The economics of production, integration and efficient use of renewable energy

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Contents

List of Figures

List of Tables

Prior Publications

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Chapter 3: The role of aggregators in facilitating industrial demand response

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Abstract

Dealing with the climate crisis requires tackling three challenges regarding the production, integration and efficient use of energy, addressed in the three chapters of this dissertation. First, energy efficiency is widely recognised as an effective means to reduce the consumption of fossil fuels, as well as a cost-efficient solution towards the decarbonisation of the economy. However, impact evaluations of existing energy efficiency policies are rare. Second, vast amounts of renewable energy are needed in order to replace fossil fuels in the energy mix. As renewable energies are being expanded, concerns about social acceptance of renewables become more pressing, especially for technologies like onshore wind power. On the other hand, policies intended to increase social acceptance may harm the expansion of renewable energy. Third, renewable energy needs to be integrated into the current energy systems using flexibility options such as demand response. However, a set of barriers needs to be overcome in power markets, in order to move from an inelastic demand side to flexible loads.

Chapter 1 evaluates the impact of energy efficiency networks, an instrument designed to boost energy efficiency in industry. In energy efficiency networks, groups of firms exchange experiences on energy conservation in regular meetings over several years. The companies implement energy efficiency measures in order to reach commonly agreed energy savings and CO_2 reduction goals. Energy efficiency networks exist in several countries, such as Germany, Sweden and China. Existing evaluations of such voluntary regional networks in Germany claim that participants improved energy efficiency at twice the speed of the industry average. Based on comprehensive data from the German manufacturing census, chapter 1 examines whether participation in energy efficiency networks has a causal impact on energy conservation and CO_2 emissions. I demonstrate that for the average participant there is no statistically significant effect on energy productivity or CO_2 emissions due to the network activities. While a small network effect may exist, power calculations show that this effect would be smaller than predicted by the previous literature. However, there is some indication that exporters may have benefitted from the networks by reducing their CO_2 emissions.

Chapter 2 shows that strict minimum distances have detrimental consequences for onshore wind power. The chapter evaluates the causal effect of the introduction of minimum distance regulation

in Bavaria on construction permits for wind turbines. In order to increase public acceptance of wind power, several countries and regions have introduced mandatory minimum distances of wind turbines to nearby residential areas. Germany's largest federal state Bavaria introduced such separation distances of ten times the height of new wind turbines in 2014. We construct a novel monthly district-level dataset of construction permits for wind turbines constructed in Germany between 2010 and 2018. We use this dataset to evaluate the causal effect of introducing the Bavarian minimum distance regulation on the issuance of construction permits for wind turbines. We find that permits decreased by up to 90 percent. This decrease is in the same order of magnitude as the reduction of land area available for wind turbines. The results are in line with findings indicating that minimum distances do not increase the public acceptance of wind power, but harm the expansion of onshore wind power. Alternative policies are better suited to facilitate acceptance without hampering the expansion of wind power.

Chapter 3 analyses the role of aggregators – intermediaries between consumers and energy markets – in facilitating industrial demand response. Based on the results from semi-structured interviews with German demand response aggregators, as well as a wider stakeholder online survey, we examine the role of aggregators in overcoming a set of barriers to industrial demand response. We find that central roles for aggregators are to raise awareness for the potentials of demand response, as well as to support implementation by engaging key actors in industrial companies. Demand response aggregators thus drive organisational change. Moreover, we develop a taxonomy that helps analyse how the different functional roles of aggregators create economic value. We find that there is considerable heterogeneity in the kind of services that aggregators offer, many of which do create significant economic value. However, some of the current aggregator roles may become obsolete once market barriers to demand response are reduced or knowledge on demand response becomes more diffused.

