-05)	(6.63e-05)	(6.67e-05)
PhD (1=yes)	0.298***	0.289***	0.310***	0.324***	0.292***
	(0.0443)	(0.0441)	(0.0439)	(0.0439)	(0.0443)
Group lead (1=yes)	0.0134	0.0285	0.0172	0.0106	0.0233
	(0.0370)	(0.0372)	(0.0373)	(0.0372)	(0.0373)
Gender (1=male)	0.0672	0.0678	0.0600	0.0437	0.0597
	(0.0695)	(0.0702)	(0.0700)	(0.0714)	(0.0711)
Proxy for age	0.0523***	0.0537***	0.0527***	0.0532***	0.0537***
	(0.00286)	(0.00289)	(0.00285)	(0.00288)	(0.00290)
Observations	3,275	3,275	3,275	3,275	3,275
No. of subjects	475	475	475	475	475
No. of failures	2,800	2,800	2,800	2,800	2,800
Time at risk	5,849.5	5,849.5	5,849.5	5,849.5	5,849.5

*** p<0.01, ** p<0.05, * p<0.1

Recent patenting experiences: Moving on to consider the role of the most recent patenting experience, Table 26 presents the results in the same form as Table 25. As with the first experiences, the most recent experiences also matter regarding reputational benefits and patent support infrastructure. Both proxies significantly increase the risk of recurrent patenting. The results indicate that the decision to continue patenting depends not only on the first experience, but also on the reputational benefits (measured as forward citations) and the support received (measured as the granted status) for the most recent patent (supporting H2a and H2b). The presence of an industry co-applicant in the most recent patent experience, on the other hand, has no influence on the decision to continue patenting. Concerning the team size, the results show that a larger team increases the likelihood of recurrent patenting, yet only at a 10% level of significance with a coefficient of 0.02 (see Column E). This weakly supports Hypothesis H2d.

Finally, the control variables show the same results as the previous subsection, i.e., a large number of publications, a PhD degree, and a higher age increase the likelihood of recurrent patenting. Gender and leadership responsibility have no impact.

***Table 26:** PWP-GT model, recent, coefficients (standard error)*

	(A)	(B)	(C)	(D)	(E)
Proxy for patent support infrastructure	0.145***				0.109***
(Granted PF; 1=yes)	(0.0384)				(0.0392)
Proxy for reputational benefits		0.0195***			0.0176***
(No. of citations)		(0.00327)			(0.00343)
PF with industry applicants (1=yes)			0.0347		-0.0485
			(0.0451)		(0.0484)
Inventor team size				0.0212**	0.0201*
				(0.00968)	(0.0104)
No. of publications	0.000448***	0.000466***	0.000462***	0.000459***	0.000453***
	(6.67e-05)	(6.62e-05)	(6.63e-05)	(6.55e-05)	(6.62e-05)
PhD (1=yes)	0.308***	0.322***	0.311***	0.317***	0.324***
	(0.0438)	(0.0439)	(0.0439)	(0.0441)	(0.0441)
Group lead (1=yes)	0.0156	0.0178	0.0174	0.0194	0.0178
	(0.0369)	(0.0371)	(0.0370)	(0.0371)	(0.0371)
Gender (1=male)	0.0570	0.0593	0.0597	0.0650	0.0624
	(0.0700)	(0.0693)	(0.0701)	(0.0698)	(0.0692)
Proxy for age	0.0514***	0.0519***	0.0525***	0.0532***	0.0517***
	(0.00288)	(0.00287)	(0.00287)	(0.00287)	(0.00293)
Observations	3,275	3,275	3,275	3,275	3,275
No. of subjects	475	475	475	475	475
No. of failures	2,800	2,800	2,800	2,800	2,800
Time at risk	5,849.5	5,849.5	5,849.5	5,849.5	5,849.5

*** p<0.01, ** p<0.05, * p<0.1

Overall patenting experiences: Finally, this section considers the overall experiences of the inventors, calculated as the average experience. The overall experience assumes that inventors base their decision to continue patenting on the average of all experiences they made up to the decision. In the case of a patentee with four patents, this means that the patentee uses the average experiences of all four prior patents to decide on the fifth patent application (see also Figure 17 in the supplementary files).

As shown in Columns A and E of Table 27, the share of granted patents is significantly related to recurrent patenting in the separate model but is not significant in the complete model. Thus, Hypothesis H2b is only partly supported. In addition, Table 27 reveals that average reputational benefits, with a coefficient of 0.066, significantly increase the risk of recurrent patenting. This implies that inventors base their decision to become a serial patentee not only on their first and most recent experience, but also on the average reputational benefits they received from their patents overall. These results support H1b, H2b, and H3b. The share of co-applicants in prior patents is not significant; see Columns C and E. Consequently, this implies that the overall participation of industry partners is irrelevant for the decision to continue patenting (H3c is rejected). In contrast to the first patent experience, a higher average size of the inventor team increases the likelihood of becoming a serial patentee. One possible reason may be that it takes time to create a large network of co-inventors. Moreover, the collected experiences may help inventors to select the team (size) more strategically. Once again, the control variables show the same results as the two previous subsections.

Table 27: *PWP-GT model, overall, coefficients (standard error)*

	(A)	(B)	(C)	(D)	(E)
Proxy for patent support infrastructure	0.283***				0.110
(Share of granted PF; 1=yes)	(0.0813)				(0.0843)
Proxy for reputational benefits		0.0704***			0.0663***
(Average no. of citations)		(0.00839)			(0.00889)
Share of PF with industry applicants (1=yes)			0.125		-0.132
			(0.0798)		(0.0879)
Average inventor team size				0.0563***	0.0451***
				(0.0140)	(0.0148)
No. of publications	0.000436***	0.000477***	0.000471***	0.000465***	0.000459***
	(6.64e-05)	(6.61e-05)	(6.64e-05)	(6.57e-05)	(6.64e-05)
PhD (1=yes)	0.299***	0.321***	0.310***	0.331***	0.333***
	(0.0439)	(0.0441)	(0.0439)	(0.0442)	(0.0443)
Group lead (1=yes)	0.0143	0.0322	0.0183	0.0175	0.0295
	(0.0369)	(0.0371)	(0.0370)	(0.0371)	(0.0371)
Gender (1=male)	0.0574	0.0839	0.0607	0.0726	0.0908
	(0.0696)	(0.0697)	(0.0699)	(0.0697)	(0.0692)
Proxy for age	0.0510***	0.0538***	0.0526***	0.0543***	0.0544***
	(0.00290)	(0.00290)	(0.00286)	(0.00289)	(0.00299)
Observations	3,275	3,275	3,275	3,275	3,275
No. of subjects	475	475	475	475	475
No. of failures	2,800	2,800	2,800	2,800	2,800
Time at risk	5,849.5	5,849.5	5,849.5	5,849.5	5,849.5

*** p<0.01, ** p<0.05, * <0.1

3.5 Discussion

Despite the vast amount of empirical research on academic patenting, we still lack an understanding of why some inventors stop patenting after their first patent, while others continue time and time again. Consequently, this research contributes to the existing discussion on academic patenting by addressing the phenomenon of serial patentees. It differentiates between one-time patentees and serial patentees, and how the kind of factors and the timing of these particular factors in a researcher's career influences his/her patenting behavior. This paper has been based on a dataset consisting of employee data of a German research institute for applied science, using patent and publication data from Patstat and Scopus. The survival analysis for recurrent data shows that previous patent activities have a positive effect on subsequent patent activities.

In general, the findings validate the relevance of timing of prior experiences in the context of academic patenting. The following main findings show what influences one-time patentees to become a serial patentee. First, the descriptive results showed that only 22% of the scientists in the dataset were inventors, but 70% of these inventors are serial patentees. It follows that it is more likely that a scientist who once chooses to participate in academic patenting will become a serial patentee (70%) than a non-patenting scientist to start patenting at all (22%). This indicates that the first patent application has a high entry barrier in terms of patenting knowledge, or, in other words, patenting has "large set-up costs" (Dobusch & Schüßler, 2013; Piersen, 2000). Furthermore, the descriptive and the survival analysis both confirmed that positive early patenting experiences are a promising indicator for continuous patenting behavior and thus becoming a serial patentee. Inventors who receive reputational benefits and patent support infrastructure for their first patent are more likely to continue patenting in the future. These results complement those of D'Este et al. (2012), who found that scientific excellence and prior invention experience positively influenced high levels of patenting activity, whereas the team size and the participation of an industry co-applicant in the first patent had no impact on becoming a serial patentee. These findings have two important consequences for KTO employees. First, it is crucial to create a positive first-time patenting experience in terms of reputational benefits (see Section 3.2.) and support infrastructure. Second, since positive first experience reveals a trend of continued patenting, KTO employees should especially address less successful first-time inventors to avoid "losing" them after the first patent experience.

These two factors also matter for patentees' most recent experiences with patenting, and thus strengthen the importance of reputational benefits and patent support infrastructure. Overall, reputational benefits are significantly correlated with recurrent patenting as well. In consequence, reputational benefits related to the first experience are relevant, but not necessarily more relevant than recent or overall experiences. One possible explanation for this may be that a higher reputation may be considered particularly important by inventors. Moreover, inventors who started successfully may also continue successfully. Likewise, Dlouhy and Biemann (2018) reported in their study on career turbulence in 456 individuals from Germany that late career patterns correlate with similar early patterns. According to their results, individuals who experienced various job switches in their early career ("career turbulence") also switched jobs more often in later career stages than individuals with less turbulent early careers. Interestingly, the overall experience with patent support infrastructure, measured by the share of prior granted patents, had no significant influence on recurrent patenting. One possible explanation for this might be that inventors learn with each patent application what a successful patent requires and they therefore may be less dependent on the patent support infrastructure over time.

The results also reveal that the average team size increases the likelihood of becoming a serial patentee, but the team size of the first patent has no impact on becoming a serial patentee. This finding might be explained by the fact that inventing is a team effort requiring ties that emerge and grow over time (Jones, 2009; Tsuji, 2002). This finding in turn has important implications for leadership, human resources, and technology transfer managers, as discussed in the next paragraph. Contrary to expectations, the participation of an industry co-applicants was not found to be an important predictor for recurrent patenting – neither for the first, nor for recent or overall experience. This result is rather puzzling, since previous studies clearly indicated the positive impact of industry contact on commercial behavior (Chen et al., 2013). One possible explanation for this might be that this research does not account for the kind and heterogeneity of industry links. The results could therefore be biased by inventors who apply patents with the same industry partner time and time again. In addition, this finding may be somewhat limited by the small number of patents with private-industry applicants in the dataset.

To conclude, becoming a patentee for the first time represents a high initial human capital investment. In addition, the knowledge required to become a technical expert in a certain field indeed even increases over time due to the general growth of knowledge available worldwide (Jones, 2009). Moreover, the inventor must acquire knowledge about the patent process, which is a learning-intensive process that can take years. The findings mentioned above imply that one-time inventors make a conscious decision to become serial patentees based on the experiences they have. This indicates that becoming a serial patentee is rather a career choice than a simple work assignment in order to achieve the research organization's technology transfer objectives. This suggestion should be examined by future researchers.

Considering the control variables, I found that inventors who publish a lot are also more likely to become serial patentees than those with a low publication record. Hence, the importance of publications for patenting behavior as a form of knowledge stock is supported (Huang, 2018; Huang et al., 2011). Another important factor is the patentee's level of education. A PhD degree significantly increases the likelihood of recurrent patenting. Both findings are in line with findings (see previous subsections). Leading a group does not seem to have an impact, as the coefficients are not significant. Gender does not seem to have an impact either. If follows those female scientists, who participate in academic patenting are as active as their male colleagues. In line with Lawson & Sterzi (2014), I conclude that women, once they choose to participate in academic patenting, are as active in patenting as their male colleagues.

3.6 Conclusion

3.6.1 Implications for theory

Most of the scientific production on inventor behavior focuses either on motives and barriers for patenting and thus treat "academic inventors" as a monolithic group (Alves & Danieal, 2018; Baldini et al., 2007) or on how inventors translate patents into economic value in the form of licenses and spinoffs (Buenstdorf & Geissler, 2013; D'Este et al., 2012; Mariani & Romanelli, 2007). Scant attention has been paid to the differences between inventors who discontinue patenting after their first patent and those who continue patenting. This research therefore aims to spark the academic discussion on continuous commercial behavior by introducing the concept of serial patentees. It contributes to the literature on inventors and their role in innovation systems by deriving theoretical explanations and practical implications on how to foster serial patentees. Second, this study contributes to the stream of literature that has analyzed the influence of institutional and individual factors on the technology transfer performance of research organizations, including their technology transfer offices (e.g., D'Este et al., 2012). In particular, the aim of the present research has been to answer the question "What causes one-time patentees to continue patenting and become serial patentees?" Employing a unique dataset of patent and publication data from the Fraunhofer-Gesellschaft, a major German research organization, allows a closer look at the variation of patenting behavior among academic inventors. It adds new insights on how the kind of prior experiences relating to patenting (reputational benefits, patent support infrastructure, and team size), and when these experiences occur, shape the subsequent patenting behavior of scientists. Based on these findings, this research indicates that becoming a serial patentee can be seen as an academic career choice.

3.6.2 Implications for practitioners

This study draws attention to the conditions that increase the likelihood of one-time inventors becoming serial patentees. As such, our findings have practical implications for the technology transfer community, scientists, and policymakers. The implications are threefold. First, the study speaks to human resources managers, transfer office employees, and other technology transfer practitioners. As discussed above, the "knowledge entry barrier" for patents is very high. Hence, technology transfer managers should aim to lower the information barrier and provide easy access to patenting-relevant information. In particular, young and less experienced researchers would benefit from such measures. In addition, it is important to support the positive perception of first patent experiences and increase the probability of success. Technology transfer managers play an important role in this aspect. They can reduce the likelihood of negative experiences by 1) undertaking stricter invention disclosure assessments to avoid patent applications being not granted (quality before quantity); 2) making realistic assumptions about the time, effort, and success expectations of patenting; and 3) supporting the licensing process after a patent has been granted. Moreover, practitioners can actively address the findings concerning the positive influence of reputational benefits, and the average team size to develop more appropriate support for inventors. For example, they can provide additional coaching for inventors with negative first – or recent – experiences. Moreover, human resources managers and research group leaders can use teambuilding to strengthen ties among inventors.

In accordance with the theory on applicant self-selection processes (Ryan et al., 2000), human resources managers and leaders can actively support the establishment of new inventor teams by promoting inventor careers in the job recruitment process. Human resources managers could also develop internal career or qualification programs to support “serial patentees” or sharpen existing ones. Given the emphasis that university managers put on commercialization and technology transfer in general, it is surprising that so few have established a specific career path for scientists interested in commercialization. The findings suggest that university managers could establish a new career path for scientists interested in academic patenting or commercialization in general, such as a “transfer professor,” accompanied by specific performance indicators and support infrastructure.

Third, policymakers can also benefit from the results of this study, as it helps to adjust formats and services to the identified needs and challenges of researchers. Research programs could include additional funding for patent-related issues, especially if research teams are associated with organizations that do not have an internal technology transfer office. In addition, it could be useful in long-term research projects to invest in teambuilding measures, especially if the research team members are distributed over different organizations, disciplines, or regions.

3.6.3 Limitations of the current study

A limitation of this study is that it only includes research organizations of Fraunhofer’s “Light and Surfaces” group. However, since the current literature of technology transfer is dominated by research on universities, the case of these five institutes provides a valuable insight into non-university research organizations and thus enlarges this body of literature. Along these lines, a study by Buenstorf and Geissler (2013) can serve as an example of how the case of a single organization provides generalizable results; they examined the Max Planck Society and provided insights on factors that affected the commercialization of academic inventions. It is unfortunate that this study did not include researchers’ career paths before their entry into the organization. Nevertheless, the Fraunhofer-Gesellschaft attracts scientists already in their early career, as explained in the section on data collection and methodology. This study analyzed inventions by using patents and omitted other forms of formal and informal intellectual property. Nevertheless, patents have been proven to be an appropriate measure by a myriad of studies, as Archibugi (1992) showed.

3.6.4 Where to go from here

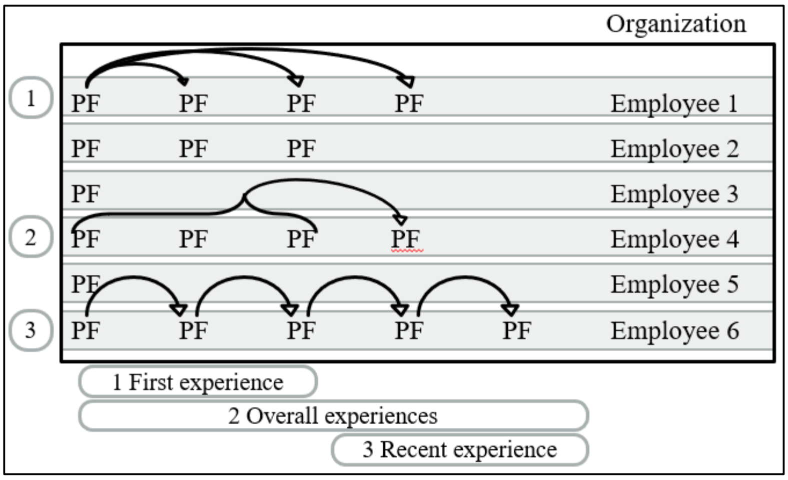
A natural progression of this work is to analyze the phenomenon of serial patentees in other scientific fields and other kinds of organizations such as universities and companies with research departments (e.g., in the pharmaceutical industry). Moreover, further studies could assess academic patenting paths across organizational contexts. Since this study focused on scientists of a single organization, the full path of the scientific career would be of interest – from academic education to the career exit. I suggest that alumni networks and KTOs monitor the transfer behavior of former employees. Another interesting aspect would be to study the influence of the team composition on serial patenting. Research on spinoffs has shown that in particular team heterogeneity, in terms of different academic and practical backgrounds of team members, has a positive influence on spinoff success (Moog et al., 2015; Visintin & Pittino, 2014). A greater focus on other commercial transfer channels and their impact on careers could produce interesting findings that account for a more comprehensive understanding of technology transfer-related research careers.

3.7 Acknowledgements

I wish to acknowledge the data collection assistance provided by Dmitry Neustroev (student assistant at the Fraunhofer Center for International Management and Knowledge Economy).

3.8 Supplementary files

Figure 17: *Visualization of different timing of experiences*



PF = patent family application

Figure 18: *Distribution of patentees differentiated by granted status of the first PF*

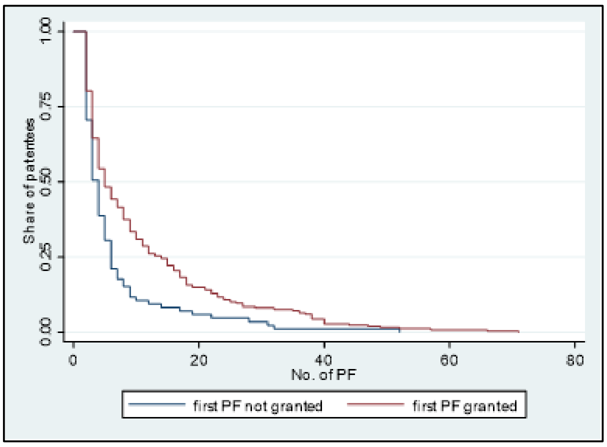


Figure 19: *Distribution of patentees differentiated by forward citation of the first PF*

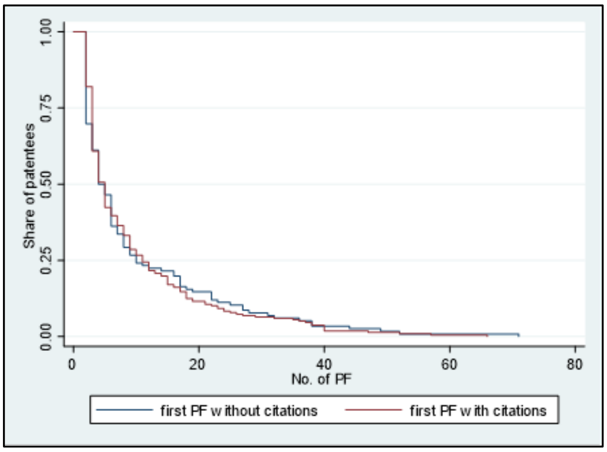


Figure 20: *Distribution of patentees differentiated by the presence of industry applicants in the first PF*

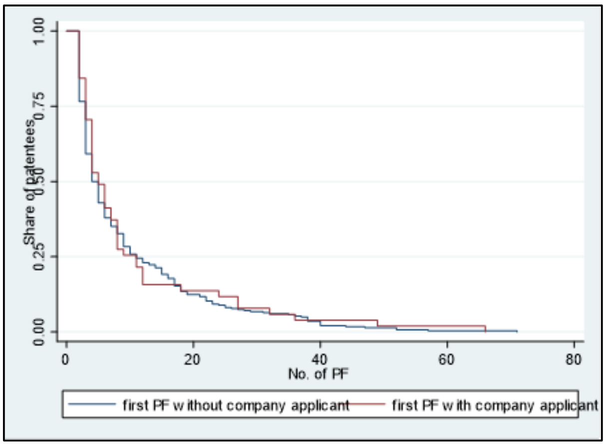


Table 28: *Likelihood of recurrent events; PWP-TT model; first PF*

	(A)	(B)	(C)	(D)	(E)
Proxy for patent support infrastructure	0.0808	0.116**			
Granted PF; 1=yes)	(0.0557)	(0.0545)			
Proxy for reputational benefits	0.0251***		0.0282***		
(No. of forward citations)	(0.00920)		(0.00896)		
PF with industry applicants (1=yes)	-0.0912			-0.0543	
	(0.0647)			(0.0671)	
Inventor team size in the first PF	0.0134				0.0148
	(0.0141)				(0.0143)
No. of publications	0.000620***	0.000606***	0.000637***	0.000608***	0.000624***
	(0.000108)	(0.000105)	(0.000110)	(0.000106)	(0.000106)
PhD (1=yes)	0.241***	0.253***	0.237***	0.254***	0.268***
	(0.0532)	(0.0560)	(0.0553)	(0.0554)	(0.0535)
Group lead (1=yes)	0.105**	0.0899*	0.103**	0.0972*	0.0862*
	(0.0480)	(0.0487)	(0.0481)	(0.0496)	(0.0493)
Gender (1=male)	-0.0188	-0.0176	-0.0122	-0.0296	-0.0308
	(0.0942)	(0.0975)	(0.0924)	(0.0979)	(0.0988)
Proxy for age	-0.340***	-0.342***	-0.341***	-0.342***	-0.341***
	(0.0201)	(0.0203)	(0.0202)	(0.0204)	(0.0203)
Observations	3,275	3,275	3,275	3,275	3,275
No. of subjects	475	475	475	475	475
No. of failures	2,800	2,800	2,800	2,800	2,800
Time at risk	5,849.5	5,849.5	5,849.5	5,849.5	5,849.5

*** p<0.01, ** p<0.05, * p<0.1

Table 29: *Likelihood of recurrent events; PWP-TT model, average*

	(A)	(B)	(C)	(D)	(E)
Proxy for patent support infrastructure	0.00638	0.147*			
Granted PF; 1=yes)	(0.0862)	(0.0848)			
Proxy for reputational benefits	0.0655***		0.0666***		
(No. of forward citations)	(0.0116)		(0.0115)		
PF with industry applicants (1=yes)	-0.106			0.0903	
	(0.119)			(0.124)	
Average inventor team size	0.0362*				0.0457**
	(0.0189)				(0.0199)
No. of publications	0.000644***	0.000605***	0.000652***	0.000628***	0.000625***
	(0.000111)	(0.000107)	(0.000113)	(0.000108)	(0.000105)
PhD (1=yes)	0.262***	0.252***	0.247***	0.259***	0.278***
	(0.0517)	(0.0558)	(0.0533)	(0.0555)	(0.0542)
Group lead (1=yes)	0.0987**	0.0890*	0.0988**	0.0911*	0.0906*
	(0.0480)	(0.0491)	(0.0475)	(0.0490)	(0.0493)
Gender (1=male)	0.00893	-0.0266	6.43e-05	-0.0257	-0.0130
	(0.0882)	(0.0981)	(0.0921)	(0.0957)	(0.0893)
Proxy for age	-0.336***	-0.343***	-0.338***	-0.342***	-0.339***
	(0.0199)	(0.0204)	(0.0199)	(0.0203)	(0.0201)
Observations	3,275	3,275	3,275	3,275	3,275
No. of subjects	475	475	475	475	475
No. of failures	2,800	2,800	2,800	2,800	2,800
Time at risk	5,849.5	5,849.5	5,849.5	5,849.5	5,849.5

*** p<0.01, ** p<0.05, * p<0.1

__Table 30:__ Likelihood of recurrent events; PWP-TT model, recent

	(A)	(B)	(C)	(D)	(E)
Proxy for patent support infrastructure	0.0741	0.116**			
Granted PF; 1=yes)	(0.0457)	(0.0453)			
Proxy for reputational benefits	0.0270***		0.0287***		
(No. of forward citations)	(0.00461)		(0.00459)		
PF with industry applicants (1=yes)	-0.0631			0.0311	
	(0.0726)			(0.0724)	
Inventor team size	0.0257**				0.0275**
	(0.0126)				(0.0128)
No. of publications	0.000612***	0.000609***	0.000629***	0.000621***	0.000615***
	(0.000106)	(0.000107)	(0.000108)	(0.000106)	(0.000105)
PhD (1=yes)	0.263***	0.255***	0.255***	0.258***	0.268***
	(0.0539)	(0.0559)	(0.0548)	(0.0558)	(0.0547)
Group lead (1=yes)	0.0877*	0.0873*	0.0894*	0.0915*	0.0925*
	(0.0486)	(0.0492)	(0.0483)	(0.0491)	(0.0492)
Gender (1=male)	-0.0173	-0.0289	-0.0237	-0.0265	-0.0179
	(0.0942)	(0.0989)	(0.0966)	(0.0978)	(0.0932)
Proxy for age	-0.338***	-0.342***	-0.340***	-0.342***	-0.340***
	(0.0201)	(0.0203)	(0.0202)	(0.0204)	(0.0201)
Observations	3,275	3,275	3,275	3,275	3,275
No. of subjects	475	475	475	475	475
No. of failures	2,800	2,800	2,800	2,800	2,800
Time at risk	5,849.5	5,849.5	5,849.5	5,849.5	5,849.5

*** p<0.01, ** p<0.05, * p<0.1

Table 31: *Conservative estimation; PWP-TT model*

	First PF	Average PF	Recent PF
Proxy for patent support infrastructure	0.152**	-0.196	-0.0711
Granted PF; 1=yes)	(0.0726)	(0.145)	(0.0560)
Proxy for reputational benefits	0.0173*	0.0345**	0.0146***
(No. of forward citations)	(0.00972)	(0.0160)	(0.00509)
PF with industry applicants (1=yes)	-0.123*	-0.0605	0.0137
	(0.0670)	(0.168)	(0.0679)
Inventor team size in the first PF	0.0168	0.0274	0.00902
	(0.0138)	(0.0346)	(0.0135)
No. of publications	0.000439***	0.000599***	0.000470***
	(0.000127)	(0.000107)	(0.000131)
PhD (1=yes)	0.300***	0.357***	0.309***
	(0.0626)	(0.0759)	(0.0638)
Group lead (1=yes)	0.214***	0.179***	0.208***
	(0.0495)	(0.0623)	(0.0498)
Gender (1=male)	0.0539	0.0419	0.0475
	(0.103)	(0.123)	(0.103)
Proxy for age	-0.148***	-0.0480***	-0.150***
	(0.0140)	(0.0132)	(0.0140)
Observations	1,890	1,890	1,890
No. of subjects	475	475	475
No. of failures	1,418	1,418	1,418
Time at risk	5,850	5,850	5,850

*** p<0.01, ** p<0.05, * p<0.1

Table 32: *Conservative estimation, gap time between events; PWP-GT model*

	First PF	Average PF	PF
Proxy for patent support infrastructure	0.185***	-0.0197	0.0749
Granted PF; 1=yes)	(0.0692)	(0.111)	(0.0562)
Proxy for reputational benefits	0.0193**	0.0450***	0.0178***
(No. of forward citations)	(0.00957)	(0.0112)	(0.00489)
PF with industry applicants (1=yes)	-0.0737	-0.0364	0.0662
	(0.0612)	(0.114)	(0.0639)
Inventor team size in the first PF	0.0157	0.0147	0.000191
	(0.0130)	(0.0223)	(0.0127)
No. of publications	0.000358***	0.000394***	0.000387***
	(7.75e-05)	(7.98e-05)	(7.65e-05)
PhD (1=yes)	0.311***	0.317***	0.324***
	(0.0543)	(0.0540)	(0.0544)
Group lead (1=yes)	0.177***	0.171***	0.172***
	(0.0426)	(0.0426)	(0.0426)
Gender (1=male)	0.0825	0.0887	0.0649
	(0.0886)	(0.0885)	(0.0877)
Proxy for age	0.0450***	0.0449***	0.0421***
	(0.00343)	(0.00343)	(0.00343)
Observations	1,890	1,890	1,890
No. of subjects	475	475	475
No. of failures	1,418	1,418	1,418
Time at risk	5,850	5,850	5,850

*** p<0.01, ** p<0.05, * p<0.1

Table 33: *Logit regression, dependent variable: serial patentee (1=yes), independent variables for the first PF*

	First PF complete	First PF (1)	First PF (2)	First PF (3)	First PF (4)
Proxy for patent support infrastructure	0.819***	0.953***			
Granted PF; 1=yes)	(0.226)	(0.218)			
Proxy for reputational benefits	0.109**		0.155***		
(No. of forward citations)	(0.0533)		(0.0522)		
PF with industry applicants (1=yes)	0.0953			0.165	
	(0.320)			(0.296)	
Inventor team size	-0.0301				0.0104
	(0.0564)				(0.0523)
No. of publications	0.0153***	0.0153***	0.0165***	0.0166***	0.0167***
	(0.00573)	(0.00570)	(0.00568)	(0.00564)	(0.00566)
PhD (1=yes)	0.530**	0.583**	0.589**	0.672***	0.665***
	(0.266)	(0.262)	(0.259)	(0.257)	(0.257)
Group lead (1=yes)	0.145	0.151	0.147	0.135	0.149
	(0.286)	(0.283)	(0.281)	(0.279)	(0.277)
Gender (1=male)	0.293	0.256	0.312	0.270	0.263
	(0.318)	(0.315)	(0.311)	(0.306)	(0.306)
Constant	-0.524	-0.530	-0.269	-0.0397	-0.0533
	(0.399)	(0.322)	(0.306)	(0.297)	(0.375)
Observations	475	475	475	475	475
LR $chi^2(9)$	72.57	67.51	59.25	48.63	48.35
Prob > chi^2	0.00	0.00	0.00	0.00	0.00
Pseudo R^2	0.1252	0.1165	0.1022	0.0839	0.0834
Log likelihood	-253.45	-255.98	-260.11	-265.42	-265.56
Classified correctly	74.11%	73.47%	71.37%	70.11%	70.95%

*** p<0.01, ** p<0.05, * p<0.1

***Table 34:** Logit regression, dependent variable: serial patentee (1=yes), independent variables for average PF*

	PF complete	PF (1)	PF (2)	PF (3)	PF (4)
Proxy for patent support infrastructure	0.598**	0.836***			
Granted PF; 1=yes)	(0.298)	(0.280)			
Proxy for reputational benefits	0.165**		0.199***		
(No. of forward citations)	(0.0721)		(0.0667)		
PF with industry applicants (1=yes)	-0.329			0.0443	
	(0.417)			(0.378)	
Inventor team size	0.00783				0.0317
	(0.0648)				(0.0617)
No. of publications	0.0148***	0.0153***	0.0154***	0.0166***	0.0168***
	(0.00557)	(0.00556)	(0.00560)	(0.00563)	(0.00567)
PhD (1=yes)	0.623**	0.637**	0.656**	0.662***	0.668***
	(0.260)	(0.258)	(0.258)	(0.256)	(0.257)
Group lead (1=yes)	0.129	0.153	0.107	0.150	0.151
	(0.282)	(0.279)	(0.280)	(0.277)	(0.277)
Gender (1=male)	0.255	0.248	0.278	0.263	0.264
	(0.313)	(0.310)	(0.310)	(0.306)	(0.306)
Constant	-0.518	-0.426	-0.289	-0.0138	-0.149
	(0.423)	(0.326)	(0.308)	(0.299)	(0.402)
Observations	475	475	475	475	475
LR $chi^2(9)$	63.54	57.35	58.92	48.32	48.58
Prob > chi^2	0.00	0.00	0.00	0.00	0.00
Pseudo R^2	0.1096	0.10	0.1017	0.0834	0.0838
Log likelihood	-257.97	-261.06	-260.28	-265.57	-268.45
Classified correctly	76.21%	76.21%	74.74%	69.89%	70.74%

*** p<0.01, ** p<0.05, * p<0.1

Table 35: *Correlation table, N=475*

	N=475	1	2	3	4	5	6	7	8	9	10	11	12	13
1	**Serial patentee (Logit regression)**	1												
2	**Proxy for patent support infrastructure for the first PF**	0.2579	1											
3	**Proxy for reputational benefits due to the first PF**	0.1644	0.2733	1										
4	**PF with industry applicant for the first PF**	0.0067	0.0261	0.0780	1									
5	**Inventor team size of the first PF**	-0.0386	0.0263	0.1101	0.3131	1								
6	**Proxy for patent support infrastructure – average**	0.1813	0.7156	0.1994	0.0565	0.0616	1							
7	**Proxy for reputational benefits – average**	0.1706	0.2488	0.6435	0.0573	-0.0073	0.3446	1						
8	**PF with industry applicant – average**	-0.0094	0.0542	0.1518	0.7151	0.2222	0.1154	0.2388	1					
9	**Inventor team size – average**	-0.0126	0.0510	0.1178	0.1885	0.7663	0.0824	0.1071	0.2820	1				
10	**No. of publications**	0.1361	0.1070	0.0210	-0.0493	-0.0564	0.0524	0.0332	-0.0540	-0.0172	1			
11	**PhD**	0.2534	0.1817	0.1475	-0.0612	-0.1394	0.1175	0.0912	-0.0428	-0.1045	0.2534	1		
12	**Group lead**	0.1207	0.0800	0.0380	0.0740	-0.0063	0.0407	0.0793	0.0245	-0.0527	0.1471	0.3359	1	
13	**Gender**	0.0702	0.0264	-0.0409	-0.0426	-0.0096	0.0345	0.0019	-0.0292	-0.0208	0.0518	0.0816	0.0985	1

Table 36: *Correlation table, N=3,275*

	N=3275	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	**Serial patentee (Logit regression)**	1																	
2	**Proxy for patent support infrastructure for the first PF**	0.1863	1																
3	**Proxy for reputational benefits due to the first PF**	0.0777	0.2188	1															
4	**PF with industry applicant for the first PF**	0.0077	0.0463	0.0442	1														
5	**Inventor team size of the first PF**	-0.0285	0.0108	0.2214	0.3671	1													
6	**Proxy for patent support infrastructure – average**	0.1990	0.5343	0.1075	0.0044	-0.0115	1												
7	**Proxy for reputational benefits – average**	0.1272	0.0986	0.5237	-0.0365	0.0155	0.2765	1											
8	**PF with industry applicant – average**	0.0224	-0.0069	0.2036	0.5344	0.2388	0.0651	0.2500	1										
9	**Inventor team size – average**	-0.0174	0.0258	0.2291	0.2144	0.7064	0.0182	0.2013	0.4043	1									
10	**Proxy for patent support infrastructure – recent**	0.0755	0.1295	0.0132	-0.0231	-0.0151	0.5928	0.1544	0.0242	-0.0191	1								
11	**Proxy for reputational benefits – recent**	0.0488	-0.0253	0.1176	-0.0359	-0.0391	0.1491	0.4767	0.0991	0.0520	0.2050	1							
12	**PF with industry applicant – continuous**	0.0144	-0.0274	0.1230	0.2005	0.1006	0.0540	0.1863	0.6468	0.2662	0.0436	0.1652	1						
13	**Inventor team size – continuous**	0.0010	0.0078	0.1186	0.0788	0.3145	0.0009	0.1475	0.2794	0.6825	-0.0131	0.0792	0.3538	1					
14	**Proxy for age**	0.1584	0.0692	-0.0576	0.0841	-0.0288	0.2411	-0.0591	-0.0076	-0.1577	0.2108	0.0448	0.0400	-0.1332	1				
15	**PhD**	0.2092	0.2141	0.0783	-0.0167	-0.1485	0.1507	0.0394	-0.0046	-0.1285	0.0433	-0.0127	-0.0136	-0.0651	0.0869	1			
16	**Gender**	0.0671	-0.0082	-0.0531	-0.0590	-0.0005	0.0475	-0.0391	-0.0630	-0.1226	0.0367	0.0067	-0.0265	-0.0790	0.1088	0.0862	1		
17	**Group lead**	0.1047	0.1165	-0.1007	0.0673	0.0039	0.0585	-0.0944	-0.0734	-0.0536	0.0003	-0.0474	-0.0552	-0.0495	0.0488	0.3163	0.0525	1	
18	**No. of publications**	0.0726	0.1146	-0.0421	-0.0746	-0.0775	0.0910	-0.0166	-0.0938	-0.0310	0.0186	-0.0143	-0.0738	-0.0066	-0.0521	0.2106	0.0587	0.1636	1

3.9 References

Agiakloglou, C., Drivas, K., & Karamanis, D. (2016). Individual inventors and market potentials: Evidence from US patents. Science and Public Policy, 43(2), 147-156.

