Technische Universität Berlin

Three Essays on Open Innovation, Technological and Institutional Change

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Von der Fakultät VII –
Wirtschaft und Management der Technischen Universität Berlin,
zur Erlangung des akademischen Grades
Doktor der Wirtschaftswissenschaften (Dr. rer. oec.)
genehmigte Dissertation

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Tag der Disputation:	21. Juli 2009
Erscheinungsort/-jahr:	Berlin 2009
Kennung:	D 83

Summary

This thesis consists of three essays. All of them aim to contribute to the theoretical and empirical strands of literature on open modes of innovation, institutional and technological change. Therefore they intend to shed light - from a resource-based perspective - on the more generic questions why and how corporate organizations will collaborate in invention, innovation and exploitation processes, whom they (should ideally) collaborate with and how this, again, may lead to institutional change blurring traditional organizational and proprietary boundaries of the firm.

The technological paradigm thinking is a key component of this primarily evolutionary, dynamic perspective on innovation processes and technological change we embrace. Anyhow, by writing these essays we intend to bridge and enrich this perspective with insights from behavioural industrial organization theorizing on market demand, competition and (non-) collaborative R&D processes - while economic selection mechanisms and general technological change persist - calibrating and testing our models on empirical evidence from specific industry sectors, i.e. biotechnology and photovoltaic industries. For these purposes we further analyse the processes of 'selection and organization of ideas' and innovation performance of German and US-based firms, mergers & acquisitions, entrepreneurs and overall industry sectors on the basis of various types of intellectual property rights, technometrics and other innovation input and output indicators of technological change and organizational competences.

To summarize, we mostly find that technological resources economics - next to other factors commonly acknowledged in the literature - substantially matter for the dynamics of invention and innovation processes inside and outside the firms organization. More precisely, when it comes to collaborative action, ex ante collaboration partner selection may be an essential driver for innovation performance (and even institutional change) whenever learning processes play a dominant role and selection establishes technological distance among partners. Secondly, we establish that open innovation practices in general - in an industry environment where excellent ideas can be scarce

or widespread but still valuable -, will impact on internal inventory performance, performance outside the firm boundaries and potentially the overall rate of technological change in the industry. Simultaneously, they partially account for organisational change internal and external to the firm which in turn may lead to long-run changes in market structure, competition levels and industry selection outcome.

Zusammenfassung

Die vorliegende Dissertation besteht aus drei kumulierten Forschungsaufsätzen. Alle drei Ansätze sollen einen Beitrag zur theoretischen, empirischen und ökonomischen Literatur 'offener' Innovationsprozesse und dem damit einhergehenden, institutionellen und technologischen Wandel leisten. In diesem Zusammenhang werden folgende, generische Fragestellungen aus einer ressourcenorientierten Untersuchungsperspektive beleuchtet: Warum und in welcher Form kooperieren Unternehmen in FuE- und Innovationsprozessen? Welchem (idealtypischen) Selektionsmechanismus folgt in diesem Zusammenhang die Partnerwahl, und welchen Einfluss hat das Kooperationsverhalten auf den institutionellen Wandel, der zu einer Aufweichung der traditionellen, organisatorischen und proprietären Unternehmensgrenzen führen kann.

Das technologische Paradigma ist eines der Schlüsselkonzepte der im Rahmen dieser Arbeit eingenommenen dynamischen, evolutionär-ökonomisch geprägten Sichtweise des Verlaufs von Innovationsprozessen und technologischem Wandel. Diese Perspektive soll unter Aufrechterhaltung ökonomischer Selektionsprozesse und generellem technologischem Wandel, mit den Forschungserkenntnissen der Industrieökonomik in behavioristischen Modellen der Marktnachfrage, des Wettbewerbs und zu (nicht-) kollaborativen R&D Prozessen bereichert werden, und die Kalibrierung und Testverfahren für die Validität unserer Modelle anhand empirischer Evidenz in verschiedenen Industriesektoren (bspw. die Biotechnologie und Photovoltaik) ermöglichen. Zu diesen Zwecken werden die 'Auswahl- und Organisationsverfahren technischer Ideen', die Organisationskompetenz und die Innovationsperfomanz auf verschiedenen Ebenen und in verschiedenen Ländern auf Grundlage unterschiedlicher Indikatoren (u.A. mittels Intellektueller Eigentumsrechte, Technometrie), beispielsweise bei Unternehmenszusammenschlüssen, bei Unternehmensgründungen, in deutschen und US-amerikanischen Unternehmen, und auf aggregierter Sektorenebene untersucht.

Zusammenfassend lässt sich festhalten, dass zum einen eine ressourcenorientierten Untersuchung, neben anderen in der Literatur genannten Faktoren, die substantielle

Bedeutung der Innovationsressourcen für die Dynamik der Erfindungs- und Innovationsprozesse inner- und außerhalb der Unternehmen belegt. Bei FuE-Kooperationen wird deutlich, dass die Partnerauswahl ex ante und die damit einhergehende technologische Distanz die Innovationsperfomanz (und letztlich den institutionellen Wandel) in Gegenwart von wechselseitigen Lernprozessen beeinflussen kann.
Eine zweite, zentrale Schlussfolgerung der Untersuchung ist daher, dass 'offene' Innovationsprozesse generell Auswirkungen auf unternehmensinterne Innovationsleistungen und Performanz außerhalb der traditionellen Unternehmensgrenzen besitzen und auch potentiell Effekte auf die Dynamik und Richtung des technologischen Wandels einzelner Industriesektoren verursachen können. Zugleich beeinflussen diese Prozesse im Netzwerkverbund jedoch auch das unternehmensinterne und -externe Akteurswachstum, welches gegebenenfalls zu einer langfristigen Veränderung der Markt- und Wettbewerbsstrukturen und sich verändernden Ergebnissen ökonomischer Selektion in Industrien führen kann.

Publication and Submission Record

The essay 'Incremental Innovation, Heterogeneous Demand and Gravity on the Technological Path' (2007), was held at the DIME Conference on Demand, Product Characteristics and Innovation, Jena, in 2007. In addition, the essay is currently under review of the *Journal of Evolutionary Economics* (submission date: March 06, 2009).

The essay 'Genetic Codes of Mergers, Post Merger Technology Evolution and Why Mergers Fail' (2008) was published in the SFB 649 Economic Risk - Working Paper Series, 2008-029, Humboldt University, Berlin. It was presented and discussed with participants at the 12th International Schumpeter Society Conference, Rio de Janeiro, Brazil, 2008, and the European School on New Institutional Economics, Corsica, France, 2008, and also invited to the 35th Conference of the European Association for Research in Industrial Economics, Toulouse, France, 2008. Furthermore the essay has been submitted to the *Journal of Economic Behaviour and Organization* (submission date: February 05, 2009).

The essay 'Three Axioms on Open Innovation and a (Non-) Parametric Application to the Entrepreneurial Case' (2008) was published in the Ewing Marion Kaufmann Foundation Research Paper Series, vol. 2, no. 11, and it was presented and discussed with participants at the DRUID-DIME Academy Winter Conference, Aalborg, Denmark, the INNO-GRIPS Workshop on IPR and Open Innovation, Manchester, UK, and the Sixth European Meeting on Applied Evolutionary Economics (EMAEE), all held in 2009. In addition, the essay is currently under review of *Small Business Economics* (submission date: March 06, 2009).

Acknowledgement

Obviously, this is the place where to name 'The People' that substantially kept me working hard on this limited set of ideas to be elaborated on in the following chapters. Many, but precisely these are to be named.

Firstly, I would like to thank my advisor Prof. Knut Blind for giving me fruitful and critical advice and an exciting introduction to the broad fields of innovation economics and policy environment. More precisely, his patience and very trust in my skills that enabled me to grow personally (at least it feels like it..), and to explore and define a research program that was in line with my scientific background and views while at the same time keeping me open and liberal to distinct perspectives and schools of thoughts. In addition, his vision in inviting my colleagues and me to join in constructing and vitalizing the Chair of Innovation Economics at the Berlin Institute of Technology in making it one of Berlins most hard-working and ambitious policy think-tanks on innovation and science was (and still remains) an exciting and challenging task.

Secondly, I am indebted to a number of other senior and junior scholars, namely:
- in memoriam Prof. Hariolf Grupp, University of Karlsruhe for being interested in my work and supporting me already at very early stages of my scientific career, Prof. Uwe Cantner, University of Jena, and Prof. Thomas Lux, University of Kiel.
- all colleagues at the Fraunhofer Institute Systems and Innovation Research whom I had the pleasure to work with, long-standing experts in their fields, i.e. PD Ulrich Schmoch, Rainer Frietsch, Stephan Gauch, Dr. Thorben Schubert, Dr. Steffen Kinkel and Oliver Kleine.
- various conference discussants at the International Schumpeter Society, of the inspiring Druid and Dime networks and participants of summer schools at ESNIE and at Jenas Max Planck Institute of Economics & Graduate School.

Thirdly, all my witty colleagues here at the chair with scientific and friendly insights at lunch time, in the office, our research colloquium or be they given at the 'Schleusenkrug'.

Thanks to all of you!: Kerstin Goluchowics, Jan Peuckert, Bent Nowack, Andre Hermanns, Florian Köhler, Axel Mangelsdorf, Katja Hillmann, Gero Stenke, Petra Meurer, Brigitte Essoun, Birgit Trogisch, Mike Weber, Dominic Gorny, Maciej Paluszynski, Eva Wachsen, Susanne Wollin, Sebastian Müller and Falk Mazelis. I still don't know how to get along without our intense, mind-freeing TT matches just after lunch, summer parties on our island, and many, many other instances (you know who you are ;-).

Lastly, but firstly to me, love and respect to all my friends, my parents & my sister, and foremost 'mi guapa'. There is no doubt: Whenever I was puzzled by thought and search, you all brought me back down to earth, took care and helped me to make sense out of it all at the end of the day. In particular, I would like to thank my parents after doing the potentially exhausting job on raising me we are now getting very close friends which I truly do enjoy, and, finally, my beloved girl moving to troublesome Berlin and becoming the essence of my very own family as time passes and together we are building.

Gratefully yours, *Alexander N.*

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1 Sequential Innovation, Heterogeneous Demand and Gravity on the Technological Path

Abstract We develop a duopoly game of sequential innovation, with an investment and a pricing stage. Our understanding of sequential innovation is one of subsequent quality improvements after initially innovating radically. Hence our model suggests, as firms engage in vertical differentiation when innovating, they are less subject to riskiness in R&D investment – a key characteristic of stochastic racing for radical innovation - than they are goal-orientated in their investment choice. Still, R&D investment does not translate directly into a specific quality level but is exposed to technological gravity. We define technological gravity as an indicator for the technology inherent difficulty for further development, a negatively defined perception of technological opportunity and appropriability. For static snapshots of the evolution of technology this indicator is assumed to be constant. Within the model, the technology is seen as a means to the end of turning R&D effort into marketable innovation, while we abstract from the capabilities of firms to cultivate a technology by symmetry assumption. The construction of the model is based on a reformulation of the Hotelling (1929) model on differentiation and a formalization of Dosi's (1982) technology path paradigm.

1.1 Introduction

There are two crucial issues which we wish to introduce for a better perception of sequential[1] innovation activities of firms: the interconnection of innovation and demand structure, in particular technological opportunity and cooperate R&D incentives.

It is commonly accepted in (radical) innovation races (Reinganum, 1989) that firms make a sunk investment in order to succeed in innovating and at the end of day maybe even coming off as a 'first to do so' winner. We agree with this conception as far as radical innovation are considered. Otherwise it would be rather difficult to believe that firms would engage in further R&D if it was only the past winners award, the

[1] Note that sequentialism accentuates that any further incremental development must be based upon *ex ante* radical innovation(s). In the following we do not focus on the mechanisms between incremental innovations themselves (Scotchmer, 1991).

original patent granted for the radical idea, that would keep investments going on.[2] Investing in such a surrounding would suggest for firms that innovation success will, by chance, miracously appear like *manna from heaven*, but leaving firms even worse off not knowing whether it would be manna or anything else falling in their hands. This may well be the adequate theoretical formulation in terms of radical innovations. For other types of innovation it may not be right.

1.2 Towards a Revised Perception of Sequential Innovation

When we approach an ambiente of sequential innovation with firms that vertically differentiate in quality, investment would often appear to be too costly to be undertaken at all. Firms would rather offer homogeneous goods (in terms of quality) than melting down profits by excessive sunk investment. The reader may now well argue that probabilities for success of R&D effort tend to be larger for sequential rather than radical innovation and, hence, common stochastic racing could be calibrated. That is surely true, but we want go further than that: The key characteristic of R&D investment in sequential innovation is not its riskiness but its goal orientiation. A common goal for the investment in quality improvements in more mature markets are demand preferences.

A second argument we wish to establish in our model is the illustration of a yet well-known idea (Dosi, 1982) in evolutionary innovation economics: Teece and Pisano (1994) influential paper introduces the concept of the technological path in a framework of dynamic capabilities of firms. Their point of view is explained through the following statements:

> *We advance the argument that the strategic dimensions of the firm are its managerial and organizational processes, its present position, and the paths available to it. By managerial and organizational processes we refer to the way things are done in the firm, or what might be referred to as its 'routines', or patterns of current practice and learning. By position we refer to its current endowment of technology and intellectual property, as well as its customer base and upstream relations with suppliers. By paths we refer to the strategic alternatives available to the firm, and the attractiveness of the opportunities which lie ahead.*

In particular they define the technological path and its inherent oppportunities as:

> *The concept of path dependencies can be given forward meaning through the consideration of an industry's technological opportunities. It is well recognized that how far and how fast a particular area of industrial activity can proceed is in part due to the technological opportunities that lie before it. Such opportunities are*

[2] Generally, incremental development tends to be patented less often than IP from radical innovations. Reasons may lie in e.g. the higher frequency of successful R&D activity that does not necessarily satisfy the regulatory conditions and/or its dynamic setting, e.g. patent length or breadth. Still, there are significant activities in sequential innovation; Audretsch (1995) suggests that 90 % of commercially significant innovations in the US are actually incremental in nature.

> *usually a lagged function of foment and diversity in basic science, and the rapidity with which new scientific breakthroughs are being made.*
>
> *(Teece and Pisano, 1994, pp. 541,547)*

Teece and Pisano offer a brilliant image of the dynamics of the innovation process. How can this illustration be transferred into an model of industrial organisation? Firstly we relate the path and its steepness to the physical world. Newtonian mechanics suggest that moving or accelerating a body in space can only be done with the implementation of force. Accelerating a body on a slope that is associated with a certain angle α yields the equation for the *inclined plane*[3]:

$$F_H = F_G \sin(\alpha) = mg \sin(\alpha) = \sin(\alpha) \tag{1}$$

Applying the force F_H will move the body up a slope and will be necessary to overcome the power of gravity.

As economists we may now interpret the phenomenon in what follows. It is assumed that firms have a present quality position in the market. When engaging in innovation activity they face technology related difficulties[4] in further developing and differentiating their products in quality. Any successful development will step-by-step push on the status quo of the technological frontier, that is by definition the end of the path. Consequently, there must be steeper technological trajectories and others, more gently inclining ones, both simple static snapshots within the evolution of the technology, depending on the sloping level $alpha$, that is a present characteristic of the technology adhesive to the industry. This idea is based on the assumption that the evolution of technology is grounded on constant (static) innovation/quality returns adhesive to the technology used, as earlier literature suggests (Sahal, 1985). The logic here implies that for a fixed R&D investment, within a given time frame, quality should evolve at a lower respectively faster speed, depending on the technology´s gravity $sin(\alpha)$ for further improvement. In other words, sequential innovations proceed in smaller, respectively larger steps.

The paper sections in a first part which resumes the original Hotelling framework (1929), followed by a reconstruction of the model in section 1.3 that introduces an investment decision depending on a technological path associated with the market. After studying potential entry and demand push effects, we closely look at opportunistic exit for alternative paths of technology in the 1.4. section. In section 1.5 we look at a historical pattern for technology evolution in the US Photovoltaic Industry, before we conclude in section 1.6.

[3]For reasons of simplicity, we will abstract from the inertia properties of the phenomena and friction issues and hence assume that the gravitational force F_G will resume to 1, as the body's inertia m is supposed to be just the reciprocal of the gravitational constant g

[4]We define technological gravity as an indicator for the technology inherent difficulty for further development, a negatively defined perception of technological opportunity and appropriability (e.g. Cohen and Levin, 1989).

1.3 The Basic Model

1.3.1 The Hotelling Framework

A well-known address-branch framework of product differentiation in geographic or product characteristic space is the Hotelling model. It suggests that product position or location of firms $a_i = [0,1]$, $i = [1;2]$[5], results from consumer preferences $h = [0,1]$ anticipating potential utility losses of consumers[6] and the positioning decision of the competitor.

The most general, textbook version of the model (Pfähler and Wiese, 1998) proceeds in two stages with complete information. Firstly, firms choose positions in product space. Secondly, they set prices. Both agents are expected to decide simultaneously. Also, we abstract from older discussions on the preconditions for stability in the original Hotelling concept (e.g. Graitson, 1982).

If we now interpret the former product space as a differentiation space in quality[7] (Shaked and Sutton, 1982), sequential innovation will become costly for firms. Offering a heterogeneous supply to consumers will then yield R&D costs c_i for both firm. For each step in quality firms will have to invest in order to succeed in quality differentiation. After briefly sketching the outlines of the basic model, we will return to the investment decision on the third stage.

Demand size for a specific product from firm 1 or 2 depends on the localization of an indifferent consumer η who is characterized by having equally large utilities from buying firm 1´s or 2´s product. Demand x_i of firm 1 or 2 therefore aggregates to[8]

$$\eta =: x_1 = \bar{a} + \frac{p_2 - p_1}{2t\Delta a}, \tag{2}$$

respectively

$$1 - \eta =: x_2 = 1 - \bar{a} + \frac{p_2 - p_1}{2t\Delta a}. \tag{3}$$

Solving the game recursively yields the following profit[9] maximizing pricing rule for firm 1

$$p_1^R(p_2) = \frac{p_2 + c_1}{2} + t\bar{a}\Delta a \tag{4}$$

[5] With no loss of generality it is assumed that $a_2 > a_1$

[6] The utility function of a consumer buying a product of firm 1 or 2 is $u_1 = W - p_1 - t(h - a_1)^2$, respectively $u_2 = W - p_2 - t(a_2 - h)^2$, with a constant willingness to pay W, quadratic transport costs and a given cost parameter t, $t > 0$. Not buying or buying outside the market is prohibited.

[7] In our model we do not rely on *vertical* differentiation as suggested by Shaked and Sutton (1982). In their model consumers will always opt for higher quality products at a given price. Rather we assume that there is *horizontal* differentiation in multidimensional sets of quality because we believe that this is an adequate formulation for markets where quality is the main driver for competition.

[8] Let us define $\bar{a} =: \frac{a_1+a_2}{2}$, $\Delta a =: a_2 - a_1$, $\bar{c} =: \frac{c_1+c_2}{2}$, $\Delta c =: c_2 - c_1$.