Zusammenfassung

Die Auseinandersetzung mit der Klimakrise bringt drei Herausforderungen bezüglich der Produktion, der Integration und der effizienten Nutzung von Energie mit sich. Diese Herausforderungen werden in den drei Kapiteln dieser Dissertation analysiert. Erstens wird Energieeffizienz weithin sowohl als ein effektives Mittel zur Reduzierung des Verbrauchs fossiler Energien als auch als kosteneffiziente Lösung zu einer Dekarbonisierung der Wirtschaft anerkannt. Es gibt jedoch nur wenig empirische Analysen der Auswirkungen bestehender Effizienzpolitiken. Zweitens werden große Mengen erneuerbarer Energien benötigt, um fossile Energieträger im bestehenden Energiemix zu ersetzen. Mit der Ausweitung erneuerbarer Energien werden allerdings auch Fragen nach der Akzeptanz von Erneuerbaren wichtiger, insbesondere bei Technologien wie der Windkraft an Land. Politikmaßnahmen, die auf eine Erhöhung der Akzeptanz abzielen, können jedoch gleichzeitig auch dem Ausbau erneuerbarer Energien schaden. Drittens müssen erneuerbare Energien durch eine Nutzung von Flexibilitätsoptionen wie Demand Response in bestehende Energiesysteme integriert werden. Um von einer unelastischen zu einer flexiblen Nachfrage zu kommen, müssen jedoch eine Reihe von Barrieren in Strommärkten überwunden werden.

In Kapitel 1 werden die Auswirkungen von Energieeffizienz-Netzwerken evaluiert. Das Ziel dieser Netzwerke ist die Förderung von Energieeffizienz in der Industrie. In den Netzwerken werden über mehrere Jahre in regelmäßigen Treffen innerhalb von Gruppen von Unternehmen Erfahrungen über Energieeinsparungen ausgetauscht. Die beteiligten Unternehmen führen Energieeffizienzmaßnahmen durch, um gemeinsam vereinbarte Energie- und CO_2-Einsparziele zu erreichen. Energieeffizienz-Netzwerke gibt es in mehreren Ländern, wie z.B. Deutschland, Schweden und China. Bisherige Auswertungen dieser freiwilligen regionalen Netzwerke in Deutschland kamen zu dem Schluss, dass die Teilnehmer ihre Energieeffizienz doppelt so schnell steigern konnten wie der Industriedurchschnitt. Basierend auf amtlichen Mikrodaten des Verarbeitenden Gewerbes wird in Kapitel 1 untersucht, ob die Teilnahme an einem Energieeffizienz-Netzwerk einen kausalen Einfluss auf die Energieeinsparung und die CO_2-Emissionen der Teilnehmer hatte. Für den durchschnittlichen Netzwerkteilnehmer lässt sich aufgrund der Netzwerkaktivitäten kein statistisch signifikanter Effekt auf Energieproduktivität und CO_2-Emissionen der Teilnehmer feststellen. Obwohl möglicherweise ein kleiner Netzwerkeffekt existiert, zeigen Berechnungen zur Teststärke,

dass dieser kleiner wäre als die Vorhersagen in der bisherigen Literatur. Es gibt jedoch einige Hinweise, dass Exporteure durch eine Reduzierung ihrer CO_2-Emissionen von den Netzwerken profitiert haben.

In Kapitel 2 wird gezeigt, dass universelle Mindestabstände verheerende Konsequenzen für die Windenergie an Land haben. In dem Kapitel werden die kausalen Effekte der Einführung gesetzlicher Mindestabstände auf die Genehmigungen von Windenergieanlagen in Bayern untersucht. Mehrere Länder und Regionen haben solche verpflichtenden Mindestabstände zu nahe gelegenen Wohngebieten eingeführt, um die Akzeptanz der Windenergie an Land zu erhöhen. In Deutschlands größtem Bundesland Bayern wurden 2014 gesetzliche Mindestabstände von der zehnfachen Höhe neuer Windräder eingeführt. Wir erstellen ein neues monatliches Panel der Genehmigungen von Windrädern in Deutschland von 2010 bis 2018. Mithilfe dieses Datensatzes evaluieren wir den kausalen Effekt der Einführung der bayerischen Mindestabstandsregel auf die Ausstellung von Baugenehmigungen für Windräder. Die Genehmigungen sinken aufgrund der Einführung der Mindestabstandsregel um bis zu 90 Prozent. Dieser Rückgang ist ähnlich groß wie die Reduktion der für die Windenergie ausgewiesenen Flächen. Die Ergebnisse stimmen mit anderen wissenschaftlichen Erkenntnissen überein, dass Mindestabstände die Akzeptanz von Windenergie nicht steigern, deren Ausbau aber hemmen. Andere Politikmaßnahmen sind besser geeignet, die Akzeptanz der Windenergie an Land zu erhöhen, ohne den Ausbau zu bremsen.