Alves, L., & Daniel, A. D. (2018, June). Protection and Commercialization of Patents in Portuguese Universities: Motivations and Perception of Obstacles by Inventors. In International Conference on Innovation, Engineering and Entrepreneurship (pp. 471-477). Springer, Cham.

Archibugi, D. (1992). Patenting as an indicator of technological innovation: a review. Science and public policy, 19(6), 357-368.

Amaral, A. M., Baptista, R., & Lima, F. (2011). Serial entrepreneurship: impact of human capital on time to re-entry. Small Business Economics, 37(1), 1-21.

Amorim, L. D., & Cai, J. (2015). Modelling recurrent events: a tutorial for analysis in epidemiology. International journal of epidemiology, 44(1), 324-333.

Arvanitis, S., Kubli, U., & Woerter, M. (2008). University-industry knowledge and technology transfer in Switzerland: What university scientists think about co-operation with private enterprises. Research Policy, 37(10), 1865-1883.

Azoulay, P., Ding, W., & Stuart, T. (2007). The determinants of faculty patenting behavior: Demographics or opportunities?. Journal of economic behavior & organization, 63(4), 599-623.

Balconi, M., Breschi, S., & Lissoni, F. (2004). Networks of inventors and the role of academia: an exploration of Italian patent data. Research policy, 33(1), 127-145.

Baldini, N., Grimaldi, R., & Sobrero, M. (2007). To patent or not to patent? A survey of Italian inventors on motivations, incentives, and obstacles to university patenting. Scientometrics, 70(2), 333-354.

Baldini, N. (2010). Do royalties really foster university patenting activity? An answer from Italy. Technovation, 30(2), 109-116.

Bercovitz, J., & Feldman, M. (2008). Academic entrepreneurs: Organizational change at the individual level. Organization science, 19(1), 69-89.

Berger, F., Blind, K., & Thumm, N. (2012). Filing behaviour regarding essential patents in industry standards. Research Policy, 41(1), 216-225.

Blind, K., Pohlisch, J., & Zi, A. (2018). Publishing, patenting, and standardization: Motives and barriers of scientists. Research Policy, 47(7), 1185-1197.

Blind, K., Filipović, E., & Lazina, L. K. (2022). Motives to publish, to patent and to standardize: an explorative study based on individual engineers' assessments. Technological Forecasting and Social Change, 175, 121420.

Bodas Freitas, I. M., & Nuvolari, A. (2012). Traditional versus heterodox motives for academic patenting: Evidence from the Netherlands. Industry and Innovation, 19(8), 671-695.

Bourelos, E., Magnusson, M., & McKelvey, M. (2012). Investigating the complexity facing academic entrepreneurs in science and engineering: the complementarities of research performance, networks and support structures in commercialisation. Cambridge Journal of Economics, 36(3), 751-780.

Buenstorf, G., & Geissler, M. (2013). Not invented here: technology licensing, knowledge transfer and innovation based on public research. In The Two Sides of Innovation (pp. 77-107). Springer, Cham.

Candelin-Palmqvist, H., Sandberg, B., & Mylly, U. M. (2012). Intellectual property rights in innovation management research: A review. Technovation, 32(9-10), 502-512.

Chen, S. H., Huang, M. H., & Chen, D. Z. (2013). Driving factors of external funding and funding effects on academic innovation performance in university–industry–government linkages. Scientometrics, 94(3), 1077- 1098.

Chen, G., Yang, G., He, F., & Chen, K. (2019). Exploring the effect of political borders on university-industry collaborative research performance: Evidence from China's Guangdong province. Technovation, 82, 58-69.

Crescenzi, R., Filippetti, A., & Iammarino, S. (2017). Academic inventors: collaboration and proximity with industry. The Journal of Technology Transfer, 42(4), 730-762.

D'Este, P., Mahdi, S., Neely, A., & Rentocchini, F. (2012). Inventors and entrepreneurs in academia: What types of skills and experience matter?. Technovation, 32(5), 293-303.

D'Este, P., & Patel, P. (2007). University–industry linkages in the UK: What are the factors underlying the variety of interactions with industry?. Research policy, 36(9), 1295-1313.

D'Este, P., & Perkmann, M. (2011). Why do academics engage with industry? The entrepreneurial university and individual motivations. The Journal of Technology Transfer, 36(3), 316-339.

Dlouhy, K., & Biemann, T. (2018). Path dependence in occupational careers: Understanding occupational mobility development throughout individuals' careers. Journal of Vocational Behavior, 104, 86-97.

Drivas, K., Economidou, C., Karamanis, D., & Zank, A. (2016). Academic patents and technology transfer. Journal of engineering and technology management, 40, 45-63.

Dobusch, L., & Schüßler, E. (2013). Theorizing path dependence: a review of positive feedback mechanisms in technology markets, regional clusters, and organizations. Industrial and Corporate Change, 22(3), 617-647.

DPMA – Deutsches Marken-und Patentamt (2019). Patentanmeldungen 2019, Liste der aktivsten Unternehmer und Institutionen https://www.dpma.de/dpma/veroeffentlichungen/statistiken/csv-statistiken/index.html. (last accessed: 23.10.2020).

Fadeyi, O., Maresova, P., Stemberkova, R., Afolayan, M., & Adeoye, F. (2019). Perspectives of University-Industry technology transfer in African emerging economies: Evaluating the Nigerian scenario via a data envelopment approach. Social sciences, 8(10), 286.

Fraunhofer-Gesellschaft e.V. (2019a). Annual report 2019: Our future mission: research for sustainable value creation. https://www.fraunhofer.de/content/dam/zv/en/Publications/Annual-Report/2019/Fraunhofer-Annual-Report-2019.pdf , last accessed: 10.09.2020.

Fraunhofer-Gesellschaft e.V. (2019b). Promovieren mit Fraunhofer: Code of conduct. https://www.fraunhofer.de/content/dam/zv/de/ueber-fraunhofer/Personalpolitik/promovieren-mit-fraunhofer.pdf, (last accessed: 10.09.2020).

Fraunhofer-Gesellschaft e.V. (2006). Regelung für die Vergütung von Erfindungen und qualifizierten technischen Verbesserungsvorschlägen. Version 1/06. München.

Giuri, P., Mariani, M., Brusoni, S., Crespi, G., Francoz, D., Gambardella, A., ... & Verspagen, B. (2007). Inventors and invention processes in Europe: Results from the PatVal-EU survey. Research policy, 36(8), 1107-1127.

Göktepe-Hulten, D., Mahagaonkar, P., 2010. Inventing and patenting activities of scientists: in the expectation of money or reputation? J. Technol. Transf. 35 (4), 401–423.

Hottenrott, H., & Lawson, C. (2017). Flying the nest: How the home department shapes researchers' career paths. Studies in Higher Education, 42(6), 1091-1109.

Huang, W. L., Feeney, M. K., & Welch, E. W. (2011). Organizational and individual determinants of patent production of academic scientists and engineers in the United States. Science and Public Policy, 38(6), 463-479.

Huang, C. Y. (2018). How background, motivation, and the cooperation tie of faculty members affect their university–industry collaboration outputs: an empirical study based on Taiwan higher education environment. Asia Pacific Education Review, 19(3), 413-431.

Hyytinen, A., & Ilmakunnas, P. (2007). What distinguishes a serial entrepreneur?. Industrial and corporate change, 16(5), 793-821.

Jones, B. F. (2009). The burden of knowledge and the “death of the renaissance man”: Is innovation getting harder?. The Review of Economic Studies, 76(1), 283-317.
Kalar, B., & Antoncic, B. (2016). Social capital of academics and their engagement in technology and knowledge transfer. Science and Public Policy, 43(5), 646-659.
Kelly, P. J., & Lim, L. L. Y. (2000). Survival analysis for recurrent event data: an application to childhood infectious diseases. Statistics in medicine, 19(1), 13-33.
Kim, Y. C., & Rhee, M. (2018). Professional collaboration in technological innovation: a case of technology licensing of university inventions. Technology Analysis & Strategic Management, 30(11), 1351-1363.
Lafontaine, F., & Shaw, K. (2016). Serial entrepreneurship: Learning by doing?. Journal of Labor Economics, 34(S2), S217-S254.
Lam, A. (2011). What motivates academic scientists to engage in research commercialization: ‘Gold’,‘ribbon’or ‘puzzle’?. Research policy, 40(10), 1354-1368.
Lawson, C., & Sterzi, V. (2014). The role of early-career factors in the formation of serial academic inventors. Science and Public Policy, 41(4), 464-479.
Long, J. S., & Freese, J. (2006). Regression models for categorical dependent variables using Stata. Stata press.
Mariani, M., & Romanelli, M. (2007). “Stacking” and “picking” inventions: The patenting behavior of European inventors. Research Policy, 36(8), 1128-1142.
Moog, P., Werner, A., Houweling, S., & Backes-Gellner, U. (2015). The impact of skills, working time allocation and peer effects on the entrepreneurial intentions of scientists. The Journal of Technology Transfer, 40(3), 493-511.
Narin, F. and Breitzman, A. (1995) ‘Inventive productivity’, Research Policy, 24: 507–20.
OECD (2013), Commercialising Public Research: New Trends and Strategies, OECD Publishing.
Owen-Smith, J., & Powell, W. W. (2003). The expanding role of university patenting in the life sciences: assessing the importance of experience and connectivity. Research Policy, 32(9), 1695-1711.
Perc, M. (2014). The Matthew effect in empirical data. Journal of The Royal Society Interface, 11(98), 20140378.
Pierson, P. (2000). Increasing returns, path dependence, and the study of politics. American political science review, 94(2), 251-267.
Powers, J. B. (2004). R&D funding sources and university technology transfer: What is stimulating universities to be more entrepreneurial?. Research in Higher Education, 45(1), 1-23.
Prentice, R. L., Williams, B. J., & Peterson, A. V. (1981). On the regression analysis of multivariate failure time data. Biometrika, 68(2), 373-379.
Ryan, A. M., Sacco, J. M., McFarland, L. A., & Kriska, S. D. (2000). Applicant self-selection: Correlates of withdrawal from a multiple hurdle process. Journal of Applied Psychology, 85(2), 163–179.
Schober, P., & Vetter, T. R. (2018). Survival analysis and interpretation of time-to-event data: the tortoise and the hare. Anesthesia and analgesia, 127(3), 792.
Scott, J. (2013). Social network analysis (3. ed.). Los Angeles, Calif. [u.a.]: Sage.
Shane, S. (2000) ‘Prior knowledge and the discovery of entrepreneurial opportunities’, Organization Science, 11: 448–69.
Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. Academy of Management Review, 25(1), 217-226.
Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality?. Management Science, 56(1), 41-56.

Sullivan, S. E., & Baruch, Y. (2009). Advances in career theory and research: A critical review and agenda for future exploration. Journal of management, 35(6), 1542-1571.

Tsuji, Y. S. (2002). Organizational behavior in the R&D process based on patent analysis:: Strategic R&D management in a Japanese electronics firm. Technovation, 22(7), 417-425.

Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. RAND Journal of Economics 21 (1), 172–187.

Van Looy, B., Callaert, J., & Debackere, K. (2006). Publication and patent behavior of academic researchers: Conflicting, reinforcing or merely co-existing?. Research Policy, 35(4), 596-608.

Vick, T. E., & Robertson, M. (2018). A systematic literature review of UK university–industry collaboration for knowledge transfer: A future research agenda. Science and Public Policy, 45(4), 579-590.

Visintin, F., & Pittino, D. (2014). Founding team composition and early performance of university—Based spin-off companies. Technovation, 34(1), 31-43.

Wright, Mike, Ken Robbie, and Christine Ennew. "Serial entrepreneurs." British Journal of Management 8.3 (1997): 251-268.

Wu, Y., Welch, E. W., & Huang, W. L. (2015). Commercialization of university inventions: Individual and institutional factors affecting licensing of university patents. Technovation, 36, 12-25.

Zucker, L. G., & Darby, M. R. (1996). Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry. Proceedings of the National Academy of Sciences, 93(23), 12709-12716.

4

4 How to Find New Industry Partners for Public Research: A Classification Approach

Karl Trela, Yuri Campbell, Friedrich Dornbusch, Anna Pohle

Abstract: Finding new industry partners poses a challenge to many public research organizations. This article explores how statistical classification can support partner selection at the example of the Fraunhofer-Gesellschaft in Germany, Europe's largest public organization for applied research. We use internal cooperation data and feature sets based on unstructured data, i.e., text and industry codes, both of which describe business activities of firms. An important advantage of this data is that it is available for most companies in Germany, even small and medium enterprises, which allows for an almost complete screening of the market, in contrast to using other data sources, e.g., patents. In addition, we also include economic variables linked to firms, as turnover, number of employees/managers and firm age. We report the performance of various classification techniques such as logistic regression, support vector machines, and random forests in our dataset for diverse combinations of feature sets. Results show that simple methods with fewer parameters remain competitive in comparison to complex ones. Overall, the performance of most classifiers is high enough to support the decision process of finding new industry partners for public research.

Keywords: Collaborative research, knowledge and technology transfer, machine learning, natural language processing, partner selection, text mining, university–industry cooperation

This is an accepted manuscript, and the final version is available in *IEEE Transactions on Engineering* Management, 68 (5, 2020, p. 1214–1231, https://doi.org/10.1109/TEM.2020.2992060).

4.1 Introduction

Policy as well as society increasingly demand from academic institutions to transfer their knowledge to industry in order to leverage scientific discoveries and inventions into innovation (OECD, 2013). Consequently, research organizations strive for ways to increase their knowledge and technology transfer activities in form of collaborations with industry partners (Perkman & Walsh, 2007, 2009). On the industry side, a rising complexity in production and its innovation leads to blurring cross-organizational boundaries. It forces companies to extend their networks way beyond their region for knowledge and technology sourcing (Chesbrough, 2003; Battiston et al., 2016). Hence, the search for new partners and the identification of the right partners is crucial for both industry as well as academia. While this is nowadays more true than ever, it is also long known to be a hard task to solve (Li et al., 2008).

A number of studies have shown that partnerships between university and industry face a number of challenges. Besides building trust, overcoming cultural and organizational differences (Perkmann & Walsh, 2007; Bruneel et al., 2010), the search for suitable collaboration partners for firms and public research organizations alike is usually a hurdle, Known as the "partner selection problem" (Yoon & Song, 2014). As cooperation capability is limited in every organization, partner selection should be based on resource complementarity among partners (Wirsich et al., 2016; Hottenrott & Lopes-Bento, 2016). Hence, this comes down to a matching problem with regard to technological-scientific and economic fit. This, however, is also difficult to solve. In both, academia and business, decision-makers are limited with regard to time, resources, and their capability to oversee all available cooperation opportunities. This favors ad hoc approaches for partner selection (Yoon & Song, 2014), which are usually based on past successful collaboration projects, personal contacts, or subjective opinion of experts (Lee et al., 2016; Jeon et al., 2011). Particularly small and medium enterprises (SMEs) tend to employ social and often locally biased networks to find suitable partners (Broekel & Binder, 2007). This leaves innovation potential untapped, both from the perspective of a single organization as well as from society and policy.

Though human interaction is crucial in building trustful and stable relations within R&D alliances (Beckman et al., 2004), we want to evaluate whether seeking for partners and making decisions can become faster, more efficient and better informed with the help of information technology. This is where the field of Tech Mining comes into play. Porter and Cunningham (2004) define Tech Mining as "the application of text mining tools to science and technology information, informed by understanding of technological innovation processes" (Porter & Cunningham, 2004). Therefore, Tech Mining has two main components, first, the use of text mining approaches, and therefore also of natural language processing (NLP), and second, the application of such tools and approaches to technology management. In turn, we argue that technology sourcing, and the knowledge sourcing related to it, are naturally tasks of technology management. Hence, the partner selection problem above is also a part of it, as long as the search for partners is based on technological fit.

Several studies before have tested the feasibility of defining and applying new systematic methods on R&D-partner identification in general, some of them are "intelligent" approaches based on machine learning techniques and NLP (Chen et al., 2010; Park et al., 2015; Wang et al., 2017). Our approach, however, differs in a crucial way. Existing approaches mainly employed patent or bibliometric data in order to create proxy-indicators for cooperation potential. The employed methods offer a way of summarizing and navigating possible matches of cooperation partners based on their technological portfolio, estimated through patent data. While this approach is sound for explorative analysis with focus on understanding technological proximity of potential partners, it has very restricted applicability in predictive analysis and no formal way of measuring performance, which are common problems to unsupervised learning approaches in general. In contrast, our method relies on large-scale real historical cooperation data from a knowledge transfer context, in this case, provided by the Fraunhofer-Gesellschaft. Hereby, we have the opportunity to predict and test cooperation potential based on real cooperation behavior. While this enables us to cover a larger range of innovation activities in R&D in comparison with patent data-based analysis, it also enables us to perform supervised learning, i.e., classification, and calculate objective performance measures on how the various partner selection algorithms generalize in reality.

As far as we know, this is the first article that addresses the sphere of cooperation between academia and industry from such a supervised learning perspective. For that, we extract information from data of qualitative nature, such as text and industry codes, using NLP techniques and integrate it with traditional econometric models. Such a combination of qualitative and quantitative data in partner selection has been called for since a long time (Wu & Barnes, 2014, 2011).

Our main goal is to test whether classification techniques along with NLP and economic data can help to find industry partners for public research. For this, we present a systematic approach, which includes prescreening a large number of companies for potential collaboration partners and ranking recommended companies according to a statistical measure. It makes use of supervised learning by stacking two classifiers, which are trained on past historical cooperation data as target variables together with text and economic indicators as dependent variables. The rest of this article is organized as follows. The following section introduces the research questions by elaborating the search behavior in innovation activities and reviews previous quantitative approaches to address the partner selection problem. Section 4.3. presents the data, the methods, and the validation strategy. Section 4.4. describes and discusses the results. Finally, we provide a discussion of limitations in Section 4.5., and the practical use of the approach is described in see Section 4.6. Finally, section 4.7. concludes the article.

4.2 Partner selection in technology transfer

The following subsection first aims to provide an in-depth understanding of the partner selection problem in technology transfer. It begins by outlining the structure of the industry partner-selection process and the challenges it poses, thereby elaborating on the need for systematic approaches to support partner selection. The succeeding subsection presents an overview of systematic methodologies introduced so far. Then, it discusses the econometric determinants of university–industry cooperation and how these may contribute to a decision support system. Finally, we present our research questions as a synopsis of the advantages and drawbacks of the existing approaches.

4.2.1 Bounded Rationality and Heuristic Search Behavior in Partner Selection

The literature discusses partner selection in the context of collaborations, especially supply chains and research alliances (Wu & Barnes, 2014, 2011). From a research organization point of view, industry partner-selection describes the process of searching and deciding for a partner to transform a research result into an innovation. This process can be divided into four stages (Wu & Barnes, 2014):

1) criteria formulation;
2) qualification;
3) final selection;
4) application feedback.

The criteria formulation stage involves the determination of criteria as well as preparation of subsequent steps. This stage tends to be characterized by uncertainty and vague information about partners and their cooperation potential. The qualification stage relates to reduction and narrowing down of potential partners to a smaller subset with higher cooperation potential. This involves the ranking of potential partners according to an either implicit or explicit matching profile. In a third step, the final selection takes place and the most relevant and suitable partners are chosen (Wu & Barnes, 2014). Finally, one evaluates the results of the selection process and makes adjustments in the application feedback stage.

This rather holistic description already shows that the main challenges in partner selection are, first, getting information and knowledge about potential partners and second, reducing the amount of available information to a level that supports efficient and well-grounded decision-making. The main reason here is that complexity in decision-making relates to the amount as well as quality—in a sense of validity and completeness—of information that needs to be gathered and processed. While scarce, vague, or biased information raises uncertainty (Baiman et al., 2000), large amounts of information can also bring decision makers to the limits of their cognitive capacity.

Accordingly, bounded rational actors and individuals deal only with a biased set of information, because the search for complete information is costly and time consuming (Broekel & Binder, 2007). To deal with such limited or imperfect information, individuals often use heuristics. Those, besides being in some cases a good and efficient way to handle complexity can often lead to suboptimal or poor solutions (Tello et al., 2010; Gigerenzer & Gaissmaier, 2011). The basic argument here is that individuals do not perform exhaustive search processes across an entire search space but prefer—if other more distant solutions are not known—the spatially and socially most proximate and cognitively satisfying solutions. Thus, applying heuristics in search processes directs the focus of decision-makers toward their existing social networks that are—favored by spatial proximity and face-to-face interactions—often biased. As a consequence, they tend to cooperate within existing networks and gathering information about new partners depends rather on word-of-mouth and relies mainly on subjective judgment, instead of quantitative factors (Geum et al., 2013).

Even though partner selection is based on existing social networks, trust and experiences are obviously the basis for network development and partner selection (Perkmann & Walsh, 2009; Bruneel et al., 2010), it can also be problematic. A long strand of literature has shown theoretically as well as empirically that it can cause path dependence on the one hand and local as well as social lock-in effects (Granovetter, 1973; Fritsch & Kauffeld-Monz, 2010; Martin & Sunley, 2006) on the other hand. Moreover, the source of new innovation-enabling knowledge, however, is most likely to be distributed worldwide and across industries. Organizations, as well as regions, that are able to identify new knowledge partners and tap new sources of knowledge efficiently, will gain a substantial competitive advantage. However, the information about adequate new partners and sources is still often collected and processed manually (from firm databases and web searches); therefore, it is difficult and time-consuming to obtain. Thus, we argue that quantitative and machine-learning-based approaches, using available data, can contribute to network development and partner selection by making the search process more efficient. A systematic process for searching technology partners is needed and would help organizations as well as regions to maintain competitiveness in an open innovation paradigm (Jeon et al., 2011; Chang et al., 2008).

4.2.2 Systematic approaches with a priori assumptions

Recently, a considerable body of work dealing with the design of systematic, or semiautomated, approaches for supporting partner selection has been proposed.[27] With regard to the level of data-usage,

[27] To perform the literature analysis, we have used Scopus (the largest source neutral abstract and citation database for peer-reviewed literature) as well as the OECD library. In the first step, we mainly looked for the literature reviews in the topics "partner selection" and "university–industry collaboration" to gain a comprehensive overview. We used the search string: TITLE (("partner selection") AND (problem OR theory OR

these methods range from purely expert rating approaches, all the way to databased methods, which make heavy use of machine learning techniques. In contrast to the heuristic procedures presented in the preceding section, systematic approaches seek to operationalize criteria for partner selection in a formal way. Two methods can be distinguished within the systematic approaches: (expert) rating methods and bibliographic methods.

For partner selection with rating methods, defined criteria are applied to identify appropriate partners according to diverse perspectives (stage 1 of industry-partner selection). Those perspectives, and in turn related criteria, are often defined by experts and hard-coded in ranking strategies (Chen et al., 2010; Solesvik & Encheva, 2010). They are fed into a weighting model or algorithm, which ranks options (stage 2).

Bibliographic methods make use of bibliographic data in order to support partner selection. These works apply patent and publication data statistics in order to find and assess how well two potential R&D partners fit together (stage 2). The statistics used for the fitness estimation varies from contribution to contribution, but falls usually into two main categories. The first is composed mainly of bibliometric analysis (Lee et al., 2016; Geum et al., 2013), for example, bibliographic coupling, citation networks, co-authorship, keyword cooccurrence, etc. The second and most modern approach uses unstructured data processing methods such as text mining and semantic analysis (Yoon & Song, 2014; Jeon et al., 2011; Wang et al., 2017) for this end. In the latter, keywords are preselected by experts and their frequency is encoded in vectors, one vector per document, e.g., a patent. The similarity between text documents is computed using cosine distance, a distance function between two keyword-frequency vectors, which is the elemental method in NLP and information retrieval. Based on the similarity between pairs of documents, partners are suggested. This suggestion depends partially on handcrafted criteria, such as keyword selection, and on how to use the similarity measure between documents. Overall, the goal of bibliographic methods is the same, to reduce information complexity in the bibliographic data in order to allow the exploration of partnership possibilities by the decision maker, usually also in a data visualization form, as a graph (Wang et al., 2017; Park et al., 2015; Geum et al., 2013) or a lattice (Yoon & Song, 2014). This is therefore an unsupervised learning approach.

The two approaches, rating methods and bibliographic methods, share that the partner preselection and ranking are essentially determined by a priori assumptions in the models. The various methods, however, differ in the expression of these assumptions. While rating methods rely solely on the operationalization of expert knowledge. Bibliographic methods convey assumptions on different levels. At times, it assumes that technological distance proxies technological fit for partnership. At other times, it relies on experts in order to compose keywords lists and their fitness.

In summary, a major issue with these methods are their explicit assumptions about the criteria that define technological fit i.e., that determine partner preselection. A complementary approach would apply observation data from cooperations to rely on statistical measures rather than assumptions in order to proxy technological fit in a supervised learning setting. Consequently, no efforts in criteria formation would be required any more. Such an approach, however, would not convey an explicit measurement of technological fit. On the other hand, a databased approach would allow to calculate performance measures to determine precisely the quality of the partner selection support solution. This would not only reduce complexity in the qualification stage (stage 2) but also in application feedback (stage 4).

---

review OR innovation OR r&d OR decision)). Thereafter, we repeated the search with a focus on methods and success factors for partner selection and collaboration in the research about academic knowledge and technology transfer as well as the literature on innovation management. In addition, we followed the snowball principle to find more literature that is relevant and asked colleagues for paper recommendations.

The former methods cannot be evaluated in a comparable way. Moreover, while these previous approaches can reduce complexity in the qualification stage (stage 2), they leave the hurdle in criteria formation untouched, as well as in application feedback.

Finally, the studies above focus on partner selection either in supply chain or in the larger context of open innovation. None of those deals directly with the issue of R&D partnership in form of contracted research between public research organizations and companies, in other words, in a knowledge transfer context. Considering the drawbacks and research needs presented in this subsection, we want to examine Research Question 1:

RQ1: Can a supervised learning approach based on cooperation data support partner selection in public research?

4.2.3 Econometric Determinants of University–Industry Cooperation

The previous subsection has shown that systematic approaches have the potential to support the identification of industry partners and to moderate the cognitive bias inherent to the search process. In turn, several empirical studies deal with the identification of determinants of university–industry cooperation.[28] Instead of aiming at decision support in partner selection, they analyze real cooperation data and investigate the effect of a specific set of variables on the cooperation activity between universities and firms. For that end, they make use of standard statistic or econometric methods. By doing so, they are bypassing the shortcomings of present systematic approaches and can therefore be relevant for our endeavor.

Giunta et al. (2016) investigated determinant indicators of university–industry cooperation in the biopharmaceuticals in Italy over a six year period between 2004 and 2010. In this article, a logistic regression (LR) model is constructed to estimate a binary dummy variable that signalizes if a given pair (university, industry) have coauthored an academic research article. The authors show an expected dependence of variables as for example prior partnership and geographical proximity on the probability of cooperation. Other works point out that the size, of institution and firms, and the firm's R&D and patents expenditure exert a significant impact on the cooperation activities (Eom & Lee, 2010; Kaiser, 2002). Further studies show that conducting R&D activities itself (Rõigas et al., 2018; Comin et al., 2019) and R&D capacity (Cardamone e al., 2015) prove to be significant factors of cooperating companies across different countries. Furthermore, they show that firms's age and business operations sector impact significantly the likelihood of R&D cooperation.

A systematic review of the literature by Rybnicek and Koenigsgruber (2019) showed that the list of determinants for successful R&D cooperations is by far larger than can be shown and discussed here. However, they show that partner selection in knowledge transfer context, and the overall performance of collaborations, depend on various factors. Besides quantifiable factors as shown above, a large part of those has qualitative dimensions. Thus, Wu and Barnes argue comprehensively in their literature review that future research should investigate how qualitative and quantitative objectives can be jointly considered in partner selection methods (Wu & Barnes, 2011).