[9] The profit function of firm i is $\pi_i = (p_i - c_i)x_i$

and for firm 2

$$p_2^R(p_1) = \frac{p_1 + c_2}{2} + t(1-\bar{a})\Delta a. \tag{5}$$

For a simultaneous timing of the decisions this leads to the Betrand Nash equilibrium (indexed B) price setting of firm 1 respectively firm 2

$$p_1^B = \frac{c_2 + 2c_1}{3} + \frac{2t\Delta a}{3}(1+\bar{a}) \tag{6}$$

$$p_2^B = \frac{c_1 + 2c_2}{3} + \frac{2t\Delta a}{3}(2-\bar{a}). \tag{7}$$

Accordingly demand and profits of firm 1 aggregate to

$$x_1^B = \frac{\Delta c}{6t\Delta a} + \frac{1+\bar{a}}{3} \tag{8}$$

$$\pi_1^B = \frac{(\Delta c)^2}{18t\Delta a} + \frac{2}{9}(1+\bar{a})[\Delta c + t\Delta a(1+\bar{a})]. \tag{9}$$

In a similar fashion results for firm 2 resume as

$$x_2^B = -\frac{\Delta c}{6t\Delta a} + \frac{2-\bar{a}}{3} \tag{10}$$

$$\pi_2^B = \frac{(\Delta c)^2}{18t\Delta a} - \frac{2}{9}(2-\bar{a})[\Delta c - t\Delta a(2-\bar{a})]. \tag{11}$$

Moving on to the next stage of the model firms consider their quality setting a_i anticipating optimal pricing from the first stage. For firm 1 quality is optimally chosen if the following expression holds,

$$\arg\max_{a_1}(\pi_1^B(a_1, a_2, c_1, c_2)) = \frac{\Delta c}{9} - \frac{2}{9}t(1+\bar{a})[-\Delta a + (1+\bar{a})] + \frac{(\Delta c)^2}{18t(\Delta a)^2}. \tag{12}$$

Equally, firm 2 will maximize its profits given that

$$\arg\max_{a_2}(\pi_2^B(a_1, a_2, c_1, c_2)) = \frac{\Delta c}{9} - \frac{2}{9}t(2-\bar{a})[\Delta a - (2-\bar{a})] - \frac{(\Delta c)^2}{18t(\Delta a)^2}. \tag{13}$$

The next section establishes a relationship between quality choice and R&D effort that implicitly derives positioning from investment choice of firms. However, for changes of quality without R&D costs, the model would still yield maximum differentiation

($a_1 = 0; a_2 = 1$) in equilibrium quality positions as the basic Hotelling framework suggests.

1.3.2 Investment Decision and Rotation of Hotelling Street

For most established markets the beneficial direction of future quality developments is well known to its eagerly waiting consumers. In the aftermath of a radical innovation consumers will quickly become critical about a new technology, its flaws and assets, and therefore will anticipate the perspective technological potential given within the basic innovation which is then a major driving force for the strategic direction of further sequential innovations.

The demand (pull) effect is slowed down by the technological pathway of the industry, e.g. in cancer research, patients preferences apparently induce strong incentives for a drug with an increasing probability of total recovery and a more efficient destruction of mutated cells. Similarly, but on the basis of much less vital interest of the consumers, demand preferences in the chip industry pull suppliers to maximize the number of transistors on a miniaturized integrated circuit for future multifunctional electronic devices. Directions of research may well be evident because of revealed preferences, whilst research and development conduct remains more or less difficult in an industry.

Assuming an industry specific technological path might well cause some doubt among economists. A theoretical approach to the issue is given in a recent paper by Molto et al. (2005) where non-cooperative firms in a single industry can choose out of a continuum of more or less compatible and equally efficient technologies. Because of potential spillovers, through e.g. patent pools or joint research, firms optimally select the same or very similar technologies which causes convergence of technologies within an industry. With strongly specialized players that have built up long-term experience in a scientific field on a markets playground in mind, it is plausible to follow Pavitt (1998) argument on the issue in the lines below:

> *For the individual firm, technological diversity gives it the basis to master and control innovation. For the economy as a whole, diversity amongst firms in their mixes of specialised technological knowledge enables them to explore and exploit a full range of product markets. But at the level of the product market or industry, there is similarity rather than diversity in the level and mix of technological activities in competing firms, and especially in those with high rates of technical change. Technological diversity is certainly not a characteristic of competition amongst innovating firms. [...]*
>
> *On the contrary, rich and well known directions of improvement in underlying technologies create opportunities for diversity and experimentation in product configurations. Technological opportunities create product diversity. There is no convincing evidence that technological diversity creates product opportunities.*
>
> *(Pavitt, 1998, pp. 10–11)*

If we now transfer this set of ideas to the framework of Hotelling it is necessary to establish some relationship between goal-orientated R&D investment c_i and consequent quality position a_i that is exogenously influenced by technological opportunity. Both firms start off with zero differentiation on the technological basis of a given radical innovation at the middle of the street facing a similar technological path that is defined by its steepness $\alpha, 0^\circ < \alpha < 90^\circ$. Each half uniformly rotates around the streets center. From the physical and trigonometric properties out of Eq. 1 it is assumed that

$$a_1 = [0.5 - c_1(1 - F_H)] = [0.5 - c_1(1 - \sin(\alpha))] \tag{14}$$

$$a_2 = [0.5 + c_2(1 - F_H)] = [0.5 + c_2(1 - \sin(\alpha))]. \tag{15}$$

R&D investment does not immediately translate to a position in quality space but is exposed to a present technological gravity F_H that is a major characteristic of the industry´s structure.

Conclusively, sequential innovation is much less subject to uncertainty than is radical innovation – much closer it is related to technological chance, (potential) competition, consumers preferences and their willingness to pay for quality differentiation.

Solving the maximization problems from Eqs. 10 and 11 then yields the symmetric Nash equilibrium strategies, $c_1 = c_2 = c_i$, for the first stage investment decision and its implicit selection of quality, optimally chosen conform to the rule of $a_1 + a_2 = 1$. Prices and profits for firm 1 and firm 2 in investment/quality equilibrium (indexed IQ) therefore resolve to

$$p_1^{IQ} = c_i + 2t[1 - \sin(\alpha)]c_i = \frac{0.5 - a_1}{[1 - \sin(\alpha)]} + t[1 - 2a_1] \tag{16}$$

$$\pi_1^{IQ} = t[1 - \sin(\alpha)]c_i = 0.5t(1 - 2a_1) > 0, \tag{17}$$

respectively

$$p_2^{IQ} = c_i + 2t[1 - \sin(\alpha)]c_i = \frac{a_2 - 0.5}{[1 - \sin(\alpha)]} + t[2a_2 - 1] \tag{18}$$

$$\pi_2^{IQ} = t[1 - \sin(\alpha)]c_i = 0.5t(2a_2 - 1) > 0, \tag{19}$$

whereas equilibrium prices recover investments plus a profit margin that depends positively on the transport parameter and negatively on the markets technological opportunity α. Hence, largest profits are generated when firms move to the extremes of the quality scale. Equally speaking, we have $a_1 = 0$, $a_2 = 1$, as a marginal solution for the first stage investment/quality optima. Assume that firms will not excess the boundaries of the quality interval[10], hence quality differentiation $(a_2 - a_1)$ and technological gravity (force) $sin(\alpha)$ for a symmetric investment $\bar{c}_i^j$, $j = [1;2;3]$, relate as illustrated in graph 1.

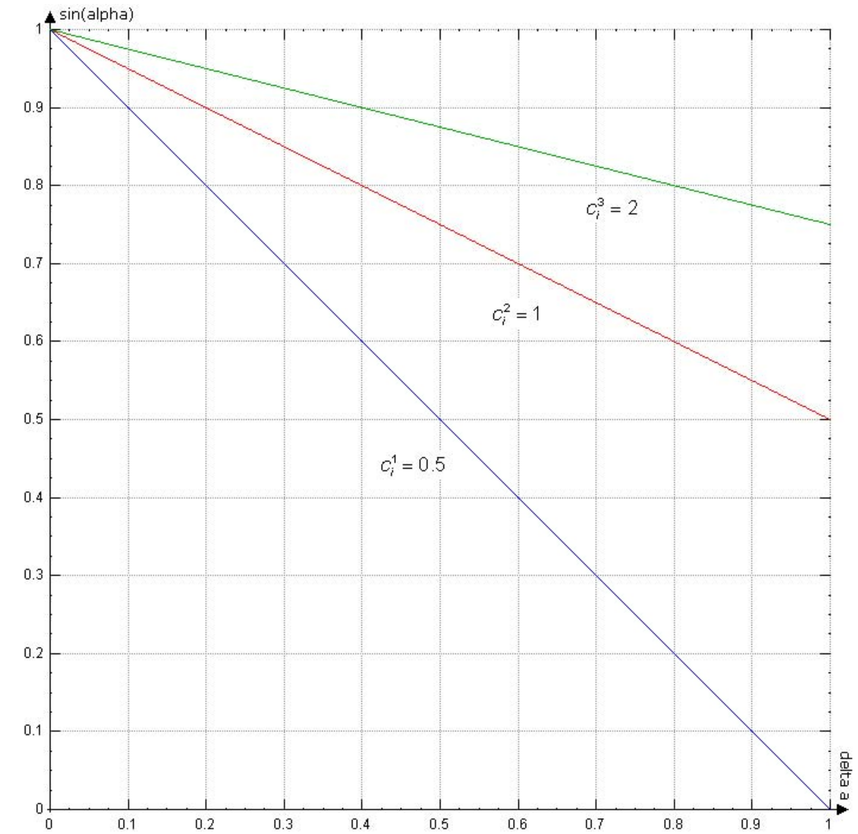

Fig. 1: technological gravity and predicted differentiation in quality with fixed investments

We can exclude alternative equilibria because it is given from the relations of a_i and c_i, that is Eqs. 12, 13 and $a_2 > a_1$, that both firms will always make an investment, $c_1 + c_2 > 0$[11], and with a positive transport parameter t it is clear that

$$0 > -\frac{1}{t[1-\sin(\alpha)]^2} + \frac{1,5}{[1-\sin(\alpha)]^2} \pm 0,75\frac{\sqrt{[1-\sin(\alpha)][-5^1/_3 t + 4t^2[1-\sin(\alpha)]]}}{t[1-\sin(\alpha)]^2}. \tag{20}$$

The willingness to pay for improvements in quality must be restricted in our model. Otherwise firms would completely transfer R&D costs to consumers, independently

[10]The interval for investment may range from $c_i = [0; \frac{0.5}{1-\sin(\alpha)}]$ restricted to the unified quality interval.

[11]Note that by the nature of its construction, a symmetric zero investment prisoner dilemma situation can not appear on the first stage of the model.

from the steepness of the technological pathway. It is therefore assumed, that the willingness to pay for product of firm 1 or 2 must be topped at

$$W^{\max} =: 0.5 + {}^{5}\!/_{4}t \geq p_1^{IQ} + t(\eta - a_1)^2 = p_2^{IQ} + t(a_2 - \eta)^2, \tag{21}$$

where the price and transport costs benchmark is due to the least favoured *indifferent* consumer from the basic Hotelling framework in a quality space with a technological degree of zero and maximum differentiation, that still satisfies zero utility conditions of consumer η. Hence, maximum investment effort c_i^{WP} is restricted to

$$c_i^{WP} \leq \frac{-1 - 2t[1-\sin(\alpha)] + \sqrt{1 + 4t[1-\sin(\alpha)] + 2t[1-\sin(\alpha)]^2 + 9t[1-\sin(\alpha)]^2}}{2t[1-\sin(\alpha)]^2}. \tag{22}$$

The next step is to study the supply side effects of potential entry on sequential innovation effort and competition. Therefore we compare our model characteristics to the three player framework suggested by Brenner (2005).

In his model he assumes homogeneous products, positive market shares and neglects problems of coordination. Hence, demand for firms 1,2 and the potential new entry[12] (indexed in) can be expressed by

$$\chi_1 = \frac{p_{in} - p_1}{2t(a_{in} - a_1)} + 0.5(a_1 + a_{in}) \tag{23}$$

$$\chi_{in} = \frac{p_2 - p_{in}}{2t(a_2 - a_{in})} - \frac{p_{in} - p_1}{2t(a_{in} - a_1)} + 0.5(a_2 - a_1) \tag{24}$$

$$\chi_2 = 1 - \frac{p_2 - p_{in}}{2t(a_2 - a_{in})} - 0.5(a_2 + a_{in}). \tag{25}$$

Accordingly, post symmetric investments, $\bar{c}_i$, of firm 1 and firm 2 as Stackelberg leaders in product quality, and with a newcomer on the market, common equilibrium pricing of each firm with these fixed locations is expressed by

$$p_i^{tri} = p_{in}^{tri} = {}^{1}\!/_{3} \left\langle \bar{c}_i + t\left\{5 - \bar{c}_i\left[1-\sin(\alpha)\right]\right\}\left\{\bar{c}_i\left[1-\sin(\alpha)\right]\right\}\right\rangle. \tag{26}$$

His model implies that outer firms differentiate less than maximally with decreasing profits when there is at least one interior firm. Let us now see how firms will react in our model to potential entry.

[12] We assume that a new firm enters the technology path at quality position $a_{in} = 0.5$.

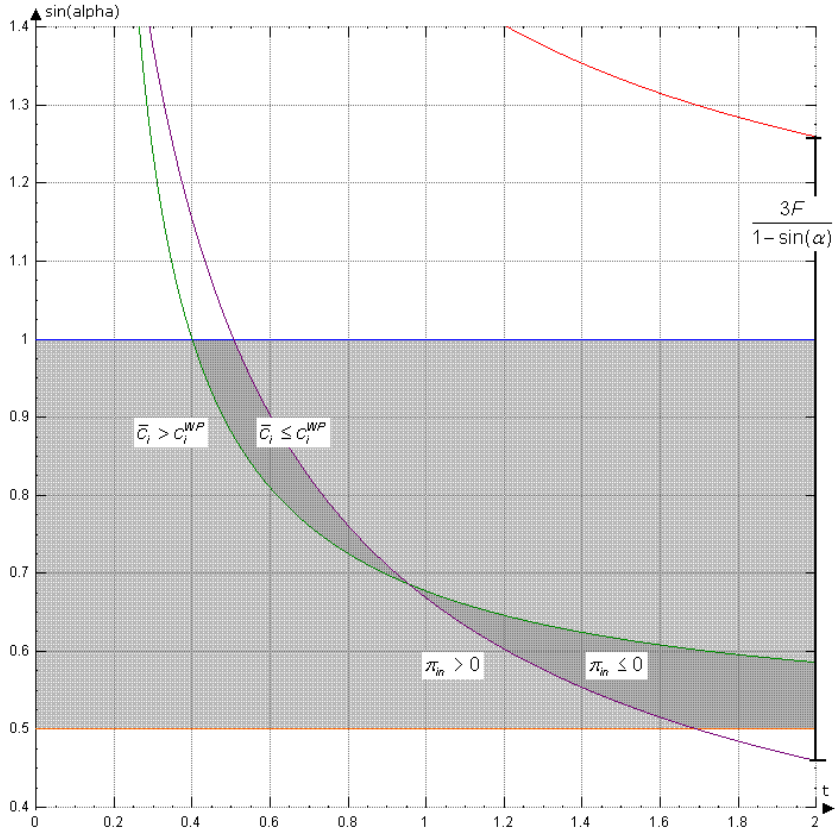

Fig. 2: technological gravity and transport cost parameter with fixed investment $\bar{c}_i = 1$ and large entry costs F_{in}

A firm will enter the market when its profits π_{in} are equal or larger than zero. Given Eqs. 20 and 22, it is easy to see that a firm will enter only if

$$F_{in} < {}^1\!/_3\bar{c}_i^2\,[1-\sin(\alpha)]\left\{1+{}^5\!/_3 t\,[1-\sin(\alpha)] - t\bar{c}_i\,[1-\sin(\alpha)]^2\right\} \tag{27}$$

with fixed market entry costs F_{in}[13], e.g. licensing fees for the technology´s key patent(s). If Eq. 23 does not holds, entry is blockaded.

Abstracting from strategic profileration issues, firms 1 and 2 will only *deter* entry when their profits in duopoly are larger than those in a tripoly scheme. It is always the case if

$$t[1-\sin(\alpha)]\bar{c}_i >$$
$${}^1\!/_6\left\langle -2\bar{c}_i + 2[1-\sin(\alpha)]\bar{c}_i^2 + t\,\{5-[1-\sin(\alpha)]\bar{c}_i\}\,\{[1-\sin(\alpha)]\bar{c}_i\}\,\{1-[1-\sin(\alpha)]\bar{c}_i\}\right\rangle .$$

[13] We refused to make any assumption on the nature of the relationship between entry costs F_{in} and market inherent technological gravity α, because this may strongly vary in reality.

(28)

Hence, it is easy to show, for all parameter values it is given that $\pi_i^{IQ} > \pi_i^{tri}$. For an illustration of the model implications let us focus on the results for a fixed and symmetric investment effort of $\bar{c}_i = 1$ and sufficiently large entry costs F_{in}, as presented in Figure 2.

On the one hand, our results suggest that monopolization at the end of the present path is more attractive to incumbent firms as potential entry is prevalent, at least for some parameter values (upper dark grey shaded field in Figure 2). Hence, for these values of t and $sin(\alpha)$, they may anticipate entry by expanding innovation and quality differentiation, not as other models suggest, by limiting innovation effort[14] (e.g. Moschini and Noh, 2006).
On the other hand, barriers to entry diminish with a decreasing technological gravity, as commonplace in technologically mature markets, and/or for smaller values of t, as entry deterrence becomes less interesting for the two incumbents. The latter, interestingly, may promote – from a welfare standpoint – inefficient entry, where there are no strong preferences of consumers and, sunk entry costs.

1.4 Extension: Opportunistic Technologies

Present business strategies are always evaluated on the background of distinct technological opportunities and their potential benefits and costs. From the nature of profit-seeking it is clear that in their behaviour firms anticipates market entry as well as it makes them exit and opt for opportunities of alternative technologies for their consumer markets.[15]

1.4.1 Sequential Innovation

Let us assume that there is a technology path for an alternative sequential innovation on a technology path with a minor gravity of β, $0 \leq \beta < \alpha$, and an identical transport cost parameter t for consumers.[16] Furthermore assume that there is an established monopolist on this alternative trajectory that does not deter entry through pricing. Firms

[14] Alternatively, firms can deter entry by the transmission of a credible signal for their future pricing strategy that would set prices above fully competitive prices, but below common pricing from Eq. 22, given that potential entry is pending, Eq. 23 holds.

[15] Note that this behaviour bears some notion of open innovation activity as firms do not solely engage in in-house R&D for radical innovation but may screen external technology markets.

[16] Clearly, investigating a technology shift to another path for a fixed consumer market is often subject to a synchronic change in transport cost parameter as other technologies are perceived differently by consumers, e.g. a larger parameter t that allows higher pricing on a different path may become a reason for change.

will leave the current technology path with gravity α if sequential innovation on an alternative path with gravity β is more rewarding, that is $\pi_i^{IQ} < \pi_i^{\beta}$,

$$F^{out,\beta} < t[\sin(\alpha) - \sin(\beta)]c_i. \quad (29)$$

Given that case, exit occurs if market entry costs $F^{out,\beta}$ are smaller than gravitational reduction of technology use for potential investment. The overall (positive) *technology push* effect on quality differentiation for the industry would thus be

$$\Delta a^{\beta} - \Delta a^{\alpha} = 2\bar{c}_i[\sin(\alpha) - \sin(\beta)]. \quad (30)$$

A significant reduction of gravity on the *similar* path could also be interpreted dynamically as a technology push effect between t_1 and t_2 for further improvement of quality.[17] Oppositely, for increases of gravity, when there is no exit option for an alternative technology path, firms may face *technological lock-in*.