In Kapitel drei wird die Rolle von Aggregatoren – Intermediäre zwischen Verbrauchern und den Energiemärkten – bei der Förderung von Demand Response in der Industrie analysiert. Basierend auf den Ergebnissen von semistrukturierten Interviews sowie einer breiteren Online-Umfrage unter Stakeholdern untersuchen wir die Rolle von deutschen Demand Response-Aggregatoren bei der Überwindung einer Reihe von Barrieren für Demand Response in der Industrie. Unsere Ergebnisse zeigen, dass das Erhöhen der Aufmerksamkeit für die Potenziale von Demand Response sowie die Unterstützung von deren Implementierung durch das Einbinden wesentlicher Akteure in den Unternehmen zentrale Rollen von Aggregatoren sind. Demand Response-Aggregatoren tragen somit zu organisatorischem Wandel bei. Wir entwickeln außerdem eine Taxonomie, mithilfe derer wir analysieren, wie die verschiedenen funktionalen Rollen der Aggregatoren ökonomischen Wert schaffen. Es gibt eine deutliche Heterogenität in der Art der durch die Aggregatoren angebotenen Leistungen, von denen viele erhebliche ökonomische Werte schaffen. Einige der derzeitigen Rollen von Aggregatoren könnten jedoch obsolet werden, wenn Marktbarrieren für Demand Response reduziert werden oder die Unternehmen zunehmend eigene Kompetenzen zu Demand Response aufbauen.

General Introduction

Dealing with the climate crisis is one of the greatest challenges of humankind. Unabated climate change would have disastrous consequences in many regions of the world, undermining food security, exacerbating human health problems and increasing displacement of people (IPCC 2014). For the first time, the top five long-term risks in terms of likelihood in the latest Global Risks Report of the World Economic Forum are climate-related (WEF 2020). At the same time, 97% of scientists agree that global warming is mainly caused by human activities (Cook et al. 2016). Consequently, in the 2015 landmark Paris Agreement, world leaders agreed to reduce greenhouse gas emissions in order to keep global warming well below 2° Celsius above pre-industrial levels, with an ambition to limit the temperature increase to 1.5°.

To fulfil its obligations under the Paris Agreement and combat anthropogenic climate change, the European Union has committed to work towards net-zero emissions by 2050 (EU 2020). In order to reach climate neutrality, greenhouse gas emissions (GHGs) have to be drastically reduced, such that remaining emissions can be balanced by removing warming gases from the atmosphere. Taking action is urgent: Global CO_2 emissions must drop by 45 percent from 2010 levels over the next decade for the world to have a chance of staying at 1.5 degrees (IPCC 2018). The highest potential for an emissions reduction lies in energy efficiency upgrades and an expansion of renewable energy (IEA 2019a). This thesis analyses the challenges of improving energy efficiency (chapter 1), expanding renewable energies (chapter 2) and integrating renewables into existing energy systems (chapter 3).

First, reducing emissions by improving energy efficiency is a major building block to reach the global climate targets. On the one hand, the world meets its overall energy demand mainly with fossil fuels: More than 80 percent of the world's primary energy consumption is based on the energy carriers oil, coal and natural gas (IEA 2019b). Energy needs to be used more efficiently and total primary energy consumption reduced, since it will be hard to fully substitute the large amounts of energy that are currently being consumed by renewable energy. Consequently, energy efficiency plays an important role in decarbonisation scenarios, for example in the industrial sector (BCG and Prognos 2018). At

the same time, energy efficiency is often the "cheapest fuel". The International Energy Agency (IEA) estimates that the bulk of cost-efficient GHG emissions reductions to reach the goals of the Paris Agreement will come from energy efficiency measures (IEA 2019a). Consequently, investments in consumer efficiency resources are increasingly prioritized in energy policies, both for reasons of effectiveness (actually reaching the climate goals) and efficiency (doing so at least cost). The European Union has embraced this "energy efficiency first" principle in its legislation on the Energy Union (EC 2016).

Second, much of the remaining energy demand needs to be supplied from renewable sources. Reaching climate neutrality warrants a substitution of the current dominance of fossil fuels by producing green electricity from renewable energy sources (IPCC 2018). In addition to replacing conventional power plants, a fuel switching to renewable electricity allows to decarbonise other sectors of the economy that currently still rely on fossil fuels (Bataille et al. 2018; Mitchell 2016). This sector integration – linking the power sector to other sectors of the economy via electrification – is likely to increase current electricity use, especially in sectors such as transport and industry (IEA 2019a). Consequently, vast amounts of electricity will have to be produced from renewable sources in order to combat climate change. The last two decades were characterised by large and sustained cost declines and rapid expansions of wind and solar photovoltaics due to technological learning, policy support and improvements in financing conditions (Creutzig et al. 2017; Egli et al. 2018). The cost of producing electricity with these technologies, without financial assistance, is now frequently lower than the one based on fossil fuels (IRENA 2019). As a result, three-quarters of new electricity generation capacity built in 2019 worldwide used renewable energy (IRENA 2020).