These approaches indicate that quantitative econometric data can be applied for understanding the econometric determinants of partner selection in a knowledge transfer context. However, no effort

---

[28] The literature search in Scopus for this chapter included variations of the following search string TITLE((("university–industry" OR "industry–academy") AND (collaboration OR link∗ OR cooperation)) OR (("third mission" OR "triple helix" OR "technology transfer") AND (university OR research)) AND ("success" OR determinants OR motiv∗ OR review)).

was made so far to combine these econometric measures with NLP approaches for supporting partner selection. In order to fill this gap, we ask Research Question 2:

RQ2: Is a combination of quantitative and qualitative information useful for supporting partner selection in public research?

4.3 New data-driven approach to support partner selection

We propose an approach to support partner selection for public research organizations that is able to identify potential partners from a vast amount of companies (e.g., all SMEs in Germany). It is different from the previous ones in the sense that it does not require any expert knowledge, but only relies on the data of previous partners.

The advantage of such a data-driven approach is that it is easily transferable, scalable, and most importantly valid. We will validate the performance of our approach by the example of the Fraunhofer-Gesellschaft, an organization for applied research with 73 institutes spread all over Germany.

Our approach consists of five parts, which we will describe in the following sections (see Figure 21). We first provide some information on our data and its preprocessing in section 4.3.1. Then, we present the methodology of our approach (see section 4.3.2.) and the way we measure its performance by means of validation (see section 4.3.3.).

4.3.1 Data

1) Fraunhofer Industry-Partner Data: In order to assess the transfer potential of our approach, it is essential to understand the context of the Fraunhofer- Gesellschaft itself and the industry partner data it provided us. The Fraunhofer- Gesellschaft is the largest nonprofit public research organization for applied sciences in the world (Comin et al., 2019). It consists of 73 research institutions and has a goal to fill the gap between basic research and industrial applications; in other words, to facilitate and perform technology transfer from universities to industry. While only a part of its budget comes from the public funding, the majority comes from contracted research with industry partners (Fraunhofer, 2017). This funding model clearly puts a lot of emphasis on acquiring industry partners for contracted research.

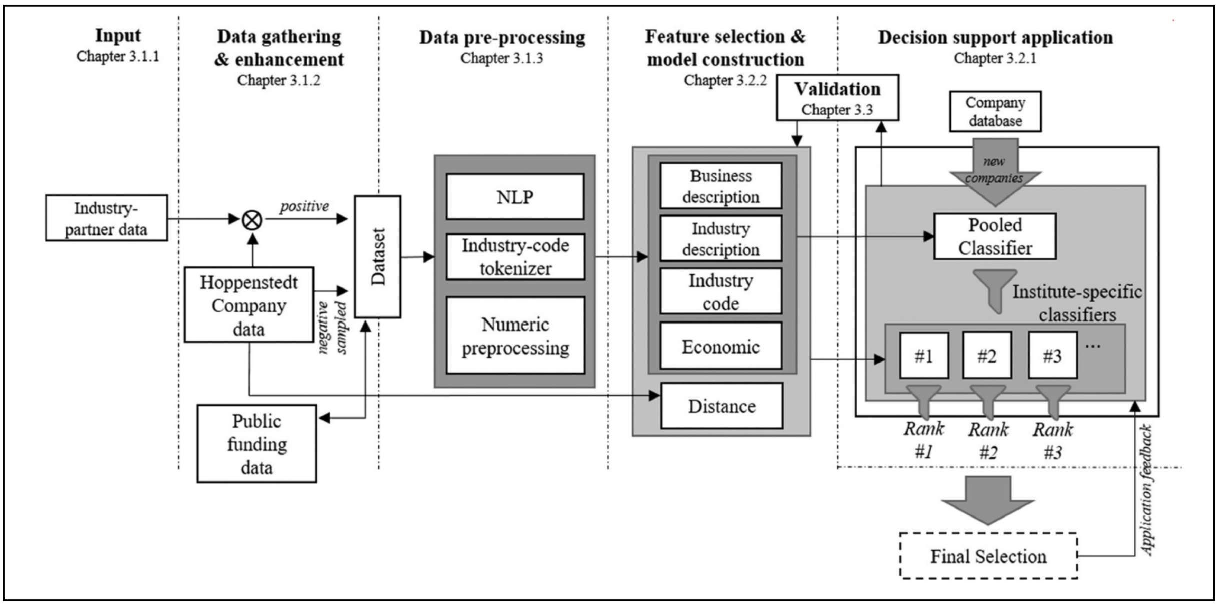
In the Fraunhofer-Gesellschaft, there is a clear focus on engineering and natural sciences among its research units. Additionally, fields related to health, social sciences, and economics are also found in the organization. Its research institutes are subsumed into eight Fraunhofer Clusters in order to enable R&D strategies coordination among institutes with related areas of technological expertise (Fraunhofer, 2017). These clusters also give a glimpse of how diverse the portfolio of the organization is. These clusters are summarized in Table 37.

Given the business areas in which the Fraunhofer-Gesellschaft is active, one expects that its industry partners are at least as diverse. The Fraunhofer-Gesellschaft documents all the past projects with its partners from the industry because these are usually contracted research projects, which must be registered and reported for financial and controlling reasons. These internal project data are the cornerstone of our case study and the main enabling component of our approach.

The Fraunhofer-Gesellschaft provided us with a snapshot of its industry-partner data containing all R&D projects with external clients from 2012 to 2018, excluding classified projects. This amounts to roughly 100,000 projects carried out between its units and companies (see Table 38). For each project, there is the name of the research institute of the Fraunhofer-Gesellschaft, the name of the industry partner, and an external unique identifier used for companies, the DUNS number.[29] This identifier allows combining the Fraunhofer dataset with proprietary external company databases in order to obtain more information on industry partners.

[29] The Data Universal Numbering System, DUNS for short, is a proprietary system developed and regulated by Dun & Bradstreet with the goal to assign a unique numeric identifier (DUNS number) to every single business entity worldwide, which sometimes are whole companies, and others subunits of larger corporations.

Figure 21: New data-driven approach to support partner selection.



2) Company Data Gathering and Enhancement: With the unique identifier for every past partner at hand, we search those in a company database. For this end, we use a proprietary database, Bisnode's Hoppenstedt database. The Hoppenstedt database contains around 1.3 million companies in Germany, Austria, and Switzerland. In this source, additional information may be found for previous Fraunhofer partners. Besides very basic information such as name and address, one can find, for example, information as last registered turnover, number of employees, number of managers, and firm age. Additionally, there is a free text field with a short business description. Finally, almost every company in the Hoppenstedt database has one or more five-digit industry-codes[30] and a standardized industry description, both from a classification system for industry branches developed by the Federal Statistical Office of Germany, Klassifikation der Wirtschaftszweige (WZ), which follows the same structure as the European NACE classification.

From all the past industry partners of Fraunhofer, we find an entry in Hoppenstedt for 9972 of them (see Table 38). This constitutes the positive class, i.e., positive examples of past partners of Fraunhofer. In order to build a balanced supervised dataset, first, we sample randomly the same amount of companies from Hoppenstedt, excluding the 9972 found Fraunhofer partners. Second, we label this random sample as negative examples. This is a common technique from Recommender Systems literature, known as negative sampling, or sample-based learning (Rendle et al., 2012; He et al., 2016). One performs this procedure in order to avoid overfitting and to guide convergence of the optimization algorithms in a positive-unlabeled supervised learning setting.

In our framework, it is natural that the interactions (or the partnerships in our case study) that did not take place are not always "unobserved signal," the unlabeled observations. At cases, it means that the researcher chose not to cooperate with the company in question. However, this negative decision is not registered anywhere. While this modeling technique in recommender systems is supported by the assumption that most of the available products are not of interest for one specific buyer, in our framework, the decision to use negative sampling is supported by the following.

According to the Leibniz-Zentrum für Europäische Wirtschaftsforschung (Leibniz Centre for European Economic Research - ZEW), 53 600 German companies engaged in R&D activities in 2017

[30] Companies have up to 19 WZ codes in our dataset.

(Rammer et al., 2021). This number amounts to 4.1% of the number of companies registered in the Hoppenstedt database. In other words, if all companies engaged in R&D were registered

in Hoppenstedt, then this would still amount to only 4.1% of the total amount of registered companies. Now, even when assuming that all the R&D active companies were good matches for the Fraunhofer-Gesellschaft, which is extravagant, and that those companies were all listed in Hoppenstedt, the ratio of good potential matches wrongly labeled as false is bounded by 4.1%. This provides an upper bound on the falsely labeled companies.

Finally, this is the necessary condition on the dataset in order to use negative sampling (Rendle, 2012), which justifies our design choice. After sampling randomly, the negative set, we have in our dataset 19,944 companies, or observations, half as positive examples of past industry partners and half of them negative. Moreover, every observation is associated with the above-mentioned variables: turnover, employees, managers, firm age, business description, industry-code, and industry-branch-text.

Table 37: *Fraunhofer clusters and their area of expertise (Comin et al., 2019; Fraunhofer, 2017)*

Fraunhofer Clusters	Institutes	Business areas
Information and communication technology	16	Mobility and transportation, e-government, public safety and security, manufacturing and logistics, media and creative sector, digital services, business and finance informatics, medical and healthcare systems, energy and sustainability
Life sciences	7	Medical technology, regenerative medicine, healthy foods, biotechnology, process, chemical, and herbicide safety
Light and surfaces	6	Surface and coating technologies, beam sources, micro and nano technology, materials processing, optical measuring techniques
Microelectronics	11	Smart and healthy living, energy efficient systems, mobility and urbanization, industrial automation
Production	12	Product development, manufacturing technologies, manufacturing systems, production processes, production organization and logistics
Defense and security	10	Crisis and disaster management, digital transformation, border security, combating terrorism and crime, resilience and protection of critical infrastructures, electronic warfare, protection and impact, networked operations and information gathering, provision of information and decision-making support
Materials	16	Health, energy and environment, mobility, construction and living, machinery and plant engineering, microsystems technology, safety
Innovation	5	Technology evaluation, structural change, transformation processes, future scenarios, innovation policy, decision support in policy making

Table 38: *Industry partners found in Hoppenstedt*

	Companies	Associated Projects
Fraunhofer industry-partner data	17,274	105,435
Found in Hoppenstedt	9,972	66,364

To complete the data enhancement phase, we integrate two more variables to our dataset for every observation. First, we search FÖKAT, a publicly available database with more than 100,000 projects funded by the federal government of Germany for the 19,944 companies in the dataset.[31] This matching generates the binary variable publicly funded, which is positive if the search returned any hit and

[31] For the identification in the FÖKAT database, the names of the companies were harmonized with regular expressions and then matched with harmonized names in Hoppenstedt. The information was extracted for both, Fraunhofer partners and randomly sampled companies from Hoppenstedt.

negative otherwise. Second, we keep the address of every company. This will be crucial to calculate the distance between every research unit of Fraunhofer and the respective company.

3) Data Preprocessing: We begin first by encountering the missing values in our data. In general, the quality of our data is satisfactory for most variables, merely turnover and employees have relatively high missing ratios, 56% and 33%, respectively (see Table 39), but still remain informative when imputed. We impute missing values of numeric variables (turnover, employees, managers, and firm age) by the median. Missing text variables (business descriptions, industry-codes, or industry descriptions) are marked as such for the latter text processing. Moreover, we log-transform numeric variables because their distribution is highly skewed to the right, as it can be seen from comparing the means and medians in Table 39. Finally, the numeric variables are centralized and rescaled.[32]

Table 39: *Descriptive statistics*

Statistic	Unit / Format	Observations	Mean	St. Dev.	Min	Median	Max
Partner / Non-partner	Binary	19,944	0.50	0.50	0	0	1
Firm age	Years	19,919	32.91	45.34	0.00	18.00	1,818.00
Employees	Count	13,266	998.71	11,300.55	1.00	38.00	546,406.00
Turnover	M Euro	8,848	183.29	1,651.20	0.01	4.75	83,312.23
Managers	Count	18,981	4.84	7.02	0.00	2.00	163.00
Publicly funded	Binary	19,944	0.17	0.37	0	0	1
Industry codes	Character	18,876	-	-	-	-	-
Industry description	Character	18,876	-	-	-	-	-
Business description	Character	17,401	-	-	-	-	-

Now, it remains to pre-process business description, industry codes, and industry descriptions. Business description and industry description are free text variables, that is, unstructured data. In order to use such information in our model, we need to transform the unstructured data. We use the following common NLP-procedure. First, all words in the texts are scanned and stored in a list. This list is the raw corpus. We exclude words with less than ten occurrences and German stop-words. After that, the words in the corpus undergo stemming, which is the process of reducing inflectional forms of a word to a common base form. For this end, we use the Snowball algorithm[33] for the German language. Finally, we adopt one-hot-encoding as the preferred technique to encode the stems in text variable in our model, which converts the text variable for every company into many binary features indicating the occurrence of a specific word/stem.[34]

For industry-code, although it is technically a categorical variable of nominal order, if we apply a canonic one-hot-encoding, we would miss a critical point in an industry classification scheme like

---

[32] All the above numeric transformations were performed in the software framework R-Studio, with code developed for this article in conjunction with standard R libraries for data handling and descriptive statistics. For the following NLP tasks, the library tidytext (Silge and Robinson 2016) was used in combination with own code and standard R libraries.
[33] [Online]. Available: https://snowballstem.org/algorithms/german/stemmer.html
[34] Alternatively, one can use word counts or normalized word-counts (e.g., TF-IDF). In our case, both methods however yield worse results with regard to the performance of the classifier.

NACE or WZ. Their classes and subclasses are leaves in a tree structure, and therefore carry much more information than just the binary one of class affiliation, as shown in Figure 22.

For example, WZ codes under the same division are more similar to each other than two WZ codes that are in different divisions. This logic holds on the whole classification tree, i.e., on all levels. Hence, it would be inattentive to miss this valuable information. In order to model in part this structural property of WZ codes, we split the code string and then encode it in a one-hot fashion. The developed tokenization scheme is shown in Figure 23. If a company has multiple WZ codes, the same procedure is simply repeated for each code.

After encoding the variables business description, industry codes, and industry description as explained above, the number of dimensions of our model's feature set jumps from handful to a couple of thousand due to the one-hot-encoding of the text fields and WZ code(s) and the numerous binary variables that are generated. Moreover, for each of those last three variables, we create one binary feature to indicate a missing value. In this way, we are able to encode every observation, even those with a missing text-variable, without the need for imputation.

We remark here that the only similarity our approach shares with the initially presented bibliometric approaches in section 4.2.2. is the encoding of texts into vectors. However, we use one-hot-encoding, which registers the presence of a word in a text. Differently from previous approaches, we encode every word and let the algorithm learn which words carry predictive information, instead of enforcing by hand so. The learned parameters assemble therefore an implicit measurement of technological fit of potential partners.

In order to finalize the construction of our feature set for every company, we compute the geographic distance from it to every Fraunhofer institute. This procedure generates 73 new features, representing the distance of the pair (company, institute). For the calculation, we retrieve the geocoordinates from

Figure 22: WZ classification (example).

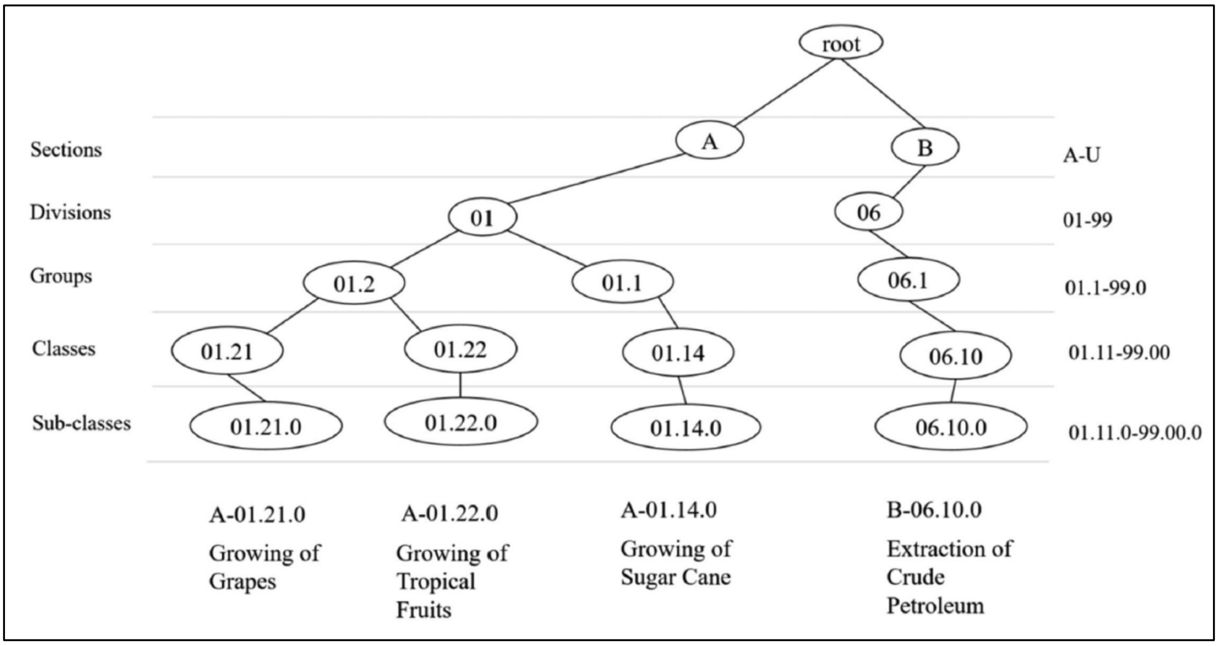
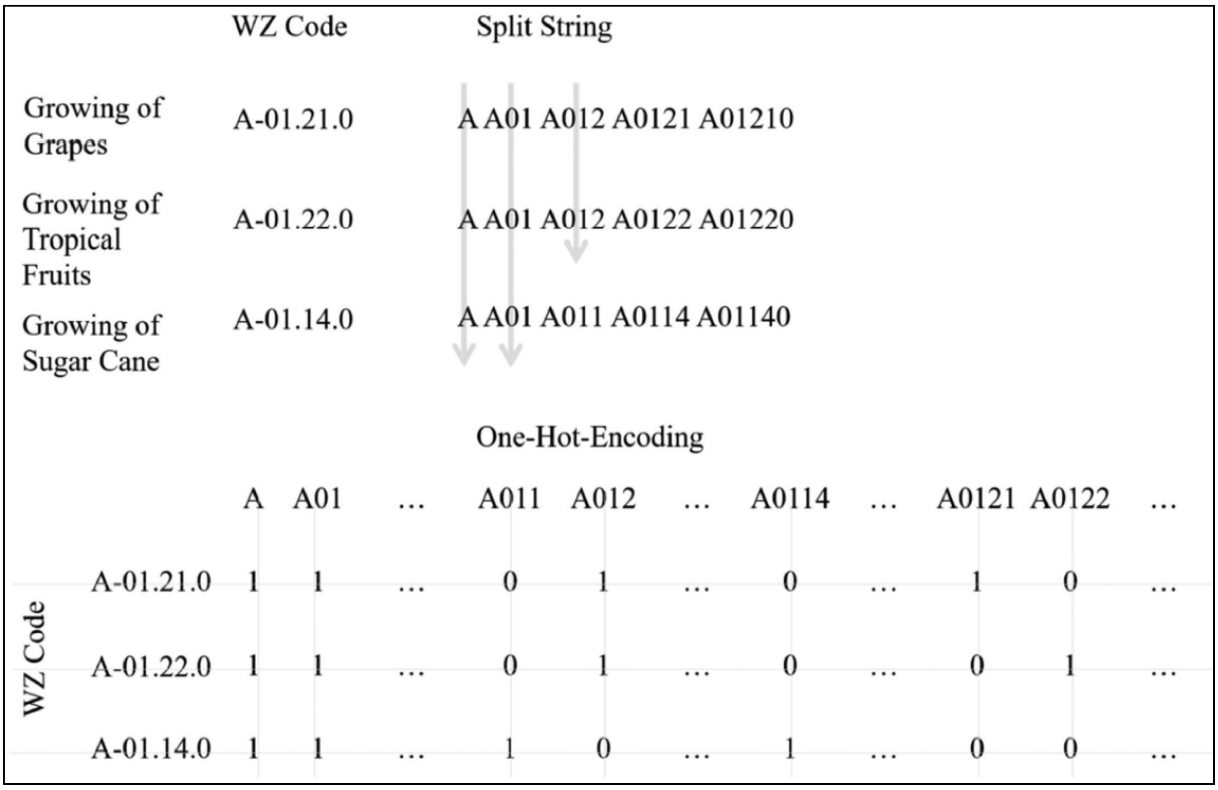


Figure 23: *WZ industry code tokenization scheme.*



OpenStreetMap and, finally, we calculate the distance using the spherical law of cosines.

Finally, for every observation (firm) in our dataset, we have the standard features *turnover*, *employees*, *managers, firm age,* and *publicly funded*; the feature sets *business description*, *industrycode,* and *industry-branch-text,* assembled from unstructured data (text); and finally, the feature set *distance.* In the following, we describe how we use this in order to support partner selection in a technology transfer context.

4.3.2 Methodology

1) Structure of the Decision Support Application: The purpose of our classification approach is to identify potential partners from a large set of companies. In our case, this means we need to assess each of the 1.3 million companies in our database. Since we are dealing with such a large amount of "new companies," our approach has two stages. First, we filter out irrelevant companies from our database with a rather generic pooled classifier. Then, we calculate a ranking of the remaining companies for each of the 70 Fraunhofer institutes with an institute-specific classifier. The provided ranking is supposed to provide the institutes with a prioritized list of potential matches. Experts' selection of suggested partners can then be used as feedback for the application, i.e., to retrain the classifiers.

As most other systematic partner-selection approaches, our approach supports the qualification stage of partner-selection by providing a ranking of the most promising recommendations. Different from other approaches, however, it also provides an interpretable quality measure for the recommendation with probabilities, because it is a supervised prediction and not a mere unsupervised dimensionality reduction (see following sections). Moreover, our approach also supports the criteria formulation phase by automatically determining which features are relevant for the specific institute according to its partner-history. Thus, it is not necessary to model the preference of the decision maker explicitly, as needed in other approaches, because the classifier learns the preference from past data.

Finally, while the selection of industry partners itself is left to the decision makers (e.g., managers at technology transfer offices), the selected firms can be used as feedback into the model to improve further recommendations.

2) Feature Selection and Model Construction: There are different requirements for the two classifier classes, which are stacked in our decision support application. For the first, it is important to cover as many of the existing industry partners as possible, while misclassifications to this regard are not as severe. For the second, it is highly undesirable to propose nonrelevant companies as high ranked recommendation.

Pooled classifier: First, we develop a pooled classifier as a prefilter, in order to discriminate good potential industry partners for the entire Fraunhofer-Gesellschaft from other companies. For this, we train one binary classifier to predict the target variable partner/non-partner (see Table 40). For model construction and validation, we use all the gathered data for all the 19,944 companies. In order to perform feature selection, we group the created features into four sets. The economic feature set contains the numerical variables (turnover, employees, managers, firm age, and publicy funded).[35] The business description set groups the cleaned, stemmed, and one-hot-encoded business description text. The industry description set assembles the binary variables generated after text pre-processing and one-hot-encoding procedure. Finally, the industry codes set collects the binary variables created by the industry code tokenizer. We do not consider the feature set distance for this classifier because the distance to the Fraunhofer-Gesellschaft as such cannot be calculated. The target variable of the pooled classifier denotes whether a company is a customer of any of the 73 Fraunhofer institutes, which are spread all over Germany.

The pooled classifier staging as a prefiltering step, i.e., preceding subsequent modules that are more complex (e.g., institute specific recommendations), might be necessary for scalability reasons. For example, a recommendation web interface might not be able to handle 1.3 million company entries with a satisfactory latency or the model might be computationally too expensive to apply it to such a large dataset. Or if operated offline, one can leverage such classifier to sort out autonomously irrelevant companies from a large company database like Hoppenstedt once it is trained, instead of doing this by hand.

A company will be sorted out by the pooled classifier, when it is from an industry with no or few contacts to Fraunhofer. This is trivial for companies, which are assigned with industry codes that never appeared among Fraunhofer customers. It becomes more difficult if a company is assigned an industry code that has appeared among Fraunhofer customers. Should we consider this company as a potential customer? First, it depends on the code itself: How informative is this code in determining a Fraunhofer partner? Second, it depends on the other codes of the company: Are there more codes that indicate that this company is similar to previous Fraunhofer partners? Are there some that indicate the opposite? How informative are the other codes? Considering all these aspects can be quite complex, however our brain is the very good in making such fuzzy decisions and surely can do this as well. What a human cannot do easily however is to perform such a task for millions of companies and thousands of previous partners at a time. This is where the pooled classifier goes a long way.

Institute-specific classifier ensemble: Second, we build an ensemble of institute-specific classifiers in order to rank and recommend good potential industry partners to specific institutes or research units. This second level of our model provides each of the Fraunhofer research institutes with

[35] We choose these specific economic variables both, because they are commonly used in the partner selection literature (see section 4.2.3.) and because they showed the highest performance for the purely economic pooled classification model (Model 1 in Table 40).

recommendations for new industry partners. For this, we train an ensemble of binary classifiers, one for each of the over 70 institutes, for discriminating between its own industry partners and industry partners of the other institutes, in a one-versus-rest manner. For each institute i, we construct a binary target variable (partner/non partner$_i$), which is positive if the company was an industry partner of the institute i and negative if the company was an industry partner of any other institute, but not institute i.

The institute-specific classifiers use only companies that were past industry partners of Fraunhofer, both for training and validation. This is because we want to capture characteristics of the companies that make them a good match for a specific institute compared to other institutes, which might be active in a completely different business area, but also have industry partners that are active in R&D. If we chose to discriminate again between industry partners of an institute and companies randomly sampled from Hoppenstedt, the classifier would put more weight on characteristics of innovative companies in general, like in the pooled regression, but not on the specific thematic characteristics of a certain business area. This labelling leads to imbalanced sample sets with regard to the target variable (partner/non partner$_i$), because most institutes worked only with a small fraction of the Fraunhofer industry partners. In extreme cases, too few positive observations do not allow for a proper estimation and validation. Therefore, we exclude institutes with less than 20 industry partners from the analysis, which leaves us with 70 out of 73 institutes, with one classifier each.

In this ensemble of institute-specific classifiers, we use the features sets economic, business description, industry description, and industry code as before, plus a new feature set, distance. Note that, every one of the institute-specific classifiers utilizes only one of the distance features. For example, the kth institute specific classifier has as feature distance (company, institute$_k$).

3) Classifier Models and Libraries: Nonlinear classification models like neural networks have become very popular for text classification because of their good performance. Nevertheless, linear models, such as logistic regressions and support vector machines (SVM), remain strong baselines for text classification and often even reach up to nonlinear models' performance, while being much faster and able to process much larger datasets (Wang et al., 2012; Joulin et al., 2016). Therefore, for both pooled and institute-specific classifiers, we use the library LIBLINEAR (Fan et al., 2008).[36]

LIBLINEAR contains various implementations of linear models for classification. Those models are based either on LR or SVM. SVMs may perform better, but LR has two main advantages. First, due to the simplicity of the model, it has straightforward coefficient analysis (see section 4.4.1.). Second, LR is a probabilistic classification method and, therefore, naturally outputs posterior probabilities that are well suited for ranking the observations on the test set, hence allowing the straightforward computation of rank-based performance measures. SVM, however, would require some additional calibration methods to emulate such probabilities.[37]

We use a L1 regularized variant of the LR classifier because it can handle high-dimensional data without overfitting. In addition, it can handle models with more features than observations. Moreover, to better assess the relevance of features, L1 regularization allows for exact zero coefficients, hence for feature selection during learning.

To test whether nonlinear models might still be worthwhile for our purpose, we also train a version of the Random Forrest (Breiman, 1996) classifier. Since we are mainly interested in probabilities for

[36] LIBLINEAR is originally written in C/C++. We use LiblineaR, which is a wrapper around it for R. [Online]. Available: https://cran.r-project.org/web/packages/LiblineaR/index.html
[37] Usually Platt scaling is used for this purpose with SVMs (Platt, 1999). It transforms the binary SVM outputs into a probability distribution by fitting a logistic regression on the sample distances to the hyperplane estimated by the SVM. This makes it slower than a plain SVM estimation and adds another layer of uncertainty.

ranking purposes, we train a so-called probability forest (Malley et al., 2012) with 500 randomized decision trees each. We use the ranger library (Wright & Ziegler, 2015), which is specifically written for high-dimensional data.

4.3.3 Validation

To see whether the proposed classification approach has the predictive power to support industry partner selection for public research (RQ 1 in Section 4.2.2.), we calculate its performance for the example of the Fraunhofer-Gesellschaft.

We perform ten-fold cross-validation[38] for all the classifiers and calculate various standard performance metrics, such as precision, recall, accuracy, f1-score, for each model specification by averaging across the folds.[39] We also compute the receiver-operating-curve, area under the curve (ROC AUC) metric, a standard performance metric for binary classification, which nowadays is provided with most validation implementations.[40] The receiver-operating-curve plots the relationship between false positive rate and recall for all possible classification thresholds.[41] ROC AUC is simply the area under this curve and is a measure of how well a classifier performs in different settings, for example, with a high threshold for a careful assignment of positive labels (e.g., clinical trials) or vice versa (e.g., cancer detection). At the same time, it is equal to the probability that a classifier ranks a random positive observation higher than a random negative observation.

While for the pooled classification all the above performance metrics are measured, for the institute-specific classification we just compute the ROC AUC score. This is because, while the latter should assess the performance of the classifier in ranking companies, the former should measure the performance of the model in deciding if a company is a prospective industry partner or not. Additionally, in the pooled classification task, a balanced dataset is used for training and testing, while this is not the case for the institute-specific classification. In fact, for each one of the 70 institute-specific classifiers in the ensemble, there is a distinct ratio of positive–negative observations. This all justifies the decision of using ROC AUC for comparison, as this measure is robust against unbalanced class distributions. ROCAUC, apart from being very useful in comparing classification models with distinct positive–negative class ratio, serves our purpose well for a second reason. ROC AUC is measuring in fact how well the models are ranking the industry partners, in comparison to the not-industry-partners. That is, given a group of companies to be tested by the model, ROC AUC scores higher if the model is able to rank higher the industry partners and lower the not industry- partners. This is very important for the usability of the ranking. When, a researcher that is looking for a partner goes through a list of companies, clearly the true potential industry partners should be on the top of this list.

By comparing the performance metrics of different feature combinations, we can also test which of the proposed sources of quantitative (i.e., economic) and qualitative information (i.e., industry codes, industry descriptions or business descriptions) on the companies can be leveraged for classification (RQ 2 in section 4.2.3.).

---

[38] Since we take a random sample for the negative class out of Hoppenstedt in the pooled classification, we needed to check our results for robustness beyond cross-validation. Therefore, we repeated cross-validation ten times for each model in the pooled regressions, with a different random sample each time. The results in fact remained very stable compared to those presented in this article.

[39] Apart from the model itself, the whole Machine Learning pipeline, from pre-processing to resampling, is set up using the MLR package in R (Bischl et al., 2016), which provides a convenient workflow for our purposes.

[40] In our case the MLR package for R.

[41] Precision, recall, accuracy, and f1-score are usually calculated with a probability threshold of 0.5.

4.4 Results and discussion

In the following, we provide an analysis of the performance of the designed solution for supported partner selection. First, we assess how well the pooled classification approach works for identifying potential partners for research organizations in general, i.e., prefiltering our dataset. While on that, we conduct a coefficient analysis on our LR model for pooled classification and analyse how the used features influence on the probability of classifying a firm as a good potential partner. We compare the performance of three different classification techniques: regularized logistic regression, SVMs, and random forest. Second, we measure the performance of the ensemble of LR models for the institute-specific classification. All the above analysis are also performed for various feature sets, which we compare among each other for the sake of completeness of the analysis.

Table 40: *Coefficients of logistic regressions for pooled classification*

	Target variable: Partner/Non- partner						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economic features							
Firm age	0.188				0.171	0.165	0.305
Employees	0.870				0.602	0.663	0.602
Turnover (M Euro)	0.183				0.259	0.200	0.195
Managers	1.360				1.026	1.021	1.036
Publicly funded	1.072				2.246	2.208	2.258
High-dimensional features							
Business description		X			X		
Industry description			X			X	
Industry codes				X			X
Obs.	19,944	19,944	19,944	19,944	19,944	19,944	19,944
Features	5	2,161	844	1,678	2,166	849	1,683

4.4.1 A Pooled Classification

Table 41 shows the results of the pooled classification models with various feature combinations using a regularized logistic regression. Interestingly, the coefficients of all economic features show a positive value and none of the coefficients was regularized to zero. This shows that the chosen economic features are indeed relevant determinants of industry partners in the case of Fraunhofer, which supports the results of the previous literature presented in section 4.2.3.