Addingly, with a fixed gravity, relaxing the transport cost parameter for an identical group of consumers implies likewise a *demand pull* effect on sequential R&D effort and may also lead to a cooperate shift of technology. For a minor tolerance of consumers for divergence of preferences and qualities on a distinct trajectory, equally speaking with higher values of t, that effect positively contributes to further quality improvements and larger differentiation using a different technology. Smaller values of t tend to slow down the monopolization of quality levels.

If both effects coincide, it depends on the net composition of the two whether or not sequential innovation investment augments or scales down. A positive demand pull effect may even overcompensate a negative technology push effect, and therefore may suffice profit-maximizing firms to change for a more challenging technology with gravity γ, $\gamma > \alpha$.

1.4.2 Radical Innovation

Firms may switch to a mode of screening science for a "window of opportunity", a pathway opened by radical innovation[18] that is distinct from the sequential innovation effort above. Monopolistic rewards of a radical innovator on that *yet unkown* pathway resumes to

$$\pi_i^{radical} = qp_ix_i - F^{out,radical} \quad (31)$$

with probability q, $q > 0$, for successful search and innovation activity, demand $x_i = 1$, sunk costs for basic science orientated R&D effort $F^{out,radical}$ spend on path detection and monopolistic pricing due to the maximum willingness to pay in Eq. 18. Under the

[17] In what follows, we will leave aside this issue for futher research and a dynamic, more complex interpretation of our model.

[18] We relate our model to the understanding of neoclassic innovation models, as in common innovation races, abstracting from dynamic issues, e.g. patent duration.

assumption that no other firm simultaneously detects the same technology path, firm 1 and/or firm 2 will leave the market and engage in radical innovation activity only if

$$F^{out,radical} < q(0.5 + t) - t[1 - \sin(\alpha)]c_i. \tag{32}$$

Hence, for larger probabilities q and/or larger technological gravity forces $sin(\alpha)$ firms will be more likely pursuing a R&D strategy for radical innovation.

1.5 Empirical Note: Estimation of Technological Gravity in the US Photovoltaic Industry 1987–98

The audience supporting an industrial and societal revolution towards environment sustaining production, products and technologies is constantly growing. For the last decades, the global Photovoltaics (PV) industry has been growing and innovating significantly due to immense financial commitment from public and private actors worldwide. However, the highly concentrated[19] US industry has had rather diminishing shares in the enlarging world market and faced declining investment (Nemet and Kammen, 2007), but production growth of an average 18 % p.a.. Even though continual (national and global) innovation activity has led to a significant increase of product qualities in the US market.[20]

Beyond cost effects through production learning and economies of scale through increasing demand on the output side, there is strong indize that R&D investment as input was biased by the evolution of technology (and gravity) in use itself. In what follows we briefly want to estimate technological gravity for the industry in the period 87–98 using different methodologies for quality indication, that is technometrics and citation analysis. Due to the lack of detailed historic data we will not test quality deterrence, consumer restriction or pricing hypotheses derived from our model.

PV production has been based on several different technologies, arising subsequently or frequently co-existing for some time, including thin or thick layer technologies on the basis of various cristalline silicium modes. From the late 80s to 97 amorphe silicium production reduced from 39.5 % to 12 % and slowly shifted to monocristalline production having the largest market shares between 92 and 97. Subsequent production relied most frequently on cheaper polycristalline silicium. In combination with thick layer cell technology that complements 75 % of production since 92, this constitutes the second key feature of the technology in use. Future development seems to rely more heavily on thin layer cell production. In the following we will focus on the production and sells of solar modules (including solar cells) for private households, leaving aside several niche applications of the technologies.

[19] In this period Siemens Solar, Solarex (and Solec) were market leaders with aggregated production shares of 70–80 %.

[20] In what follows we abstract from international knowledge spillovers and, controversly, consider a common national knowledge stock in the industry with no diffusion limitations within the national IPR system.

The rate of change of public and private R&D investment in the US PV industry is assumed to be linear to the change of aggregated investment in renewable energy. From the data (US National Science Foundation) we find that it increased for the period 87–91, stayed rather constant between 91–95 and then fell again until 1998. Differently from Europe or Japan with their various *roof* programs, US public investment has focused in this period on direct grants to research and development projects rather than it focused on stimulation of demand.

Technometrics is an established measurement instrument for quality position of products (Grupp, 1997), allowing the intersubjective examination and validity through the analysis of technical product characteristic, independent from subjective perception. For the PV case we identify four key technical dimensions for product quality of solar modules that are merged on an interval scale and equally weighted : effective power, effectiveness of a module, weight and term of guarantee.

Hence, calculation of technometrics data for the US industry follows the subsequent method according to Grupp: The o-th element of the characteristics of product u is the specification or attribute $A(o,u)$, that may vary in measurement units. By transformation, the metric attribute M (for firm i) in date t is therefore obtained by

$$M(o,u,i,t) = \frac{[\,A(o,u,i,t) - A_{min}(o,u,i_{min},t_0)]}{[\,A_{max}(o,u,i_{max},t_0) - A_{min}(o,u,i_{min},t_0)]}, \tag{33}$$

whereby A_{max}, A_{min} being the maximum and minimum attribute. i_{min} and i_{max} denote the firms i for which A is minimum respective maximum with respect to the total subset. If the scale of the specification is inverse, that is, if the smallest value of A represents the most sophisticated quality level, then an inverse formula holds

$$M_{inv}(o,u,i,t) = 1 - M(o,u,i,t). \tag{34}$$

From this single-item definition a general quality profile can be brought together at the level of all o specifications of product u, given that all characteristic are weighted equally.[21] Hence, aggregated technometrics of a product yield:

$$M_{agg}(u,i,t) = \sum_o M(o,u,i,t)/o. \tag{35}$$

Observations of product (generations) for the final indicator M_T can be either of *static* nature (for the years 87, 91, 96 and 98), that are defined by static vertical differentiation in the industry´s market

$$M_T = M_{agg}^{max}(u,i,t) - M_{agg}^{min}(u,i,t), \tag{36}$$

[21] Alternatively, preferences for loading certain dimensions or specifications could be derived by market observation, from expert knowledge or by hedonic pricing, etc.

or can be *dynamic* (in regard to intraperiod development), that is

$$= \left[M_{agg}(u,i,t) - M_{agg}(u,i,t-1)\right]^{max} - \left[M_{agg}(u,i,t) - M_{agg}(u,i,t-1)\right]^{min}. \quad (37)$$

The indicator estimates for the US PV industry from 87–98 are presented in graph 3. We observe that quality leadership frequently changed between competitors.

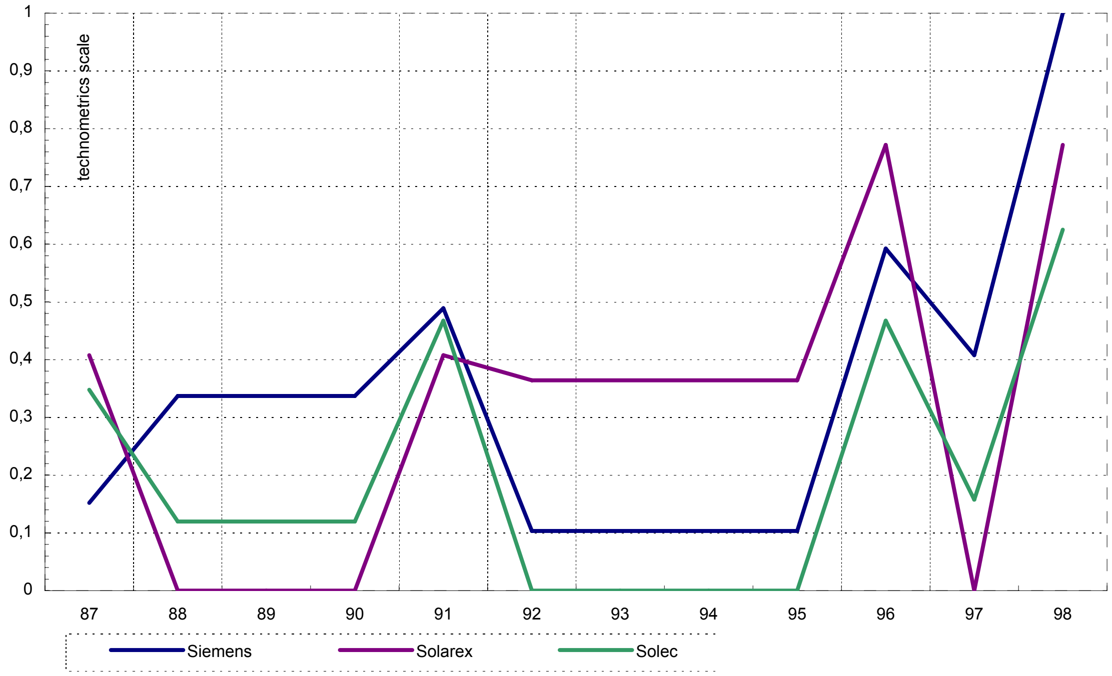

Fig. 3: Technometrics for the US Photovoltaic Industry 87–98. Data collected from Photon Journal and Ecology Institute Freiburg. Basis for calculation are the characteristics of the 1987 product generation from Siemens Solar, Solec and German Photowatt solar modules.

Alternatively, one may choose an alternative quality indicator for the analysis of gravity. With some restrictions we may assume that the number of patents (and, in particular, citations received) reflect the quality improvements throughout the innovation process (Hall et al., 2001; Harhoff et al., 1999). Especially in the ambiente of sequential innovations the time to market appears to be rather short[22], different to (radical) inventions and related time lags to marketable product. For each patent in the PV industry the number of times it is cited by subsequent patents is calculated. *High-value* patents (HV) are those that received twice as many citations as the average patent in that technology category. Between 5 to 10 % of the patents examined qualified as high-value.

[22]Furthermore, the necessary duration for successful protection of sequential innovations is rather short-handed as the value of patents and innovation itself sharply decreases. On the opposite, it is to question whether a majority of sequential innovations is patented or rather protected through alternative instruments, e.g. secrecy.

Finally, we scale down by setting the absolute numbers for HV patents in relation to the highest annual (see Figure 4).

Both concepts of quality (M_T, HV) are applied to estimate technological gravity $sin(\xi)$ as suggested by Eqs. 12 and 13 in our model

$$\sin(\xi^{MT}) = 1 - \frac{\Delta a}{2c_i} = 1 - \frac{M_T}{2c_i}, \tag{38}$$

respectively, for citation analysis

$$\sin(\xi^{HV}) = 1 - \frac{HV}{2c_i}, \tag{39}$$

where the average firms investment level c_i is intervall-scaled and proxied by the annual rate of change for overall renewable energy investment.

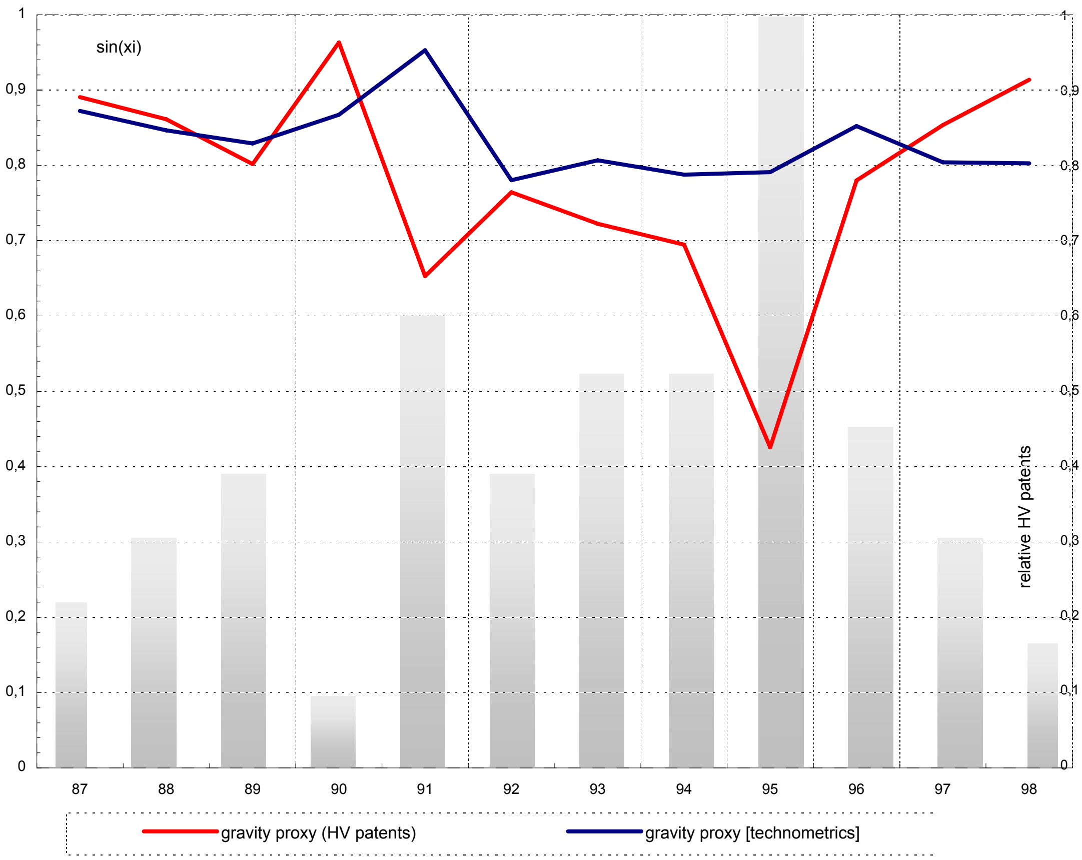

Fig. 4: Technological gravity estimates and relative number of HV patents. Basis for calculation of investment change rate is public and private R&D investment in 1987. Source: NBER citations data and National Science Foundation.

The results are matched and illustrated in graph 4. Both methodologies imply quite similar evolutions of technological gravity, even though it is not made explicitly nor by a very thorough argument, what innovation phases are sequential rather radical ones. Still, this implies that (sequential) innovation activity is strongly correlated with the vertical differentiation process in the market. We proxy that particular high-value patents suggest periods of radical change (10–12 citations received), while the rest is possibly subject to incremental improvements. An alternative approach that could be used for separation is using technological mapping via a more complex citation analysis (Verspagen, 2007). However, for the sake of further qualitative interpretation of the estimates let us assume that there are two radical changes in PV technology (91 and 95), that separate evolution in three periods of sequential innovation activity.

– First period (87–90): Both indicators yield very similar proxies for technological gravity, both slightly decreasing until 89. Then again, they strongly increase towards disruptive change in 91, which maybe the cooperate ratio for change of path [see subsection 1.4.2 of the model, in the taxonomy: search for and change to a radical innovation path].

– Second period (92–94): Mainly relying on the amorphe silicium associated technologies so far, there is a shift to dominance of monocristalline silicium use which the latter prevails throughout the period, maybe even little further. We find significant decreasing gravity for each indicator, still that does not necessarily contradict our model hypotheses. Rather it is intuitional, that path exit and choice is not solely backed by technological gravity, but also can be explained by e.g. expansion of sells and potential economies of scale in production. The technological path described here persists for approximate 3–5 years.

– Third period (96–98): Technology choice in the third period seems to be closely linked to the second period, as firms change to a path with constantly increasing gravity. In addition to the explanation mentioned above, a change in the structure of demand may have caused demand pull effects [see subsection 1.4.1 of the model, in the taxonomy: change to an alternative, path of sequential innovation], e.g. Japanese kick-off for demand stimulating federal grant program, that are not controlled for in our estimation of technological gravity.

As we lack a detailed data on consumer evaluation of supplied product quality, we can solely interpret relative changes of technological gravity, and we are not aware of static values or evolution of the transport parameter t, nor the overall size of the quality street. Hence, testing of the pricing or revenues hypothesis of firms is not possible as we cannot control for demand pull effects. Furthermore, pricing behaviour maybe subject to additional strategic interaction in the industry, in particular from a dynamic perspective (e.g. high-priced lead users crediting sequential investment of firms).

The expansion of PV production is another crucial issue for the analysis of the case, as the basic Hotelling model suggest constant demand size and equal distribution along the quality spectrum. Whether or not that causes a change of the distribution of the population, an increasing variety of preferences along the spectrum (equally speaking, an enlargement of the path) or maybe a change of the transport cost parameter itself.

Due to the lack of data, we must admit that a comparison with a separate national market using similar technologies, would be very helpful but is not feasible, even though it would be a necessary condition to prove the existence of constant (static) gravity of a technology suggested in our model. Furthermore, the dynamic phenomena of surviving routines from evolutionary thought and more generally, the capability of the individual firm in cultivating a specific technology are neglected in both parts of the essay, the model and within the emprirical testing section.

1.6 Conclusions

Our model, a formalization of the technological path paradigm, implies that quality differentiation relaxes price competition and hence, has explanatory power for sequential innovation (incentives). The mere existence and the timing of sequential innovation inside the diffusion process becomes obligatory, as soon as original inventions are not fully exclusive to radical innovators but face competition on a path, as for most cases e.g. with incomplete patent protection.

With simultaneous choice on the location stage, firms will invest symmetrically in (Nash) equilibrium, only restricted by consumers willingness to pay. These sequential innovations lead to a differentiation in quality that positively depends on the tolerance cost parameter and negatively on the degree of gravity and is not necessarily maximal.

Given potential entry, cooperate ratio for sequential innovation spending can hinder potential entry by enhancing quality and hence, increasing innovation effort. Barriers to entry slowly diminish with lowering parameter values of technological gravity. Furthermore, we elaborate on switches to distinct trajectories triggered by technology push, respectively demand pull effects.

Still, our construction of the path paradigm lacks some essential features. The model does not explicitly integrate the interaction of incremental innovation effort and the evolution of technological gravity, what was branded “inner dynamics” of the engineering dimension by Dosi (1982). *Moving* on the path is subject to path dependency as well as knowledge flows inbetween competitors, e.g. by leapfrogging, maybe even waiting of buyers for further quality development. A more complex game or simulation model should shed light on these issues.

Logically, our model raises several hypotheses that still lack empirical testing. However, the technological gravity indicator may deliver fruitful implications for STI policy making e.g. whether federal grants or demand subsidies can impact and drive technology use or even path change, or, oppositely, on the micro-level, may be integrated into a more sophisticated cooperate strategy for technology selection.

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2 Genetic Codes of Mergers, Post Merger Technology Evolution and Why Mergers Fail*

Abstract This paper addresses the key determinants of merger failure, in particular the role of innovation (post-merger performance) and technology (ex-ante selection) when firms decide to separate. After a brief review of the existing literature we introduce a model of process innovation where merged firms exibit intra-merger spillover of knowledge under different market regimes, depending on whether firms integrate vertically or horizontally. Secondly, we describe an ideal matching pattern for ex-ante selection criteria of technological partnering, abstracting from financial market power issues. In a final section we test the model implications for merger failure for M&A data from the US biotechnology industry in the 90s. We find that post-merger innovation performance, in particular with large spillovers, increases the probability of survival, while we have no evidence that market power effects do so in long run. Additionally, we find extensive technology sourcing activity by firms (already in the 90s) which contradicts the notion of failure and suits well the open innovation paradigm.

2.1 Introductory Note

With the end of Daimler Chrysler decade another "world company" resolved back into its national components. As the Daimler CEO Zetsche states, ratios for the demerger where to be found in "constantly decreasing synergies within the merger", next to the capital market risks related to ongoing financial transfers to support Chryslers lossy production. The former argument is mostly associated with supply side economies of scale and scope in the merged organization and production in the early merger stages. Anyhow, in our study we investigate that the post merger evolution of technology, i.e. technological synergies, may in the long run become a key aspect why former partners separate.

Increasing overall numbers of Multinational Enterprises (MNE), growing volumes of FDI and volumes of trade are persistent phenomena in the process of globalization (Narula and Zanfei, 2004; OECD, 2007). Multiple attempts have been made to construct

*This project was co-funded by the Deutsche Forschungsgemeinschaft (DFG) through the collaborative research center 649 "Economic Risk" at Humboldt University, Berlin.

efficient "world companies" that can master survival in global competition. International activities reflect that firms are less focused on national resources of production than they were some years before. In particular, the strategic orientation of R&D processes has recently been subject to change (Blanc and Sierra, 1999; Granstrand et al., 1993; Von Zedtwitz and Gassmann, 2002): Some firms opt for new business models such as Open Innovation (Von Hippel and von Krogh, 2006; Chesbrough et al., 2006) which explicitly tries to capture and complement knowledge sources external to the firm to internal ones, as new combinations of technological components (e.g. Fleming, 2001; Rosenkopf and Almeida, 2003) may lead to successful further development in the invention process. Hence, these firms engage in screening and sensing (international) technology markets for new potential resources, and cooperate with partners e.g. through alliances, licensing or mergers and acquisitions (M&A). For the latter, the extent of search processes and subsequent selection of partner are partly subject to commitment and strategic beliefs of firms regarding the general value of technological capabilities (Langlois, 1992) for success and their own absorptive capacity (Cohen and Levinthal, 1990).

Next to non-technological arguments which clarify the original merger decision such as the managers Hybris motive or capital market based ratios (Müller, 2003; Gugler et al., 2006) for behaviour, there is a technological perspective for M&A activity (Hall, 1988) where firms source for knowledge globally or locally, and, that not exclusively relates to efficiencies in production or competition effects in post merger markets (Kleinert and Klodt, 2002).

In contrast, we suggest that demerger decisions are grounded more deeply in verifiable, rationalized facts like innovative or product market performance in the intraperiod of merger existence, and can also be to some extent referred and quantified by the evolution of technology, at least in high-tech industries, as it is well established that demerger may go along with the risk of negative stock market evaluation (e.g. Agrawal et al., 1992), organization reconstruction or even delisting (costs).

Subsequent innovative performance has been another focus of recent research (Hagedoorn and Duysters, 2002; Colombo et al., 2005, sector-specific: Stephan and Gantumur, 2007), e.g. by measuring post merger patent intensity, R&D personnel and R&D productivity. Other studies combine both approaches, the selection problem and ex post performance, or most recently investigate competition effects in regard to technological relatedness (Hussinger and Grimpe, 2008).

Demerging unlocks resources, e.g. financial constraints and limited human resources, for further search processes and internalization of external technological knowledge through (inhouse) spillovers (Jaffe, 1986), hence demerger may not necessarily be caused by the lack of post merger innovative performance and insufficient technology evolution, but may be motivated by completed, successful internalization of technological knowledge, in particular in high-tech industries. Needless to say, demerger must not bear the connotation of (technological or organizational) failure of a riskful merger experiment driven by mismanagement, but may also have a natural date of expiration.

Below discourse addresses the key determinants of merger failure. A second question focuses on the particular role of innovation and technology when firms decide to separate. In section 2.2 we introduce a model of process innovation where merged firms exhibit intra-merger spillover of knowledge under different market regimes, depending on whether firms integrate vertically or horizontally. Secondly, we describe an ideal matching pattern for ex-ante selection criteria of technological partnering. In Section 2.3 we test the model implications for merger failure for M&A data from the US biotechnology industry in the 90s, section 2.4 concludes. We find that post-merger innovation performance, in particular with large spillovers, increases the probability of survival, while we have no evidence that market power effects do so in long run.

2.2 Linkages between Merger (Failure) and Innovation

When merger pairs form and possibly separate they run through a process of selection and a process of de-selection. To see what really drives these processes it is necessary to fully understand their motives and causes. The end of a merger is not necessarily the point in time when investigation should end.

Firstly, the selection process may be initiated by a variety of motives. Possibly, these may include individual pursuit of managements, increase in market power or maybe following technology sourcing motives e.g. to amplify a firms technological profile. The causes that finally govern the selection process may differ from original motives of the merger, as, in most cases, capital markets and a firms individual or relative[1] financial power on these markets may even change rational selection decision.

Secondly, the potential process of de-selection is much more complex to analyze as *only one* of the primary sources causing failure may lie in a posteriori misled selection process. General production performance, that is production synergies from post-merger economies of scale and scope, or when focusing on innovation performance, potential process and e.g. or product innovation success, again, by increases in R&D efficiency via scale and scope economies, via a reduction of substitutional research, or via intra-merger spillovers by mutual learning processes in the common labs that, for the case of process innovation, may have product quality-enhancing or production cost-reducing effects. Next to selection and performance causes of demerger, failure may be well intended and can be motivated i.e. by technological restructuring of a company. Still, other motives to separate include traditionally unexpected failed, bad performance or drastic changes in the market environment itself.[2]

[1] The balance between the acquirers and targets financial power i.e. plays a role if the merger is a hostile takeover. Similarly, several acquirers may bid for an interesting target candidate.

[2] These changes in framework conditions of the market maybe caused i.e. by disruptive technologies developed by a third party firm, changes in market regulation or unexpected shift of demand.

2.2.1 The Role of Genetic Codes of Technology and Integration Choice: Market Dominance, Post-merger Performance and Merger Failure

Grounded on the basic insights of the model from Kamien and Zang (1999, in the following KZ) we develop a two stage game in which a newly formed merger couple can perform process innovations under different levels of market concentration. On the models first stage the merger entity decides on common R&D investment, then, on a second stage it optimally sets prices and quantities for a given market structure. As all this happens in the post-merger phase, technological codes of merging partners are predefined, that is exogenously given. Still, these codes define the level of intra-merger spillovers due to the level of the partners individual (technological) experience, technological proximity of partners (Jaffe, 1986) and common R&D effort of the merger couple Kim (1998). Referencing on the absorptive capacity paradigm from Cohen and Levinthal (1990) KZ propose a representation of a firm's 'effective' R&D effort that incorporates absorptive capacity as a strategic variable, which we take here as predefined and which we will review in the next section, into their research joint venture model. Specifically, they propose that the i-th firm's 'effective' R&D effort X be represented by

$$\mathrm{X}_i = \chi_i + (1-\delta_i)(1-\delta_j)\beta\chi_i^{\delta_i}\chi_j^{1-\delta_i}. \tag{1}$$

In our post-merger scenario, given that partners invest symmetrically, the intra-merger spillovers that additionally, with rate ξ, empower the investment level x of the merger pair summarize to

$$X = x[1+(1-\delta_i)(1-\delta_j)\beta] = \xi x \tag{2}$$

with $\chi_i = \chi_j$ and $x = 2\chi_i$. χ_i respectively χ_j refers to each partners own R&D expenditure level or reduction in its unit production costs, with $0 \le \delta_i \le 1$, $0 \le \delta_j \le 1$ and $0 \le \beta \le 1$. Now the exogenously given parameter β is the fraction of one partner's R&D effort that virtually spills over to other partner's R&D efforts. In the general joint venture literature it represents the involuntary spillovers from a partner's R&D activity that it has only a limited ability to curtail, such as the information disclosed when patents are granted, information provided in trade and scientific publications, information provided through reverse engineering, information disclosed through the migration of employees, suppliers, and customers, and industry-wide rumors and gossip. In our context, we re-interpret the parameter as a measure of technological proximity (Hussinger, 2005) between merging partners that restricts or enhances well-intended, intra-merger spillovers, basically saying that partners with technologically closer competences can learn faster and more profound from each other as they are carriers of similar technological regimes (Nelson and Winter, 1977; Marsili and Verspagen, 2002) and most probably employ members of the same/a similar technological community (Rappa and Debackere, 1992).

The term δ, on the other hand, refers to the endogenous control the i-th partner can exert on the spillovers its R&D activity generates through the choice of an R&D approach. A very narrow, firm-specific approach corresponds to $\delta = 1$ and generates no spillovers to others because the information it provides is to some extent irrelevant to them, it can only hardly be decoded and learned. On the other hand, it also limits the firm's absorptive capacity. At the other extreme, a totally non-specific approach, i.e. a basic approach, corresponds to $\delta = 0$ and generates the maximum spillover to others but also maximizes the firm's absorptive capacity for any level of its R&D spending. Again, as we treat δ as a non-strategic, exogenous parameter, each partners absorptive capacity (AC) is predefined, so that for partner i respectively j, with symmetric investment, it is given that

$$AC_i = (1 - \delta_i)\chi_i^{\delta_i} \tag{3}$$

and

$$AC_j = (1 - \delta_j)\chi_j^{\delta_j} = (1 - \delta_j)\chi_i^{\delta_j}. \tag{4}$$

In the merger context, absorptive capacities reflect the individual *potentials* for successful technological integration of merging partners, and, hence, may offer a first *ex ante criteria* for profound analysis on technological synergies developed in the post-merging innovation performance phase.

When solving the model recursively, we assume a simple, Cournot competition market model where the merger couple faces an inverse, linear demand function, $p = a - Q$, with an *overall* merger output of Q, given that $a > Q \geq 0$. Furthermore, without loss of generality, we suppose a negative demand curve slope of -1. The mergers profit function π^z as modeled by KZ compounds potential process innovation effects of 'effective' investment reducing common marginal production costs $C(Q, X)$ – from their initial level of A to somewhere below that level –, and an exponential, non-negative cost function for R&D effort[3], $\bar{C}(R\&D)$. More precisely, it resumes to

$$\pi^z = pQ - C(Q, X) - \bar{C}(R\&D) = pQ - [A - X]Q - 0.5\gamma x^2, \tag{5}$$

with $[A - X] \geq 0$ and $\gamma > 0$.

Depending on the structure of the market z, $z = [mon, duo]$, the equilibrium solutions of the game change. Let us suppose that horizontal mergers – more than vertical ones – are associated with larger, immediate market power, i.e. that firms merging horizontally may perform in a monopoly structure while vertical mergers compete with some third party in a duopoly. Then, for the former structure, solving the profit-maximization problem of the horizontally merging entity from equation (5) resolves to

$$\max_x \pi^{mon} = \tfrac{1}{4}(a - A)^2 + \tfrac{1}{4}x[(\xi^2 - 2\gamma)x + 2\xi(a - A)] \tag{6}$$

[3]Note that throughout the model it is assumed that different R&D approaches rely on similar R&D cost functions.

with an optimal, common investment level $\tilde{x}^{mon}$ of

$$\tilde{x}^{mon} = \frac{(a - A)\xi}{2\gamma - \xi^2} \tag{7}$$

under monopoly pricing and quantities on the second stage, so that profits summarize to

$$\pi^{mon}(\tilde{x}^{mon}) = \tfrac{1}{4}\left\{(a - A)^2 + \frac{[(a - A)\xi]^2}{2\gamma - \xi^2}\right\}. \tag{8}$$

Analogously, under a duopoly scheme, with no spillovers to the third party firm assumed, the profit-maximizing problem of a vertical merger pair on the first stage is

$$\max_x \pi^{duo} = \tfrac{2}{9}(a - A)^2 + \tfrac{2}{9}x[(\xi^2 - \tfrac{9}{4}\gamma)x + 2\xi(a - A)]. \tag{9}$$

Again, the optimal R&D effort $\tilde{x}^{duo}$ derived from the F.O.C. is

$$\tilde{x}^{duo} = \frac{(a - A)\xi}{\frac{9}{4}\gamma - \xi^2} \tag{10}$$

respectively, for maximal profit

$$\pi^{duo}(\tilde{x}^{duo}) = \tfrac{2}{9}\left\{(a - A)^2 + \frac{[(a - A)\xi]^2}{\frac{9}{4}\gamma - \xi^2}\right\}. \tag{11}$$

It is easy to see (Eqs. 8 and 11) that profits under the monopoly scheme are somewhat higher, given identical parameters in both markets, than in a duopoly market, put differently it is always the case $\pi^{mon}(\tilde{x}^{mon}) > \pi^{duo}(\tilde{x}^{duo})$. Anyhow, considering investment incentives under each market regime, $\tilde{x}^z$, it is interesting that even though potential amortization of process innovation efforts seem to be higher due to the larger scale of production as a duopolist, they are outweighed by the option of the monopoly pricing margin as a direct transfer mechanism of R&D costs to consumers.[4]

H 1. *For an identical set of parameters $[a, A, \gamma, \xi]$ in both market structures, the immediate effect of market power on profits is higher for horizontal merger than for firms merging vertically, given that above market structure – integration type – assumption holds. Hence, horizontal integration may decrease the risk of merger failure in the long-run while vertical integration generates a lower probability of survival.*

We find that generated profits from market power may crucially depend on the intra-merger spillover effects $\xi(\delta_i, \delta_j, \beta)$ on process innovations whatever type of merger one

[4] These structural results are in the Schumpeterian line of reasoning that more concentrated markets lead to higher levels of innovation.

considers, when keeping all other parameters $[a, A, \gamma]$ fixed. Then, it may be even the case that due to large spillovers the acquirer may wish to opt for a vertical rather than horizontal partnering firm/target as the market power effect is overpowered by the effectiveness of R&D investment on process innovation and, hence, drastic increases in profits. Conclusively, it will become important to elaborate on *how merger pairs should be formed* that maximize spillovers – if we abstract from the market integration issue–, and, hence, make common R&D efforts more effective and help increase profits from process innovations.

H 2. *For larger (smaller) values of ξ, that is higher (lower) levels of intra-merger spillovers, the effectiveness of R&D effort is enhanced (reduced) so that the altitude of process innovations and, hence, joint profits should increase (decrease). From a dynamic perspective, this may lower (increase) the probability of merger failure.*

Different to the KZ model where firms set R&D approaches strategically for the purposes of successful joint venture in research on an additional stage of the model, we apply exogenously set R&D approaches as a key (technological) characteristic in the (strategic) selection process for finding the adequate merging partner, for a given technological proximity of partners. Firms with different R&D approaches are either high or low types, which in our model translates to broader, respectively narrow approaches (smaller or larger δ). Basically, the selection process points towards certain, optimal patterns of matching and technology sourcing (Malerba and Orsenigo, 1993) which we will investigate on in the following section.

2.2.2 Positive Assortative Matching Patterns: The Role of Genetic Codes of Technology for Merger Selection and Failure

Suppose, we have two types[5], $\delta_i' > \delta_i$ and $\delta_j' > \delta_j$, for each firm i and j as binary gender (either acquirers or targets) in a two-sided model with *assortative matching* Legros and Newman (2007, in the following LN). Let I be the set of acquirers on one side of the market and let J be the set of targeted firms on the other. The description of a specific economy[6] includes an assignment of individuals to types via maps $\rho : I \rightarrow P$ and $\alpha : J \rightarrow A$, where P and A are compact subsets of $\mathbb{R}$. To simplify the exposition, we assume that I and J have the same cardinality. The joint R&D payoff function of the matched merger pair is described by the level of spillover exhibited due to common R&D effort (Eq. 2), so that the firm-specific utility maximization problem ϕ for firm i in finding the optimal matching partner simplifies to

$$\phi(\delta_i, \delta_j, s) = \max_{\delta_j, s}(1-s)\xi x \tag{12}$$

[5]De facto we observe the discrete case with a continuum of types.

[6]Two further assumptions are generally made on matching models, namely (1) that the payoff possibilities depend only on the types of the agents and not on their individual identities, and (2) the utility possibilities of the pair of agents do not depend on what other agents in the economy are doing, that is, there are no externalities across coalitions.

$$s.t.s = \frac{AC_j}{AC_i + AC_j} \tag{13}$$

with the sharing rule s, $0 \leq s \leq 1$, that is implicitly contracted by the predefined absorptive capacities of each partner (Eqs. 3 and 4). The utility share firm i gets from exhibited spillovers is $(1 - s)$ while firm j gets a share of s. Obviously, for non-symmetric cases of ACs firms then profit very differently from spillover effect inside the merger, when, from an evolutionary perspective[7], i.e. the *potentials to learn* from each others technological competences vary. Put differently, the difference in the pace of learning may lead to an asymmetric technological integration success in short- or mid-term run that may be perceived – at least from the partner with minor AC potentials – as a minor level of technological synergies in individual, post-merging innovation performance while the higher AC firm may benefit from this particular formation, even though product market profits from common, *median* process innovation altitude are assumed to remain unchanged in the long run.[8]

H 3. *With significantly different absorptive capacities of merging partners sharing of exhibited intra-merger spillovers is asymmetric as they learn at a different speed from each other, which may enforce merger failure in the (early or mid-term) phases of technological integration.*

Ideally, the selection process of merging firms should lead to a *positive assortative matching* (PAM) pattern, that is high (low) types will match with high (low) types, as this should maximize spillovers and, hence, altitude of process innovation. This is the case if firm i's utility function from exhibited spillover (Eqs. 12 and 13), and analogously firm j's, are increasing (or more precisely, non-decreasing) in type, in other words, if matching with a broader R&D approach partner this should increase the joint spillover payoff. So given that below equations hold

$$\phi_1(\delta_i, \delta_j, s) \leq 0 \tag{14}$$

$$\phi_1(\delta_i, \delta_j, s) = (s-1)(1-\delta_j)x\beta - s'x\left[1 + (1-\delta_i)(1-\delta_j)\beta\right] \leq 0 \tag{15}$$

and

$$\phi_2(\delta_i, \delta_j, s) \leq 0 \tag{16}$$

[7] Rather than focusing on profit-maximizing product market orientation, this perspective considers the evolution of merger cooperation and its implications for post-merger innovation performance.

[8] Please note that our application of the KZ model does not explicitly consider a specific post-merger phases of technological integration activity. Still, it may be quite useful to think of i.e. post-merger period of re-organization of R&D facilities, general learning on mutual skills and developing a set-up of a common R&D agenda.

$$\phi_2(\delta_i, \delta_j, s) = (s-1)(1-\delta_i)x\beta - s'x\left[1 + (1-\delta_i)(1-\delta_j)\beta\right] \leq 0, \tag{17}$$

individual payoff functions are type increasing as

$$s' > 0, \tag{18}$$

if, and only if

$$1 - \delta_j \geq \frac{1}{\ln(\frac{x}{2})}, \quad 1 - \delta_i \geq \frac{1}{\ln(\frac{x}{2})} \tag{19}$$

which basically requests that a certain level of common R&D effort is made for spillover effects to unfold fully inside the merger.

Additionally, sufficient conditions for PAM according to the *generalized increasing difference conditions* suggested by LN must satisfy

$$\phi_{12}(\delta_i, \delta_j, s) \geq 0 \tag{20}$$

$$\phi_{12}(\delta_i, \delta_j, s) = -(s-1)x\beta + s'x\beta\left[(1-\delta_i) + (1-\delta_j)\right] - s''x[1 + (1-\delta_i)(1-\delta_j)\beta] \geq 0, \tag{21}$$

and

$$\phi_{13}(\delta_i, \delta_j, s) \geq 0 \tag{22}$$

$$\phi_{13}(\delta_i, \delta_j, s) = s'(1-\delta_j)x\beta - s''x[1 + (1-\delta_i)(1-\delta_j)\beta] \geq 0. \tag{23}$$

If Eqs. 18 and 19 hold, then it easy to show that $s'' \leq 0$. Generally speaking, condition 20 secures type-type complementarity as commonly used in matching models, while condition 22 secures an additional type-payoff complementarity that guarantees PAM, even in those cases with type-related, limited (or non-) transferability of utilities where agents may be limited in the bidding competition for the higher type partner.