However, from a machine learning perspective, we are rather interested in the performance of the respective models in cross validation. Model (1) includes only economic features like firm age, size (turnover, employees, and managers), and a binary feature, which indicates whether a firm received public funding or not, publicly funded. This simple model shows a reasonable performance. The precision performance metric indicates that 88% of the companies that were labelled as positive by the classifier in cross validation were indeed Fraunhofer industry partners. Because the dataset is balanced with regard to the target variable, this compares to a baseline of 50%, which would result from a naïve approach, for example, if one labelled all companies positive or negative. None of the high-dimensional models (2)–(4), which include several hundreds of features constructed from business or industry descriptions or industry codes, reaches such a high precision as in (1). However, the recall of the low-dimensional model shows that only 73% of the industry partners present in the dataset were identified as such by the classifier. In this regard, the high-dimensional models using industry descriptions and industry codes perform better, with a recall of 76% and 78%, respectively. In order to compare the different models, one would normally use the F1-score, being the harmonic mean of the precision and recall, because we are only interested in the performance with regard to the positive class. Accuracy on the other hand assesses the performance for both classes, positive and negative. Both measures show that the economic model outperforms the high-dimensional models with a single source of information (2)–(4). However, a combination of economic indicators with high-dimensional features in models (5)–(7) dominates clearly all previous models with regard to all measures. Model (7) slightly beats all others with an accuracy and f1-score of 85%, precision of 86%, and recall of 84%.[42] This means that there is an increase of 11% in recall, the performance measure of main interest for pooled classification, between model (1) and model (7). However, the question is: Is this a considerable increase? To answer this question, consider how many partners one would miss if model (1) was used instead of model (7). Since there are 9972 confirmed industry partners in the dataset, we would miss almost 1100 companies.[43] We consider this as a substantial improvement.

As can be seen in Table 41, more elaborate classification techniques, suitable for high-dimensional classification problems like SVMs with linear kernel or nonlinear random forests, do not perform noticeably better than the simple LR learner with regularization.[44] The best random forest model outperforms the best LR model (7) only by 1%of F1-Score, while the ROC AUC remains the same.

Hence, it seems that linear models indeed are sufficient and other nonlinear techniques are not very promising in our case. At the same time, LR models have the advantage of being interpretable to the decision makers and providing well-calibrated probabilities for ranking companies. Therefore, in the following, we only report the results of the regularized LR models.

4.4.2 Institute-Specific Classifications

Figure 24 shows the performance distribution of the institute specific classifiers for different model specifications using regularized LR learners.[45] For ease of representation, and since we are mainly interested in the quality of the probability rankings for this classification task, we only consider the ROC AUC performance metrics and no other metrics like precision or recall (see section 4.3.3.). The jittered points show the averaged tenfold ROC AUC score of each of the 70 classifiers. The bell curves show the kernel-density estimates of the score distributions and the vertical lines mark the according median of the sample.

[42] Note that we do not report all combinations of available features. A combination of economic features, business description, industry description, and industry codes indeed improve the f1-score, but only by 1% and it is computationally much more costly, because it has much more features (4688). None of the combinations however yields a better ROC AUC value than the best previous feature combination (model 7 with industry codes).
[43] For the other performance measure of interest in this article, ROC AUC, such an analogy is not possible, and improvements can unfortunately only be assessed in a relative manner.
[44] Note that the ROC AUC measure is not available for SVM without further modifications and hence is not reported (see Section III.C).
[45] Note that these model specifications differ from those of the pooled classifier in section 4.4.1. because some features, which are available for the institute specific classifier (e.g., geographic distance between the company and the respective institute) are not available for the pooled classifier.

As expected, classifiers with low-dimensional economic features only (Model A) do not perform well in distinguishing industry partners between the different institutes. The best classifiers only reach up to a ROC AUC of around 70% and the median lies only slightly above 60%. Adding geographic distance between the companies and the respective institute (Model B) increases the performance of the classifiers considerably, with three classifiers reaching up to a ROC AUC of around 80%, but two institute-classifiers still remaining useless at below50% ROCAUC. Classifiers using business descriptions from Hoppenstedt converted to high-dimensional word one hot-encoding (Model C) perform better than classifiers using economic features only (Model A), but worse than geo economic

features (Model B). However, most classifiers remain in the range between 60% and 70%, and many even below, which is not a satisfactory result.

Model (D) and (E) perform much better by using features constructed from text and code information on industry sector. Some classifiers range clearly above 80% ROC AUC, which compares to the performance of pooled classifier, despite the institute-specific classification being a much harder task. Most classifiers have a ROCAUC metric of above 70%, which is quite reasonable. There is no clear preference for one of the models, since the mean and median performances are almost the same. However, Model (D) seems to be more stable across institutes, as Model (E) has very low performance of below 50% for one institute.

As in the previous classification task, improved results are obtained with models that combine economic and high dimensional features, as in Model (F), and even better results are achieved by adding geographic distance (Model G). The combinations of all three, however, yield even better results (Models H and I). The inclusion of this additional information helps us to increase the performance of most classifiers, but the best performers from Model (D) do not improve that much by adding economic or geographic information. A possible interpretation is that for some very diverse institutes, for whom it is difficult to make recommendations based on the business activity of their industry partners, location and economic information matter, while for the others information on business activity descriptions are sufficient. On average, classifiers including industry code features, economic features, and geographic distance perform the best.

The results show that those feature sets that describe the companies' industry, by either text or code, are the most important for the institute-classifiers in order to rank companies. However, adding economic or geographic information can improve the performance considerably.

4.5 Limitations

One limitation of our approach is that the information provided on Fraunhofer industry partners is positive-unlabeled. This means that we only know partners, but not non partners. This may hinder the training of the classifiers, because some of the companies marked as negative might still be good candidates for industry partners. The gravity of this effect differs between the pooled classification and institute-specific classifications.

For the pooled classification, we decided to randomly sample companies from Hoppenstedt as negative nonpartners. The argument why this shall not compromise the overall performance of our system is that, although this is indeed possible, it is also very unlikely. The database Hoppenstedt has around 1.3 million companies from which we sample randomly around 10,000, in order to balance our dataset. From all the companies listed in Hoppenstedt, the vast majority are not interesting for the Fraunhofer-Gesellschaft as a partner. First, because only a minority of all companies engages in innovation-oriented activities, as we address in section 4.3.1.2. Second, because an even smaller number among those could profit directly from the research portfolio the Fraunhofer-Gesellschaft has to offer.

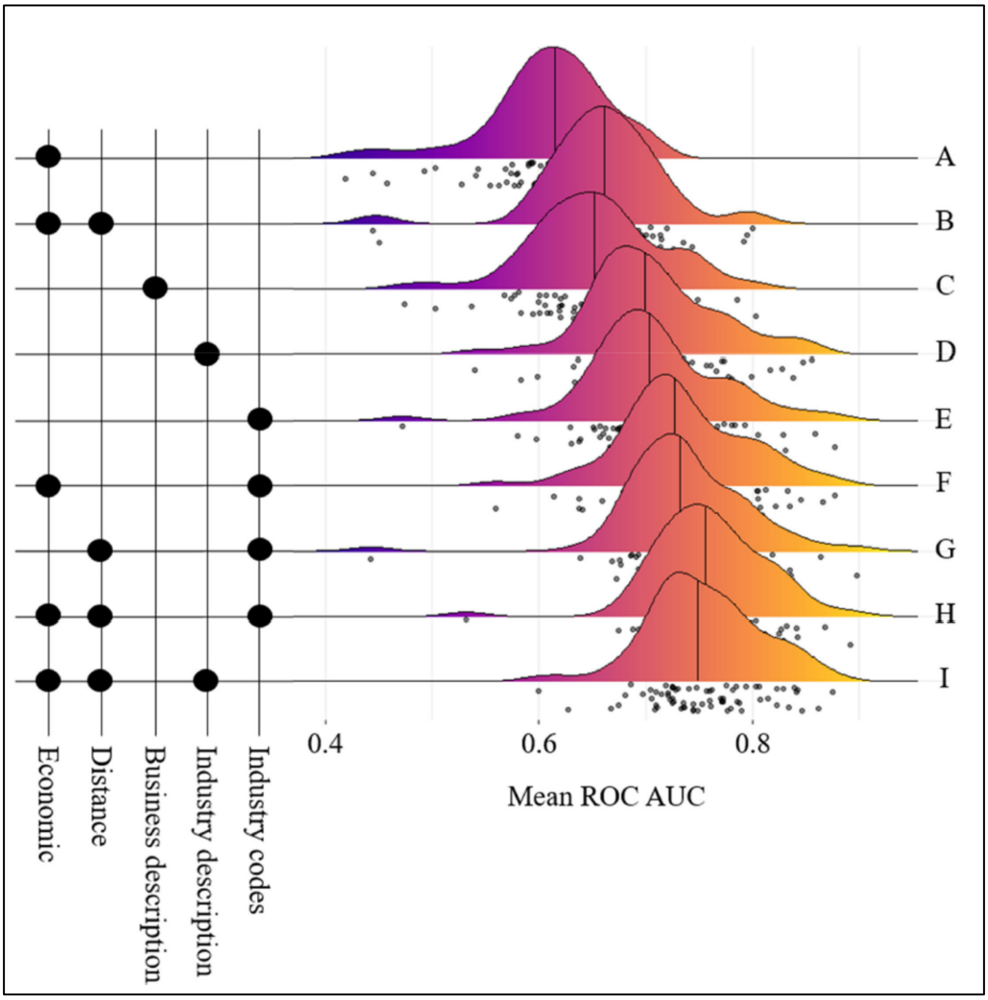
Hence, randomly sampling Hoppenstedt will return almost exclusively nonrelevant companies and we assume that it does not affect the training and validation of the pooled classifier. While one could argue that this is the reason this separation task is easy, it is certainly painstakingly hard to find manually a small group of interesting companies in a universe of 1.3 million different firms.

Table 41: *Performance of logistic regressions, svms, and random forests*

Performance (pooled classification)

	Target variable: Partner/Non-Partner						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economic features	X				X	X	X
Business description		X			X		
Industry description			X			X	
Industry codes				X			X
Obs.	19,944	19,944	19,944	19,944	19,944	19,944	19,944
Features	5	2,161	844	1,678	2,166	849	1,683
	Logistic Regression						
Precision	88%	84%	82%	81%	88%	89%	86%
Recall	73%	73%	76%	78%	79%	80%	84%
Accuracy	82%	80%	80%	80%	84%	85%	85%
F1-Score	80%	78%	79%	79%	83%	84%	85%
ROC AUC	88%	86%	87%	88%	92%	93%	93%
	Support Vector Machine						
Precision	89%	83%	82%	80%	88%	89%	87%
Recall	72%	72%	76%	79%	78%	79%	83%
Accuracy	82%	79%	80%	79%	84%	85%	85%
F1-Score	80%	77%	79%	79%	83%	84%	85%
ROC AUC	-	-	-	-	-	-	-
	Random Forest						
Precision	86%	82%	81%	80%	88%	86%	86%
Recall	77%	78%	77%	80%	82%	86%	86%
Accuracy	82%	80%	80%	80%	85%	86%	86%
F1-Score	81%	80%	79%	80%	85%	86%	86%
ROC AUC	90%	87%	88%	88%	93%	93%	93%

Figure 24: *Performance of the institute-specific classifiers (logistic regression).*



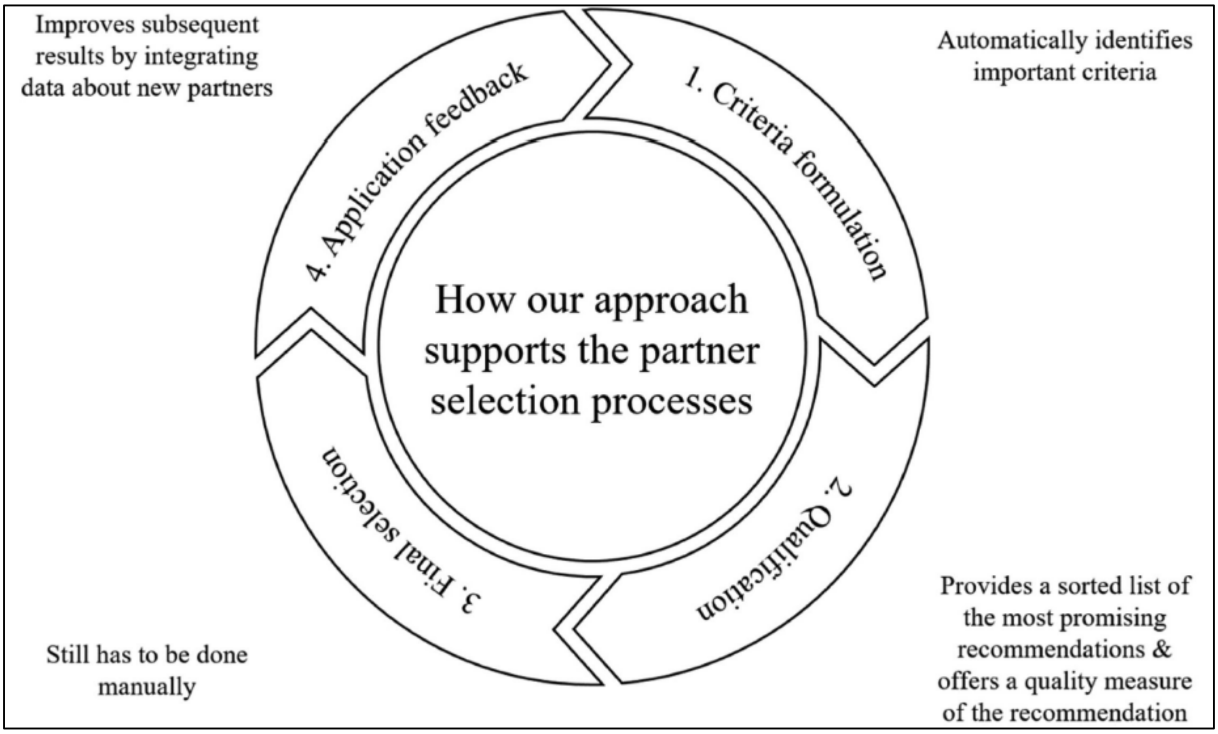
For the training of institute-specific classifiers, we choose to use Fraunhofer industry partners only. As mentioned in section 4.3.2.1., this helps the classifiers to learn to distinguish between specific thematic or technological characteristics of the companies rather than to distinguish between innovative and noninnovative or R&D active and nonactive companies in general. The downside of this approach is that it aggravates the problem that companies labelled as nonpartners might still be good candidates. Because the negative set encompasses Fraunhofer industry partners only. Therefore, the probability is high that the negative set includes companies, which are good candidates for institutes beyond those that have been industry partners according to industry-partner data. Note that, on the contrary to the pooled classifier, here one does not have a statistical measure to upper bound the ratio of falsely negative-labelled good potential partners.

On one hand, this "erroneous" labelling of nonpartners may affect the training of the classifiers considerably. For example, consider two institutes that do not share any industry partners (e.g., because of their geographic location), but their industry partners are very similar with regard to their business description, industry description or industry codes and represent potential partners for both institutes. Our two classifiers would assign low weights to features (i.e., words or codes), which the partners have in common because they appear for both industry partners and nonpartners. On the other hand, the classifiers will put more weight to features that are special for the respective institute and rank companies higher that match this particular institute only, which indeed is a desired effect for the decision support application.

An improvement of our results could potentially be reached by using observation weights in our classifications. Such weights could be, for example, constructed based on the number of projects or value of projects between a certain company and Fraunhofer. Moreover, it would be interesting to analyze if texts longer than the business activity, for example, from the homepages of the companies, would help the classifiers to make better predictions. In this case, however, a more thorough analysis of the various text-preprocessing options would be needed. Another interesting strand for further research could be how to make use of inter institute correlations present in our data, for example, with recommender systems or multilabel problem transformation methods (Probst et al., 2017). These methods usually use user–item interaction (in this case company-institute) data in order to predict preferences of other users by taking advantage of user–user correlation. Finally, it would be interesting to analyze empirically whether the use of our approach indeed improves the partner-selection process compared to the manual selection. This would be of great interest in order to settle, for example, the question if the pooled classifier is indeed helping researchers find new partners among the whole 1.3 million possibilities, or if they would prefer performing this step by hand.

Another practical limitation of our approach is that it makes only recommendations that are similar to previous partners, which is problematic for research institutes that want to explore a new branch of industry partners. On the other hand, our approach can be easily adapted to solve this problem. Instead of using previous customers to train a classifier one could also use a set of hand-selected examples of potential partners. The trained classifier would then be able to recommend further potential partners of this new type.

Figure 25: *Proposed support system for partner selection; adopted from (Wu & Barnes, 2011).*



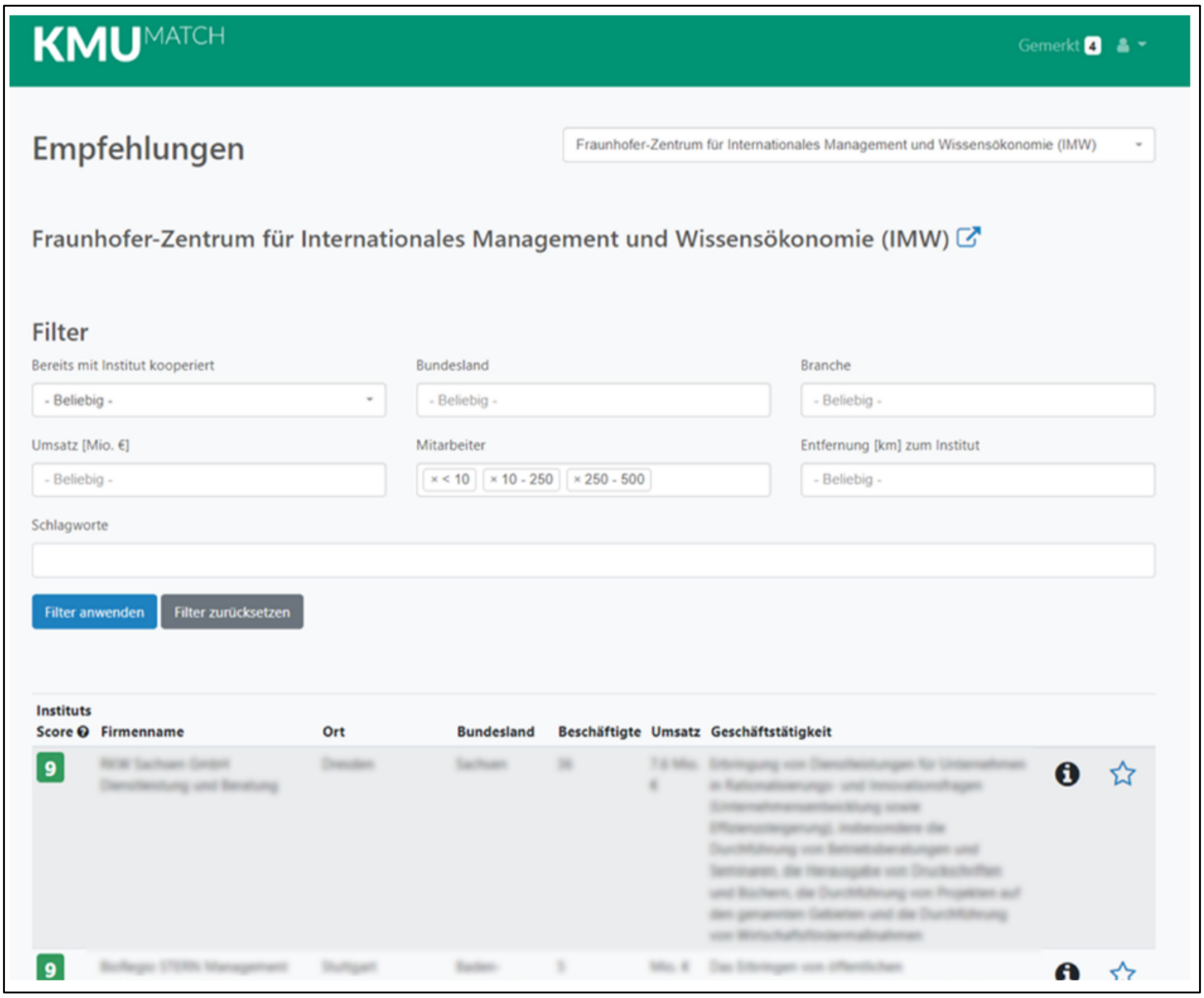
4.6 Practical use

The practical use of our article is to support research organizations at finding new industry partners by facilitating the partner selection process. Figure 25 shows how managers in technology transfer offices and scientists can benefit from the proposed approach.

In Stage 1, our approach automatically identifies important criteria for the partner selection. Then, it provides in Stage 2 a ranked preselection of the best-fitting partners out of an overwhelming pool of organizations. Both phases base themselves exclusively on former cooperation behavior data and company data, reducing hence the entire initial hurdle in finding a partner. Proceeding, this recommendation is provided to the decision maker who performs the final selection. In the last phase of partner selection process, data from selected partners are added to the existing dataset and the models improve future recommendations.

Since our research is part of a research project for the Fraunhofer-Gesellschaft, we implemented the results in a web application called SME-Match (see Figure 26). Fraunhofer researchers can use this prototype tool to look for new industry partners. The focus of this application lies on the recommendation of SMEs, because there is an overwhelming number of potential SME partners, while most large corporations are already known.

Figure 26: *Screenshot of prototype web-application SME-Match.*



We prefilter companies coming from the Hoppenstedt database using a pooled classifier. Then, we calculate Institute-Scores for these prefiltered companies, which indicate how well a company fits a particular institute according to its industry partner history.

Finally, we argue that this way of recommending potential good industry partners for public research organizations has a lot of transfer potential and is not restricted to our case study, the Fraunhofer-Gesellschaft. Considering the general nature of the partner selection problem, we point out that our model can be applied in various settings, both related to knowledge transfer and in a more general context. First, our approach can be easily transferred to any research organization that gathers historical cooperation data between firms and its internal research units. This is clearly the case for any university, with all its independent departments cooperating with companies. Although being independent, all those departments have to report their activities to the central administration, which therefore is in the position of using our method to find new good cooperation partners for its units. Any other public research organization with such a structure could also make use of our approach. Naturally, the performance could vary, depending on the quality of the available data. Second, any parent company with its independent subsidiaries could also take advantage of our approach to support partner selection. As before, the subsidiaries have also partners, for example, suppliers. This activity is sometimes reported to the parent company, which can benefit from its historical data with our approach. However, it is important to know what kind of partnership is registered in the historical data, because the mixture of historical cooperation data of different kinds, like suppliers and clients, can spoil the quality of the recommendations. In our case, the kind of partnership was clear; knowledge was transferred or acquired by the companies.

4.7 Conclusion

Coming to the overall conclusion, we state that our classification approach indeed proved its feasibility and potential to support the industry-partner selection process at Fraunhofer, which answers our first research question. With precision and recall of around 85% for the pooled classification and ROC AUC scores between 70% and 90% for most institute-specific classifiers, the overall performance of the approach is certainly satisfactory for practical use. In doing so, it appears to be applicable to other public research organizations or even large corporations with a wide range of technologies and industry partners as well. Of course, given the necessary industry-partner data are available. Moreover, it allows for an almost complete screening of the market, because it uses data that is available for almost all companies in Germany, which is easy to substitute with other texts or codes describing the business activity of companies. In both steps of our classification approach, prefiltering with a pooled classifier and ranking relevant companies with institute specific classifiers, the combination of economic features and industry-related features performs best. Economic information of a company on age, employees, and turnover supposedly helps to determine whether a company is able to cooperate with a research institute, with regard to financial capacity and absorptive capacity. Information on specific business activity of a company, extracted with NLP-techniques from texts or codes describing its industry affiliation, supposedly helps to determine whether this company fits the research area of a specific institute. With regard to our second research question, we therefore conclude that the combination of quantitative and qualitative information, economic data and business descriptions of companies in our case, is indeed useful for the partner selection support in public research.

4.8 References

Baiman, S., Fischer, P. E., & Rajan, M. V. (2000). Information, contracting, and quality costs. Management Science, 46(6), 776-789.

Battiston, F., Iacovacci, J., Nicosia, V., Bianconi, G., & Latora, V. (2016). Emergence of multiplex communities in collaboration networks. PloS one, 11(1), e0147451.

Beckman, C. M., Haunschild, P. R., & Phillips, D. J. (2004). Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. Organization science, 15(3), 259-275.

Bischl, B., Lang, M., Kotthoff, L., Schiffner, J., Richter, J., Studerus, E., ... & Jones, Z. M. (2016). mlr: Machine Learning in R. The Journal of Machine Learning Research, 17(1), 5938-5942.

Breiman, L. (1996). Bagging predictors. Machine learning, 24(2), 123-140.

Broekel, T., & Binder, M. (2007). The regional dimension of knowledge transfers—a behavioral approach. Industry and Innovation, 14(2), 151-175.

Bruneel, J., d'Este, P., & Salter, A. (2010). Investigating the factors that diminish the barriers to university–industry collaboration. Research policy, 39(7), 858-868.

Cardamone, P., Pupo, V., & Ricotta, F. (2015). University Technology Transfer and Manufacturing Innovation: The Case of I taly. Review of Policy Research, 32(3), 297-322.

Chang, H., Gausemeier, J., Ihmels, S., & Wenzelmann, C. (2008). Innovative technology management system with bibliometrics in the context of technology intelligence. Trends in Intelligent Systems and Computer Engineering, 349-361.

Chen, S. H., Wang, P. W., Chen, C. M., & Lee, H. T. (2010). An analytic hierarchy process approach with linguistic variables for selection of an R&D strategic alliance partner. Computers & Industrial Engineering, 58(2), 278-287.

Chesbrough, H. W. (2003). Open innovation: The new imperative for creating and profiting from technology. Harvard Business Press.

Comin, D., Licht, G., Pellens, M., & Schubert, T. (2019). Do companies benefit from public research organizations? The impact of the Fraunhofer Society in Germany. The Impact of the Fraunhofer Society in Germany, 19-006.

Eom, B. Y., & Lee, K. (2010). Determinants of industry–academy linkages and, their impact on firm performance: The case of Korea as a latecomer in knowledge industrialization. Research Policy, 39(5), 625-639.

Fan, R. E., Chang, K. W., Hsieh, C. J., Wang, X. R., & Lin, C. J. (2008). LIBLINEAR: A library for large linear classification. the Journal of machine Learning research, 9, 1871-1874.

Fraunhofer (2017), "Annual report," Munich, Germany. Accessed: Jun. 28, 2019. [Online]. Available: https://www.fraunhofer.de/en/media-center/ publications/fraunhofer-annual-report.html

Fritsch, M., & Kauffeld-Monz, M. (2010). The impact of network structure on knowledge transfer: an application of social network analysis in the context of regional innovation networks. The Annals of Regional Science, 44(1), 21-38.

Geum, Y., Lee, S., Yoon, B., & Park, Y. (2013). Identifying and evaluating strategic partners for collaborative R&D: Index-based approach using patents and publications. Technovation, 33(6-7), 211-224.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. Annual review of psychology, 62, 451-482.

Giunta, A., Pericoli, F. M., & Pierucci, E. (2016). University–industry collaboration in the biopharmaceuticals: The Italian case. The Journal of Technology Transfer, 41(4), 818-840.

Granovetter, M. S. (1973). The strength of weak ties. American journal of sociology, 78(6), 1360-1380.

He, X., Zhang, H., Kan, M. Y., & Chua, T. S. (2016). Fast matrix factorization for online recommendation with implicit feedback. In Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval (pp. 549-558).

Hottenrott, H., & Lopes-Bento, C. (2016). R&D partnerships and innovation performance: Can there be too much of a good thing?. Journal of Product Innovation Management, 33(6), 773-794.

Jeon, J., Lee, C., & Park, Y. (2011). How to use patent information to search potential technology partners in open innovation.

Joulin, A., Grave, E., Bojanowski, P., & Mikolov, T. (2016). Bag of tricks for efficient text classification. arXiv preprint arXiv:1607.01759.

Kaiser, U. (2002). An empirical test of models explaining research expenditures and research cooperation: evidence for the German service sector. International Journal of Industrial Organization, 20(6), 747-774.

Lee, K., Park, I., & Yoon, B. (2016). An approach for r&d partner selection in alliances between large companies, and small and medium enterprises (smes): Application of bayesian network and patent analysis. Sustainability, 8(2), 117.

Li, D., Eden, L., Hitt, M. A., & Ireland, R. D. (2008). Friends, acquaintances, or strangers? Partner selection in R&D alliances. Academy of management journal, 51(2), 315-334.

Malley, J. D., Kruppa, J., Dasgupta, A., Malley, K. G., & Ziegler, A. (2012). Probability machines. Methods of information in medicine, 51(01), 74-81.

Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. Journal of economic geography, 6(4), 395-437.

OECD. Publishing. (2014). Commercialising public research: New trends and strategies. OECD publishing.

Park, I., Jeong, Y., Yoon, B., & Mortara, L. (2015). Exploring potential R&D collaboration partners through patent analysis based on bibliographic coupling and latent semantic analysis. Technology Analysis & Strategic Management, 27(7), 759-781.

Perkmann, M., & Walsh, K. (2009). The two faces of collaboration: impacts of university-industry relations on public research. Industrial and Corporate Change, 18(6), 1033-1065.

Perkmann, M., & Walsh, K. (2007). University–industry relationships and open innovation: Towards a research agenda. International journal of management reviews, 9(4), 259-280.

Porter, A. L., & Cunningham, S. W. (2004). Tech mining: Exploiting new technologies for competitive advantage. John Wiley & Sons.

Probst, P., Au, Q., Casalicchio, G., Stachl, C., & Bischl, B. (2017). Multilabel classification with R package mlr. arXiv preprint arXiv:1703.08991.

Rammer, C., Doherr, T., Krieger, B., Marks, H., Niggemann, H., Peters, B., ... & von der Burg, J. (2021). Innovationen in der deutschen Wirtschaft: Indikatorenbericht zur Innovationserhebung 2020. ZEW-Innovationserhebung-Mannheimer Innovationspanel (MIP).

Rendle, S., Freudenthaler, C., Gantner, Z., & Schmidt-Thieme, L. (2012). BPR: Bayesian personalized ranking from implicit feedback. arXiv preprint arXiv:1205.2618.

Rõigas, K., Mohnen, P., & Varblane, U. (2018). Which firms use universities as cooperation partners?-A comparative view in Europe. International Journal of Technology Management, 76(1-2), 32-57.

Rybnicek, R., & Königsgruber, R. (2019). What makes industry–university collaboration succeed? A systematic review of the literature. Journal of business economics, 89(2), 221-250.

Silge, J., & Robinson, D. (2016). tidytext: text mining and analysis using tidy data principles in RJ Open Source Softw. 1 (3), 37.

Solesvik, M. Z., & Encheva, S. (2010). Partner selection for interfirm collaboration in ship design. Industrial Management & Data Systems.

Tello, S., Latham, S., & Kijewski, V. (2010). Individual choice or institutional practice: Which guides the technology transfer decision-making process?. Management Decision.

Wang, S. I., & Manning, C. D. (2012). Baselines and bigrams: Simple, good sentiment and topic classification. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers) (pp. 90-94).

Wang, X., Wang, Z., Huang, Y., Liu, Y., Zhang, J., Heng, X., & Zhu, D. (2017). Identifying R&D partners through Subject-Action-Object semantic analysis in a problem & solution pattern. Technology Analysis & Strategic Management, 29(10), 1167-1180.

Wirsich, A., Kock, A., Strumann, C., & Schultz, C. (2016). Effects of university–industry collaboration on technological newness of firms. Journal of Product Innovation Management, 33(6), 708-725.

Wright, M. N., & Ziegler, A. (2015). ranger: A fast implementation of random forests for high dimensional data in C++ and R. arXiv preprint arXiv:1508.04409.

Wu, C., & Barnes, D. (2014). Partner selection in agile supply chains: a fuzzy intelligent approach. Production Planning & Control, 25(10), 821-839.

Wu, C., & Barnes, D. (2011). A literature review of decision-making models and approaches for partner selection in agile supply chains. Journal of Purchasing and Supply Management, 17(4), 256-274.

Yoon, B., & Song, B. (2014). A systematic approach of partner selection for open innovation. Industrial Management & Data Systems.