In our context, the implications from the ideal PAM result suggest that for the technology sourcing firm searching for the right partner, technologically most proximate firms with more narrow R&D approaches and firms with broader R&D approaches should match. Technologically-driven merger selection whose success or failure crucially depends on post-merger innovation performance must consider the potential effects of spillovers as well as the aspect of sharing/absorbing these effects in the integration phase.

2.3 Testing

2.3.1 Data Description

In order to test the derived hypotheses H1-3 we develop a data set of 3804 M&A deals in the US biotechnology sector, as a high-tech and innovation-driven industry, for the period from 1990 to 2000, excluding cross-boarder transactions, and also well before international stock crisis right after the turn of the century. Additionally, we explicitly focus on those deals in the THOMPSON© SDC Platinum M&A data bank where full legal ownership changed from target to acquirer, that is i.e. 100 % stakes were transferred. The data supplies date of acquisition, industry classification of targets, respectively acquirers, and some general information on primary business activities of both parties. 44 of these deals could be identified as being cases of demerger for the observed period of time. The rate of failure may seem too low and may contradict other studies on the issue (see for example Porter (1987) who assumes about 50 % of mergers to fail) at first sight, but as we assumed that demerging was present when targets re-appeared[9] on the M&A market for technology after being acquired in the first place, numbers become more reasonable. Most probably, we still may have a certain bias in our data as we solely considers divesture cases where the re-acquired target still had some technological value for others, and we cannot identify those merger failures e.g. were the merger was delisted or even went bankrupt. Figure 1 presents the survival time of these failure cases for the biotechnology industry in comparison to merger life cycles we found in other US high-tech sectors. Table 1 summarizes the biotechnology sample used in the next section.

Table 1
Descriptive statistics of US biotechnology domestic mergers (1990–2000) sample. Horizontal merger if target and acquirer have identical SIC/industry class., vertical formation is otherwise assumed.

	vertical mergers	horizontal mergers	overall no.
failure cases	31	13	44
survival cases	2632	1128	3760

The cases of merger failure identified were supplemented by a sample of surviving mergers that was drafted randomly, and, both are matched to a separate, extensive patent analysis of 68 companies patent portfolios with USPTO patent data. For the latter analysis we exclusively focused on (US) patent applications – as an indicator of the present margin of a firms innovation activity and the firms profile of central technological competences – and, we also assumed a constant depreciation rate of knowledge of .15 when calculating actual patent stocks of each company. Each individual application is assigned to a technology class according to the International Patent Classification (IPC) that covers eight different technology fields, A-H, and an extensive sub-categorization where, for the purpose of our analysis, we applied the 4-digit level. In order to control for the importance of the individual patent classes for the firm

[9] It is assumed that with the second transaction date the failing merger ends.

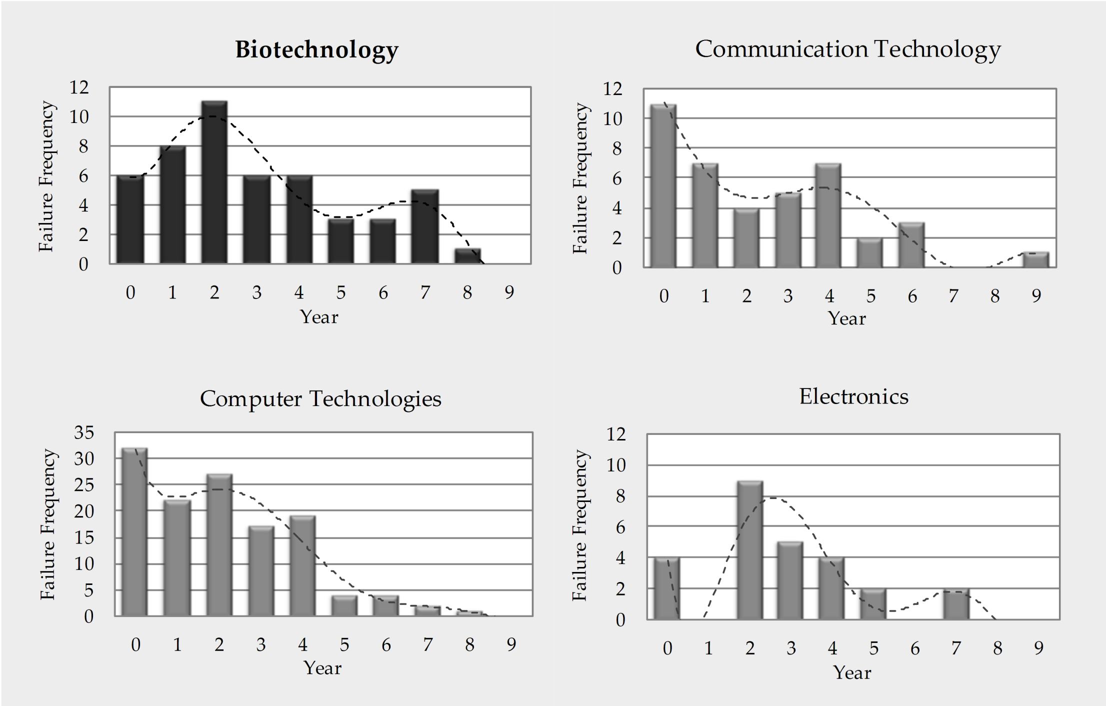

Fig. 1: Life cycle/survival time of failed domestic mergers in the US biotechnology, electronics, computer and communication industries, 1990–2000.

the percentage of the firm's total patent application stock is used rather than absolute numbers. Relative stocks in each sub-category then map the conclusive technological profile/vector of each firm.

Technological proximity β between two firms i and j is defined as the *angular separation or uncentered correlation* measure. Based on their technology vectors F_i and F_j technological relatedness is calculated as

$$\beta = \frac{F_i F_j}{\sqrt{(F_i' F_j)(F_i F_j')}} \tag{24}$$

with $0 \leq \beta \leq 1$.

Additionally, we measure the narrowness/broadness of R&D approaches δ of a firm i by its entropy regarding specific scientific fields l (Grupp, 1997), that is a compound measure for *concentration* of a company's innovation activities in terms of broadness and intensity

$$\delta_i = -\sum_l p_{li} \ln p_{li}, \tag{25}$$

where p_{li} is the share of activities of i in patent class sub-category l, given the secondary condition that $\sum_{l} p_{lk} = 1$ holds. Hence, in the case that activities are concentrated in only one IPC field the entropy index is $\delta_i = 0$, while for an equidistribution of shares in all relevant subcategories the entropy level simplifies to $\delta_i = -\ln(\frac{1}{l})$.

2.3.2 Estimation and Results

For testing our merger survival hypotheses we use a Cox proportional hazard model that estimates the probability of survival past time t. It also has the property that it leaves the baseline hazard unparameterized $h_0(t)$, that is there is no assumption about the shape of the hazard over time. This semiparametric model, with coefficients ω_k' and variables x_u, is of the general form

$$h(t|x) = h_0(t) \exp(\omega_k' x_u) \tag{26}$$

Furthermore, we integrate dynamic measures for rates of change (pre- vs. post-merger performance[10]) in absolute numbers of patents and in joint entropy of the merger pairs [entro-rate; patnum-rate], as covariates exponentially varying over time. All other static variables [sic-market; proxi; entro-diff; both-entropy] are treated as fixed in the model. After running the estimation (Table 2), we test the proportional hazard assumptions based on Schoenfeld residuals (see appendix, Table 3) to secure the general validity/non-violation of the global model.

Table 2
Semiparametric Cox proportional hazard model

_t	Coef.	Std. Err.	Haz. Ratio
rh			
proxi	$-3.01895^{\dagger}$	1.09849	$.04885^{\dagger}$
sic-market	.00018	.00027	1.00018
entro-diff	.35392	.58127	1.42464
both-entropy	.12288	.26058	1.13075
entro-rate	24.19165	21.30897	$3.21e^{10}$
patnum-rate	$-4.51115^{\dagger}$	2.04449	$.01099^{\dagger}$
t			
entro-rate	-3.15682	2.93896	.04256
patnum-rate	$.55964^{\dagger}$	.27479	$1.75004^{\dagger}$

Note: N = 34, time at risk = 46,578, χ^2 = 20.96, † = 95 % conf. interval

Estimation results suggest that we have no evidence that market power/market relatedness effects play a significant role for demerger [sic-market]. That is saying, matching vertically – having a different SIC industry classification – does not restrict the probability of survival, so H1 can be rejected. This suits well the notion that the effect itself

[10]Innovation performance for failure cases is measured for the period of merger duration and for a similar period ex ante, while for non-failure cases we observe four-years performance ex ante including the merger birth date, respectively ex post.

may be a more immediate than long-term one. Alternatively, the above assumption on market power – integration type that forms the basis for H1 may be violated.

For H2 the evidence is much harder to grasp fully as the level of spillovers depends on the common broadness of R&D approaches [both-entropy] and technological proximity of merging partners [proxi]. Partly, it must be rejected as entropy measures have no significant impact on hazard rates, even when we adjust for technological proximity. On the other hand, proximity of partners seems to reduce the separation risk as more proximate merger pairs have a hazard of failure that is only about 5 % of the hazard for those who have very technologically distant competence profiles. Intuitively, this results suggest that proximity is enhancing intra-merger knowledge spillovers but it maybe also attributed to some extent to an increase of R&D efficiencies inside the merger where similar competences, and hence, R&D resources – clearing of substitutional research – are refocused on existing complementary or new fields of R&D. Hence, H2 is, at least partly, satisfied but still needs further investigation.

Asymmetry in absorptive capacities has no significant impact on hazard rates, so that H3 must be rejected. As asymmetry [entro-diff] is an ex ante criteria with only early integration stage influence it is of minor importance for long-term failure decisions. Anyhow, lets keep in mind that some of the criteria of selection seem to be essential for the separation process.

Turning to the more post-merger performance orientated criteria, indicators [entro-rate; patnum-rate] suggest that changes in joint entropy are not significant while the effect of absolute patent application number rates is somewhat puzzling. If we treat the rate as a fixed variable in the model we get the general notion that a good innovation performance, indicated by an (100 %) increase in applications, should reduce the risk of failure, that is the relative hazard is only 1 %. Oppositely, if we assume the variable to vary over time, as we really should expect, the hazard for high-patenting mergers is about 75 % higher than the hazard of a minor performance pair. With respect to the data context here (our definition of failure cases) it may be the case that high-performance becomes an indicator of a successful absorption process of the partners technological competences where failure is only a strategic re-orientation of management. The finalization of such a technological sourcing procedure in the data contradicts the commonly acknowledged notion of bad innovation performance as a cause for failure.

2.4 Conclusive Remarks

Federal or European policies of merger control have been mostly concerned with protecting consumer rents from post merger reaping of extra profits from increased market power. If we consider the economic logic of technology sourcing this view may well be short-sighted. Given that mergers are expected to be temporary constructs internalizing technology, and, can be identified ex ante by the authorities, short-term product market profits should not be the only decision principle. Long-term macro effects for sustainable growth in the whole industry that are driven by successful technological change via spillover and increasing innovation may overcompensate the latter effects for consumers.

Similarly, a broader evaluation scheme by stock market analyst can now turn out to be positive, with respect to the technological potential for future firm growth enhanced by demerger. However, the original merger partner choice, whether technologically proximate firms are selected or not, and the continuing analysis of post-merger performance, based on the revealed patterns from Hypotheses (2), should have an impact on firm selection itself and, possibly, stay or exit strategies inserted by managers.

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A Appendix

Table 3
Hazard assumptions global test by Schoenfeld residuals

	rho	*chi2*	*df*	*Prob>chi2*
proxi	− .56779	7.00	1	.0082
sic-market	.44505	6.34	1	.0118
entro-diff	.37359	5.94	1	.0148
both-entropy	.31318	2.69	1	.1010
entro-rate	.05758	.07	1	.7955
patnum-rate	.15558	.32	1	.5690
entro-rate	− .08776	.17	1	.6793
patnum-rate	− .19614	.54	1	.4637
global test		15.53	8	.0496

3 Three Axioms on Open Innovation and a (Non-)Parametric Application to the Entrepreneurial Case

Abstract After a brief discussion of the economics and resource-based principles underlying the open innovation (OI) paradigma we empirically investigate the impact of open innovation and alike activities on entrepreneurial knowledge and firm growth. For these purposes we use parametric as well as non-parametric techniques on panel data of US-entrepreneurs (2005-2007), the latter allowing for the analysis of multiple output maximization problems with multiple inputs in efficiency terms relaxing linearity and distributional assumptions of general regression estimation.
We find that outside-in processes of OI significantly increase both dimensions of growth while inside-out processes (weakly) decrease firm growth. For efficient observation within the sample the knowledge production frontier shifts from proprietary innovation sources of information (i. e. R&D staff) towards higher levels of use on external sources (i. e. IP-licensing-in) over time. When firm size (or employment generation) is included as an output goal – next to the stock of knowledge – we observe minor efficiency gains over time whereby a mixed pattern of (internal and external) information sources rather than an exclusive use becomes more dominant with increasing firm size. Additionally, the efficient design of coupled processes for firm growth and knowledge production tends to shift, in particular for very small entities, from internal capacity-building objectives, that is related to the use of outside-in processes, to a dominant external exploitation pattern of proprietary knowledge assets, that is related to the use of inside-out processes.

3.1 Introductory Note

Not every cooperation on innovation inside an innovation system linking distant actors (Metcalfe, 2007) knowledge pools satisfies the notion of 'Open Innovation' (OI) in the narrow sense of the term. OI is a general term for various innovation-related activities having a specific reference (and underlying various types of transfer channels, e.g. IPRs) on some external resource (of information, researcher, production, etc.) that blurs the traditional organizational, resource-based boundaries of the firm (Penrose, 1959; Teece et al., 1997), but still allows for profit-internalization and leveraging inside. Typically, concepts of OI have been used in a broad strand of the still-young literature with a particular focus on 'nouveau' actors (consumer or user integration, von Hippel (see 2005)) in the innovation process or innovation system (Malerba, 2002), or elsewise a number of descriptive (case) studies (OECD, 2008) have emphasised the dominant role of large globally-networking firms in some few industries where OI is often a complementary instrument to traditional innovation strategy in exploration and exploitation (in the sense of non-chronological, possibly co-evolving processes) phases of the often 'tacit and sticky' (e.g. Dasgupta and Stiglitz, 1988) knowledge assets of a business. Anyhow, on the one hand, we believe that the OI paradigm should ressemble all types of collaboration partners – not only inter-firm ones – but should open for a broader scheme for knowledge transfer between multiple and distinct actors (e.g. PROs etc.) that is, on the other hand – in its essence – 'conditional, scale-related or complementary-structural' to the technological rate of change of the cooperating firm, eventually having an impact on the technological paradigm of the overall industry (Dosi, 1982).

The second section of this paper will in short try to clarify the few metaconcepts that underly the various perceptions of OI present in the literature and in recent policy discussion. By doing this we can implicitly exclude some types of collaboration and knowledge transfer that are not OI by nature as we will define. However, it is partially unclear how the OI paradigm applies to the special case of 'embryonic' firms – entrepreneurs[1] – that have just started innovating on or imitating a business identity and are in the process of finding a sustainable market (niche) position in an existing or emerging market structure. We therefore will elaborate on the very early (open) innovation-related entrepreneurial growth processes, right after a business is founded, and this may have implications for survival in an 'ideally' strongly competitive industry environment (Klepper, 1996) with several other entrepreneur(s) and incumbent(s). Hence, entrepreneurial entities at this stage need to outbalance the potentially opposing forces of and persistent tension of 'limitedness/scarcity' (in terms of internal resources) and (market) 'opportunity'. So far the OI literature has had a slightly limited sight, primarily focusing on the perspectives of large (knowledge or capacity) 'buying' entities rather than on the particular effects on SMEs and entrepreneurs unintentional 'being bought' in the processes of OI. In the first and second section of the paper we therefore address the implications for entrepreneurial (open vs. closed) innovation and different facets of growth.

We will heavily focus our analysis on the OI channels of protected intangibles (e.g. one-way-, cross-licensing or common pooling of multiple protected assets), even though we are aware that the use of IPRs in start-ups is (again) fairly limited due to financial constraints or alternative motivation to (not) patent as start up (Graham and Sichelman, 2008).

[1]There is no single-minded definition of entrepreneurship i.e. based on a certain organizational form. Still, from a dynamic perspective *'Entrepreneurs are agents of change and growth in a market economy and they can act to accelerate the generation, dissemination and application of innovative ideas entrepreneurs not only seek out and identify potentially profitable economic opportunities but are also willing to take risks to see if their hunches are right'* : OECD (1998)

Table 1
US-entrepreneurial licensing-in, licensing-out and overall-sample intangible stocks among different types of IPRs.

	patents	*copyrights*	*trademarks*
entrepreneur holds IPRs			
license in	.22	.16	.11
license out	.08	.14	.04
entrepreneur holds no IPRs			
license in	.02	.03	.03
license out	–	–	–
overall sample	.03	.09	.15
abs. no. observations	249	822	1308

Interestingly, we find in recent US-entrepreneurial data by the Kauffman Foundation in table 1 that, at a first glance, a considerable number of start-ups participate intensively in the market for technology, firstly, by licensing-out patents, copyrights and trademarks from their rather limited – in comparison to large companies (Arora et al., 2001) – IP stocks to others, and, secondly, that those entrepreneurs without stocks do already – at a relatively smaller scale – participate in these markets by licensing-in protected rights.

Alternative (but difficult to measure) channels of knowledge transfer that lie outside this rather 'traditional' use of markets for technology (Cassiman and Veugelers, 2000) are e.g. by commonly pursuing a secrecy strategy, by a pre-protection cooperation generating or exploiting the technological assets of OI partners, by engaging in open-source development[2] or by simply giving away knowledge assets to the industry free of charge, in the very seldom cases e.g. where firms forsake finding a technical solution to a fundamental R&D problem internally and, hence, instead of canceling the whole project, decide on turning outside (e.g. the example of Royal Phillips at the turn of this century). Oppositely, (sub-)markets for technology generally may differ in their characteristics in terms of content-related accessibility (e.g. the novelty threshold for application of a patent), their territory- and industry-specific legal quality and structure of the protection systems (e.g. regarding the average-item value of the protected intangible, structural miniaturization of system[3] or efficiencies in IP enforcement), the stability of the intangible 'exchange currencies' (e.g. the discount rates for older protected intangibles) and industry-specific and firm-size-dependent participation/involvement rates.

[2]An open-source-environment is created i.e. by making (protected) technological assets accessible and transforming them to some extent into a public good, in the most extreme cases, by proactively diffusing and advertising the assets underlying informations to the public/some relevant (scientific) community that is capable to contribute to inventory processes in a multipolar setting.

[3]A strong fragmentation in structure, that is relatively small degree of novelty contribution of each item, may increase the probability of patent thickets, trolls or general strategic patenting (Shapiro, 2000; Bessen and Meurer, 2008).

Section three of the paper picks up axioms and discussion from section two & three and applies them to most recent US-survey-data on entrepreneurial activity and the entrepreneurs evolution as an organization itself, in terms of innovation performance, tech-market-involvement and firm growth. Section four concludes.

3.2 Dissecting the Open Innovation Paradigm

Imagine a situation where two actors inside an innovation system, e.g. assume for simplicity firm X and firm Y, hold two distinct technological assets or artefacts A and B, with $A \neq B$, that may incur as production factors in knowledge production function f (resp. g) and in a manufacturing function k (resp. l) of a firm, or elsewise both (Dasgupta, 1988; von Weizsäcker, 1980). Assume further that these firms align their strategic orientation and routines in production and innovation neither exclusively along profit-maximizing behaviour, that is in maximizing their short- or long-term payoffs, nor exclusively along motives for survival in selection processes of the relevant industry or regional system, but along some binary pattern of behaviour that combines and may harmonize both, evolutionary and neo-classical perspectives of economic activity. Each firm has to decide on exploration (in a R&D process-related sense) – that is on further development or production of knowledge – and on exploitation (in a product-market-related sense) – that is application, purchase and diffusion of new-to-demand products – of their technological assets that e.g. may originate from either past successful innovation effort, derive from human capital formation/R&D personnel or these assets where acquired by capital-means from some third party.

In the following we will dissect the heuristics of 'within or outside boundaries' innovation processes in terms of the 'conditio', 'scales' or 'complementaries' of cooperative economic behaviour which brings forth the three axioms defining OI:

axiom one. $f[A|g(B)] \vee g[B|f(A)]$

The axiom is built on the notion of 'standing on the shoulders of giants' (Scotchmer, 1991) external to the firm, that is further development or incremental innovation is *conditional* to R&D capabilities and effort outside firm X boundaries. From a resource-based view certain technologies may have become more 'complex' in general (Kash and Kingston, 2000; Harhoff et al., 2008) and related knowledge can be increasingly 'dispersed' among actors or 'communities of practice' (Rappa and Debackere, 1992), both regionally and in terms of absolute numbers of required sources of information. In the aftermath of globalizing production capacities to low-wage-countries firms have increasingly started to also internationalize R&D facilities mostly due to national skilled labour-force constraints or faster learning on national demand structures abroad (Blanc and Sierra, 1999; Granstrand et al., 1993; von Zedtwitz and Gassmann, 2002). Alternatively, there are scientific or technological fields of R&D that tend to 'converge' (Rosenberg, 1976; Blind and Gauch, 2008), e.g. a present cluster of telecommunications, information technology, electronics and electrical engineering, or the 'biotechnology' cluster including health technology, agriculture technology, chemistry and food technology, which may strongly drive businesses of any size into collaborative R&D behaviour (e.g. IPR-markets, RJVs, alliances, mergers) in order to keep up with the content-dynamics of technological change of the relevant industry. This obligatory sharing of knowledge is partially observed in the phenomena on markets for technology where firm X succeeds in licensing-in intangible asset B – if, and only if firm Y is willing to license-out and share on the pricing-basis of loyalties asset B. Given the obligation of sharing knowledge is 'ideally' two-folded, that is $f[A|g(B)] \wedge g[B|f(A)]$, then both firms will engage in cross-licensing (or alternative transfer payment) or pooling of knowledge assets. Additionally, firm commitment and strategic beliefs of firms regarding the general value of technological capabilities (Langlois, 1992) for firm success and their own absorptive capacity (Cohen and Levinthal, 1990) may partially explain involvement in markets for technology. From a transaction cost perspective (Williamson, 1979) IP-related search and contracting costs may limit these kind of technological sourcing activities – in particular for financially-constrained SMEs and entrepreneurs – and, therefore, are mostly reserved to larger entities and their business motives. Even though entrepreneur may become involved in OI processes rather unintentionally or by being targeted, OI sharing proprietary knowledge may reduce their exclusive exploitation of assets in the first place (and, hence, may significantly reduce short-term exploitation profits) but may be beneficial in terms of being a non-excludable[4], obligatory feature in the innovation processes of others (possibly large firms) in the long run which can create a competitive advantage and a ratio for sustainable existence of the entrepreneur in the market.

axiom two. $f(A+B) \leq f(A) + g(B)$

Axiom two amplifies above 'conditional' axiom for OI as far as it further states that collaborative firms can exploit scale economies in common knowledge production increasing in the number of *different* sources of knowledge producing entities, rather than producing both assets on their own. At first sight this may be at odds with the potential economies of scope of a single knowledge producing entity and the general cost expectations of cooperation. As the classic argument runs, the number of partners included should increase vice-versa transaction costs e.g. for contracting on inputs and uncertain outcome, learning effort (again, Cohen and Levinthal, 1990), or with monitoring and enforcement efforts. Additionally, multi-actor cooperations may rise the potentials for free-riding of individual parties on common resources and, thus, can limit ex ante commitment of partners (Morasch, 1995). Therefore, cooperations in R&D altogether bear significant risk of failure (e.g. for mergers see Cuntz, 2008) accessory to the risky nature of innovation. Still, firms do co-operate, though as most of the empirical studies suggest increasingly in organization size (Röller, 1997). One plausible explanation are risk-sharing motives (Acs, 1999) of partners which will generate incentives to innovate jointly that might otherwise not suffice detached, even though this can predefine (again) an increase in complexity in ex post knowledge and technologies.

[4]This attribute is based on the implicit assumptions that knowledge is to some extent 'tacit' or 'sticky' and, hence, the (mere) license is not a perfect public good of information once acquired – but the licensee will need services, complementary products (again, Cassiman and Veugelers (2000)) or additional adaption development from the licensor.

The fragmentation of information sources for innovation processes is also related to an expanding 'specialization' in the markets for technology of various (mostly science-based) industry sectors where firms do not only have high R&D intensities but have become primarily knowledge producing entities that do not exploit assets in traditional product markets. The latter phenomena is particularly true for SMEs and generally risk-friendly entrepreneurs (Schumpeter, 1911) with limited (product market) production capacities and strong investment-risk-bearing constraints in medium-high-tech industries. In these situations, analogously to product market production with scale economies on increases in output, firms may exhibit positive scale economies in the production of knowledge that outweigh the potential costs of cooperation. The fundamental argument lies in the black-box nature of innovation on the basis of a 'variety' of the assets, as a larger number of possible combinations of tacit and different technological knowledge (Fleming, 2001; Rosenkopf and Almeida, 2003) should enhance itself successful further development in the creative processes that govern invention. Hence, co-operative behaviour in R&D and market-for-technology involvement should be more prominent in industries that exhibit increasing economies of variety in knowledge production, that is axiom two holds.

axiom three. $f[(A)|l(A)+k(A)] \vee g[(B)|l(B)+k(B)]$

Lastly, 'complementarities' between knowledge production and product market exploitation *across* firms may lead to an OI orientation of entities. The axiom defines that if assets are not commonly exploited, e.g. generating scales on output, incentives to innovate respectively produce further knowledge are insufficient for the asset-holder itself, that is $f[(A|l(A)] \equiv 0$ holds, analogously for firm Y. Hence, if assets are not also exploited externally individual R&D effort can be significantly reduced or canceled. We assume no explicit timing or clear-cut causal interlinkages of knowledge production and exploitation, rather think of multiple feedbacks or loops in-between processes. From an innovation system perspective it is conceivable e.g. that synchronous demand exploration via exploitation generates additional (technical) information on preferences of consumers or perceived quality which then in turn may contribute to knowledge production. So alternatively (for the more extreme cases of OI) complementaries can be also of the kind $f[(A)|l(B)] \vee g[(B)|k(A)]$ or $l[(A)|g(B)] \vee k[(B)|f(A)]$. Here the knowledge production and exploitation outputs of firms X and Y are only very loosely or not linked (in terms of underlying assets, still, $A \neq B$) but still 'processing' itself is enhanced and based on (one-way or vice-versa) technical information-sharing, e.g. exploitation production experiences in asset B reveal potentials for knowledge production of asset A. In contrast to involuntary inter-firm spillovers mechanisms entities with OI orientation will try to contract on internalization of spillovers ex ante, e.g. via formalized exchange on markets for technology or of technical staff etc., and proactively search for these kind of information flows in their market environment. Axiom three yields analogous implications for growth and failure of entrepreneurs as the 'conditional' axiom as far as 'complementarities' can become a long-term parameter of competition in an industry that distinguishes OI entrepreneurs from other closed-form innovating start-ups.

In conclusion, above axioms may specify the nature of open innovation and the concepts value for further inquiry and theorizing in innovation. However it is not stated in above discussions that all axioms defined here have to hold simultaneously to fulfill the notion of OI. We suggest that rather singular axioms or axiom combinatorics are more probable to be observed on the firm level, in a few cases on the overall level of an industry sector or across sectors. As noted above, complexity of technology is a major source for openly innovating such that 1-on-1 situations exemplified here should be extended to (firm and non-firm) multi-actor axioms allowing for a variety of sources.

In the next section we address the (one-sided) effects of open innovation and alike activities on knowledge and firm growth of entrepreneurs in the very early, post-entry phases of their existence. More precisely, we do not focus and evaluate on the overall welfare or multiple-sided effects of open innovation activities and projects in comparison to closed form innovation and technological change.

3.3 Empirical Inquiry: Open Innovation Impact on Entrepreneurial Knowledge and Firm Growth

A long strand of the literature has intensively discussed the impact of innovation performance on firm profitability and growth (Malerba and Orsenigo, 1997, e.g.), as generating a stationary competitive advantage against competitors or incumbents inside a technology-specific market environment. Partially, this discussion also included the underlying hypothesis that growth performance itself would be endogenously predefined by firm size, whereby Gibrats law of proportionate growth was rejected by most empirical work (Mansfield, 1962; Hall, 1987; Bottazzi et al., 2006) – rather pointing towards a slightly negative effect in size, if any systematic effect on growth rates was to be found at all[5]. In particular, *entrepreneurial* growth is shaped by characteristics specific to the founder (e.g. human capital of the founder), the firm, as well as the industry environment (Almus and Nerlinger 1998). Some studies have so far supported the view that small firms, in general, have slightly higher innovation rates than their larger counterparts, but the overall evidence is not clearcut, as several other factors may impact on general innovation performance such as industry-specific market structure or the prevailing technological regime (Audretsch, 2002), and, hence this may reverse performance hierarchy. Additionally, in particular highly innovative small firms have higher survival rates and may persist shake-outs in their industry and do better – when it comes to selection processes – than their non-innovative, small counterparts (Acs and Audretsch 1988, and Audretsch 1991). Still, within the group of small firms, rates of survival seem to depend positively on firm size and the age/date of market entry of the organization. The essential, firsthand conclusions we derive from these long-standing discourse is that small firms, respectively start-up companies can (strategically) follow up a path of organizational growth *and* persistent innovation that may enhance their

[5] *'It seems that there is little more that we can say about firm growth rates apart from that they are largely unpredictable, stochastic, and idiosyncratic.'*: Coad and Rao (2006)

profitability and firm survival, even though this simultaneous growth process is most likely expected to slow down in the long run.

Innovation processes within a firm can be categorized by a process dimension of *exploration* and dimension of *exploitation* of knowledge assets (Levinthal, 1993; Beckman et al., 2004), where these assets contribute to further (in-house) production of knowledge enlarging the stock of knowledge, respectively knowledge assets lead to in-house product market applications/commercialization and thereby contribute to general manufacturing/production activities. In our framework, both dimensions of the innovation process can involve out-flows of knowledge assets – inside-out processes – as well as in-flows to the firm – outside-in processes – (Gassmann, 2006) *complementing or substituting* exploration and exploitation activities within the firms boundaries.

In terms of entrepreneurial firm growth the effect of *outside-in* processes is expected to be two-folded: On the one hand it is primarily a rather simple 'make-or-buy' decision on knowledge asset creation at first sight, that is e.g. balancing the trade-off[6] between building up own research staff versus knowledge acquisition in the market for technology in the exploration dimension. On the other hand this may simultaneously impact on organizational growth with regard to the overall number of employees in the exploration and, possibly, in an exploitation dimension.

Hypothesis one. *When knowledge assets are primarily used for further exploration in knowledge an increase in R&D staff should positively effect overall organization size ('make'), while being zero in the case of an acquisition of assets ('buy').*

The picture then becomes more puzzling when we take into account the exploitation dimension. Given a knowledge asset was created by exploration of in-house research staff but is exploited elsewhere outside the firms boundaries and we compare this to a situation where assets are acquired externally and exploited in-house, there is a yet unclear, relative effect on overall employment as in-house R&D and manufacturing staff both increase. So possibly, (choices on) inside-out processes here may be effected by opportunity costs for outside-in activities.

Outside-in processes can positively impact on entrepreneurial knowledge growth, in particular within and across industry sectors that are dominated by the OI paradigm.

Hypothesis two. *Given axioms one and two hold*[7]*, acquisition of knowledge assets may enhance innovation performance of the entrepreneur by either allowing for (new) combinations of assets leading to inventions elsewise not realized, or by increasing variety of sources and thereby leveraging knowledge production to a higher scale.*

In the case of entrepreneurial units the limits[8] of outside-in engagement most probably lie in a sufficient capacity level to absorb and (re-)cultivate knowledge external to

[6]The trade-off should take into account pricing and risk of these R&D activities (cost and uncertainty) as well as *efficient allocation* of these inputs in terms of (knowledge and employment) output maximization.

[7]Axiom three seems to be of minor relevance here.

[8]In so far the binary decision scheme of 'make-or-buy' is only an useful simplification or abstraction applied in the discourse for a complex managerial decision-making.

the firm – next to financial constraints –, if not actually outside-in is already restricted ex ante in limited resources for search and sourcing the market for technology. Hence, building sufficient levels of absorption capacity may imply building up proprietary R&D resources (infrastructure and staff) inside the firms organization. By this way, the outside-in related process may feedback into organizational growth.

The effect of *inside-out* processes on employment and innovation dynamics in the exploitation dimension similarly can be proxied by a binary decision of 'exploit-or-sell' knowledge assets. In the entrepreneurial case this choice may strongly depend on limited production capacities or scale of production that may drive firms into e.g. licensing-out proprietary knowledge assets in exchange for loyalty or fixed-fee payments. But it should be noticed that selling assets does not necessarily exclude self-exploitation with own manufacturing capacities – even though joint exploitation may generate significantly lower profitability for the individual firm than if exploited exclusively (Katz and Shapiro, 1985) as this can implicitly effect on market structure.

Hypothesis three. *Employment generation is, hence, expected to grow (stagnate) if proprietary assets are sold to other firms for exploitation and, additionally, are (not) exploited in-house.*

The impact on entrepreneurial innovation is strongly dependent on axiom three, that is, in OI dominated technological change within and across industries, joint exploitation with external partners can be a rationale for investment in innovation.

Hypothesis four. *Hence, an increase in knowledge output is expected from inside-out processes, if, and only if axiom three holds,*

– even though this way of 'capacity sharing' should not significantly reduce overall competitive advantage of the entrepreneur and exclusivity of market (niche) position in terms of technology (assets or resources).

Additionally, i.e. if proprietary assets of a firm also form a precondition of further knowledge exploration of other parties (given axioms one and/or two hold), the entrepreneur may become involved in outside-in processes external to his organization. At this stage of the analysis *coupled processes* come into play where effects on employment and knowledge growth are not clearcut any more. Depending on the perspective one adopts knowledge assets are exchanged in a coupled process by e.g. cross-licensing IPRs between firms. Ideally, both partners face *vice-versa* conditionality in their knowledge productions (i.e. axiom one holds; axioms two and three can be resolved under an analogous scheme) and, hence, desired transfer direction of their assets is rectified and – at best – firms value these equally, that is firm A requires firm B's asset (likewise for firm B) and both price assets similarly. In this way each partner may potentially increase its innovation performance by co-operating, simultaneously using inside-out and outside-in processes with respect to the mechanisms described above. Anyhow, in most cases of OI-related transfer in reality *rectification of preferences* is not given, and exchange within coupled processes can be worked through e.g. by either additional transfer payment, pooling of knowledge assets or by exercising market power[9] on the market for technology.

3.3.1 Methodology and Data Description

The Kauffman Firm Survey (KFS, Ewing Marion Kauffman Foundation, Kansas City, MO[10]) is a panel study of new US-businesses founded in 2004 and tracked over their early (three) years of operation. For the study population, a business 'starting' in 2004 was defined as a new, independent business that was created by a single person or a team of people, the purchase of an existing business or the purchase of a franchise. Businesses were excluded if they had an Employer Identification Number, 'schedule C' income (income or loss report from a business that is submitted with personal income tax) or a legal form or had paid ('unemployment insurance' or 'first state unemployment') taxes prior to 2004. The baseline survey was run in 2005, a first-follow-up in 2006 and a second-follow-up in 2007. Furthermore, we excluded observations without significant economic activities in the baseline survey from the original (public[11]) KFS sample, that is either firms that had no sales or customers, or total revenues were below annually $1000 as it is commonly exemplified in entrepreneurship literature.

Two indicators for IP-related open innovation engagement are built along the notions of *inside-out*, respectively *outside-in* OI processes, e.g. licensing-out, respectively licensing-in intangibles. We then combined various types of protected assets (patents, copyrights and trademarks) having an identical direction of knowledge flow for an observation – that is where firms have indicated either licensing-out or licensing-in (given as binary variables) for the different IP-types – on a 10-point scale (Herstad et al., 2008), a high score meaning multiple-type activities and a large degree of 'openess' in a single direction. Additionally, we checked for sufficient quality of the indicators' *composition* by using Cronbach's Alpha (Cronbach (1951), results see table 2) whereas $\alpha_{insideout} = .7759$ and $\alpha_{outsidein} = .6770$ and, hence, both indicators are above critical level of .6 assumed in the literature. A composition of a single OI indicator combining inside-out and outside-in processes generated significantly lower levels of α, so lastly, an overall indicator was not constructed.

Firstly, we use (parametric) linear regression models for the balanced panel (see KFS summary statistics in table 4) to analyse the general impact of the created OI indicators on the (A) production of knowledge and (B) entrepreneurial firm growth.

[9] In general, in the latter case OI implied incentive structures may be blurred due to limited transparency and/or actors autonomy of choice inside the market for technology.

[10] Certain Data included herein are derived from the Kauffman Form Survey release 1.0. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the Ewing Marion Kauffman Foundation.

[11] The KFS public-data set can be found at `http://www.kauffman.org/kfs/`.

For estimation of (A) we apply a slightly modified version of the knowledge or patent production described in Jaffe (1986) and (Griliches, 1979) basic paper in a random effect model:

$$\begin{gathered} KNOWLEDGEGROWTH_{i,t} = \\ \beta_1 PATENTS_{i,(t-1)} + \beta_2 OUTSIDEIN_{i,t} + \beta_3 RDSTAFF_{i,t} + \beta_4 TTEMPLOYEES_{i,t} \\ +\beta_5 OEXPERIENCE_{i,t} + \beta_6 OEDUCATION_{i,t} + \beta_7 OAGE_{i,t} \\ +\beta_8 OGENDER_{i,t} + \beta_9 ORACE_{i,t} + \beta_{10} INDUSTRY_{i,t} + \varepsilon_{i,t} \end{gathered} \tag{1}$$

KNOWLEDGEGROWTH$_{i,t}$ is calculated as the difference in logs of total patent stock at t, respectively $t-1$. Growth rates should depend – according to our model structure – partially on the level of *internal* or *external information sources for innovation* (or further knowledge growth) that are either sourced for and purchased-in from outside the firm boundaries (OUTSIDEIN$_{i,t}$) or they are sources of information held inside the firms organization (RDSTAFF$_{i,t}$, that is the overall no. of R&D employees). As common in the entrepreneurship literature we added a number of control variables – next to firm size (TTEMPLOYEES$_{i,t}$) – related to the owner characteristics such as the years of relevant industry experience of the owner (OEXPERIENCE$_{i,t}$), the education level[12] of the owner (OEDUCATION$_{i,t}$), and age, race and gender[13] variables (OAGE$_{i,t}$, OGENDER$_{i,t}$, ORACE$_{i,t}$). Additionally, we created an industry-dummy for high-tech, most likely patenting-affine sectors according to the NAICS-coding[14] given for each observation. We checked all regression models for autocorrelation in the panel data with Wooldridge (2002) testing and used Hausman (1978) estimation for validity of model choice. Additionally, for the random effects model we applied the Breusch/Pagan Lagrangian multiplier test (Baltagi and Li, 1990) for random effects[15].