5

5 Personnel motivation in knowledge transfer offices: The role of university-level and organizational-level antecedents

Anna Pohle, Elisa Villani, Rosa Grimaldi

Abstract: Knowledge transfer offices (KTOs) have become key actors in economic growth, innovation, and social and technological progress. Accordingly, scholars have dedicated increasing attention to KTOs' activities and performance. Surprisingly, these topics have mainly been addressed at the macro level through environmental and institutional variables, while scant attention has been given to the effect of micro- and behavioral dynamics on KTO outcomes. By considering four Italian KTOs, our paper aims to better understand the motivational aspects of KTO employees—and particularly the antecedents of such motivation. Focusing on self-determination theory (SDT), we link the three basic needs (relatedness, competence and autonomy) that explain KTO employees' intrinsic motivation to specific university-level and organizational-level antecedents. Regarding the former, we show that university government plays a key role in satisfying the need for autonomy among KTO personnel, while KTO organizational antecedents are more important in addressing the needs for competence and relatedness.

Keywords: technology transfer, self-determination theory, intrinsic motivation, psychological needs, KTOs

This is an accepted manuscript version and was published in *Technological Forecasting and Social Change* (181, 2022, 121765; https://doi.org/10.1016/j.techfore.2022.121765).

5.1 Introduction

More than 40 years after the introduction of the Bay-Dole act in the US, many scholars around the world have examined knowledge transfer offices (KTOs) as intermediaries between producers of knowledge and inventions (i.e., university scientists) and the actors who can commercialize those outputs (i.e., firms, entrepreneurs, and venture capitalists). KTOs can help sustain economic and technological growth by improving university-industry relations (Chau, Gilman & Serbanica, 2017; Villani, Rasmussen & Grimaldi, 2017), as well as commercializing academic research toward possible market innovation through out-licensing of university patents and/or spin-off creation (Brescia, Colombo & Landoni, 2016; Zhou & Tang, 2020).

KTOs have been analyzed with respect to their characteristics, their actions, their activities and how they influence the effectiveness of the process through which knowledge originated by public bodies is then transferred to the marketplace (Siegel et al., 2003). Siegel et al. (2003) explored the productivity of 113 KTOs and highlighted the fact that environmental and institutional factors explain most of the variation in KTO efficiency. Other studies have pointed out the importance of KTOs increasing their effectiveness by bolstering their reputation and legitimacy (O'Kane et al., 2015). All in all, we find that the existing literature has paid attention to different factors, but mostly focused on macro-level dynamics (i.e., institutional and organizational) (e.g., Battaglia, Landoni & Rizzitelli, 2017; Zhou & Tang, 2020); meanwhile, limited attention has been paid to micro-process and micro-organizational factors that can have a huge effect on performance outcomes. Intrinsic motivation is one such factor that has not been sufficiently explored.

This is somewhat surprising, given the relevance of intrinsic motivation to work performance (Brief & Aldag, 1977; Cerasoli, Nicklin & Ford, 2014; Grant, 2008; Hackman & Oldham, 1976; Menges et al., 2017; Piccolo & Colquitt, 2006; Shin & Grant, 2019). Intrinsic motivation makes effort less daunting, thus leading employees to work harder, smarter, longer, and more productively (Gagne & Deci, 2005; Menges et al., 2017). If employees are not motivated to fulfill their tasks and achieve their goals, the organization cannot attain success (Barney, 1991; Dobre, 2013). If intrinsic motivation is low, even the most talented employee will not deliver. In other words, an energized and highly motivated employee can reach good performance despite some knowledge gaps (Landy & Conte, 2016). Thus, despite the importance of macro-level aspects to KTOs' performance (one reason why the extant literature has extensively studied them), there is still a need to understand the micro-level mechanisms (i.e., motivation) that also shape KTOs' effectiveness and outcomes.

Intrinsic motivation is a fundamental component of any credible model of human performance (Gagnè & Deci, 2005; Shin & Grant, 2019). It is defined as "the doing of an activity for its inherent satisfactions rather than for some separable consequence" (Ryan & Deci, 2000, p. 56). Despite the importance of intrinsic motivation in work settings, many jobs are not designed to enable intrinsic motivation (Shin & Grant, 2019). In some work settings, individuals must act in the presence of challenging conditions (e.g., having little discretion in tasks, decisions, work methods, and schedules) (Morgeson & Humphrey, 2006; Humphrey, Nahrgang & Morgeson, 2007) that can undermine the arousal, magnitude, direction and maintenance of effort in their job. This is pretty much the case of KTOs, most of which are characterized by the presence of different institutional logics, low routinization, and fast-changing external dynamics—and at the same time, a high dependency on internal rules and regulations. While motivation has been a prominent area of interest in organizational behavioral research, and continues to be one of the most frequently discussed topics in the field of psychology (Rousseau, 1997), scant attention has been given to understanding the intrinsic motivations of KTO personnel. Nonetheless, these individuals operate in very complex work settings that constantly strive to balance different and diverging factors in their daily job activities (Balven et al., 2018). Moving from these premises, this paper aims to answer the following research question: *How do contextual* *factors enable KTOs' employees to reach intrinsic motivation, in a work context where satisfaction may be threatened?*

To address this question, we conducted a multiple comparative case study of four KTOs in Italy (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). The selected KTOs are comparable in terms of their main characteristics and activities, located as they are in regions of Northern Italy that display similar economic characteristics and technological development (Istat, 2020). Three of them have been doing very well over the last ten years; a fourth has exhibited weaker performance. Comparing them should offer insights into how KTO employees achieve intrinsic motivation—and more importantly, what antecedent conditions, and at what different levels, enable the satisfaction of such motivation. We believe this is a very important gap to fill, as it allows not only to understand how to get employees motivated towards their job, but also to understand how organizational and university-level processes and activities can be defined and organized to achieve better and more effective outcomes through (intrinsically) motivated employees.

To shed light on this issue, we build on self-determination theory (SDT) (Gagné & Deci, 2005), and particularly the basic psychological needs for competence, autonomy and relatedness, which play a critical role in explaining individual intrinsic motivation at work.

Our findings contribute to the growing area of technology transfer by adopting a micro-level perspective for explaining KTO performance. More generally, we shed light on micro-organizational factors that support intrinsic motivation and, in turn, allow for more effective technology transfer and knowledge share processes. Here we understand KTOs as organizational units within public entities that are characterized by constraints, procedural rigidity, protocols, and regulations, and which are involved in non-routinized, complex tasks that require a strong commitment in addition to appropriate skills and competencies (Fitzgerald & Cunningham, 2016; Bright, 2008). Indeed, KTO employees' arduous tasks include: managing tensions between academic and market logics; balancing academic versus managerial goals; interacting with different stakeholders (scientists, university managers, companies, VCs and other financial institutions); and managing different internal priorities (requests from different departments and structures). We believe that our study provides an original contribution with regard to the drivers of intrinsic motivation that KTO personnel face every day and with limited incentives. While KTOs are unique/peculiar compared to other units/offices within research organizations, our findings may still be applicable to other organizational contexts that face similar dynamics and complexities. From a theoretical point of view, we also generally contribute to SDT by corroborating the importance of contextual factors for intrinsic motivation. In particular, we shed light on the specific antecedent factors that support KTO employees' intrinsic motivation at the university and organizational level.

From a managerial point of view, understanding the link between needs satisfaction and university-level antecedents will help different stakeholders shape the university context in a way that simultaneously a) supports successful knowledge and technology transfer and b) enhances employee motivation. The paper also contains managerial implications for KTO managers who feel an increasing pressure to deliver results, given the availability of knowledge transfer objectives and performance indicators in many universities' strategic plans. At a minimum, they should be aware that intrinsic motivation is a powerful driver for KTO performance, beyond macro-level factors.

This paper also features policy implications. To the extent that countries and governments are investing in technology transfer and knowledge sharing to spur economic, social, technological, and environmental impact, it is important to create legal frameworks that legitimate the role of KTO professionals and support their motivation. While this paper finds that intrinsic motivation is a key determinant of performance, it would be appropriate to also account for extrinsic factors, such as remuneration based on meeting challenging results.

5.2 Literature review

Knowledge can move through different channels (not all of which generate economic impact), such as publications, graduating students entering the workforce, scholarly relationships with industry, and formal licensing of intellectual property to third parties such as start-up companies. Examples of knowledge transfer and sharing can be found across virtually every scientific and industrial area, such as pharmaceuticals and medical devices, agriculture, aerospace, environmental improvements. Many of the products and technological advances we take for granted in our everyday lives came from university research before being transferred to the marketplace through knowledge transfer processes. University KTOs are the key players in these knowledge-sharing processes, as they oversee the commercial valorization of research results and knowledge flows that generate economic impact.

5.2.1 Characteristics and nature of university KTOs

The research on university KTOs has grown quickly due to their relevance in making academic knowledge more useful and exploitable within society (Siegel et al., 2003). Most scientific inquiry has focused on the practices that KTOs adopt and how they impact performance (Siegel et al., 2003), specifically in relation to knowledge commercialization (Belitski, Aginskaja & Marozau, 2019), intellectual property rights (Siegel, Veugelers & Wright, 2007), spin-off creation and academic entrepreneurship (Grimaldi et al., 2011), and the role of KTOs as boundary spanners (O'Kane et al., 2020; Villani et al., 2017). In this respect, much attention has been paid to the generation of ‘measurable outcomes’, which include patents, licences and spinoffs (Giuri et al., 2020; Siegel et al., 2003). A few studies, meanwhile, have focused on the organizational practices and strategies adopted by KTOs (e.g., Giuri et al., 2019; Siegel et al., 2003). However, very little research has been devoted to better understanding the peculiar characteristics that make university KTOs a unique organizational setting (Good et al., 2019), nor to the micro-level processes through which organizational practices translate into individual behavior. In their conceptual paper featuring qualitative interviews with KTOs employees, Balven and colleagues (2018) identified motivation as a critical, yet overlooked micro-process that affects academic entrepreneurship. More attention on this and other micro-level processes would facilitate a better understanding of the effectiveness of technology transfer activities. To that end, we need to first establish a broader picture of KTOs’ operational context.

University KTOs are integrated into the university structure; therefore, in most cases, they are subject to public regulations. Internal university regulations are very important for academic entrepreneurship and spinoff creation; indeed, they represent an important mechanism for fostering or hindering knowledge transfer activities (Muscio et al., 2016). In this respect, Alexander et al. (2020) emphasized that the practical management of knowledge transfer by KTOs is often hampered by the procedural rigidity of protocols and regulations. Indeed, bureaucracy and inflexible rules are two pillars that usually characterize the functioning of university KTOs (Alexander et al., 2020; Siegel et al., 2003).

Moreover, university KTOs represent pluralistic contexts characterized by competing strategic demands and divergent stakeholder goals (O’Kane et al., 2015). O’Kane et al. (2015) reported that KTOs have two principal stakeholders within the university (i.e., academics and administrative staff) that are often characterized by non-overlapping objectives. Similarly, Siegel et al. (2004) explained that KTOs are populated by different actors: university scientists, university technology managers and administrators, and firms and other third parties. Additionally, KTOs often interact with external actors, including business incubators and financing institutions, e.g., business angels and venture capitalists who are interested in scouting promising entrepreneurial ideas and technologies for commercial exploitation. These external actors (that KTO personnel interact with) are additional stakeholders in their eyes, with their own agendas and objectives. Matching these external needs with internal requirements in order to accomplish their institutional mission can be very challenging. Finally, many KTOs have become increasingly active in supporting student entrepreneurship. They bring together students from a variety of disciplines to generate innovative solutions sought by external stakeholders (e.g., hackathons, challenge-based events, business plan competitions), which makes KTOs even more multifaceted. Accordingly, KTO employees must balance their economic and academic priorities amidst overlapping boundaries. In the face of competing institutional logics—in the form of different interests, goals, cultural backgrounds and behaviors (Pache & Santos, 2013)—KTOs are typically subject to conflict and uncertainty.

The extant literature (e.g., Howells, 2006; Villani et al., 2017) has extensively documented how university KTOs serve as external boundary spanners that bridge the different logics of the "suppliers" of research results (i.e., academic scientists and the community of academic researchers at large) and the potential "customers" (i.e., firms, entrepreneurs, venture capitalists and other actors and institutional players in the local, national, and international ecosystems). However, less attention has been given to their internal boundary-spanning activities (Huyghe et al., 2014). Indeed, university KTOs have the complex task of interacting with different university departments and faculties involved in the commercialization of academic research (Markman et al., 2008). In other words, KTO employees face the challenge of managing cross-organizational and cross-departmental relationships, in addition to dealing with more practical technology transfer issues (Huyghe et al., 2014; O'Kane et al., 2015). They must engage in internal boundary-spanning among university governance, administrators, technicians, department heads, school coordinators, researchers, and students, which makes their jobs highly interrelated with many other internal university structures. Therefore, university KTOs are a central organization within a broader organization, and their employees must be able to engage many different units.

Another characteristic of university KTOs is that they are part of a wider technology transfer ecosystem that includes incubators, science parks, enterprises, regional agencies, institutions and other universities (Belitski et al., 2019; Good et al., 2019). These actors are part of dynamic external networks whose evolution is likely to influence KTOs' activities and organization. Beyond these local context dynamics, normative evolution at the regional and national levels (e.g., laws in support of new venture creation, spinoff capitalization, financial incentives for companies investing in R&D, grants and other subsidies in favor of the valorization of research results) must also be taken into account. As a result, university KTOs must grapple with the fast-changing dynamics of the broader ecosystem. In short, KTOs both influence and are influenced by uncertain and ever-changing external environments in terms of regulations, funding schemes, laws, support mechanisms, and regional and national programs.

5.2.2 Key contingencies of university KTOs effectiveness

Scholars recognize that the needs for autonomy, competence and relatedness are psychological in nature and are essential for nurturing intrinsic motivation (Ryan & Deci, 2000). However, the unique work context of KTOs can threaten such needs because (a) public regulations and bureaucracy might suppress employees' autonomy; (b) the complexity of boundary-spanning activities (both internal and external) might interact with low skill variety to undermine the sense of competence; and (c) the dimensions of the ecosystem might lead to a huge number of relationships that are too weak and scattered to provide a true sense of relatedness. In this scenario, how can people achieve daily intrinsic motivation for the job?

Scholars generally recognize that employee intrinsic motivation significantly influences performance in most organizations (Brief & Aldag, 1977; Cerasoli, Nicklin & Ford, 2014; Dobre, 2013; Grant, 2008; Hackman & Oldham, 1976; Menges et al., 2017; Piccolo & Colquitt, 2006; Shin & Grant, 2019). However, the issue has never been explored in university KTOs. Although university KTOs may be seen as 'standard' public-sector organizations, they are increasingly forced to adopt a business-oriented approach in order to improve their productivity and efficiency. Accordingly, performance outputs have become the key measure for comparing KTOs' effectiveness. Many studies have addressed different factors that affect university KTOs' performance at a macro-level (i.e., organizational and contextual) (Balven et al., 2018; Belitski et al., 2019; Miller et al., 2018), including entrepreneurial ecosystems (Al-Tabbaa & Ankrah, 2016; Audretsch, 2014; Villani & Lechner, 2021; Perkmann & Walsh, 2010), organizational structure and business models (Baglieri, Baldi & Tucci, 2020; Bercovitz et al., 2001; O'Shea et al., 2005; Siegel et al., 2007), patenting, licensing and spin-off creation capability (Rasmussen & Wright, 2015; Wright, 2007), and geographical and cognitive proximity to academia and industry (Bercovitz & Feldman, 2006; Villani et al., 2017). By contrast, research has remained silent on the relationship between intrinsic motivation and performance in KTOs.

5.2.3 Role and impact of intrinsic motivation in university KTOs

Intrinsic motivation is pivotal to the productivity, profitability and sustainability of every organization (Barney, 1991; Balven et al., 2018; Cerasoli et al., 2014; Menges et al., 2017; Shin & Grant, 2019). Shin and Grant (2019) consider motivation to be a powerful tool that reinforces behavior and triggers the tendency to persist. Others (Cerasoli et al., 2014; Grant, 2008) regard motivation as a foundational driver of performance. Indeed, the level of organizational performance mainly flows from employees' actual skills and level of motivation (Barney, 1991). However, whether a gap in skills may be closed through learning new knowledge, a lack of motivation is much more complex to be filled.

Self-determination theory (SDT) is the dominant theory of intrinsic motivation (Cerasoli et al., 2014; Ryan & Deci, 2000) due to its capacity to predict human behavior in multiple contexts (González-Cutre et al., 2016; Ryan & Deci, 2000). It features prominently in psychology but has also received empirical validation in domains ranging from education, healthcare, and sports to the fields of work motivation and management (Deci et al., 2017). SDT rests on two key concepts: First, SDT identifies three basic psychological needs that must be satisfied to achieve intrinsic motivation (Gagné & Deci, 2005; Ryan & Deci, 2000). The *need for autonomy* (Ryan & Deci, 2000) represents individuals' inherent desire to experience a general sense of choice and volition. In particular, it refers to the sense of authorship of one's actions and the feeling of being psychologically free. The need for autonomy is frustrated when employees cannot stand behind their actions or feel they must act against their will (Olafsen et al., 2017; Ryan & Deci, 2000). The *need for competence* reflects individuals' inclination to influence the environment and obtain desired outcomes (Ryan & Deci, 2000). Competence frustration occurs when employees feel that they are ineffective and cannot achieve desirable end-states in their work (Gillet et al., 2012). Finally, the *need for relatedness* (Baumeister & Leary, 1995) refers to individuals' inherent propensity to feel connected to and be cared for by others as a member of a group. This need is frustrated when employees do not feel a sense of communion and lack the experience of having close and intimate relationships with other people (Ryan & Deci, 2000).

Research from various life domains has shown that satisfying these three basic needs is positively associated with intrinsic (i.e., autonomous) motivation and work outcomes (e.g., Gillet et al., 2012; González-Cutre et al., 2016). By contrast, thwarted satisfaction of those needs undermines motivation and has maladaptive consequences. For example, Gillet et al. (2012) revealed that satisfaction (vs. frustration) of the three needs led to greater (vs. lower) well-being in organizational contexts. De Cooman et al. (2013) found that employees who felt greater need satisfaction on the job also displayed greater intrinsic motivation and effort expenditure. Similarly, in their meta-analysis, Van den Broeck et al. (2016) showed that each basic need had a significant positive relationship with introjected, intrinsic motivation. Thus, the satisfaction of autonomy, competence, and relatedness provides the basis for intrinsic motivation and is conducive to optimal functioning and wellness among employees, which poses obvious benefits for the organization (Olafsen et al., 2017). Since various studies have confirmed that the presence of intrinsic motivation—or at least, the satisfaction of the associated basic needs—can predict positive work-related outcomes, we consider it necessary to explore the antecedents of motivation in order to understand how to promote wellness and high-quality performance in organizations. Accordingly, we turn to the second key aspect addressed by SDT, which relate to the importance of contextual characteristics.

SDT emphasizes the importance of contextual factors that hinder or undermine self-motivation, social functioning, and personal well-being (Gagné & Deci, 2005; Ryan & Deci, 2000). The research has consistently found that social contexts such as workplaces that support the satisfaction of the abovementioned needs can facilitate intrinsic motivation, psychological and physical wellness, and enhanced performance (Deci & Ryan, 2000; Deci et al., 2017). A social environment that affords competence but fails to nurture relatedness is expected to result in some impoverishment of wellbeing. Worse yet, work contexts that engender conflicts between basic needs establish the conditions for alienation and psychopathology (Ryan, 1995). For example, Hon (2012) found that hotel employees are more autonomously motivated and creative when they perceive their managers to be supportive of autonomy, and their co-workers to be supportive of relatedness. Consequently, intrinsic motivation and creativity decrease dramatically in the case of pressure and coercion. Similarly, Williams et al. (2014) showed that managers' support for employees' basic psychological needs prompted more intrinsic motivation, as well as fewer psychosomatic symptoms and less emotional exhaustion, turnover intentions, and absenteeism (Deci et al., 2017).

By joining these two key aspects, SDT provides a useful lens for examining the multifaceted nature of human motivation and its relationship with social values and norms. SDT treats intrinsic motivation as the outcome of the interaction between contextual factors and individuals' psychological needs. Accordingly, organizations that obtain better outcomes are those where employees feel supported in their autonomy, competence, and relatedness and are therefore self-motivated (Gagné & Deci, 2005; Ryan & Deci, 2000). This should also be true for university KTOs, despite common perceptions of KTO employees being extrinsically motivated (Balven et al., 2018). In sum, SDT represents an interesting lens because it allows going beyond the more traditional, economic, extrinsic incentives usually analyzed in association with job characteristics, by enabling to understand the challenging, interesting, and internally rewarding part – without the prospect of any external reward – of job activities.

5.3 Methods

When investigating overlooked phenomena with an explorative research question, a qualitative approach is warranted (Yin, 2003). Multiple case study is a suitable analytical approach for analyzing complex social phenomena in a real-life context (Yin, 2003). This research design is particularly recommended when the study's objective is to build new theory (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). Relative to the single-case approach, multiple cases allow for more powerful conclusions by integrating diverse data sources into a replication logic (Yin, 2003). In our study, we conducted an in-depth comparative case study (Eisenhardt, 1989; Yin, 2013) of four university KTOs in Italy, with the aim of better describing the KTOs' motivational aspects—and particularly, the university-level antecedents of that motivation across KTOs (Eisenhardt, 1989). Following our research question, our study's unit of analysis is the contextual factors (i.e., at the KTO and university level) that represent the antecedents of KTO employees' motivation. The level of analysis, meanwhile, is the individual: namely, KTO employees and managers. This comparative case study is ideal because the institutions were created under the same legal framework and around the same time. Whereas KTO1, KTO2 and KTO3 are considered among the ten most-successful KTOs in Italy in terms of outcomes, KTO4 is considered a less successful one (NETVAL, 2018). We added KTO4 as a contrasting case to validate our results. The following sections provide more details about the analysis of our cases. Thus, a qualitative approach is very much appropriate here – in the presence of a "how" question – where the objective is not to examine the effect of an already known variable on a defined outcome, but to figure out and understand more in depth the way some contextual factors function to fulfill the three psychological needs and, therefore, support intrinsic motivation.

5.3.1 Research setting and cases selection

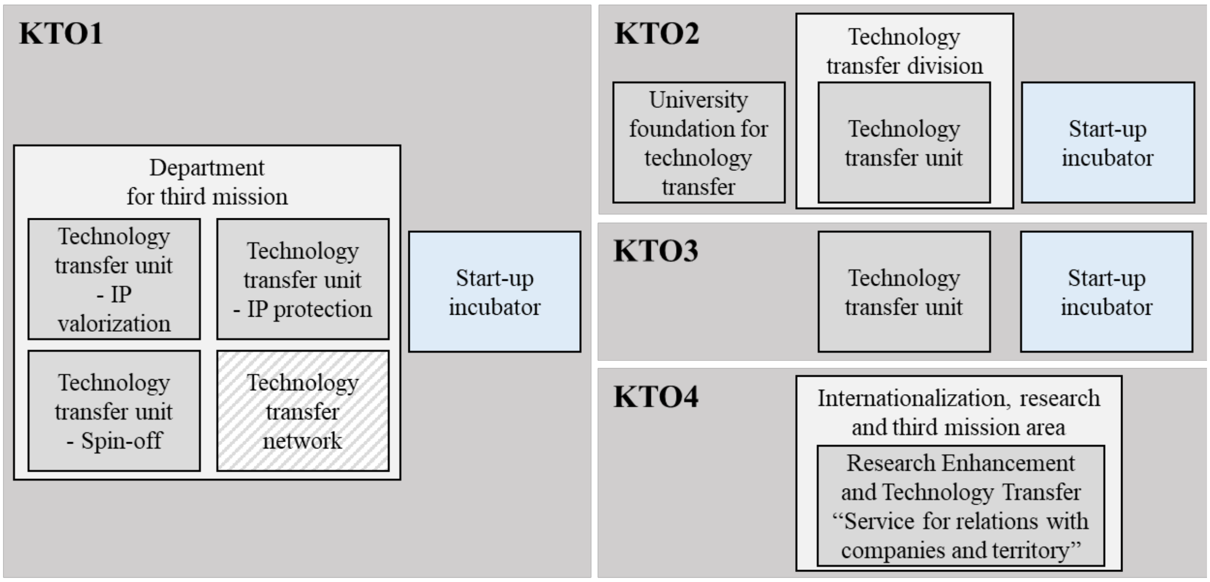
In university KTOs, there are manifold knowledge and technology transfer channels that range from informal (such as networking activities) to formal (such as licensing) (OECD, 2013). In addition, formal channels can be divided into non-commercialization channels (such as publications) and commercialization channels (such as spinoff creation or contract research). University KTOs mostly deal with commercial technology transfer channels, but they also offer a great variety of support activities for researchers and students. The most important activities of our KTOs are as follows: patenting, licensing, spin-off establishment, implementation of ready-for-commerce services/products, and consulting activities. The four KTOs all engage in the same activities, even if their structures vary considerably. In Table 42, we summarize the key characteristics of the four university KTOs included in our study, while Figure 27 graphically represents their structure.

***Table 42:** Case studies*

Technology transfer characteristics	***KTO1***	***KTO2***	***KTO3***	***KTO4***
Description of the third mission within the university's mission	"[…] the maintenance of dynamic relationships and exchanges with society as a whole and the world of work".	"[…] to become 'a reference point for the world of innovation, in all its forms, and applied research'".	"[…] dissemination of knowledge and culture as well as the transfer and exploitation of knowledge in the context of the economic and cultural development of the territories, in compliance with the principles of environmental and social sustainability […]".	"It contributes to the social, economic and cultural development of the territory, promotes the enhancement of scientific research results, support for new businesses and innovative projects, lifelong learning and continuous training"[#]
No of internal KTO units	3 + 1 network	1 + 1 foundation	1	1
No of active patents	370+ (2018)	140+	100+ (2019)	97 (2021)
No of spin-offs	~32	~57	~27 (2019)	~ 45
Establishment of TT activities	2004	Early 2000	Early 2000	Early 2000
No of employees	~21	~28	~5	~5
University characteristics	***University1***	***University2***	***University3***	***University 4***
Institutional control	Public	Public	Public	Public
No of students	85,000+ (2018/19)	55,000+ (2017/18)	50,000+	32,000+
No of teaching and research staff	2700+	2,200+ (2017/18)	1,500+	1.250+
No of PhD students	1,400+	1.400+	700+	1,100+
No of research departments	32 (2018/19)	32	20	22
No of scientific documents*	130,000+	125,000+	85,000+	82,000+

Source: All numbers are based on the latest documents from the three universities and KTOs. This includes annual reports, strategy documents and official websites. All data are from 2020, except for the cases where the year is explicitly mentioned.; * The number is based on the Scopus database, last accessed on 1 October 2020.; # The university mission is not available. Therefore, we added the self-description of the unit.

Figure 27: *KTO units related to the case studies**



* Grey boxes represent KTO units under university control; grey hatched boxes illustrate internal networks; blue boxes with scattered frames represent KTO-like organizations without university control.

Given our research interest, we selected the university KTOs based on theoretical sampling (Eisenhardt, 1989; Glaser & Strauss, 1967). Since previous literature has demonstrated a direct positive relationship between intrinsic motivation and organizational performance (Cerasoli et al., 2014; Grant, 2008; Menges et al., 2017; Shin & Grant, 2019), we followed a literal replication strategy by selecting three very successful KTOs (i.e., KTO1, KTO2 and KTO3). Indeed, their high performance predicted very motivated employees; we therefore expected similar results in terms of the university-level antecedents of intrinsic motivation. Accordingly, they represent the KTOs that ground our model. However, in order to improve and validate our theory, as well as bolster the reliability and generalizability of our results, we followed a theoretical replication strategy by selecting a fourth KTO (i.e., KTO4). We wanted a case that would predict contrasting results in terms of the university-level antecedents of intrinsic motivation (Eisenhardt, 1989). Accordingly, we sought low-motivation employees by including a less successful KTO.

The KTOs' success was measured in terms of the dimensions of technology transfer in Italy, such as the number of inventions, number of patents and licensing contracts, and number of spinoffs normalized by the number of KTO personnel (NETVAL, 2018). While KTO1, KTO2 and KTO3 were among the top ten university KTOs out of 69 examined (NETVAL, 2018), KTO4 was at the bottom end of the ranking due to a reduction in resources and staff, poor performance in technology transfer outcomes, and shifts in management positions.

As a second criterion, we decided to focus on large- and middle-sized KTOs with at least five employees (i.e., 5.6 is the average number of people employed in Italian KTOs) to ensure that there would be enough variety among employees' perspectives. However, we introduced some degree of variance in our selection criteria by including KTOs with one, two and three sub-units, with public and private legal forms, and different team sizes.

Since our main objective is to understand how contextual factors support intrinsic motivation in KTOs, we sought to avoid contextual biases. Indeed, the nature of knowledge transfer activities may differ greatly across regions and university quality (Minguillo & Thelwall, 2015). On one hand, the four KTOs are affiliated with four universities that are among the 20-most research-intensive universities in Italy (Times Higher Education World University Rankings 2021, category “research”). On the other hand, the four regions are comparable in terms of many relevant aspects, such as the number of people working on R&D, the size of enterprises, the sector of activities, the amount of R&D expense in relation to PIL, and the number of innovative enterprises. We report the main organizational characteristics of each KTO below.

At KTO 1, knowledge transfer activities are organized within a university department that is responsible for third mission activities and communications more in general. The whole department has twelve units and three of them (the “core units”) are in charge of patenting, licensing and spin-off related tasks. The “IP protection” unit consists of six people whose mission is to promote and implement the protection of research results, including technical-legal analysis and contractual services. Closely connected with this unit is the “IP enhancement” unit, which also has a staff of six people who pursue implying IP valorization strategies and agreements with researchers and companies. Finally, the largest unit (nine people) is the “spin-off and start-up” unit, which strives to proactively create and develop new businesses based on the work of researchers and skilled students. This team coordinates calls for spin-off ideas and new company creations, as well as manages a makerspace.

At University 2, the KTO unit is part of the department for research relations with companies. The KTO focuses on IP protection and spin-off support, but also includes a departmental unit that oversees the establishment and maintenance of industry relations and related services. This second unit was originally founded as an Ltd. Company and transformed into a university foundation in 2019. With approximately 20 persons between them, the two units strive to “[… take] part to the scientific excellence of [university 2] by involving professors, researchers, students, companies and public institutions in technology transfer activities and postgraduate education aimed at the social and economic development” (strategy document). Holistically, these units focus on valorizing IP, establishing contract research, and organizing networking opportunities. Because of the units’ close alignment, we treated them as the singular KTO 2.

At University 3, the third mission is defined by the department for “innovation ecosystem and enhancement of research placement”, which also includes the KTO. Since the early 2000s, the KTO unit of University 3 has sought to create economic and societal value by translating scientific discoveries into patents and spin-off creations (e.g., fostering an entrepreneurial mindset, business modeling, finding funding, etc.), as well as networking with companies. KTO 3 is organized as a single group and is formally led by the general director of the university.

Finally, University 4 established a department called “Internationalization, research and third mission area”, which is responsible for processes related to international student mobility, (international) cooperation and research initiatives, and promotion and enhancement of scientific research results via spin-offs, patents, contract research and trainings. Therefore, the KTO represents a specific unit (“Research enhancement and technology transfer sector”) of that department. Its primary services revolve around the commercialization and legal protection of knowledge and technologies.

5.3.2 Data collection

For the data collection, we followed common recommendations for case study analysis (e.g., Eisenhardt, 1989; Yin, 2013) by combining preliminary unstructured interviews, formal semi-structured interviews, archival documents (including university reports and regulations), strategy documents, KTO brochures, web-based resources (such as KTO websites and LinkedIn person and unit profiles), and informal talks (see Table 43). We employed a ‘snowball technique’ to identify our informants. We had a preliminary discussion with the president of the NETVAL, a network that represents nearly all the

Italian universities and public research centers that commercially exploit their research results. With his deep understanding of knowledge transfer in Italy, he helped us identify the managers who would be the most knowledgeable about and involved in the KTOs' internal processes and dynamics. We conducted the first set of interviews with those individuals, and then asked each of them to suggest other people who could provide relevant information. These semi-structured interviews lasted between 46 and 97 minutes (69 minutes on average) and followed an interview protocol that evolved throughout the data collection process (Strauss & Corbin, 1998). The interview protocol was organized in sections: five for KTO managers and four for KTO employees. The first section included questions about the individual situation, including the reasons for joining the KTO alongside their experiences and (current and future) expectations. The second and third sections were about the KTO and the university's contextual characteristics, the relationship between them, and their ability to fulfill individual psychological needs (i.e., autonomy, competence and relatedness). The last section for employees was about the perceived influence of their own motivation on clients' (i.e., researchers and industrial partners) behaviors. In the case of the managers, the additional fifth section concerned the opportunities and struggles in fulfilling employees' psychological needs and finding ways to motivate them. We recorded and transcribed thirteen interviews; the remaining six were documented in the form of a detailed protocol. In the analysis, we used codes to preserve the anonymity of the organizations and individuals.

Table 43: *Data sources*

Description	***KTO1***	***KTO2***	***KTO3***	***KTO4***
Interviews	*# of interviews (LinkedIn profiles)*	*# of interviews (LinkedIn profiles)*	*# of interviews (LinkedIn profiles)*	*# of interviews (LinkedIn profiles)*
Managers	5 (2)	2 (1)	1 (0)	1 (0)
Employees	2 (1)	3 (2)	2 (0)	2 (0)
Total	**7 (3)**	**5 (3)**	**3 (0)**	**3 (0)**
Archival materials	*Approx. # of pages*	*Approx. # of pages*	*Approx. # of pages*	*Approx. # of pages*
University (strategy) reports	60	283	321	42
Patent and Spin-off regulations	9	28	19	22
Brochures and press releases	66	21	26	2
Other (charts, databases)	1	33	1	89
Total	**136**	**365**	**367**	**155**

5.3.3 Data analysis

Given the limited empirical research on the micro-level aspects of university KTOs—and more specifically, the impact of organizational and university-level antecedents on KTO employees' intrinsic motivation—we adopted an inductive approach aimed at developing theory (Eisenhardt, 1989). Our analytic approach followed common practice in qualitative research (e.g., Gioia et al., 2013). Through an iterative procedure, we inductively coded interviews and documents with the aim of identifying important relationships between existing literature, data, and emerging themes.

The data analysis included two different steps: (a) a comparative analysis of the successful cases (i.e., KTO1, KTO2 and KTO3) based on literal replication, and (b) a comparative analysis of the successful cases with the less successful one (i.e., KTO4) based on theoretical replication. Whereas step (a) represented the core analysis of our study, aimed at identifying similarities among cases to address our research question, step (b) was added as additional evidence to corroborate our results and improve their rigor and consistency. In this sense, step (a) involved two different phases: (1) checking that the direct positive relationship between performance and intrinsic motivation was observed in our cases, and (2) identifying university-level antecedents of KTO employees' intrinsic motivation. Whereas phase one was just intended to confirm the direct relationship between intrinsic motivation and performance already observed and discussed by previous literature (e.g., Cerasoli et al., 2014; Menges et al., 2017), phase two represents the core part of the findings and it is focused on the identification of common contextual factors in KTO1, KTO2 and KTO3. The two different phases followed common rules, but in the first phase we adopted a priori specification of the three psychological needs identified by SDT.

We treated all interview transcripts and archival documents separately according to their associated case (within-case analysis) and then proceeded to analyze cross case patterns (Eisenhardt, 1989; Yin, 2003). We performed an opened coding for each case, whereby we aimed to find recurrent topics using simple guiding research questions. As our analysis progressed, we became increasingly familiar with the contexts and specifically refined the codes to better distinguish antecedents at different levels (i.e., university and organizational), which led us to a set of first-order codes for each guiding question (Gioia et al., 2013). This phase was extremely useful for exploring emerging patterns in the collected data (Strauss & Corbin, 1998) and identifying in vivo codes or terms that adequately captured the meaning behind the informants' experience (e.g., 'creation of a technology-transfer-related university brand', 'creation of a matrix structure in the department', 'team management by shared public value to deal with the diversity').

We then proceeded with axial coding (Strauss & Corbin, 1998), with the objective of giving the same codes to perceptions, acts or occurrences that shared common characteristics. At this stage, our aim was to theorize the in vivo codes as higher-order themes by identifying the initial relationships among them (e.g., 'Managing based on a public-good ideology', 'Providing clear and challenging goals', 'Enhancing overall knowledge-transfer perception', 'Being inspired by knowledge-transfer challenges'). We continued with this process until additional analyses did not provide further insights in terms of new categories or the relationships between the existing categories. In other words, we proceeded until we reached data saturation.

Finally, we considered the data and the current literature in tandem until significant theoretical relationships among the first-order codes resulted in more abstract second-order themes. In particular, according to phase (1), we finally observed the satisfaction of the three psychological needs treated by SDT, which led to the following second-order codes: *expression of the need for relatedness*, *expression of the need for autonomy*, and *expression of the need for competence*. For the university-level antecedents, we uncovered a distinction between university and organizational antecedents that affected the fulfillment of these needs, leading us to the following second-order codes: *strategic plan, structural set-up for hybrid demands,* and *scientific support* for university-level antecedents, and *hybrid team management, goal setting* and *skill maintenance* for organizational-level antecedents. Tables 44, 45 and 46 present the structure of our data, including the first- and second-order codes for motives and for university-level and organizational-level antecedents, respectively.

__Table 44:__ Representative quotes for the occurrence of basic needs

Representative quotes	**#No./EM*/org.**	**Motives (first-order codes)**	**Need expression (second-order code))**
"And this is how I arrived at this big family on the tech transfer, because I think we can see the tech transfer as a family. […] I like to move; I like to meet different people. So, I think this is the perfect job for me". "I would say, feel most committed to students and also small companies".	#2, E, KTO 2 #12, E, KTO 2	Opening-up to external relations	Expression of the need for relatedness
"I think [name of advisor] is a very powerful person. I really admire her, so I have a personal need do accomplish something that is okay for her".	#4, E, KTO 1	Teaming-up beyond work duties	
"When a researcher comes to me it is usually because he wants to create a spin-off company [...] and what I feel is that I can influence, I think I can improve his motivation, giving him or her all the skills, all the information to reach their goal". "I'm basically in love. I'm in love with the university because I started at the [name of the university], I obtained my [name of degree] there".	#2, E, KTO 2 #8, E, KTO 1	Sense of contributing to the public-good	
"[...] but it's a job that doesn't have a particularly procedural aspect. It's something that you have to create. You have to use flexibility, imagination; […] you have to put some of your own into it, in short, even when we are confronted at an international, European level". "[What] I am trying to do is to create initiatives and activities and attempt to focus on the creation of the opportunities of business".	#7, M, KTO 1 #4, E, KTO 1	Adopting an entrepreneurial behavior	Expression of the need for autonomy
"I would say that I do like a lot of the variety of content, that is a good opportunity to learn and to put yourself in every time in a sort of challenge, and it challenges you every time."	#6, E, KTO1	Maintaining updated expertise	Expression of the need for competence
"The job is such that every day you go to the office, and you will find at least three things that you don't know". "[…] a very interesting job, a job that also gives [one] the feeling of being on the frontier, of being the most, so to speak, the most evolved, the most advanced, the most up-to-date people in the university, that is, the least closed".	#1, M, KTO 1 #13, M, KTO 2	Being inspired by knowledge-transfer challenges	

* E=Employee; M=Manager

Table 45: *Representative quotes for university-level antecedents of the basic needs*

Representative quotes	**#No./EM*/org.**	**University-level antecedents (first-order codes)**	**Need relation (second-order code)**
"I really think that our current management has invested a lot in this area [TT]. This was part of their strategy from the beginning, I would say; so, they maybe thought it was important". "[…] limited to the technology transfer part, there are, as in all universities, the strategic objectives decided at the university's top management level and approved by the board of directors. And then there are the objectives that the director general assigns to each executive through a negotiation process. [...] our managerial objectives must be clearly inspired, they must be in line, they must be consequential to the strategic objectives of the university, and they must be implemented in practice [...]".	#1, M, KTO 1 #13, M, KTO 2	Contributing to social and economic development	Strategic plan to fulfill the need for relatedness
"I think we have a really good brand at the [university 1], and we are not at the right level. I mean, we could do it much better […]". "I think researchers feel that our work is not so useful because the results just have to jump to society. So, we should probably work on the perceived value, I think".	#4, E, KTO 1 #6, M, KTO 1	Enhancing overall knowledge-transfer perception	
"[…] we must necessarily do as the competition does, we cannot choose the staff we want, or, rather, the we are made to choose […] it is not always easy. [Name of another unit] instead chooses people by doing, it is always with public evidence, but it puts a notice of selection on its site, who responds, and then it does some interviews and chooses who you want in short. In this sense, [name of another unit] allows us to overcome some of these difficulties, these obstacles". "I cannot stand, for example, one of the things that I don't like from my job today is the badge".	#13, M, KTO 2 #4, E, KTO 1	Grounding on unconventional public-body regulations	Structural set-up for hybrid demand to fulfill the need for autonomy
"I try to take an approach that is not particularly hierarchical because in my opinion in the university there are not even the tools to have a hierarchical relationship, so it is much more functional". "[…] we have established small teams at the moment covering three areas, which are bio economy, engineering and health. […] covering the whole process […] developed a matrix organizational structure where the business development teams related to the different research areas connect with legal people in my team, connect with the team in terms of IP-protection or management of IP". Evidence in the organizational chart, see Figure 27.	#7, M, KTO 1 #1, M, KTO 1	Specialization of organizational units	✧ to fulfill indirectly the need for competence
"I can also tell you that when we are asking something, and they [university government] do listen to us. […] we can discuss our idea. So, I think that this is important, and this is good for the environment".	#3, M, KTO 2	Establishing direct contact with KTO management	✧ to fulfill indirectly the need for relatedness
"[...] the current governance, it seems to me, that it [technology transfer] certainly has a lot of importance, i.e., what I have perceived from the current governance is precisely that there is the ultimate example of having invented one of the roles within governance as well as [name of the scientific advisor]".	#7, M, KTO 1	Supporting scientifically KTO activities	Scientific support to fulfill the need for competence

* E=Employee; M=Manager/✧ Expression of an additional need

Table 46: *Representative quotes for university-level organizational (KTO) antecedents of the basic needs*

Representative quotes	#No./EM*/org.	Organizational antecedents (first-order codes)	Need relation (second order code
"I am able to talk for 5 minutes with any scientist because, for better or worse, I know what he does, […] I know what motivates him, I know what that discipline is […]". "And now we are like 90 companies. So, they are calling us because they would like to be part of our system and then to be part of the service so that we can give them despite [...]".	#13, M, KTO 2 #3, M, KTO 2	Taking advantage of rich relational opportunities	Hybrid team management to fulfill the need for relatedness
"The mind-set is 'commercial' – everyone has to 'catch contracts' and at the same time they are project managers of those projects". "Most of the colleagues of mine are people who are really open minded, curious".	#12, E, KTO 2 #14, M, KTO 1	Supporting an entrepreneurial team-spirit	
"I think I'm lucky because I have this relationship with bosses […] I completely share with them the vision and the values of the job. Also, with the governance at the moment and with our director of the division". "I would exchange a higher level of royalty when I can get a higher impact from a contract".	#8, E, KTO 1 #8, E, KTO 1	Managing by a public-good ideology	
"So we are very autonomous. Basically, I can set my own goals. Even though of course the goals are within a general framework of the office and the university. But I think that my job is very autonomous". "I would like more autonomy. I would like to achieve my goals in a sort of autonomy and not with the sort of oppression or a boss".	#8, E, KTO 1 #2, E, KTO 2	Providing clear and challenging goals	Goal setting to fulfill the need for autonomy and competence
"[...] with the patent, and what I feel is that I can influence, I think I can improve his motivation giving him or her all the skills, all the information to reach their goal". "And this gives me satisfaction; this gives me a lot of satisfaction: to know that I have contributed to bringing that thing. It's ok, first of all on the market, and then it's also good for society".	#2, E, KTO 2 #7, M, KTO 1	Relying on a system based on feedback	Skill maintenance to fulfill the need for competence
"The project in Argentina, I think is a sort of incentive. A personal incentive because I had the opportunity to go abroad […], to discover a new world […]".	#2, E, KTO 2	Taking advantage of multiple learning opportunities	

* E=Employee; M=Manager

One risk of the inductive approach is that the authors might lose their higher-level perspective because they identify too much with their subjects. For this reason, we decided to split the research team. Hence, two authors analyzed the cases, while a third author adopted the outsider's (or "devil's advocate") perspective in order to ascertain the accuracy of the theory produced (Eisenhardt, 1989; Gioia et al., 2013). This step was very important for assessing the internal validity of our theory.

After building our theory from the comparative analysis of KTO1, KTO2 and KTO3, we initiated step (b) with KTO4, which followed the same data analysis process explained above. Since we chose this unsuccessful case based on theoretical replication, we expected to confirm our theory by finding contrasting evidence to our model. The analysis of KTO4 again confirmed the positive and direct relationship between performance and intrinsic motivation (i.e., employees in KTO4 were characterized by high levels of demotivation), while confirming the absence of the organizational-level and university-level antecedents identified in step (a). Examples of first-order codes that were missing—and therefore threatened need satisfaction in KTO4—were: *adopting entrepreneurial behaviors, enhancing the overall knowledge-transfer perception, opening up to external relations, taking advantage of rich* *relational opportunities, supporting an entrepreneurial team spirit, specialization of organizational units* and *supporting scientifically KTO activities*.

5.4 Findings

The findings section is divided into three main parts. First, we wanted to ensure that our three cases truly reflected the direct positive relationship between performance and intrinsic motivation uncovered by previous literature (Cerasoli et al., 2014; Grant, 2008; Menges et al., 2017; Shin & Grant, 2019). In other words, we wanted to confirm that we were actually dealing with highly motivated employees (i.e., able to fulfill the three basic psychological needs), which was necessary for addressing our research question. In the second part of our findings, we identify the similarities among the three successful cases and define the antecedent contextual factors that satisfy the needs underlying KTO employees' motivation. Finally, we present the results from the comparative analysis between the three cases and KTO4, which represents the low-performing case. This section is intended to corroborate our model by providing contrasting evidence from low-motivation employees (i.e., from a low-performing KTO).

5.4.1 Part I – Intrinsic motivation of KTOs' employees

Speaking with the employees of our three high-performance KTOs, we observed that they were generally very satisfied with their current job, as expressed by statements such as, *"[what] I do is close to my ideal job, actually"* (interview #13, KTO 2), *"I'd say it satisfies me, it's certainly a job that fascinates me, it satisfies me"* (interview #7, KTO 1), or *"So, I think this is the perfect job for me"* (interview #2, KTO 2). We discovered that most of these KTOs' employees and managers – who lack extrinsic incentives, especially financial ones – are instead motivated by rewards that foster intrinsic motivation. Note the following salient statements of two interviewees:

> *"The people are not here for the money. […] Not that the money is rewarding – you don't get rich here, but everyone feels that you can influence the path […]"* (interview #12, KTO 2).
>
> *"Not so much because this is very small amount of money. So, it is not so interesting. I would prefer to have the possibility to do more specialization courses or education in this sector, which is paid by the university as an incentive"* (interview #5, KTO 2).

While the employees of these three KTOs displayed highly motivated behavior, we wanted to also show how they are able to fulfill the three specific needs – autonomy, competence and relatedness – that underlie intrinsic motivation. In the following sections, we will detail the patterns that materialized across the three KTOs.

5.4.1.1 Fulfillment of the need for relatedness

The need for relatedness describes the desire to connect with others and build meaningful relationships. Thus, people often show affection toward individuals or groups who help satisfy this need (Deci & Ryan, 2004). In addition, they feel comfortable in dependent relationships and are more likely to show prosocial behaviors (Reeve, 2014). Among our three KTOs, we found three first-order codes that illuminate how KTOs' employees can satisfy their need for relatedness: *teaming up beyond work duties*, *opening up to external relationships*, and *sense of contributing to the public good*.

For teaming up beyond work duties, we found that the employees of all KTOs appreciated the connection they made with the internal team, which included their colleagues and superiors. In particular, they emphasized colleagues who shared their motivational attitude. One of them reported the following:

"I like the fact that I am involved with a good team. And it's like this because I have very motivated, young, colleagues" (interview #3, KTO 2).

The superior's role is often described as inspirational and especially motivating, particularly if it is combined with trusting relationships:

"What I like the most is that I have the trust of [name of superior] who is my boss and also I think of [name of department head] who is [name of superior] boss […]. They listen to me a lot, and this is very important for me" (interview #4, KTO 1).

These aspects make it possible to establish relationships that go beyond issues that are strictly related to the job and extend to leisure activities. An employee in KTO3 stated the following:

"*We meet quite regularly after working hours for a drink or during the weekend for pizza […] you know, this is very important to increase cohesion at work and build a team spirit that is based on real collaboration and synergy*" (interview #10, KTO 3).

Furthermore, we found that KTO managers and employees make use of a wide range of actors to experience social connections far beyond the core KTO team (*opening up to external relationships*). This is partly due to the inherent job description as connectors or translators of the scientific and industry culture. Thus, they build relationships with researchers and students as well as company employees, as noted by one employee in KTO 1:

"I'm very glad to spend time and interact with very intelligent and interesting people. […] You can be a sort of bridge to different cultures. The academic and the industrial cultures. […] I like the social relationships that you can build thanks to this job because I interact a lot with the research but also a lot with companies so with different subjects, actors and stakeholders of the industrial world. I think this a sort of privilege, and I like to be part of the relationships" (interview #8, KTO 1).

KTO employees actually identify with the associations and communities of knowledge transfer at the national and European levels depending on the KTO's specific target groups and networks (e.g., as indicated by memberships in different associations and networks – such as Netval and ASTP Proton - A World of Knowledge Transfer – in the curricula vitae and LinkedIn profiles of our interviewees). The employees highlighted the opportunity to build relations in European projects. An important community mentioned by all KTOs is the Italian KTO network (NETVAL). As one of them said,

"Our job involves the same things. We… I feel like I am part of a team, a big team, and I feel well in this team. [...] There is a sort of big team, big Italian team [NETVAL]" (interview #2, KTO 2).

Third, we found a s*ense of contributing to the public good.* The employees across all three KTOs reported that they enjoyed helping *"professors and post-docs [to find] a way out of a golden cage"* (interview #12, KTO 2). Employees find motivation by serving the university and the local economy, as well as the potential customers of the products developed from the licensed technologies. What stands out is many employees' high identification with the university and their desire to actively be a part of it. One employee stated the following:

"*I'm a big fan of this university and was really happy to contribute and work for the university"* (interview #8, KTO 1).

In many cases, employees reported that they studied at the university. Some even reported that they held a bachelor's, master's and PhD degree from the university, and they intentionally wanted to keep as many contacts as possible from the university. Hence, we argue that taking an active part in the public good fulfills the need for relatedness and is thus part of intrinsic motivation. In sum, we observe that creating bonds within and beyond the KTO team, in tandem with serving the public good, supports the need for relatedness.

5.4.1.2 Fulfillment of the need for autonomy

People perceive a sense of autonomy when they feel that they are in charge of the activities in their lives (Legault, 2016). Autonomous individuals act willingly (a sense of volition) according to their beliefs (perceived locus of causality) and are able to make decisions among desired alternatives (perceived choice) (Reeve, 2014). KTO managers and employees expressed their need for autonomy by *adopting entrepreneurial behaviors.* The managers reported that they were highly motivated by the opportunity to shape their organization and their own initiatives. Many of the KTO managers were senior figures who played key roles in defining the organizational processes and activities. One manager reported the following:

> "*So, it [the foundation of the unit] was kind of really a startup dealing with innovation, dealing with new things. And feeling that the project was mine because we were, really, three, four people. So, we could shape it as we liked it"* (interview #14, KTO 2).

Similarly, the employees in all KTOs reported a sense of freedom in choosing activities and topics according to their interests and competences. They expressed feeling self-directed since they could draw on their own interests when forming new initiatives. Knowledge transfer is not based on routines per se; however, the people working in KTOs highly valued the opportunity to set their own goals and be recognized for their individual impact. In particular, an employee of KTO3 commented in the following way:

> "*It's now many years that I have worked in this context, and one of the characteristics that I like most is that of being part of a team but, at the same time, having enough freedom to set the direction and have an impact on final goals. I mean […] there is a path that we share, but then it's up to me to come up with new proposals, ideas, etcetera. You know, you can reach the goal anyway, but how you reach it makes a huge difference… that's your impact!"* (interview #9, KTO 3).

The importance of entrepreneurial behavior for KTO employees also appeared in situations where the unit was facing a shortage of human resources. In such cases, employees mostly felt driven by the pressure to accomplish specific tasks rather than inject creativity into their job. Nonetheless, individuals still distinctively valued the ability to see and influence the overall organizational process. In other words, they focused on the consequences of their work. One manager stated the following:

> *"I think that the technology transfer is a good opportunity to see the effects of the research and of the education inside society, […] you're quite lucky to see the last step of the research and of the education within that society as well as the market and the company enterprises"* (interview #6, KTO 1).

It follows that the entrepreneurial attitude expresses the need for autonomy.

5.4.1.3 Fulfillment of the need for competence

The need for competence refers to the desire for feelings of mastery and the innate tendency to employ one's full potential (Deci & Ryan, 2000; Legault, 2017). People strive for "just-manageable" challenges in relation to their talent and skills that are neither too simple nor too complex (Legault, 2017). We found two first-order codes related to how the KTO employees satisfy their need for competence: *being inspired by knowledge-transfer challenges* and *maintaining updated expertise*. The first code is driven by employees' fascination with the variety of challenges implied by knowledge transfer, which lead to rich learning opportunities. Across all three KTOs, this aspect mainly involves the pleasure of dealing with demanding problems that require a certain degree of obstinacy in order to find solutions that can satisfy most parties. This is what has been described as "*the capability of doing common things uncommonly well*" (interview #10, KTO 3). One employee described the high individuality of each case as exciting and challenging:

> *"I would say that I do like a lot the variety of content, that is a good opportunity to learn and to put yourself in at every time in a sort of challenge, and it challenges you every time*" (interview #6, KTO 1).

Being inspired by knowledge-transfer challenges is also explained by the pure interest in deepening one's expertise on knowledge and technology transfer topics. The individual need for learning opportunities goes beyond the classic training sessions to include training experiences at the international level and the possibility of pursuing more research-driven training options (e.g., conducting a doctoral thesis on technology transfer) that allow for a richer knowledge base. This is exemplified in the following statement:

> *"[...] I learn from European colleagues and see how it works in other context, and my boss is really supportive so that for me is a reward that I have the opportunity to learn, to take on new challenges that are still related to tech. transfer*" (interview #1, KTO 1).

The second code – *maintaining updated expertise* – is better explained by employees' desire to remain constantly aware of different partners' daily activities. Although each employee strives to be a specialist in a specific domain, they still gain a sense of affection for the different topics they encounter through their work. Thus, the engineer may become enamored with the technologies developed by the scientists and seek to protect and/or license them in the best way possible (e.g., *"I'm involved in projects that will make me smart"* (interview #3, KTO 2)); the lawyer may be more generally enthusiastic about all the legal aspects related to patenting, licensing and collaboration (e.g., *"I like all the legal aspects of this office because my job is really dealing with contracts all the time, and I am a legal so I like contracts"* (interview #5, KTO 2)); and the business person may appreciate opportunities to focus on innovation and networking (e.g., *"I am very interested in innovation and design thinking and want to learn more about that"* (interview #12, KTO 2)). To conclude, employees who are *inspired by knowledge-transfer challenges* and *maintain updated expertise* express the need for competence.

5.4.2 Part II – University-level antecedents of psychological needs fulfilment

Having discussed how KTO personnel satisfy the three basic needs to reach intrinsic motivation, we now turn to the antecedents – university-level and organizational-level (KTO) – that enable the fulfilment of those needs. In the next two subsections, we will consider the specific antecedents and use our three cases to describe how university government (university-level antecedents) and KTO managers (organizational-level antecedents) can create conditions that satisfy employees' basic needs and foster intrinsic motivation. Beyond identifying the different antecedents, we also explain the relationship between specific antecedents and their satisfied need.

5.4.2.1 University-level antecedents

The university-level antecedents address the three basic needs on a rather abstract level that predominantly encompasses structural aspects. These include three different dimensions that represent our second-order codes: *strategic plan*, *structural set-up for hybrid demands*, and *scientific support.* Each of these dimensions works to address one or more of the psychological needs through specific mechanisms (i.e., our first-order codes) that we present in the following sections (see also Table 45).

Strategic plan to fulfill the need for relatedness

The first university-level antecedent includes two main actions: *contributing to social and economic development* and *enhancing the overall perception of knowledge-transfer.* The university's strategic formulation of the third mission establishes not only the objectives, but also the quantity and nature of the resources that will be allocated for knowledge and technology transfer. It is important that the strategic plan outlines the contribution of knowledge transfer activities to the region's social and economic development (i.e., *contributing to social and economic development*). As an example, University 3 addresses the notion of contributing to the public good and establishing external relationships in the following way:

> *"[…] the transfer and exploitation of knowledge in the context of the economic and cultural development of the territories has to be in compliance with the principles of environmental and social sustainability [...] In doing that, we have to pay careful attention to regional needs, while establishing close relations with public and private institutions"* (strategy of University 3).

As another example, the strategic plan of University 2 clearly states that the KTO must be a participant in at least ten European projects per year that involve public entities and ventures. On this point, one employee said:

> *"[…] the activities we deal with need to have a clear impact on our territory, at least! We have to go continuously outside looking for collaboration and new relationships that could turn to potential projects. We have to sell our job and speak, speak, and speak with ne people* […] *That's a big challenge but the best opportunity we have to enlarge our network*" (interview #12, KTO 2).

In setting a strategic direction, the university also needs to *enhance overall knowledge-transfer perception* among researchers, students and external parties. One informant stated the following:

> *"I think that if governance focuses on technology transfer as an item that is important for the organization itself, for example, the KTO performs a value that could be understood both by the researchers and by us [...] that facilitates us to work with researchers and students as well, [...] that allows the creation of a culture about technology transfer and [provides a] direction where to move"* (interview #6, KTO 1).

The university government can enhance this perception by establishing a technology-transfer-related university "brand" and bolstering its reputation among researchers. For this purpose, University 1 created a technology transfer network – an internal scientist network – that serves as an open community for entrepreneurship. Here, researchers with technology transfer experience can exchange their ideas, challenges, and suggestions, which helps to spread a technology transfer image from within. First, this process helps to create contacts and relationships among people who were previously unconnected; second, it stimulates curiosity in people with less experience and pushes them to connect with colleagues who have the information they need. KTOs can leverage these networks to communicate their services, promote success stories, advertise events, and generally broaden public awareness about knowledge transfer issues. By fostering a positive perception of technology transfer, the university directly addresses the need for relatedness in three main ways. First, by showing appreciation for KTO employees, it enhances their loyalty to the university and cultivates their desire to contribute to the public good. Second, the different activities undertaken help to widen the network around knowledge transfer activities (i.e., to include external academics, experts). Third, the diffusion of a positive perception of technology transfer helps KTO employees to bond with researchers and thereby address the need for relatedness. In short, the definition of a clear and specific strategic plan can help fulfill the need for relatedness.

Structural set-up for hybrid demands to fulfill the need for autonomy

The *structural set-up for hybrid demands* includes three specific aspects: *specialization of organizational units, grounding on unconventional public-body regulations,* and *establishing direct contact with KTO management*.

KTOs typically operate through a 'matrix structure' that defines the specialized legal form of their unit(s). The matrix structure unfolds along two dimensions: a) the technology transfer area (e.g., intellectual property (IP) office, licence/valorization unit, spin-off unit, incubator) and b) the scientific field or industry sector. In addition, separation according to target groups is possible, e.g., students and researchers. At University 1, for example, the KTO has a matrix structure with three internal units: IP protection, IP valorization, and spin-off. Thus, within each unit, employees specialize in different scientific fields such as the 'bioeconomy'. In this way, different units oversee different topics and initiate their associated activities and processes. For example, employees within the IP protection unit can exchange legal issues within the unit but discuss field issues across units. This type of structure optimizes the allocation of topics and tasks while reducing the risk of being overburdened by deadlines, which then enhances employees' autonomy. In this way, the matrix structure also indirectly affects the need for competence by allowing employees to deepen their understanding of certain issues and apply their core competencies to certain tasks. In legal terms, the versatility of the matrix structure allows units to be designed in a way that maximizes their functioning. For instance, the spinoff and valorization units usually benefit from having external ownership, which facilitates better and faster interactions with external parties (e.g., start-ups, institutions, companies). We found that all three KTOs were affiliated with an external start-up incubator. Moreover, semiprivate ownership allows those units to find a better fit with their main stakeholders and act in a more autonomous way compared to standard public bodies. For example, University 2 established the valorization unit as a university foundation and tasked its nearly 20 employees with *"[... taking] part in the scientific excellence of [University 2] by involving professors, researchers, students, companies and public institutions in technology transfer activities and postgraduate education aimed at social and economic development*" (mission of the foundation in KTO 2). Thanks to the unit's greater procedural autonomy, the managers of KTO 2 have more control over recruiting and the definition of incentive systems. By contrast, universities' normal recruitment process generally involves strict rules that downplay the importance of a person-job fit. This specialization also has important implications for the allocation of tangible resources (e.g., money). KTOs with more resources had more capacity to develop services in an independent way (satisfying the need for autonomy), and more opportunity to learn from trial and error (indirectly satisfying the need for competence).

The other university-level antecedent, i.e., *grounding on unconventional public-body regulations*, relates to two main factors: (a) internal and external recruitment processes and (b) the adaptation of bureaucratic procedures. With respect to the first issue, one interviewee stated the following:

> "*[…] years ago, we had a sort of reorganization of our central administration, and so I was just taken and put in this new office. […] Things have changed a lot in the last years, and we now have a strong influence on those decisions"* (interview #5, KTO 2).

The need for autonomy also relates to the second factor, which refers to the need to overcome bureaucratic hurdles (i.e., 'red tape'). As one interviewee put it:

> *"[…] we had to ask all the time for permission because there is a lot of political influence in our work. I mean, I had to ask for permission to send an e-mail. It was impossible to work like this. […] of course, we work within an organization that has specific functioning rules, but as far as we operate within them, we need to have freedom. After a strong battle, we are now there"* (interview #4, KTO 1).

Regarding the last antecedent of autonomy (i.e., *establishing direct contact with KTO management*), we found that KTO employees highlighted the importance of having trustful relationships with the head of the KTO and more generally with the university government. A manager of one KTO unit stated the following:

> *"I can also tell you that when we ask for something, they [the university government] do listen to us"* (interview #3, KTO 2).

Having a direct tie with the university level enables a continuous and iterative discussion about the KTO's objectives and services. To enable strong ties, all universities ensured that the KTO was under a unit directly led by the university government. Yet, in university 1, for example, the head of the department that includes the KTO is also responsible for nine other units. Strong ties and iterative communication allow KTO managers to obtain quick feedback regarding their own ideas, as well as discuss potential structural changes for improving KTO operation. Accordingly, KTO managers have a higher perceived locus of causality, which is essential for autonomy. While this aspect has a direct impact on KTO employees' degree of autonomy, it also indirectly satisfies the need for relatedness by allowing KTO managers to build meaningful, reciprocal relationships with the university government. In short, the presence of strong, direct ties between university governance and KTO management is beneficial for satisfying both the need for autonomy and, indirectly, the need for relatedness.

Scientific support to fulfill the need for competence

The last university-level antecedent we found is *scientifically supporting KTO activities*, which is extremely important to fulfilling the need for competence. University 1, for example, founded an internal technology transfer network that includes all academics whose research focuses on technology transfer and innovation issues, alongside other relevant stakeholders in that domain (e.g., consultants, entrepreneurs). This allows KTO managers and employees, academics, and other interested parties to jointly discuss knowledge-transfer ideas and topics, and thereby become more informed on various topics. Whereas stakeholders who are external to the KTO may obtain a better perception of the KTO's needs and processes, KTO employees can implement the latest scientific insights and acquire additional competences in order to better support academics. For instance, KTO3 organized some hackathons dealing with emerging entrepreneurial and societal issues (i.e., the impact of COVID on firms' innovation processes; the impact of new technological solutions on elderly people in the Covid era) where the objective was to find solutions that involved transferring knowledge between external experts and academics. These initiatives represented a great opportunity for KTO employees to improve their knowledge of scientific domains and new methodological approaches. In short, having the scientific support encourages KTO employees to maintain and update their expertise, and thereby satisfies their need for competence.

5.4.2.2 Organizational (KTO) antecedents

Beyond the university-level antecedents, which mainly focus on the structural and strategic aspects, we also found some university-level organizational (KTO) antecedents that essentially deal with managerial issues (see Table 46). In particular, *hybrid team management* supports the need for relatedness, *goal setting* supports the need for autonomy and competence, and *skill maintenance* supports the need for competence.

Hybrid team management to fulfill the need for relatedness

As hybrid organizations engaging with academic researchers and industrial partners, KTOs must find the best strategies to help those stakeholders work together effectively. This proved to be an important aspect for most of the interviewees, who explicitly said that their job within a public university is indeed very different from other public-organization jobs, specifically in terms of the opportunity to make contact and interact with many people, even those belonging to different sectors. Accordingly, one important antecedent – of the need for relatedness – proved to be the ability of KTO managers to *take advantage of rich relational opportunities*. This specific antecedent seems to be inherent to KTO employees' job, but it still must be properly stimulated. One strategy that the KTO managers used to reach that objective was to actively support employees in establishing new relationships with different actors, even across the core target group of researchers and companies. For example, managers in KTO 1 and 3 assigned employees to European and international projects, while one manager in KTO 1 additionally provided memberships in inter/national networks (such as ASTP – A World of Knowledge Transfer). One manager stated the following:

> *"So, because I think that we literally need to build communications, maybe even stronger communications between each other [the KTOs in Italy], as they try to help each other. So, in order to exchange the best practice in order to grow […]"* (interview #3, KTO 2).