For fixed effect model estimation of (B) the firm growth equation of Coad and Rao (2006) is utilized in the following manner:

$$\begin{gathered} FIRMGROWTH_{i,t} = \\ \gamma_1 TTEMPLOYEES_{i,(t-1)} + \gamma_2 PATENTS_{i,t} + \gamma_3 OUTSIDEIN_{i,t} + \gamma_4 INSIDEOUT_{i,t} \\ +\gamma_5 OEXPERIENCE_{i,t} + \gamma_6 OEDUCATION_{i,t} + \gamma_7 OAGE_{i,t} \\ +\gamma_8 OGENDER_{i,t} + \gamma_9 ORACE_{i,t} + \varepsilon_{i,t} \end{gathered} \tag{2}$$

Similarly to above patent growth model we used logged differences of total employees (TTEMPLOYEES) indicating absolute firm growth (FIMRGROWTH$_{i,t}$) and included owner-specific variables explained above. The model includes innovation performance applying patent stocks at t as an output indicator of innovation (PATENTS$_{i,t}$), but also may account for potential employment effects of outside-in and inside-out (INSIDEOUT$_{i,t}$) processes on organization size.

[12]The level of education ranges from 'less than 9th grade' to 'professional school or doctorate', that is the OEDUCATION$_{i,t}$ score is 1, respectively 10.

[13]If the owner is female (male) OGENDER$_{i,t}$ scores zero (one), if the owner is white (other) ORACE$_{i,t}$ is one, otherwise zero.

[14]INDUSTRY$_{i,t}$ is generated as a binary variable that comprehends codes NAICS $= 32, 33, 54$ if one, zero elsewise.

[15]Test results can be obtained by the author upon request.

In a second phase of the problem analysis we drop the linearity (functional) and distributional assumptions underlying above regression analysis and start re-investigating the panel (and various subsamples) by an inquiry on what is called 'technical efficiency' in the terms of *non-parametric* frontier function analysis. The general purpose of this non-parametric, data envelopment analysis (DEA) approach (for a more general introduction see Cooper et al. (2004)) in our view is to identify and select those observations (or in the common DEA jargon they are branded DMUs, i.e. decision making units) that are relative benchmarks in efficient use simultaneously minimizing input(s) – given as a vector of inputs x – while maximizing their output(s) – given as a vector of outputs y. The additional efficiency criteria of selection raised here is of particular interest in the entrepreneurial case as it was mentioned before many firms may operate under severe resource constraints in the early phases of their existence. Each DMU is to be evaluated in terms of its abilities to convert inputs into outputs, DEA assumes that this production set (of inputs and outputs) ψ or individual production 'technology' of each DMU is convex and free disposable (Charnes et al., 1978). Technical or 'relative' efficiency is therefore defined – for a real data application of the theoretical Pareto-Koopmans (Koopmans, 1951) definition – as:

> *A DMU is to be rated as fully (100 %) efficient on the basis of available evidence if and only if the performances of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs.*

Note that this definition avoids reference to prices or other assumptions on weights which would reflect relative importance of different inputs and outputs. The mathematical programming described in (Härdle and Jeong, 2005) for a DEA of an observed sample χ is defined as the smallest free disposable and convex set containing χ:

$$\begin{aligned}\psi = \{(x,y) \in \Re^p_+ \times \Re^q_+ | x \geq \sum_{i=1}^{n} \kappa_i x_i, y \leq \sum_{i=1}^{n} \kappa_i y_i,\\ \text{for some} \quad (\kappa_i, \ldots, \kappa_n) \quad \text{such that}\\ \sum_{i=1}^{n} \kappa_i = 1, \kappa_i \geq 0 \; \forall i = 1, \ldots, n\},\end{aligned} \tag{3}$$

whereas the DEA efficiency scores θ for a given input-output-level (x_0, y_0) are obtained via:

$$\begin{aligned}\theta^{IN}(x_0, y_0) = \min\{\theta > 0 | (\theta x_0, y_0) \in \psi\},\\ \theta^{OUT}(x_0, y_0) = \max\{\theta > 0 | (x_0, \theta y_0) \in \psi\}.\end{aligned} \tag{4}$$

Hence, for a given level (x_0, y_0) the DEA efficient levels in terms of an 'input-', respectively 'output-orientated' analysis are given by:

$$x^{\partial}(y_0) = \theta^{IN}(x_0, y_0)x_0; \quad y^{\partial}(x_0) = \theta^{OUT}(x_0, y_0)y_0. \tag{5}$$

In an input-orientation analysis one improves efficiency through proportional reduction of inputs, whereas an output-orientation requires proportional augmentation of outputs. In the constant returns to scale case we assume in our DEA analysis, that is for $\sigma \geq 0$ and $P \in \psi$, $\sigma P \in \psi$, it can be shown that the correspondence relation between both orientations of analysis is just a reciprocal one and, hence, is of minor interest for further interpretation of results. (In-)efficiency of an observation in the sample is measured radially – via a ray from the origin to the best-practice real or virtual[16] observation on the production frontier. For the asymptotic sections of the frontier curve non-zero-slacks and potential alternate optima are controlled for by our mode of analysis (For details, again, see (Charnes et al., 1978)).

In a first (second), input- (output-)orientated DEA the input $X \in \Re_0^2$ and output $Y \in \Re_0^1$ variables are the following:

X$_1$: OUTSIDEIN$_{i,t}$

X$_2$: RDSTAFF$_{i,t}$

Y$_1$: PATENTS$_{i,t}$

Before running the analysis we adjusted the original panel data by dropping all observations were information on these variables was incomplete over time (see summary statistics of (all) subsamples in table 5) and, *ad manus proprias*, marginally increased zero-value inputs or outputs to avoid incomputabilities when calculating efficiency ratios for input-, respectively output-orientated analysis which does not change evaluation outcomes. The core intention in this first two DEA analysis was to compare frontier functions over time using an window analysis scheme[17] (periods = 3, width = 1), with respect to efficient DMU technology sets in the baseline, first- and second-follow up surveys ($t = base, first, second$), and in terms of their knowledge production based on different combinations of internal and external sources of information.

In a third (fourth), output-orientated DEA two subsamples are created that included only observation with TTEMPLOYEES$_{i,base} \leq 5$ (respectively TTEMPLOYEES$_{i,base} > 5$). Additionally, we also refer the analysis at this point to a set of *multiple* outputs studying how an efficient use of internal and external information sources would relate to a simultaneous maximization problem of innovation performance *and* firm growth over time. Hence, the variables injected in the window analysis on the input, $X \in \Re_0^2$, respectively output $Y \in \Re_0^2$ side were:

X$_1$: OUTSIDEIN$_{i,t}$

X$_2$: RDSTAFF$_{i,t}$

Y$_1$: PATENTS$_{i,t}$

Y$_2$: TTEMPLOYEES$_{i,t}$

The fifth (sixth) DEA separates again into two subsamples of smaller and larger start-ups, analogously to the two latter DEAs. In order to generate a sufficient sample of

[16] Virtual observations are convex combinations of (real) peer observations on the production frontier.

[17] The window analysis framework allows to compare frontiers at different points of time due to a comprehensive scaling of input and output values ('all time best frontier') in the overall sample. Still, it only evaluates each DMU according to the other DMUs at t, as window width was chosen here to be equal 1, that is intraperiod-wise comparison.

observations, DMUs are now pooled in a single period – even though we then do lose the dynamic character of a panel. More precisely, we allow comparison of DMU across different survey lines (and therefore run the risk of comparing and evaluating DMUs in potentially different phases of organizational growth) as only a relatively smaller number of observations indicated INSIDEOUT$_{i,t}$ activities in any of the periods. Still, it should be worth studying the overall, vice-versa 'permeability', i.e. how processes of inside-out and outside-in – technological sourcing and 'being sourced' – efficiently *combine* in the light of simultaneous knowledge production and firm growth. So, input $X \in \Re_0^2$ and output $Y \in \Re_0^2$ variables resume to:

X$_1$: OUTSIDEIN$_{i,t}$

X$_2$: INSIDEOUT$_{i,t}$

Y$_1$: PATENTS$_{i,t}$

Y$_2$: TTEMPLOYEES$_{i,t}$

In a third and final course of our analysis we *link* the parametric and non-parametric conception by inserting three dummy variables in regression equations (1) and (2), whereas dummies EFFICIENCY1, EFFICIENCY2 and EFFICIENCY3 are constructed by setting DEA efficient observation *i* at time *t* to one, elsewise zero. Again, the EFFICIENCY1 dummy here represents DMUs that suffice the effiency criteria introduced in terms of use and allocation of external or internal sources of information for knowledge production (patents). EFFICIENCY2 bears similar arguments but additionally includes overall employment (organizational size) as an output component. Lastly, EFFICIENCY3 refers to efficient use of coupled input processes, that is insideout and outsidein, in maximizing both output dimensions simultaneously, knowledge stock and overall employment. We expect (in-)efficiency measures to have a rather limited long-term impact on estimated firm growth while having a more pronounced impact on *short-term, static total profits*[18]. Hence, in order to capture these time-effects related to efficiency we additionally estimated a total revenue equation (6), in a random effects model, given as:

$$\begin{gathered} TTREVENUES_{i,t} = \\ \varsigma_1 PATENTS_{i,t} + \varsigma_2 INSIDEOUT_{i,t} + \varsigma_3 OUTSIDEIN_{i,t} + \varsigma_4 EFFICIENCY1_{i,t} \\ + \varsigma_5 EFFICIENCY2_{i,t} + \varsigma_6 EFFICIENCY3_{i,t} + \varepsilon_{i,t}. \end{gathered} \tag{6}$$

The next section presents parametric estimation and non-parametric DEA evaluation results and elaborates on careful interpretation with respect to the dissected open innovation paradigm.

3.3.2 Estimation and Results

Parametric estimation, as a starting point of the analysis, focuses on the open innovation influence on entrepreneurial growth in a knowledge and firm organization dimen-

[18]We used total revenue variable values as indicated by each observation.

sion. From separate regressions in table 3 we find that outside-in processes significantly increase both facets of start-up growth, hence, hypothesis one and two seem to hold. In industries that are dominated by open innovation processes outside-in commitment and behaviour of entrepreneurs may stem from the suggested 'variety' and/or 'conditionality' notions given by axiom one and two. Still, we do not explicitly investigate or proof presence of these notions and particular incentive structures for firms, rather we provide incentive-'neutral' evidence on the various effects of OI *and alike* activities.

Table 2
Random (fixed) effects panel regression on knowledge (firm) growth, using general (efficiency) controls in model 1 (2).

	Knowledge Growth		*Firm Growth*	
	Model 1	*Model 2*	*Model 1*	*Model 2*
LAG. PATENTS	.0832‡‡ (.0067)	.0843‡‡ (.0069)		
LAG. TTEMPLOYEES			– .1755‡‡ (.0421)	– .1648‡‡ (.0419)
OUTSIDEIN	.0417‡‡ (.0163)	.0418‡‡ (.0162)	.1559‡‡ (.0740)	.1572‡‡ (.0725)
INSIDEOUT			– .2847‡ (.1642)	– .3024‡ (.1613)
RDSTAFF	– .0941‡‡ (.0299)	– .0908‡‡ (.0301)		
PATENTS			–	–
TTEMPLOYEES	–	–		
Controls				
OEXPERIENCE	–		–	
OGENDER	–		–	
INDUSTRY	– .2226‡ (.1315)			
ORACE	–		–	
OAGE	–		–	
OEDUCATION	.0764‡ (.0402)		–	
DEA Controls				
EFFICIENCY1		–		– .5388 (.3870)
EFFICIENCY2		.1275 (.0949)		–
EFFICIENCY3		–		–
Cons	–	.0513‡‡ (.0986)	1.7292 (.6945)	1.7293‡‡ (.6733)
N	173	177	127	133

General control dummies (*model 1*) show that, on the one hand, (knowledge) growth is human-capital based, that is the level education of the business owner tends to enhance inventory and potential for patenting activities, on the other hand, interestingly, knowledge production in high-tech sectors (INDUSTRY) seems to decline over the panel. It can be argued that the latter result may derive from a post-entry consolidation and (re-)evaluation of pre-formation patent portfolios of entrepreneurs or (relatively higher) competitive pressure in these industries which both reduces overall portfolio size. Note furthermore that an increase in R&D staff reduces 'average' per period innovation performance of firms. A possible explanation for the latter result is that building up proprietary staff for research and development can be seen as a form of long-term investment that may unfold knowledge output effects only in the long-run performance, partially this may also be due to the limited number of observed panel periods.

For the case of inside-out activities of entrepreneurs we estimate that they tend to decrease average firm growth by $-.2847$ at the 90%-significance level, given all other variables are kept constant. As above hypothesis three suggests, if firms do not exploit knowledge assets inside their boundaries but (stationary) purchase their assets for exploitation elsewhere, this causes stagnation or even reduction of organizational growth. Alternatively, inside-out processes may cause a change in general product market structure and competition levels (that cannot be observed within the panel) which potentially can effect related sales and this may, again, reduce manufacturing capacities of firms.

In general, we find no significant evidence that innovation (as indicated by the total number of PATENTS) impacts on entrepreneurial firm growth. Additionally, when we look closely at lagged variables included the latter process of organizational growth itself seems to have either an unsystematic, rather stochastic nature – as it was proposed by Coad (see above) – i.e. the average growth path may change signs, or, oppositely, there may be very fast (slow)-growing small (large) organization entrepreneurs within the early three years of their existence.

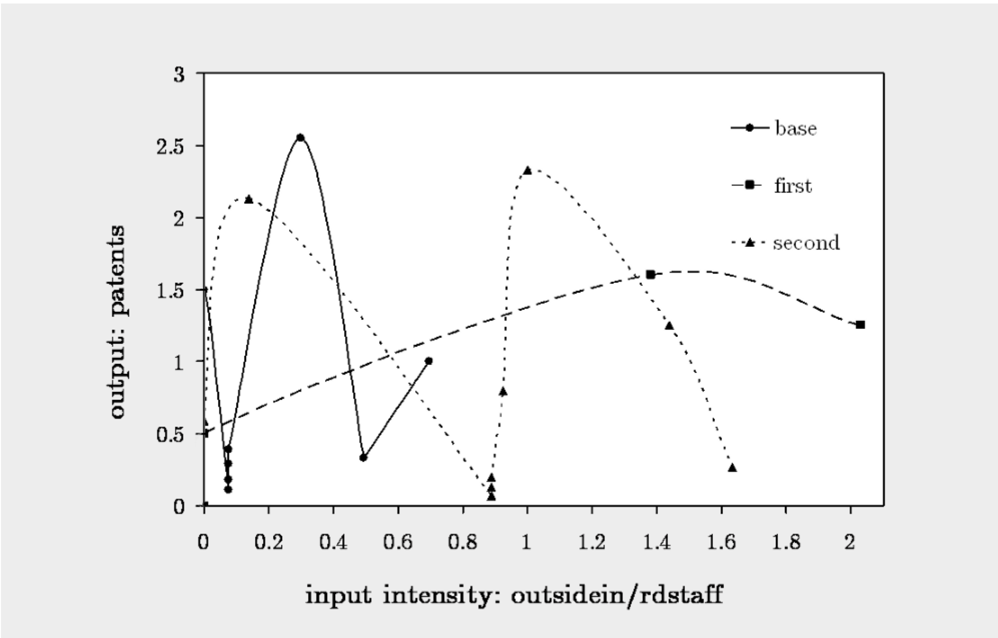

Fig. 1: Efficient DMUs, DEA windows analysis (periods = 3, width = 1) with inputs (OUTSIDEIN & RDSTAFF) and output (PATENTS), radial measure, input-orientation.

Control dummies introduced in estimation *model 2* for observations that suffice DEA efficiency criteria show a rather ambiguous, overall effect on entrepreneurial growth processes. There is a very weak, but positive impact of efficiency (EFFICIENCY2) on knowledge growth whereas in regard to firm growth there is a negative influence of efficiency. By construction, the EFFICIENCY1 dummy relates to efficient allocation and modes of production ('technologies') applied for changes in knowledge production which at the same time seems to have an opposing effect on firm growth, still, we find no significant feedback 'loop' in the opposite direction. Estimation results of the (absolute) total revenue eq. (6), as an alternate, short-term-related measure of firm growth, – given in table 6 – yield a strong, positive impact for both of these efficiency criteria which supports above view that the efficiency corollary is a relevant analysis criteria (of subsample selection) but it is strongly dependent on time.

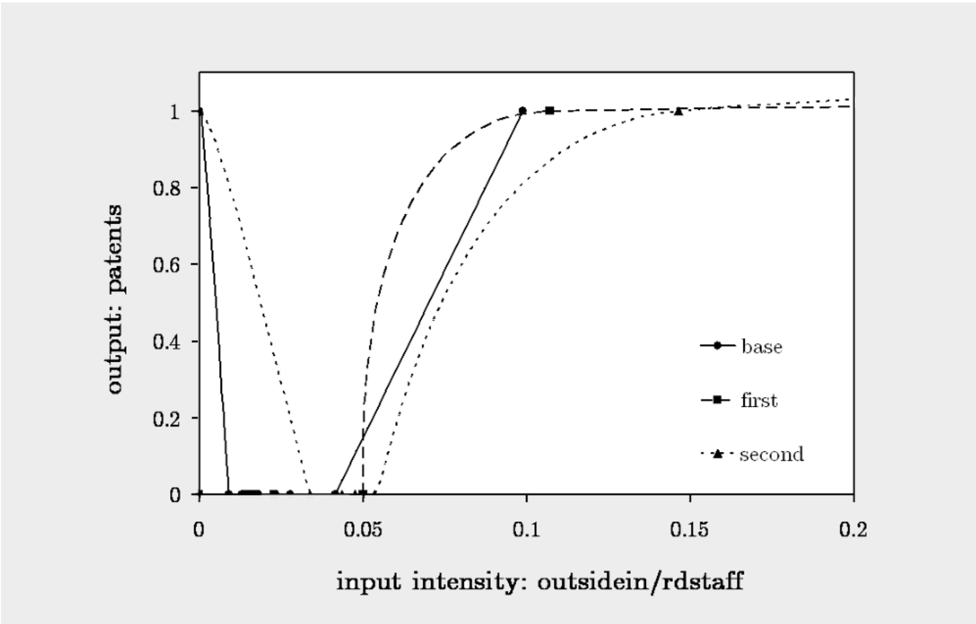

Fig. 2: Efficient DMUs, DEA windows analysis (periods = 3, width = 1) with inputs (OUTSIDEIN & RDSTAFF) and output (PATENTS), radial measure, output-orientation.

Figures 1 and 2 show that there is a right-shifting knowledge production frontier over time which implies either a reduction of R&D staff or a broadening of outside-in activities, that is an increase in the input intensity ratio. On the production frontier DMUs suffice efficiency whereby efficient observations at time t are not necessarily selected for the construction of the frontier at $t + 1$. Independent from the DEA mode of analysis input- and output-orientation yield similar insights that only differ in absolute values and scaling due to the reciprocity theorem given when constant returns to scale in production are assumed. These results should not implicitly lead to the conclusion that efficient observations are also (the fastest) growing organizations.