A second strategy was to reinforce existing relationships with the KTOs' main stakeholders (i.e., researchers and ventures). In this respect, there is strategic value in involving local industry and becoming more familiar with sectoral peculiarities so as to establish the right connections between academics and enterprises. With this objective in mind, the managers of all KTOs organized periodical events: follow-up meetings on technology transfer matters, as well as more general initiatives where students were also involved (e.g., with job interviews). The format of these events was increasingly appreciated within the university: Some departments in University 1 even organized the yearly department meeting – with approximately two hundred researchers, companies, and other institutions – around the topic of the 'third mission'. The many related sessions not only increased participants' awareness of knowledge transfer, but also allowed them to build strong relationships with one another. In sum, addressing the motive to open-up to external relations satisfies the need for relatedness.

The second organizational antecedent we found is *managing by a public-good ideology*. Our interviews showed that the climate within the KTO is fundamental to cultivating shared values among employees. One manager stated the following:

> *"What instruments do we have? I would say the main is the climate; being able to create a good climate inside the office"* (interview #6, KTO 1).

The KTO employees reported that they highly appreciated the alignment of their activities with public values. Thus, KTO managers had to manage the team by fostering shared public values that aligned with organizational strategy (e.g., serving the local economy; fostering sustainable and social spin-off creation). This was considered an important skill among the KTO managers because it allowed them to create common ideals that fostered affection and prosocial behavior among colleagues. Some informants even used the word 'family' to describe their team. In KTO 1, the management of the public-good ideology was also observable in decision-making at the organizational level, as one informant summarized:

> *"I would exchange a higher level of royalty when I can get a higher impact from a contract"* (interview #8, KTO 1).

To conclude, managing by public values addresses the need for relatedness in terms of two previously discussed motives: the affection for colleagues beyond work duties and the sense of contributing to the public good.

Finally, we found *supporting an entrepreneurial team spirit* to be an important antecedent for employees' needs satisfaction. By entrepreneurial spirit, we refer to a managerial attitude that supports flexible and creative methods and iterative learning. To build an effective organizational system such as this, it was absolutely essential to invest in trusting relationships between managers and employees. Accordingly, KTO managers seeking to transform KTOs into more entrepreneurial organizations should incorporate practices such as periodic brainstorming activities and focus groups on specific issues. This commitment to practices intended to foster greater freedom of expression and a more creative mindset was absolutely fundamental in the core three KTOs for enhancing team cohesiveness. In that regard, one interviewee in KTO 3 reported the following:

> *"I'm a social animal, and when I started this job, I was quite terrified of the idea of sticking to the boring routine and demotivating rules of a public organization. Surprisingly, I found an enlightened person* [the manager] *who has been able to create a stimulating and close team thanks to her business approach and practices"* (interview #11, KTO 3).

Goal setting to fulfill the need for autonomy and competence

Providing clear and challenging goals is an organizational antecedent that satisfies both the need for autonomy and competence. In particular, the definition of clear and challenging goals represents a fundamental managerial step to fostering employees' motivation in their own work. In this respect, we found that our KTOs' managerial practices involved helping their employees set their own optimal goals and providing the proper stimuli to build a constructive and stimulating work environment. Managers at all three KTOs supported their employees in translating the university's abstract strategic objectives into individual-level objectives. These individual-level objectives prevented confusion and frustration. An employee in KTO 3 reported the following:

> *"It is really important to be clear about the outcomes expected of our activities [...], I mean, they have to be clearly stated and requested. I always say to my boss that I prefer to be scolded for my failures – but knowing in advance what she expects from me – instead of being commended for something that I reach by chance [...]. It is important to properly value my skills but also to be autonomous in setting the direction, without asking every time: is this okay, is this what you expected or not?"* (Interview #9, KTO 3).

Similarly, when we asked the employees at KTO2 if they had precise technology-transfer-related goals, the answers were as follows:

> *"I would like to be a specialist on the kind of process called design thinking"* (interview #12, KTO 2) or

> *"Yes, of course. I am more focused on the first part of the innovation process, let's say the funnel in the first part, [...] and also particular activities in order to arrive at a prototype"* (interview #4, KTO 1).

Hence, establishing the frame and aligning individual goal development with the KTO's overall objectives is an important managerial strategy or enabling and enhancing employees' autonomy and competence. This kind of objective gives employees the freedom to adopt an entrepreneurial behavior and better co-develop own objectives. At the same time, it enables employees to set objectives that expand their expertise. In short, KTO managers that adopt a goal-setting approach can support employees' intrinsic motivation.

Skill maintenance to fulfill the need for competence

The last organizational antecedent that we observed encompasses two organizational activities: *relying on a system based on feedback* and *taking advantage of multiple learning opportunities*. Both are considered important in fulfilling the need for competence by preserving employees' skills. The first aspect refers to the managerial ability to provide periodic feedback to employees on their activities. This allows employees to implement a trial-and-error learning process that reinforces individual competence on specific tasks. The feedback comes from the managers but can even come from the task itself in terms of successful or unsuccessful results on knowledge transfer activities between academics and entrepreneurs. In KTO1, the manager of the IP protection unit used periodic group meetings to report on the processes and strategies used in successful licensing contracts, with the objective of sharing best practices with all the employees and, in that way, increasing their knowledge on the topic.

The second organizational antecedent refers to the promotion of international experience, research opportunities, and the diversification of project portfolios. These efforts inspire new knowledge-transfer channels that nurture the motive to work. Additionally, as with any learning opportunity, the purpose is to enhance employees' skills and abilities on specific topics. This is a great incentive, as stated by one manager:

> *"We cannot pay people more, but we can offer them opportunities in terms of training if they are interested in growing their competences. This is something that I usually offer and support in order to always keep employees updated on the most recent procedures; you know, our sector changes very quickly"* (interview #1, KTO 1).

One employee even had the opportunity to combine the job at the KTO with a PhD in technology transfer. In summary, KTO managers can satisfy employees' need for competence by offering them continuous feedback and rich learning opportunities.

5.4.3 Part III – Comparative analysis with KTO4

Compared to KTO1, KTO2 and KTO3, the interviews with the employees of KTO4 illuminated a sense of frustration and weak motivation. For instance, several employees reported that they continued with the job due to extrinsic motives (i.e., they were rather close to retirement or personally preferred the job security offered by a public organization). Compounding matters, KTO4 had experienced a high job-turnover rate in the preceding five years, and the resulting struggles affected employees' needs satisfaction. The main challenges have been: 1) some changes in the university government; 2) cuts to the KTO's financial resources, which has reduced the number of KTO employees and diminished the KTO's standing in the community; and 3) the lack of an explicit "third mission" strategy from the university government. By comparing KTO1, KTO2 and KTO3 with KTO4, we were able to better understand the relationship between basic needs satisfaction (i.e., intrinsic motivation) and university-level antecedents of that satisfaction. More specifically, we were able to see what happens to intrinsic motivation if certain antecedents are missing. Notably, the analysis of KTO4 did not reveal any new antecedents.

5.4.3.1 Needs fulfillment threatened in KTO4

Employees in KTO4 reported that they enjoy maintaining the existing relationships (i.e., internal and external), but they did not have time to establish new relationships. The manager of the KTO explicitly said that she "*would like to invest in new projects with new ventures and start-ups* […] *and I would also love to invest my time in getting in touch with new people that might be interested in knowing what we do. Instead, I'm always closed in my office dealing with those repetitive and routinary tasks that we have to carry out*" (interview #18, KTO4). It was evident that the employees of KTO4 faced restrictions regarding the need for relatedness.

Likewise, KTO4 employees did not claim to have the autonomy to create and implement initiatives according to their own ideas. Indeed, due to the lack of human and financial resources, they had to focus on the legal and administrative sides of knowledge transfer activities, and could not pursue more exciting activities. Given their meager opportunities for adopting entrepreneurial behaviors, KTO4 employees were threatened with a diminished need for autonomy.

Finally, the interviewees made clear that the university government perceived the KTO like any other administrative office. However, "*a different role should be recognized to our office, because it is not like dealing with pay slips* […] *Things here are changing very fast, if we lack appropriate and updated skills and knowledge, does not make any sense to even say that we are doing knowledge transfer*" (interview #16, KTO4). Without the opportunity to expand their skills and knowledge, the KTO4 employees experienced a threat to their need for competence.

5.4.3.2 KTO4: evidence on university-level antecedents

Having reaffirmed the positive relationship between performance and intrinsic motivation (i.e., that poor performance is related to low-motivation employees), we now compare the university-level antecedents found in the analysis of KTO1, KTO2 and KTO3 with evidence from KTO4.

Whereas the first three KTOs invested considerable effort in defining a strategic plan for knowledge transfer activities, KTO4 did not. The reduction of the KTO's size—in terms of both available budget and number of employees—signalled the KTO's marginal role within the university. Without this legitimacy, the employees could not easily build stable relationships with researchers and establish the relevance of knowledge transfer. The external image also suffered because KTO employees lacked the time and resources to advertise the university's knowledge and develop industry relationships. As a consequence, the unit could not invest in activities that would support the region's social and economic development, and thus avoided even participating in such projects. In short, the evidence from KTO4 affirms the relationship between having a strategic plan (for both internal and external knowledge-transfer) and satisfying the need for relatedness.

Similarly, KTO4 did not exhibit the *structural set-up for hybrid demands* that characterized the other three KTOs. More specifically, the functioning of KTO4 more closely aligned with a traditional administrative office within a public-sector organization (i.e., based on fixed and strict rules and processes). University 4 did not create workarounds for the KTO unit in order to grant it greater flexibility and autonomy in organizational activities. In addition, the manager of the office said:

> *"With respect to most KTOs, we do not have an external spin-off unit, and neither a division of the KTOs in sub-units specialized in different matters. All of us deal with every kind of knowledge transfer issue"* (interview #18, KTO4).

KTO4 consists of a single unit without specializations. Hence, KTO4's employees must supervise the legal and commercial issues across all disciplines. Employees are therefore driven by tasks and feel little autonomy. In addition, the KTO manager struggled to build a direct relationship with university governance due to continuous personnel changes and a general lack of awareness about knowledge transfer issues on the governance side. These issues serve to marginalize the KTO's role within the university (thereby threatening the need for relatedness), as well as reduce the amount of support for implementing new ideas and solutions (thereby threatening the need for autonomy). As one employee reported:

> *"Sometimes it is convenient to remain in the shade* […] *Very often, it happens that we do not see anyone knocking to our door for days, anyone is really interested in what we do. On the positive side, anyone asks you doing more than what we always do, more or less always in the same way since years"* (interview #17, KTO4).

In sum, these findings confirm that a structural set-up is crucial to satisfying KTO employees' need for autonomy.

5.4.3.3 KTO4: evidence on organizational antecedents

Turning now to the organizational antecedents, we found that KTO4 lacked all the mechanisms put in place by the other three KTOs. Employees in KTO4 lacked the time and opportunity to build new relationships, forcing them to rely exclusively on researchers' personal networks to reach external partners for potential projects. Further, KTO4 lacked a strategy for appealing to different target groups, and thus could not provide the rich relational opportunities that are important for satisfying employees' need for relatedness. Moreover, the KTO manager reported that she was unable to implement and support an entrepreneurial spirit in her office, since the unit's vast amount of administrative and legal tasks consumed most of the employees' time. This factor also impeded employees' ability to satisfy their need for relatedness.

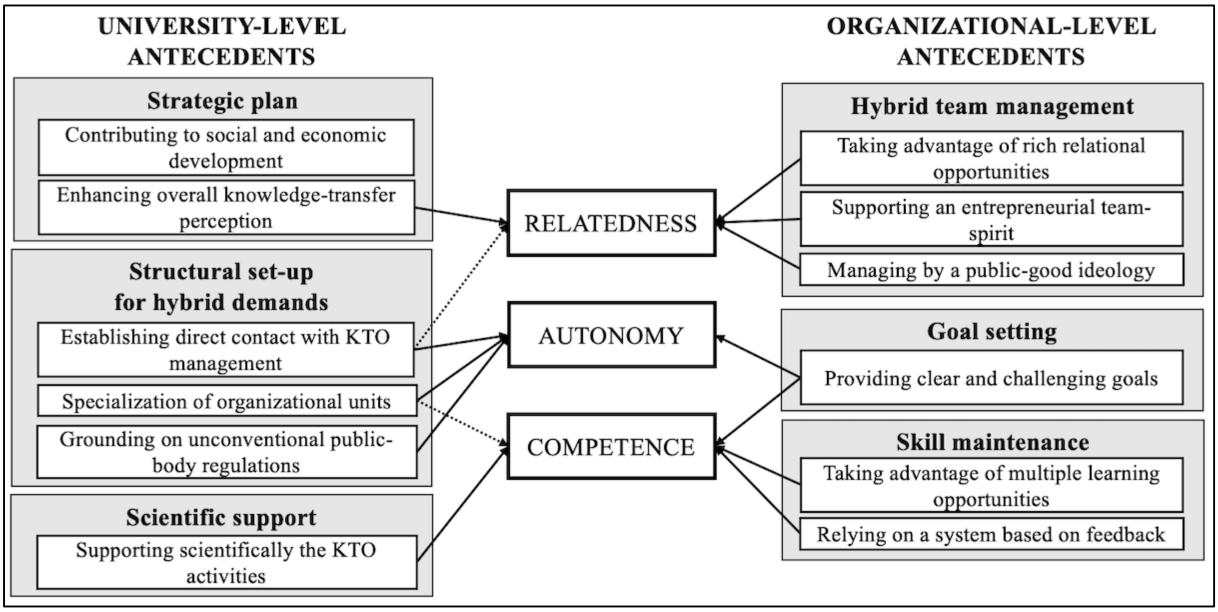
The same was true for efforts to fulfill the need for autonomy. University 4 delineated goals for all administrative units, including the KTO, but the goals were mainly outcome-related and did not offer much operational freedom.

Finally, the employees in KTO4 were not able to extend their skills and take advantage of learning opportunities to improve their expertise and update their knowledge on fast-changing topics. The manager even stated that although the KTO won a European project, they had to refuse it because no employees had the time to work on the project. This experience caused frustration internally and hindered the satisfaction of the need for competence.

5.4.4 Final model

Ultimately, we found that university governments and managers in KTOs employ different actions to satisfy KTO employees' psychological needs. Figure 28 provides a visual representation of the university-level and organizational-level antecedents for basic needs satisfaction in KTOs.

Figure 28: *Model of KTO employees' psychological needs satisfaction through university-level and organizational-level antecedents*



*Dashed line represents indirect effect.

On the university side, university governance primarily establishes the strategic (and structural) context for needs satisfaction; on the organizational side, KTO managers can adopt diverse managerial strategies to fulfill employees' basic needs. By establishing the strategic context, universities can actively steer the direction of technology transfer activities and foster the perception of technology transfer among researchers, KTO personnel and other external stakeholders. Although university-level practices affect the satisfaction of all three psychological needs, they seem to be particularly impactful on the need for autonomy. Indeed, without a proper organizational structure and appropriate rules, KTOs risk operating under the same conditions as other public organizations, which usually do not provide the necessary autonomy in relation to decision-making or recruiting. However, KTOs are not well tailored for standard public procedures due to having to accommodate competing interests (i.e., university and industry) through streamlined processes. Accordingly, university-level arrangements that account for that risk (e.g., *grounding on unconventional public-body regulations* and *specialization of organizational units*, which involve structural diversity in terms of a matrix structure and different legal forms for different units) allow KTOs to operate at full speed without sacrificing their autonomy.

While the need for autonomy can be formally addressed at the strategic and structural level, the needs for relatedness and competence are better addressed by managerial practices that are defined and adopted within the KTO itself. In particular, KTO employees work with various actors who follow different logics. On the one hand, this aspect may represent a rich relational opportunity; on the other hand, it may foster the perception that different stakeholders are behaving unfairly. Accordingly, KTOs benefit from a managerial approach that capitalizes on hybrid skills. For instance, managerial strategies that foster constant learning – both within and outside the KTO – are recognized as a successful way to continually update employees' skills and thereby satisfy the need for competence. Therefore, it is important that managers have the ability to jointly address relational and competence issues.

5.5 Discussion and conclusions

5.5.1 Theoretical contributions

This study sheds light on how employees' motivation can be supported in KTOs. More specifically, we identify the specific university- and organizational-level factors that allow the satisfaction of the three psychological needs at the heart of intrinsic motivation. More than that, we find that whereas organizational-level antecedents (i.e., *hybrid team management*, *goal setting*, and *skill maintenance*) are more important to satisfy the needs for relatedness and competence, the university-level antecedents (i.e., *strategic plan*, *structural set-up for hybrid demands*, and *scientific support*) are key for fulfilling the need for autonomy. Thus, we show that – in addition to macro-level aspects (e.g., for example look at Rasmussen & Wright, 2015) – also micro-level dimensions (i.e., intrinsic motivation) are important to allow for more effective technology transfer and knowledge share processes.

In doing so, our study offers some theoretical contributions, as well as some managerial and policy implications. First, we shed light on the overlooked relationship between intrinsic motivation and performance in KTOs. This study addresses this gap by closely considering the organizational behavior dynamics within KTOs, with a specific emphasis on KTO personnel's intrinsic motivation. With their experience, networks, and abilities, KTO employees represent the heart of knowledge transfer at public universities and research institutions. Indeed, the quality and engagement of such employees will strongly determine whether frontier knowledge and research results are successfully translated into commercial ventures. In this sense, understanding these individuals' intrinsic motivation is critical to bolstering KTOs' contribution to economic, technological, social, cultural and environmental outcomes.

Second, we contribute to the stream of literature concerned with the performance of organizational units within public entities that are characterized by constraints, procedural rigidity, regulations and an absence of incentives, and yet face complex tasks that include managing the tensions between different logics (academic versus market), goals (academic versus managerial), stakeholders (e.g., scientists, university managers, and companies), and internal priorities (e.g., requests from different departments and structures). The tensions and complexities that define bridging institutions like KTOs can dampen individual motivation, especially when coupled with a lack of incentives and a demand for procedural transparency and equity. These settings are not typically designed to fulfill employees' psychological needs and thereby generate intrinsic motivation; thus, there is great value in understanding the antecedents of employees' motivation and uncovering ways to maintain and bolster it.

Third, in line with SDT, we confirmed the importance of contextual factors for intrinsic motivation. SDT is specifically framed in terms of environmental factors that facilitate or undermine intrinsic motivation. This language reflects the assumption that intrinsic motivation arises when individuals experience conditions that galvanize its expression (Ryan & Deci, 2000). Accordingly, we provide evidence on the specific contextual antecedents that catalyze employees' intrinsic motivation in KTOs. Specifically, we show that the need for autonomy is mainly supported by university-level factors in KTOs, while the needs for competence and relatedness are satisfied by organizational practices and mechanisms.

Given the fact that our insights highlight the establishment of specific organizational conditions that enhance employees' intrinsic motivation and eventually performance, future research could use the literature on contextual ambidexterity (Gibson & Birkinshaw, 2004) to further investigate the topic.

5.5.2 Managerial implications

Our findings also have implications for effective KTO management. KTO employees face an inherent level of complexity due to bridging different cultures and managing tensions within public organizations. Concurrently, they must comply with public organizational norms, rules, and restrictions, which can conflict with the fulfillment of psychological needs. However, employees' intrinsic motivation is a crucial determinant of their behavior, and by extension, the KTO's performance—and thus, uncovering ways to support said motivation has apparent value.

In many public organizations, employees are not selected for a specific task within a specific unit in the organization, as they are in the private sector. Selection procedures in the public domain are often subject to public regulations and financial restrictions, with the goal of identifying candidates with administrative and management competencies that are applicable regardless of the assigned tasks (which can vary over the years). When selecting newcomers within public organizations – and specifically within KTOs – it is important to consider employees' motivational profile and ensure that it properly suits their needs, the work context, and the accompanying tasks. Further, we are aware that many public organizations rotate managers in order to expose them to different domains and encourage more transversal views of processes that span the entire organization. However, in some settings like KTOs—where employees' prior knowledge, expertise and relations are important for achieving results whose benefits may only materialize in the long-run—managers should pay close attention to the contextual factors that can satisfy the needs that underlie motivation.

Beyond the issue of 'fit creation', there is also the often-neglected issue of skill 'maintenance'. On this point, organizations should strive to ensure that their employees are routinely 'in-flow' (Nakamura & Csikszentmihalyi, 2014): that their individual skills and competencies match the challenge level of the assigned tasks, and thereby satisfy the need for competence. This 'in-flow' state may vary over time due to different factors: employee growth and competence evolution; changes in university governance that reflect new policies, visions, challenges and objectives; and changes in the KTO management structure. In light of such changes, KTO managers need to continuously re-evaluate and realign human capital to achieve better performance. On the learning and growing side, for example, employees should have access to external sources of knowledge, stimuli and inspiration (mobility, masters, workshops). Similarly, KTO employees should have the opportunity to engage in discussions and receive feedback in order to better perceive the bigger picture. Having the space to learn from errors and incorporate feedback is crucial to satisfying the need for competence.

5.5.3 Policy implications

Finally, our study features several policy-level implications. While our results underscore the importance of intrinsic motivation for KTOs' personnel performance, they do not suggest that extrinsic motivational factors are irrelevant. From a policy perspective, countries and governments that are investing in technology transfer and knowledge sharing should create legal frameworks that facilitate both intrinsic and extrinsic motivation—an example of the latter being remuneration that varies based on meeting challenging results.

5.6 Acknowledgements

We acknowledge all the interviewees who committed their time to make this project possible. In particular, we very much thank all the managers and employees of the three KTOs for sharing relevant information and data.

5.7 References

Alexander, A., Martin, D.P., Manolchev, C., Miller, K. (2020). University–industry collaboration: Using meta-rules to overcome barriers to knowledge transfer. The Journal of Technology Transfer, 45(2), 371-92.

Al-Tabbaa, O., & Ankrah, S. (2016). Social capital to facilitate 'engineered'university–industry collaboration for technology transfer: A dynamic perspective. Technological Forecasting and Social Change, 104, 1-15.

Audretsch, D. B. (2014). From the entrepreneurial university to the university for the entrepreneurial society. The Journal of Technology Transfer, 39(3), 313-321.

Baglieri, D., Baldi, F., & Tucci, C. (2014). How Different are Universities in Technology Commercialization? Institutional Logics and Multi-Sided Business Models. In The Micro-Foundations of Triple Helix.

Balven, R., Fenters, V., Siegel, D. S., & Waldman, D. (2018). Academic entrepreneurship: The roles of identity, motivation, championing, education, work-life balance, and organizational justice. Academy of Management Perspectives, 32(1), 21-42.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17, 99–120.

Battaglia, D., Landoni, P., & Rizzitelli, F. (2017). Organizational structures for external growth of University Technology Transfer Offices: An explorative analysis. Technological Forecasting and Social Change, 123, 45-56.

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: desire for interpersonal attachments as a fundamental human motivation. Psychological bulletin, 117(3), 497.

Belitski, M., Aginskaja, A., & Marozau, R. (2019). Commercializing university research in transition economies: Technology transfer offices or direct industrial funding?. Research policy, 48(3), 601-615.

Bercovitz, J., & Feldman, M. (2006). Entpreprenerial universities and technology transfer: A conceptual framework for understanding knowledge-based economic development. The Journal of Technology Transfer, 31(1), 175-188.

Bercovitz, J., Feldman, M., Feller, I., & Burton, R. (2001). Organizational structure as a determinant of academic patent and licensing behavior: An exploratory study of Duke, Johns Hopkins, and Pennsylvania State Universities. The Journal of Technology Transfer, 26(1), 21-35.

Brescia, F., Colombo, G., & Landoni, P. (2016). Organizational structures of Knowledge Transfer Offices: an analysis of the world's top-ranked universities. The Journal of Technology Transfer, 41(1), 132-151.

Brief, A. P., & Aldag, R. J. (1977). The intrinsic-extrinsic dichotomy: Toward conceptual clarity. Academy of Management review, 2(3), 496-500.

Bright, L. (2008). Does public service motivation really make a difference on the job satisfaction and turnover intentions of public employees?. The American review of public administration, 38(2), 149-166.

Cerasoli, C. P., Nicklin, J. M., & Ford, M. T. (2014). Intrinsic motivation and extrinsic incentives jointly predict performance: a 40-year meta-analysis. Psychological bulletin, 140(4), 980.

Chau, V. S., Gilman, M., & Serbanica, C. (2017). Aligning university–industry interactions: The role of boundary spanning in intellectual capital transfer. Technological Forecasting and Social Change, 123, 199-209.

De Cooman, R., Stynen, D., Van den Broeck, A., Sels, L., & De Witte, H. (2013). How job characteristics relate to need satisfaction and autonomous motivation: Implications for work effort. Journal of Applied Social Psychology, 43(6), 1342-1352.

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. Annual review of organizational psychology and organizational behavior, 4, 19-43.
Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. Psychological inquiry, 11(4), 227-268.
Deci, E. L., & Ryan, R. M. (Eds.). (2004). Handbook of self-determination research. University Rochester Press.
Dobre, O. I. (2013). Employee motivation and organizational performance. Review of applied socio-economic research, 5(1).
Eisenhardt, K. M. (1989). Building theories from case study research. Academy of management review, 14(4), 532-550.
Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. Academy of management journal, 50(1), 25-32.
Fitzgerald, C., & Cunningham, J. A. (2016). Inside the university technology transfer office: mission statement analysis. The Journal of Technology Transfer, 41(5), 1235-1246.
Gagné, M., & Deci, E. L. (2005). Self-determination theory and work motivation. Journal of Organizational behavior, 26(4), 331-362.
Gibson, C. B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. Academy of management Journal, 47(2), 209-226.
Gillet, N., Fouquereau, E., Forest, J., Brunault, P., & Colombat, P. (2012). The impact of organizational factors on psychological needs and their relations with well-being. Journal of Business and Psychology, 27(4), 437-450.
Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. Organizational research methods, 16(1), 15-31.
Giuri, P., Grimaldi, R., Kochenkova, A., Munari, F., & Toschi, L. (2020). The effects of university-level policies on women's participation in academic patenting in Italy. The Journal of Technology Transfer, 45(1), 122-150.
Giuri, P., Munari, F., Scandura, A., & Toschi, L. (2019). The strategic orientation of universities in knowledge transfer activities. Technological Forecasting and Social Change, 138, 261-278.
Glaser, B., & Strauss, A. (1967). The discovery of grounded theory Aldine Publishing Company. Hawthorne, New York.
González-Cutre, D., Sicilia, Á., Sierra, A. C., Ferriz, R., & Hagger, M. S. (2016). Understanding the need for novelty from the perspective of self-determination theory. Personality and individual differences, 102, 159-169.
Good, M., Knockaert, M., Soppe, B., & Wright, M. (2019). The technology transfer ecosystem in academia. An organizational design perspective. Technovation, 82, 35-50.
Grant, A. M. (2008). Does intrinsic motivation fuel the prosocial fire? Motivational synergy in predicting persistence, performance, and productivity. Journal of applied psychology, 93(1), 48.
Grimaldi, R., Kenney, M., Siegel, D. S., & Wright, M. (2011). 30 years after Bayh–Dole: Reassessing academic entrepreneurship. Research policy, 40(8), 1045-1057.
Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. Organizational behavior and human performance, 16(2), 250-279.
Hon, A. H. (2012). Shaping environments conductive to creativity: The role of intrinsic motivation. Cornell Hospitality Quarterly, 53(1), 53-64.
Howells, J. (2006). Intermediation and the role of intermediaries in innovation. Research policy, 35(5), 715-728.

Huyghe, A., Knockaert, M., Wright, M., & Piva, E. (2014). Technology transfer offices as boundary spanners in the pre-spin-off process: The case of a hybrid model. Small Business Economics, 43(2), 289-307.

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta-analytic of the summary and theoretical extension work design literature. Journal of Applied Psychology, 92(5), 1332-1356.

Istat, 2020. Rapporto sul territorio (2020): Ambiente, economia e società. https://www.istat.it/storage/rapporti-tematici/territorio2020/Rapportoterritorio2020.pdf

Landy, F. J., & Conte, J. M. (2016). Work in the 21st century: An introduction to industrial and organizational psychology. John Wiley & Sons.

Legault, L., (2016). The need for autonomy, in: Zeigler-Hill, V., Shackelford, T.K. (Eds), Encyclopedia of Personality and Individual Differences. Springer International Publishing, New York, NY, pp. 1120-2.

Legault, L., (2017). The Need for Competence, in: Zeigler-Hill, V., Shackelford, T.K. (Eds), Encyclopedia of Personality and Individual Differences. Springer International Publishing, Cham, pp. 1-3.

Markman, G. D., Gianiodis, P. T., & Phan, P. H. (2008). Full-time faculty or part-time entrepreneurs. IEEE transactions on engineering management, 55(1), 29-36.

Menges, J. I., Tussing, D. V., Wihler, A., & Grant, A. M. (2017). When job performance is all relative: How family motivation energizes effort and compensates for intrinsic motivation. Academy of Management Journal, 60(2), 695-719.

Miller, K., McAdam, R., & McAdam, M. (2018). A systematic literature review of university technology transfer from a quadruple helix perspective: toward a research agenda. R&d Management, 48(1), 7-24.

Minguillo, D., & Thelwall, M. (2015). Which are the best innovation support infrastructures for universities? Evidence from R&D output and commercial activities. Scientometrics, 102(1), 1057-1081.

Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): developing and validating a comprehensive measure for assessing job design and the nature of work. Journal of applied psychology, 91(6), 1321.

Muscio, A., Quaglione, D., & Ramaciotti, L. (2016). The effects of university rules on spinoff creation: The case of academia in Italy. Research Policy, 45(7), 1386-1396.

Nakamura, J., Csikszentmihalyi, M., (2014). The concept of flow, in: Csikszentmihalyi, M. (Ed), Flow and the Foundations of Positive Psychology. Springer, Netherlands, pp. 239-63.

NETVAL, (2018). XIV Rapporto Netval La rete del trasferimento tecnologico si rafforza con la clinical innovation. https://netval.it/static/media/uploads/rapporto_netval_2018.pdf (accessed 1 October 2020).

O'Kane, C., Mangematin, V., Geoghegan, W., & Fitzgerald, C. (2015). University technology transfer offices: The search for identity to build legitimacy. Research Policy, 44(2), 421-437.

O'Kane, C., Mangematin, V., Zhang, J. A., & Cunningham, J. A. (2020). How university-based principal investigators shape a hybrid role identity. Technological Forecasting and Social Change, 159, 120179.

O'Shea, R. P., Allen, T. J., Chevalier, A., & Roche, F. (2005). Entrepreneurial orientation, technology transfer and spinoff performance of US universities. Research policy, 34(7), 994-1009.

OECD, (2013). Commercialising Public Research: New Trends and Strategies. OECD Publishing, Paris.

Olafsen, A. H., Niemiec, C. P., Halvari, H., Deci, E. L., & Williams, G. C. (2017). On the dark side of work: A longitudinal analysis using self-determination theory. European Journal of Work and Organizational Psychology, 26(2), 275-285.

Pache, A. C., & Santos, F. (2013). Inside the hybrid organization: Selective coupling as a response to competing institutional logics. Academy of management journal, 56(4), 972-1001.

Perkmann, M., & Walsh, K. (2010). 12. How firms source knowledge from universities: partnering versus contracting. In Creating wealth from knowledge: meeting the innovation challenge (p. 273). Edward Elgar Publishing.

Piccolo, R. F., & Colquitt, J. A. (2006). Transformational leadership and job behaviors: The mediating role of core job characteristics. Academy of Management journal, 49(2), 327-340.

Rasmussen, E., & Wright, M. (2015). How can universities facilitate academic spin-offs? An entrepreneurial competency perspective. The Journal of Technology Transfer, 40(5), 782-799.

Reeve, J., (2014). Understanding Motivation and Emotion. John Wiley & Sons, Hoboken, NJ.

Rousseau, D. M. (1997). Organizational behavior in the new organizational era. Annual review of psychology, 48(1), 515-546.

Ryan, R. M. (1995). Psychological needs and the facilitation of integrative processes. Journal of personality, 63(3), 397-427.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. Contemporary educational psychology, 25(1), 54-67.

Shin, J., & Grant, A. M. (2019). Bored by interest: How intrinsic motivation in one task can reduce performance on other tasks. Academy of Management Journal, 62(2), 415-436.

Siegel, D. S., Veugelers, R., & Wright, M. (2007). Technology transfer offices and commercialization of university intellectual property: performance and policy implications. Oxford review of economic policy, 23(4), 640-660.

Siegel, D. S., Waldman, D., & Link, A. (2003). Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: an exploratory study. Research policy, 32(1), 27-48.

Siegel, D. S., Waldman, D. A., Atwater, L. E., & Link, A. N. (2004). Toward a model of the effective transfer of scientific knowledge from academicians to practitioners: qualitative evidence from the commercialization of university technologies. Journal of engineering and technology management, 21(1-2), 115-142.

Strauss, A., & Corbin, J. (1998). Basics of qualitative research techniques (pp. 1-312). Thousand oaks, CA: Sage publications.

Van den Broeck, A., Ferris, D. L., Chang, C. H., & Rosen, C. C. (2016). A review of self-determination theory's basic psychological needs at work. Journal of Management, 42(5), 1195-1229.

Villani, E., & Lechner, C. (2021). How to acquire legitimacy and become a player in a regional innovation ecosystem? The case of a young university. The Journal of Technology Transfer, 46(4), 1017-1045.

Villani, E., Rasmussen, E., & Grimaldi, R. (2017). How intermediary organizations facilitate university–industry technology transfer: A proximity approach. Technological forecasting and social change, 114, 86-102.

Williams, G. C., Halvari, H., Niemiec, C. P., Sørebø, Ø., Olafsen, A. H., & Westbye, C. (2014). Managerial support for basic psychological needs, somatic symptom burden and work-related correlates: A self-determination theory perspective. Work & Stress, 28(4), 404-419.

Wright, M. (2007). Academic entrepreneurship in Europe. Edward Elgar Publishing.

Yin, R. K. (2003). Designing case studies. Qualitative Research Methods, 5, 359-386.

Yin, R. K. (2013). Validity and generalization in future case study evaluations. Evaluation, 19(3), 321-332.
Zhou, R., & Tang, P. (2020). The role of university Knowledge Transfer Offices: Not just commercialize research outputs!. Technovation, 90, 102100.

.

6

6 Conclusion

6.1 Summary of the main findings

The commercialization of knowledge and technology from research to industry is not only beneficial for various actors but also socially and economically desirable. Thus, over the last decades, research organizations have experienced a substantial organizational change to master this new mission. However, the commercial outcomes are far below expectations, and scientists often conduct commercialization as a symbolic gesture or refuse to engage in commercial activities at all. Previous research claimed that organizational-change leaders often underestimate the central role of individuals (Choi, 2011). To address this problem, this dissertation set out to expand and deepen the understanding of the behavior of individuals involved in the commercialization of academic knowledge, namely scientists and KTO employees. By applying insights from OBHRM to the challenges that accompany the commercialization of academic knowledge, this dissertation contributes to an improved understanding of the micro-processes behind commercialization, enabling practitioners to design appropriate organizational contexts (see Figure 29).

Chapter 2's meta-analysis identified 97 determinants that influence the commercialization of academic knowledge. The findings will help practitioners (i.e., university governance and TTO managers) to identify the relevant (1) organizational, (2) individual, (3) TTO-related, (4) field-related, and (5) environmental determinants that increase the quality and quantity of scientists' commercial activities. With 65 determinants, characteristics of research organizations and researchers (organizational and individual determinants) attracted the most interest from former scientists. Likewise, patenting and spin-off creation have been the most extensively examined commercialization channels (42 and 40 studies). However, the channel "consulting" and the influence of "environmental determinants" require further research. The analysis of effect sizes suggests that huge research organizations with a high volume of public funding and a high share of academic knowledge from the natural sciences are more successful in patenting than others. The findings regarding spin-off creation imply that supplementary support activities are necessary for fostering female entrepreneurship. Furthermore, spin-off creation is fostered by an innovation climate in research organizations and KTOs with high expertise. Finally, the chapter contributes to theory as it provides a new framework for studying the determinants of commercialization (see Figure 10); thus, it derives research gaps in the context of determinants, commercialization channels, commercialization processes, and actors, as well as data and methodological issues.

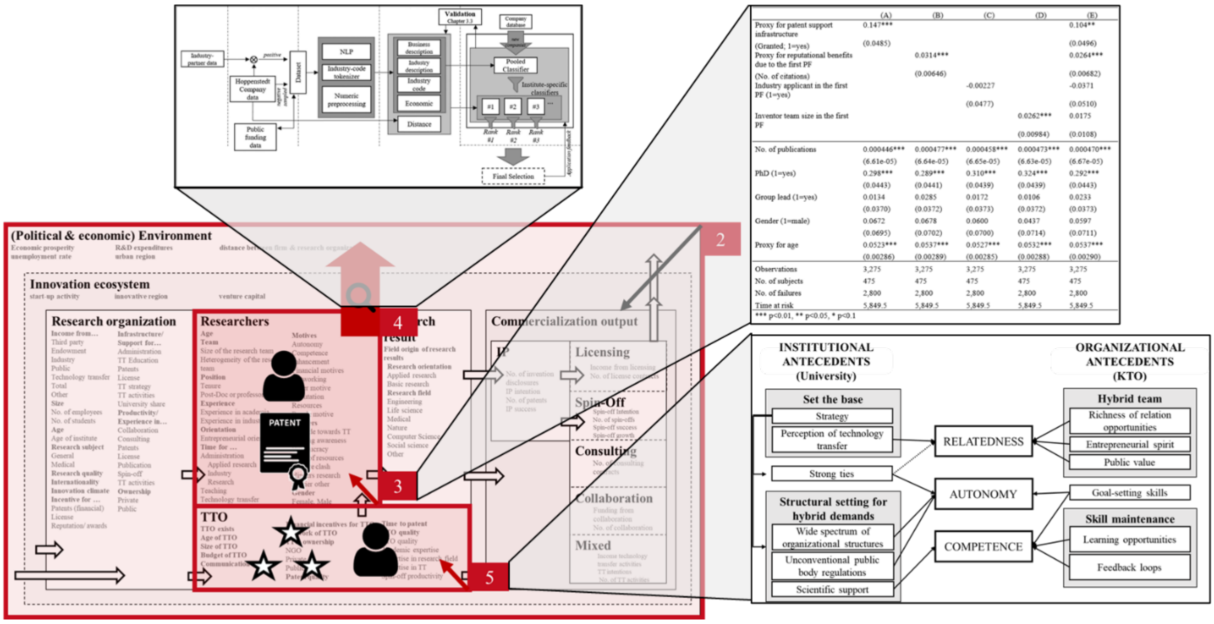
Chapter 3 introduced the phenomenon of serial patentees to explain why some inventors stop after the first patent while others continue. The survival analysis for recurrent event data was based on 475 inventors and confirmed the influence of positive former experiences on continuous patenting. First-time patent experiences already reveal a trend for serial patenting; that is, an inventor who received personal benefits and a sufficient patent support infrastructure for his or her first patent is more likely to become a serial patentee. Moreover, the average inventor team size over all patents increases the 'risk' of continuous patenting, whereas the team size of the first patent has no impact on becoming a serial patentee. The findings indicate that one-time inventors make the conscious decision to become a serial patentee based on their prior patent experiences. Therefore, the chapter concludes that becoming a serial patentee is a career choice rather than a simple duty for achieving the third mission. The results provide critical insights for KTO employees and decision makers in research and policy as they enable them to develop a better-fitting support infrastructure for academic inventors' careers.

Chapter 4 assumed that scientists are characterized by bounded rationality. This in turn impedes their ability to select the best-fitting industry partner for their commercial activities. Hence, my co-authors and I argued that selecting and seeking industry partners with the help of information technology enables decision making in a faster, more efficient, and more informed manner. We developed and tested a supervised learning approach based on cooperation data from the Fraunhofer Gesellschaft (including quantitative and qualitative information; see Figure 26). The precision and recall of approximately 85% for the pooled classification and ROC AUC scores, and of between 70% and 90% for most institute-specific classifiers, proved that the overall performance of the approach is certainly satisfactory for practical use. Thus, the classification approach indeed proved its feasibility and potential for supporting the industry-partner selection process. Moreover, in both steps of our classification approach, namely prefiltering with a pooled classifier and ranking relevant companies with institute-specific classifiers, a combination of economic features (quantitative) and industry-related features (qualitative) performed best. Even though Chapter 4 was based on data from the Fraunhofer-Gesellschaft, the proposed approach can be applied in various settings. For example, (1) it can be applied in other research organizations with their internal research units, (2) other parent companies with independent subsidiaries, and (3) other partnership relations – always on the condition that sufficient data are available. Overall, Chapter 4 can be practically used to support scientists in finding industry partners by facilitating the partner-selection process.

Finally, Chapter 5 examined the micro-processes in KTOs. Specifically, we studied the intrinsic motivation of KTO employees by analyzing the university- and KTO-level antecedents of basic need satisfaction (i.e., the needs for relatedness, competence, and autonomy). The findings of the four case studies suggested that university management can, above all, shape the structural setup of a KTO such that it enables the need for autonomy to be satisfied. This includes the specialization of KTO units, direct contact between university governance and KTO management, and workarounds for public-body regulations. The analysis of the KTO-level antecedents, on the other hand, revealed that KTO managers have various antecedents for satisfying the needs for relatedness and competence, including hybrid team management and skill maintenance. Taken together, Chapter 5 demonstrated that the differences in need satisfaction – and thus intrinsic motivation – can be explained in various antecedents (see the framework in Figure 28). Thus, it contributes not only to the literature on commercialization but also to that on public organizations, characterized by bureaucracy, regulations, and the persistence of existing routines (e.g., Bercovitz & Feldman, 2008; Hoag, 2002). Moreover, on the practitioner side, the findings in the chapter will enable university management and KTO managers to enhance the well-being of their employees.

Overall, Chapters 2 to 5 have revealed that the commercial activities of scientists and KTO employees are affected by a multitude of factors. While Chapter 2 provided a comprehensive overview of determinants that integrates the identified determinants and commercialization output indicators, Chapters 3 to 5 delved deeper into individual commercial behavior. Chapter 3 revealed how the kind and timing of prior experiences related to the four factors foster the continuous commercial activities of scientists based on the example of patenting. Next, Chapter 4 discussed the difficulties that scientists face in finding the best-fitting industry partners for their knowledge and technologies. It demonstrated the benefits acquired through integrating a statistical learning approach to industry-partner selection. Chapter 5 revealed the antecedents of intrinsic motivation of KTO employees as crucial supporters of scientists' commercial activities. Taken together, these findings have significant implications for future research, practitioners, and policymakers, which are discussed in the following sections.

Figure 29: *Zoom-in of selected main findings*



6.2 Theoretical and methodical implications

Theoretical implications

This dissertation makes several contributions to the literature. The aim of the present research was to examine the behavior of individuals involved in the commercialization of academic knowledge. Therefore, this dissertation set out to contribute to a solid micro-foundation of the underling dynamics of commercialization and thus also to coherently explain the determinants that influence the commercialization of academic knowledge. I used insights from OBHRM to examine, frame, and explain particular issues related to the commercialization of academic knowledge (i.e., career management of academic inventors, motivation in hybrid context, and decision making of individuals characterized by bounded rationality). Therefore, this dissertation contributes to both the literature on OBHRM and that on the commercialization of knowledge and technology from research to industry.

Since I examined universities and PROs, I also addressed literature on public organizations, which are typically characterized by highly institutionalized contexts and an organizational structure that rather hinders organizational change (Bercovitz & Feldman, 2008; Gail & Caruth, 2013, Marshall, 2010). In this context, Chapter 2 offered 34 organizational determinants that influence the success of commercialization activities. In total, 97 determinants contributed to the discussion of commercialization by simplifying the identification of determinants for scientists and practitioners. Moreover, we identified commercialization output indicators for the different channels. Thus, we linked already studied determinants with commercialization channels and demonstrated that one determinant can have different effects on different channels. This differentiation also revealed that profound research exists on spin-off creation and patenting, while other channels require more attention from scientists. The analysis resulted in a new comprehensive framework, which was designed for a holistic mapping of future commercialization research (Chapter 2, Figure 10). The chapter further contributes to the literature with its extensive overview of research gaps and examples of research questions (Chapter 2, Table 14).

Furthermore, the meta-analysis revealed that the vast majority of studies have focused on universities, and also that a need exists for more insights on PROs. Chapters three and four addressed this need by examining the largest organization for applied science in Europe, namely the Fraunhofer-Gesellschaft. Although the organizational context was not the focus of these chapters, we demonstrated how the central collection of cooperation data can be used to improve industry-partner selection for Fraunhofer researchers in Chapter 4. Moreover, in Chapter 3, we introduced the patenting incentives at the Fraunhofer-Gesellschaft and examined the patenting behavior of Fraunhofer researchers.

Besides research on serial entrepreneurship, Chapter 3 is also the first attempt to explain continuous commercial behavior through introducing the concept of serial inventors. I demonstrated that the kind and timing of former patent experiences related to four different factors (i.e., personal benefits, patent support infrastructure, team size, and industry relations) increase the likelihood of scientists becoming serial patentees using a survival analysis for recurrent event data. Thus, the chapter raises critical questions regarding the debate about one-time commercial behavior versus continuous behavior, as well as the differences between motives to try a behavior for the first time versus motives for continuous behavior.

Moreover, Chapter 4 contributes to starting a debate on the use of machine learning to support scientists and transfer professionals. The results suggested that our supervised learning approach facilitated the industry partner-selection process by automatically identifying important criteria, providing a ranked preselection of the best-fitting partners out of an overwhelming pool of organizations, and constantly improving recommendations based on feedback of further selected partners. Thus far, however, the potential of machine learning to support individuals involved in the commercialization of academic knowledge is far from exhausted. Hence, this chapter offers an original contribution by analyzing the impact of scientists' bounded rationality on their commercial activities and subsequently offering a supervised learning approach to deal with this issue. Yet, further research is still required in this direction. The prospective research section provided some examples of research gaps linked to the use of machine learning to support scientists and KTO employees.

In addition, Chapter 5 offered a micro-perspective of KTOs through a closer examination of the organizational behavior dynamics that occur within KTOs, with a specific emphasis on KTO personnel motivation. Thus, we speak to the literature about intermediary organizations and addressed the recent call for more research on this specific group of individuals. Furthermore, my co-authors and I brought motivational insights of self-determination theory together with threats to the intrinsic motivation of employees in hybrid organizations. We provided a deeper understanding of the link between need satisfaction, which is the base for intrinsic motivation, and its antecedents of need satisfaction. Therefore, we created a theoretical framework of university-level antecedents and KTO-level antecedents and their impact on basic needs. Further quantitative proof is required to complete the framework.

Overall, the principal theoretical implication of this study is that research on the commercialization of academic knowledge benefits from insights into OBHRM. However, as indicated in the introduction (Table 2), 32 out of the 37 OBHRM topics must still be examined in the context of commercialization. The most promising topics are discussed in the future research section (Section 6.5).

Methodological implications

This dissertation also has some methodological implications. To begin with, the review and meta-analysis in Chapter 2 indicated that most previous studies about the commercialization of academic knowledge have collected data from surveys at one point in time. Additionally, survey studies may produce biased results as they depend on the knowledge and attitudes of respondents. The lack of panel data hinders the measurement of the effects of interventions over time. Moreover, my co-authors and I found various operationalizations for the same determinant within determinants and outcomes; for example, to express the size of research organizations, scientists have used the number of employees, professors, or students. Likewise, to express successful patenting, scientists have used the number of patents, level of the intention to patent, or patenting activity as a binary or categorical variable. The only standardized panel survey is the AUTM survey. To handle these issues, future research could consider other data collection methods, attempt to integrate other objective data sources, and collect data based on standardized indicators. For example, the OECD-developed International Technology Transfer measures and Guiding Framework for Entrepreneurial Universities could be used to collect further data (Kowalski et al., 2017; OECD & EU, 2012). Moreover, Secundo et. al. (2016) developed indicators for measuring “university technology transfer efficiency,” and Campbell et al. (2020) wrote a report for the EC titled “Knowledge transfer metrics: Towards a European-wide set of harmonized indicators.”

Likewise, collecting data for the meta-analysis proved to be difficult, as studies often have not reported effect sizes or any other statistics that can be converted into effect sizes. Thus, we could only calculate effect sizes for 48 of the 99 studies. We recommend that researchers report complete correlation matrices in the future to facilitate the accumulation of research findings. Moreover, the editorial boards of scientific journals may request correlation tables in the supplementary files as a mandatory requirement.

In Chapter 4, my co-authors and I highlighted the importance of data quality for transferring our approach to other research organizations as well as commercialization channels other than cooperation with firms. Yet, the meta-analysis revealed that some commercial activities, especially consulting activities, are difficult to track. Therefore, we recommended that research organizations establish easy-to-use databases to track commercial activities. Finally, in the study presented in Chapter 4, we found that the combination of quantitative and qualitative features performs best. However, we were limited to industry codes, business, and industry descriptions as qualitative features. Therefore, researchers should attempt to collect additional data from other sources. A useful additional data source could be the joint patents of research organizations and firms, participation in similar or the same standardization committees, and reciprocal links on firm/ research organizations’ websites (Benner & Waldfogel, 2008; Blind, 2018; Krüger et al., 2020).

6.3 Implications for practitioners

A variety of implications for practitioners can be derived from this dissertation. Specifically, the findings can improve the governance of research organizations and the management of intermediary organizations.

Implications for university and PRO governance

Decision makers in universities and PROs can use Chapter 2’s findings to better align their KTT strategy and improve their KTT support. The matrix of determinants and commercialization channels (Table 11, Chapter 2) will enable them to set appropriate foci as well as to better understand the consequences of their interventions. The findings indicated that research results from some scientific disciplines are more prone to certain commercialization channels than others. In addition, my co-authors and I found that the environmental conditions strengthen certain channels more; for example, spin-of creation is facilitated in regions characterized by a high level of economic prosperity and the availability of venture capital. Thus, research organizations that aim to increase the commercialization of academic knowledge should align their KTO strategy depending on their scientific disciplines and other contextual factors. Depending on the foci of commercial activities, universities and PROs can establish specific KTOs and connect more strategically with intermediary organizations and KTT networks. For example, a university that aims to strengthen its spin-off activities will rather connect with incubators and co-working spaces. By contrast, a PRO seeking more international license contracts will probably participate in Licensing Executives Society International or similar networks.

Considering the setup of KTOs, Chapter 5 derived recommendations for how to shape organizational contexts of KTOs in a way that enhances the intrinsic motivation of employees, thus supporting the successful commercialization of academic knowledge. First, university management should be aware of bureaucratic processes, persistent existing routines, and established traditions that limit the scope of action of KTO managers. The findings revealed that universities that have established matrix structures of KTO units along relevant dimensions, such as transfer area, scientific field or industry sector, and target group, allow KTO employees to satisfy their need for autonomy. Likewise, adapted internal and external recruitment processes for KTOs as well as trustful iterative discussions between KTO managers and university governance also foster the satisfaction of the need for autonomy. Universities that want to support the satisfaction of the need for relatedness will invest in a positive transfer image among scientists and local industry. Lastly, bringing together KTO employees and scientists, who conduct research in the field of KTT, supports KTO employees in satisfying their need for competence.

Given the high relevance that university governance attributes to commercialization and technology transfer in general, it is surprising that they have established no specific career path for scientists interested in commercialization. To date, most universities have focused on four types of professor positions that all focus on research and teaching (i.e., assistant professor, associate professor, full professor, and distinguished professor). However, the findings in Chapter 4 suggested that decision makers of research organizations can implement certain measures to promote continuous patenting. Thus, it would be reasonable to establish a new career path for scientists, such as a "transfer professor," accompanied by specific measures, resources, training, and infrastructure. Chapter 3's findings indicated that the receipt of personal benefits, sufficient patent support infrastructure, and a high average team size increase the likelihood of continuously inventing and applying new patents. This can be used as a starting point for establishing a new career path along with other insights from career management of serial patentees. Thus, universities as well as other types of research organization could make commercialization an active choice instead of a "stumble-in-career."

A supervised learning approach, as presented in Chapter 4, represents another option that decision makers in research organizations can use to support commercial activities. We not only developed a supervised learning approach but also implemented the results in a web application called https://corporate-match.imw.fraunhofer.de/ (Fraunhofer IMW. n.d., see Figure 26, Chapter 4). Fraunhofer researchers can already use this prototype web application to look for new industry partners. However, as previously stated, research organizations' managers that wish to benefit from the findings must collect sufficient cooperation data. Presuming that this condition is fulfilled, universities and PROs could use our findings to provide scientists and KTO employees with tools that help them to select the best-fitting industry partners for their specific commercial activity. For example, scientists could use such a tool to find new partners for cooperative projects and consulting activities, while KTO employees could enhance their job performance with a similar tool that helps them to find proper licensees.

Implications for intermediary organizations

The findings of this dissertation can also aid managers and employees of intermediary organizations, especially KTOs, in improving their commercial support services. Furthermore, the findings will help KTO managers to more effectively address the intrinsic motivation of employees.

Regarding commercial support services, the meta-analysis revealed that female scientists have founded significantly fewer spin-offs than male scientists. Therefore, KTOs as well as incubators should create services especially targeted at female scientists. Recent results from Perkmann et al. (2021) confirmed the importance of supporting female entrepreneurship. In this context, UnternehmerTUM

GmbH in Munich provides events and workshops where women can network; it even provides a "Woman start-up newsletter" (UnternehmerTUM GmbH, n.d.). In addition, intermediary organizations could use the findings from other literature on female entrepreneurship (like Estrin & Mickiewicz, 2011, or Di Paola, 2021).

Second, based on the insights from Chapter 3, intermediary organizations should be aware of the role of prior experiences of inventors. Since the "knowledge entry barrier" for patents is very high, technology transfer managers should aim to lower the information barrier and provide easy access to patenting-relevant information. In particular, young and less experienced researchers would benefit here. Additionally, they can actively address the findings on the positive influence of personal benefits and average team size, developing better-fitting support for inventors by providing additional coaching for those with negative first or recent experiences. To support scientists in continuing to patent in the long run, KTO employees and human resource managers could develop an internal career or qualification program to support "serial patentees." Along this line, the findings suggest that university governments may establish a new career path for scientists, such as a "transfer professor."

While KTOs and other intermediary organizations connect research and industry, finding the right industry partners is problematic not only for scientists but also transfer professionals. This is complicated if new industry partners are beyond the familiar regional scope or belong to an industry sector not known by the transfer professional. Accordingly, the supervised learning approach represents the third contribution of this dissertation for improving support services. As demonstrated above, depending on the available cooperation data, employees in intermediary organization can also use the findings to implement a web application tailored to their needs.

Turning to the implications for KTO managers, Chapter 5 provides valuable insights into how they can shape working conditions that foster the satisfaction of their employees' basic needs. KTO managers can help their employees to connect with others and build meaningful relationships (i.e., the need for relatedness) by properly offering various relational opportunities and establishing an entrepreneurial team spirit. Moreover, the findings suggest that showing employees how they contribute to the public good increases their affection as well as prosocial behavior. KTO managers who help employees to align individual goals with the overall objectives of the KTO foster the satisfaction of the need for autonomy. Finally, KTO managers can help their employees to unfold their full personal potential by maintaining their skills. In particular, constant feedback and personal learning opportunities (e.g., international experiences, research opportunities, and the diversification of project portfolios) help employees to satisfy their need for competence. This is especially critical, as the meta-analysis revealed the high relevance of the expertise of transfer professionals for spin-off creation. Even though our research focused on university KTOs, we believe that our results hold valuable insights for other intermediary organizations.

6.4 Implications for innovation policy

Political awareness of the importance of the commercialization of academic research in general seems to exist, as indicated by changes in legal acts across the world and massive funding for KTT (see Chapter 1). Yet, this dissertation also holds some implications for innovation policy makers that should be considered to support the commercial activities of scientists and research organizations, thus ensuring the successful transfer of academic knowledge to the market. The increased understanding of the organizational processes and individual characteristics that influence the commercialization of academic knowledge helps decision makers in policy to more effectively evaluate the impact of existing and redeveloped support mechanisms (OECD, 2012; Bercovitz & Feldman, 2008). Therefore, research organizations and KTOs could exchange best practices for OBHRM measures that increase commercial activities in international networks, such as the Competence Centre on Technology Transfer or the European TTO circle (European Commission, n.d.).

Furthermore, policy makers should create legal frameworks for knowledge and technology transfer that consider the needs of scientists and KTO professionals. Chapter 2 suggested that female scientists would benefit from customized entrepreneurship support for enhancing the number of spin-offs founded by women. Thus, besides the aforementioned recommendations for KTOs, policy makers can also take the necessary steps to support female entrepreneurship. To begin with, greater transparency of female entrepreneurship in science would help to raise awareness. The EC could also integrate a female spin-off index in the "European and Regional Innovation Scoreboard" (European Commission, 2021). For example, the OECD provides an overview of female entrepreneurship in general, yet without differentiating between start-ups and spin-offs (OECD, 2021).

In addition, the meta-analysis revealed the importance of public funding for commercial activities. Considering funding in general, additional third-party funding for research on machine learning support for KTT-related processes would be valuable for improving commercial activities. Chapter 4 proved that a supervised learning approach would help scientists and KTO professionals to select the best industry partners. However, even more issues are of interest. For example, in 2021, the German Minister for Research and Education published a call for a research project on "digitization in knowledge transfer within science" (BMBF, 2021). Another option is third-party funding that addresses the joint projects of KTO employees and scientists in the field of machine learning.

Another funding aspect relates to academic careers. This dissertation has revealed that certain mechanisms foster continuous activities. In addition, some commercialization channels are characterized by longer time horizons and request more resources than others (see Chapter 3). Thus, government agencies may financially support research organizations to introduce new academic career paths that integrate commercial activities by definition.

Finally, this dissertation has demonstrated that the commercialization of academic knowledge is also affected by the research organization's geographical location. Local policy makers can use the insights about environmental and innovation ecosystem related determinants to strategically foster favored commercial activities based on the strategy of research organizations and the needs of local industry. In the case of a preference for spin-off creations, local city marketing may, for example, target international venture capitalists.

6.5 Future research

The purpose of this dissertation was to deepen the understanding of the micro-processes of the commercialization of academic knowledge by applying insights from OBHRM. However, it only provides a step in this direction, as a multitude of additional research questions arose with each new finding. In addition, the entirety of OBHRM topics goes far beyond the scope of this dissertation (see Table 2, Chapter 1). Furthermore, due to limitations in the research design, some findings should be confined to the realm of their analysis. Yet, this section focuses on limitations and future research directions that are content-related, since methodological aspects were already addressed in previous sections.

A natural progression of this dissertation is to apply other insights from OBHRM to explain the micro-processes of the commercialization of academic knowledge. Particularly promising approaches are insights from "strategic human resource management," "selection, staffing, and recruiting," "impression management," and "leadership." The findings on serial inventors as well as KTO employees' motivation represent two cases that would benefit from effective human resource management strategies. Considering serial inventors, further research might deepen the findings on the relevance of certain support mechanisms' timing. Hmieleski and Powell (2018) recommend further examining how commercial activities evolve over academic careers. Furthermore, Chapter 5 illustrated how a positive image of the commercialization of academic knowledge among scientists would help KTO employees to build trustful relations with them. Hence, impression management holds promising strategies for creating a positive self-presentation of the research organization's commercial activities to motivate more scientists. In addition, insights from signaling theory might be useful for enhancing the attention paid to the commercialization of academic knowledge (Hmieleski & Powell, 2018). Moreover, future research should examine which leadership styles effectively activate the commercial activities of scientists and KTO employees. Balven et al. (2018) claimed that more research on academic entrepreneurship would benefit from insights into leadership and companionship (i.e., the role of the department chair for faculty commercialization efforts).

Some research gaps revealed in the meta-analysis should be highlighted again. Further studies must address types of research organizations other than universities as well as countries other than the USA. Doing so would allow researchers to compare the impacts of different legal and organizational contexts. In addition, considerably more work is required for understanding the following commercialization channels: professional training for industry as well as participation in standardization committees. In particular, the links, trade-offs, and synergies between the channels are of interest to increase the efficiency of commercial activities. Furthermore, the findings highlighted the role of KTO employees' expertise. Hence, more information on the profession of transfer experts would help to advance the recruitment, staffing, and training of transfer professionals.

Finally, Chapter 4 provided a first step in the direction of machine learning support for commercial activities; that is, we demonstrated how a supervised learning approach helps scientists, who are characterized by bounded rationality, to deal with the partner-selection problem. A further study could examine how machine learning approaches would help KTO employees to identify research projects with high commercial potential in their affiliated research organizations, since at most a dozen KTO employees are responsible for thousands of scientists and research projects. Another useful scenario for machine learning support is to enable company employees to find the best-fitting contact person within a university or PRO. Considering bounded rationality, further research might explore other related aspects that hinder the commercial activities of scientists and KTO employees. For example, Norton et al. (2012) found that their participants valued products more if they invested their own time and effort into producing them (the "IKEA effect"). Hence, future scientists may examine what this finding means for KTO employees who help to commercialize academic results from others. Likewise, the seminal studies of Nobel Prize winners and behavioral scientists Daniel Kahneman and Richard Thaler provide various other examples that may be of interest for future scientists in the field of KTT.

6.6 References

Benner, M., & Waldfogel, J. (2008). Close to you? Bias and precision in patent-based measures of technological proximity. Research Policy, 37(9), 1556-1567.

Blind, K. (2016). The impact of standardisation and standards on innovation. In Handbook of innovation policy impact. Edward Elgar Publishing.

BMBF. (2021). Bekanntmachung. BMBF. Retrieved March 17, 2022, from https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2021/01/3331_bekanntmachung

Campbell, A., Cavalade, C., Haunold, C., Karanikic, P., Piccaluga, A., & Dinnetz, M. (2020). Knowledge transfer metrics. Towards a European-wide set of harmonised indicators, Karlsson Dinnetz, M.(Ed.), EUR, 30218.

Choi, M. (2011). Employees' attitudes toward organizational change: A literature review. Human resource management, 50(4), 479-500.

Di Paola, N. (2021). Pathways to academic entrepreneurship: The determinants of female scholars' entrepreneurial intentions. The Journal of Technology Transfer, 46(5), 1417-1441.

Estrin, S., & Mickiewicz, T. (2011). Institutions and female entrepreneurship. Small business economics, 37(4), 397-415.

European Commission. (2022, February 23). European TTO Circle. JRC Science Hub Communities - European Commission. Retrieved March 17, 2022, from https://ec.europa.eu/jrc/communities/en/community/tto-circle-community.

European Commission. (2021). EIS-RIS 2021. EIS-RIS 2021 | Research and Innovation. Retrieved March 17, 2022, from https://ec.europa.eu/research-and-innovation/en/statistics/performance-indicators/european-innovation-scoreboard/eis#.

European Commission. (n.d.). Competence Centre on Technology Transfer. Technology Transfer. Retrieved March 17, 2022, from https://knowledge4policy.ec.europa.eu/technology-transfer_en.

Fraunhofer IMW. (n.d.). Passende Unternehmen Finden. Corporate. Retrieved March 15, 2022, from https://corporate-match.imw.fraunhofer.de/.

Global Public Policy Institute (GPPi). (n.d.). Free universities: Putting the academic freedom index into action. Free Universities: Putting the Academic Freedom Index Into Action. Retrieved March 15, 2022, from https://www.gppi.net/2021/03/11/free-universities.

Kowalski, P., Rabaioli, D., & Vallejo, S. (2017, November 20). International Technology Transfer measures in an interconnected world. OECD iLibrary. Retrieved March 15, 2022, from https://www.oecd-ilibrary.org/trade/international-technology-transfer-measures-in-an-interconnected-world_ada51ec0-en.

Krüger, M., Kinne, J., Lenz, D., & Resch, B. (2020). The Digital Layer: How innovative firms relate on the Web. ZEW-Centre for European Economic Research Discussion Paper, (20-003).

Norton, M. I., Mochon, D., & Ariely, D. (2012). The IKEA effect: When labor leads to love. Journal of consumer psychology, 22(3), 453-460.

OECD. (2021). Indicators of female entrepreneurship - OECD statistics. Entrepreneurship: Indicators of female entrepreneurship. Retrieved March 17, 2022, from https://stats.oecd.org/index.aspx?queryid=83119.

OECD and EU. (2012, December 18). A guiding framework for Entrepreneurial Universities - OECD. A Guiding Framework for Entrepreneurial Universities. Retrieved March 15, 2022, from https://www.oecd.org/site/cfecpr/EC-OECD%20entrepreneurial%20Universities%20Framework.pdf.

Secundo, G., De Beer, C., Passiante, G. (2016). Measuring University Technology Transfer Efficiency: A maturity level approach. Measuring Business Excellence, 20(3), 42–54. https://doi.org/10.1108/mbe-03-2016-0018.

UnternehmerTUM GmbH. (n.d.). Empowering Female Entrepreneurs. Woman Start-up. Retrieved March 16, 2022, from https://www.unternehmertum.de/ueber/women-start-up

Enjoy commercializing your knowledge!