When we expand the DEA analysis to multiple output goals (and hereby separating into two subsamples of TTEMPLOYMENT, i.e. the small(-est) respectively larger entrepreneurial organizations) as exercised in figures 3 and 4 we find that 'technologies' of production assign to mixed instruments in the case of larger entities compared to the exclusive-use-patterns (either proprietary R&D staff or outside-in activities) by smaller organizations. Furthermore, minor efficiency gains[19] in the deployment of knowledge

[19]Efficiency gains (losses) imply a radial shift of the production frontier towards (away from) the origin.

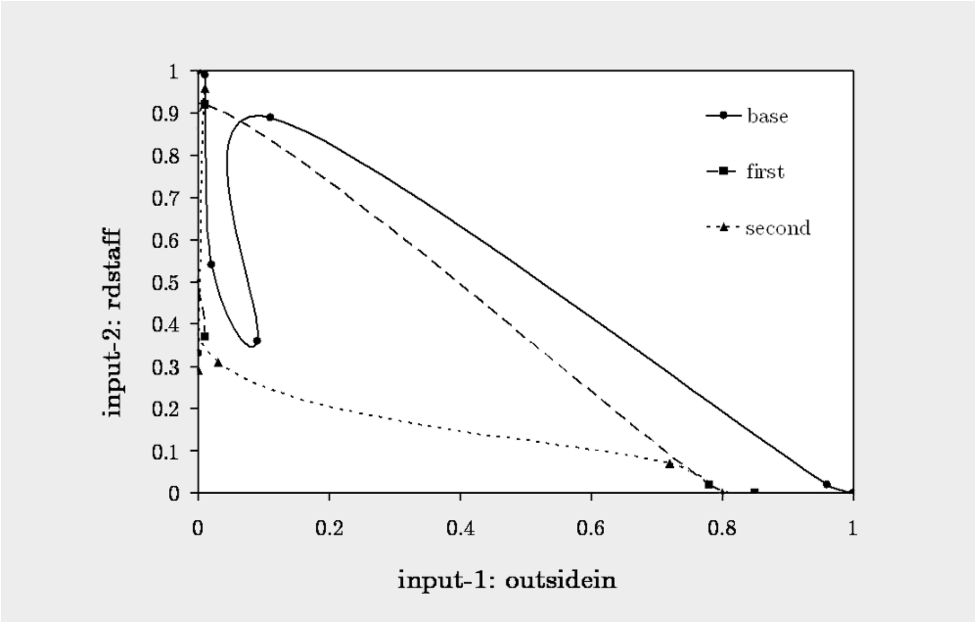

Fig. 3: Efficient DMUs with TTEMPLOYEES ≤ 5, DEA windows analysis (periods = 3, width = 1) with inputs (OUTSIDEIN & RDSTAFF) and outputs (TTEMPLOYEES & PATENTS), radial measure, output-orientation.

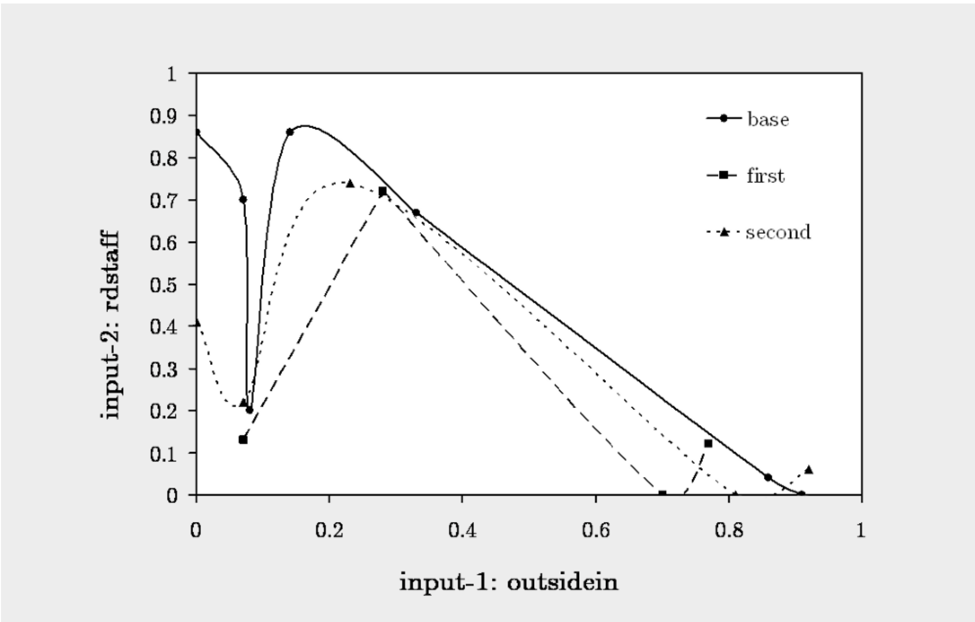

Fig. 4: Efficient DMUs with TTEMPLOYEES > 5, DEA windows analysis (periods = 3, width = 1) with inputs (OUTSIDEIN & RDSTAFF) and outputs (TTEMPLOYEES & PATENTS), radial measure, output-orientation.

inputs with respect to firm size and knowledge production can be observed over time in both samples. Still, if we assume positive firm growth for efficient observations, we do see no clearcut shifting process of small DMUs in figure 3 away from the axes as figure 4 suggests. This may, again, stem from the limited number of observation periods.

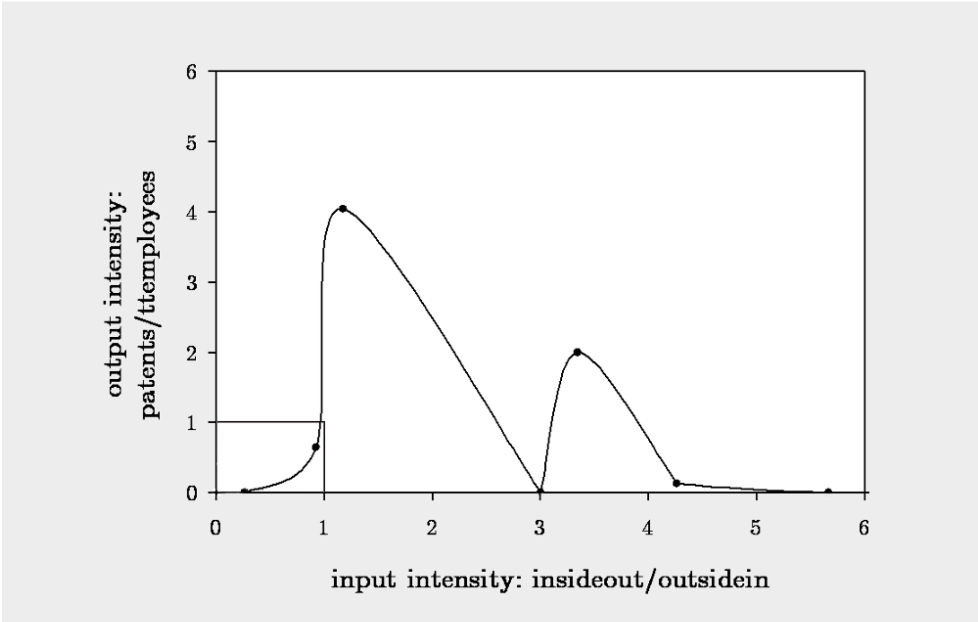

Fig. 5: Efficient DMUs with TTEMPLOYEES ≤ 5, DEA windows analysis (periods = 1, width = 1) with inputs (OUTSIDEIN & INSIDEOUT) and outputs (TTEMPLOYEES & PATENTS), radial measure, input-orientation.

In a similar, input-orientated DEA mode of analysis figures 5 and 6 seek to describe the impact of coupled processes (simultaneous outside-in and inside-out) on firm size and knowledge production along different stages of (efficient) firm growth. Please note that these subsamples are relatively small and DMUs are pooled over time and, hence, may have finite power of representation (see summary statistics in table 5). From the changes in input intensities, with a tendency of INSIDEOUT OUTSIDEIN>1 to INSIDEOUT OUTSIDEIN<1, we draw the conclusion that in efficiency terms most smaller entities rely more heavily on inside-out than on outside-in processes while being the other way around for larger size entrepreneurs. This observation partially contradicts the stylized stages of the entrepreneurial growth cycle described above that is grounded, firstly, on a phase of capacity-building where outside-in is the more prominent feature of open innovation and alike activities on the basis of a relatively smaller knowledge stock[20] and, secondly, this building process is followed up or complemented by a phase

[20]Figure 6 shows higher output levels in comparison to figure 5 if we look at output intensities, put differently, in 'average employee patenting'. The low level of output intensity in figure 6 may also be caused by an significance loss of the patent indicator for knowledge production itself as small(est) firms potentially prefer alternate, (non-legal) protection instruments for their inventions such as secrecy.

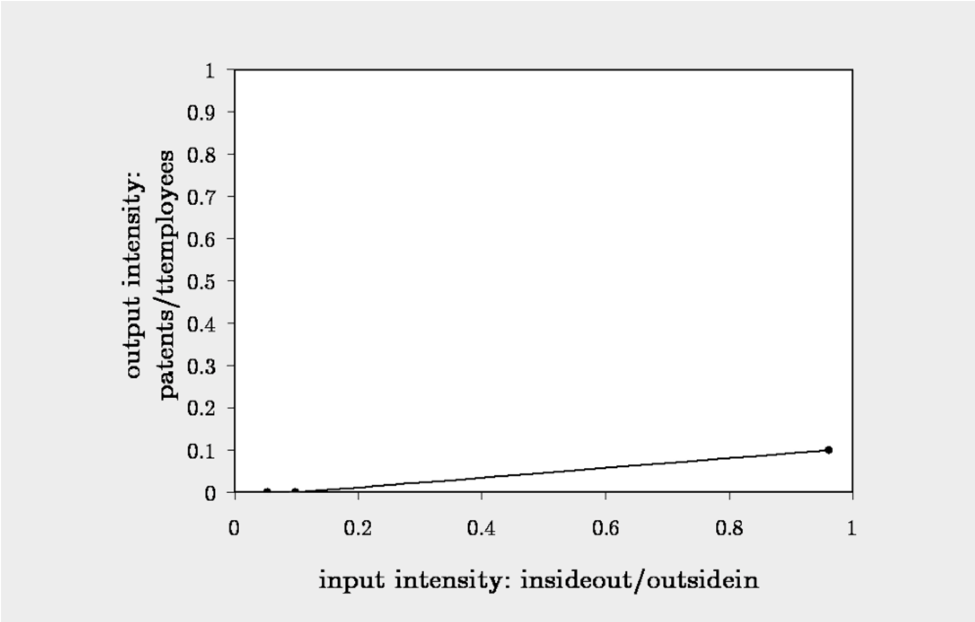

Fig. 6: Efficient DMUs with TTEMPLOYEES > 5, DEA windows analysis (periods = 1, width = 1) with inputs (OUTSIDEIN & INSIDEOUT) and outputs (TTEMPLOYEES & PATENTS), radial measure, input-orientation.

of (knowledge asset) capacity-exploitation where inside-out processes begin to dominate the picture while organizational growth becomes an (relatively) arbitrary goal. Oppositely, our results suggest a reversed order of these growth processes where exploitation motives temporarily are dominated by learning motives, in particular, this holds for very small organizations.

3.4 Conclusion and Policy Implications

We find from parametric estimation that outside-in processes of OI significantly increase both dimensions of growth while inside-out processes (weakly) decrease firm growth. For DEA efficient observation within the sample the knowledge production frontier shifts from proprietary innovation sources of information towards higher levels of use on external sources over time. If external knowledge assets cannot be acquised for various reasons[21], outside-in processes may be hindered and, lastly, firm and knowledge growth may be degraded. In the worst case this downgraded performance in both dimensions may become a central causality for market failure of the entrepreneur, partially also because OI co-operations (inside-out, i.e. being a 'conditional' information source for another firms knowledge production) can represent a strategic advantage for SMEs and entrepreneurs in a strongly competitive environment.

[21] As described above acquisition of assets may be restricted by financial constraints of entrepreneurs, by limited market power or missing technological opportunity on the market for technology.

When firm size (or employment generation) is included as an output goal – next to the stock of knowledge – we observe minor efficiency gains over time whereby a mixed pattern of (internal and external) information sources rather than an exclusive use becomes more dominant with increasing firm size. Additionally, the efficient design of coupled processes for firm growth and knowledge production tends to shift, in particular for very small entities, from internal capacity-building objectives, that is related to the use of outside-in processes, to a dominant external exploitation pattern of proprietary knowledge assets, that is related to the use of inside-out processes. We also can show that the efficiency criteria raised has a (weak) but significant on growth performance of firms.

Above discourse also raises several other research questions: Can one still assign adequately a single 'original' inventor to an innovation or can we still, at least, disclose the initial momentum of an initiative for innovation[22]? What are the limits of an OI strategy on the firm level and what are its implications for technological change on the industry level?

Broadly speaking, the potential success of an individual firms open innovation strategy also depends on the surrounding innovation system (Lundvall 1992), its actors and institutions. The 'quality of the partnering match' in terms of technological and innovation performance is highly constrained by the overall 'sample size' of potential candidates at stake for selection. Additionally, this sample is most likely limited to the number of firms that are also willing to perform a 'more' open innovation strategy different to mostly traditional closed-form R&D. For the S&T policy-making this particular perspective points towards a strategy that focuses e.g. on funding of collaborative research projects, setting and supporting infrastructure of research networks, as this should help to raise the perception and awareness of firms, in particular SMEs and entrepreneurs, for success or failure of open innovation projects and strategies, partly also because the general transparency of the markets for technology may increase. Hence, these measures can upgrade the potential selection process and the subsequent innovation performance of firms dedicated to open innovation in an innovation system. Tentatively, all these issues are open for further inquiry.

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[22]In the scheme of OI an initial momentum could be the writing of a contract on common exploitation (X, Y) of an asset of firms X which would be the basis for further knowledge production of X.

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A Appendix

Table 3
Cronbach's alpha test for license-out- and license-in-*composite* indicators.

item	*obs.*	*sign*	*item-test correlation*	*item-rest correlation*	*average inter-item correlation*	*alpha*
license-out						
patent	217	+	.8841	.5171	.5411	.7022
copyright	752	+	.9171	.5419	.5081	.6738
trademark	1160	+	.9366	.5299	.5542	.7131
test scale					.5357	**.7759**
license-in						
patent	7378	+	.7751	.4529	.4661	.6358
copyright	7401	+	.7982	.5006	.4048	.5763
trademark	7399	+	.8134	.5341	.3630	.5326
test scale					.4113	**.6770**

Table 4
Summary statistics of overall KFS sample.

In/Output Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Obs.*
TTEMPLOYEES	4.1430	5.2510	0	35	7327
PATENTS	.1221	1.8919	0	100	7345
OUTSIDEIN	.3610	1.4242	0	10	7410
INSIDEOUT	3.0638	2.2319	0	10	225
RDSTAFF	.9247	.9543	0	5	5273
OEXPERIENCE	13.3228	10.4748	0	40	7358
OAGE	3.5648	1.0908	1	7	7348
OEDUCATION	6.3720	2.0671	1	10	7358
OGENDER	.7528	.4314	0	1	7359
ORACE	.8876	.3159	0	1	7337
INDUSTRY	.4025	.4904	0	1	8748

Table 5
Summary statistics of subsamples.

Summary statistics of subsamples for first & second data envelopment analysis (DEA).

In/Output Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Obs.*
Base					
OUTSIDEIN	.4497	1.6345	.0001	10	
RDSTAFF	1.0713	.9551	.0001	5	
PATENTS	.1481	1.2727	0	28	
First					
OUTSIDEIN	.4090	1.5233	.0001	10	
RDSTAFF	.9297	1.0120	.0001	5	
PATENTS	.1059	.8051	0	15	
Second					
OUTSIDEIN	.4122	1.5531	.0001	10	
RDSTAFF	.9279	.9779	.0001	5	
PATENTS	.1275	.9909	0	17	
N					1067

Summary statistics of subsamples for third & fourth data envelopment analysis (DEA).

In/Output Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Obs.*
TTEMPLOYEES $\leq$ 5					
Base					
OUTSIDEIN	.3570	1.4466	.0001	10	
RDSTAFF	.7620	.8818	.0001	5	
TTEMPLOYEES	2.7738	1.1453	0	5	
PATENTS	.1151	1.0079	0	22	
First					
OUTSIDEIN	.3790	1.4560	.0001	10	
RDSTAFF	.5675	.8375	.0001	5	
TTEMPLOYEES	4.1495	3.5356	0	34	
PATENTS	.09921	.8777	0	15	
Second					
OUTSIDEIN	.3746	1.5118	.0001	10	
RDSTAFF	.6151	.9054	.0001	5	
TTEMPLOYEES	4.3995	4.0015	0	35	
PATENTS	.1085	.9258	0	15	
N					756
TTEMPLOYEES > 5					
Base					
OUTSIDEIN	.7572	2.1188	.0001	10	
RDSTAFF	1.2122	1.1766	.0001	5	
TTEMPLOYEES	11.3144	6.3236	6	32	
PATENTS	.2689	1.9045	0	28	
First					
OUTSIDEIN	.5300	1.7588	.0001	10	
RDSTAFF	1.0606	1.2712	.0001	5	
TTEMPLOYEES	12.9242	7.6398	1	30	
PATENTS	.1364	.6381	0	5	
Second					
OUTSIDEIN	.5804	1.7668	.0001	10	
RDSTAFF	1.0190	1.1551	.0001	5	
TTEMPLOYEES	13.25	7.9402	1	31	
PATENTS	.2008	1.2276	0	17	
N					264

Table 5 (continued)
Summary statistics of subsamples.

Summary statistics of subsamples for fifth & sixth data envelopment analysis (DEA).					
In/Output Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Obs.*
TTEMPLOYEES $\leq$ 5					
Pooled					
INSIDEOUT	3.1452	2.0807	.0001	10	
OUTSIDEIN	1.6654	2.4081	.0001	10	
PATENTS	1.5556	4.1816	0	22	
TTEMPLOYEES	2.4667	2.0674	0	16	
N					90
TTEMPLOYEES > 5					
Pooled					
INSIDEOUT	2.8711	2.6065	.0001	10	
OUTSIDEIN	2.9287	3.0619	.0001	10	
PATENTS	3.7586	13.5664	0	100	
TTEMPLOYEES	12.9310	7.1399	3	33	
N					58

Table 6
Random effects panel regression on firm size, using general (efficiency) controls in model 1 (2).

	Firm Size (TTREVENUE)	
	Model 1	*Model 2*
PATENTS	.0476‡‡ (.0237)	.0345 (.0252)
INSIDEOUT	− .2384‡‡ (.0914)	− .1983‡ (.0900)
OUTSIDEIN	–	–
Controls		
OGENDER	–	
ORACE	1.1442† (.7941)	
OEDUCATION	.3333‡‡ (.1245)	
OEXPERIENCE	–	
TTDEBT	− .0877‡ (.0541)	
OAGE	–	
DEA Controls		
EFFICIENCY1		1.4657‡‡ (.3870)
EFFICIENCY2		1.2071‡ (.6886)
EFFICIENCY3		–
Cons	2.8593‡‡ (1.3067)	6.7051‡‡ (.3728)
N	193	197