Third, integrating renewable energies into the current energy systems is a major challenge. Renewable electricity from wind and solar is subject to intermittency. This means that the electricity production is characterised by non-controllable variability and partial unpredictability (Perez-Arriaga and Batlle 2012). The integration of renewables will therefore require an increasingly flexible energy system. A range of flexibility options exists, such as more flexible generation resources, or electric storage (e.g. batteries). Another option is demand response (DR), voluntary changes by end-consumers of their usual electricity use pattern. Demand response is triggered either in response to changes in the price of electricity over time, or to incentive payments (Hurley et al. 2013). Due to their comparatively low costs, demand response measures are predicted to play an important role for the integration of renewable energy (Schill and Zerrahn 2018).

This thesis analyses these three challenges on the way towards a low-carbon future – energy efficiency, the production of renewable electricity and its integration into energy markets – by

focussing on the evaluation of energy markets and policies in Germany. Germany is the largest economy within the European Union, which as a whole makes up close to ten percent of global GHG emissions (JRC 2019). Within the EU, Germany is by far the largest single emitter, contributing to more than 20 percent of the bloc's GHG emissions (Eurostat 2019a). Germany is a particularly interesting case, because it is currently undergoing a major energy transition. The German energy transition (*Energiewende*) focusses on (1) a shift to renewable energy in the power sector, displacing nuclear energy and (in the future) coal power, as well as (2) a set of policies to support energy efficiency in buildings and industry (BMWi 2010). Since the introduction of its support policy for renewable energy 20 years ago, the share of renewable energies in the German electricity mix has increased seven-fold, from six percent in 2000 to 42 percent in 2019 (BMWi 2020). Moreover, Germany has a history of bold energy efficiency policies, most notably support for retrofits in the buildings sector, as well as (voluntary) measures in industry (Galvin and Sunikka-Blank 2013; BMWi 2016).

Chapter 1 of this thesis looks at energy efficiency in the industrial sector. Reducing industrial emission matters: Industry accounts for 20 percent of direct GHG emission within the EU (EEA 2019). At the same time, industrial firms create one-fifth of European gross value added and 15 percent of jobs (Eurostat 2019b). In Germany, small and medium-sized companies (*Mittelstand*) create close to 60 percent of all jobs, many of which are in manufacturing (BMWi 2018). From a policy perspective, it is therefore crucial that decarbonisation efforts in industry do not harm the competitiveness of manufacturers relative to international competitors (Naegele and Zaklan 2019).

Supporting measures to increase energy efficiency in the industrial sector are often seen as no-regrets policies: Such action has the potential to cut CO_2 emissions by reducing energy consumption per unit of output, while reduced energy costs make companies more competitive. There is a high potential for cost-effective energy efficiency upgrades in industry, much of which can be tapped by a diffusion of existing energy-efficient technologies (Brugger et al. 2019). However, there is an "energy efficiency gap" (Jaffe and Stavins 1994), due to a range of market failures and investment barriers such as behavioural anomalies (Gillingham and Palmer 2014; Stede 2017). Consequently, there is a role for energy efficiency policies correcting for market failures and underinvestment. In Germany, energy efficiency policy in industry is characterised by a focus on voluntary measures.

In chapter 1, I scrutinise energy efficiency networks, voluntary agreements targeted at reducing energy consumption in industry. Energy efficiency networks are a policy measure intended to bridge the industrial energy efficiency gap. In these networks, 10 to 15 firms from different economic sectors exchange experiences at regular moderated meetings over a period of 3-4 years in order to achieve

jointly agreed energy efficiency and CO_2 savings targets (Jochem and Gruber 2007; Köwener et al. 2014; Rohde et al. 2015). Such energy efficiency networks now exist in several OECD and large non-OECD countries, such as Switzerland, Germany, Sweden and China (Jochem et al. 2016; Paramonova and Thollander 2016; OECD/IPEEC 2017). Energy efficiency networks are one of the most important industrial energy efficiency policies in Germany. The German government planned to deliver savings of up to five million tonnes of CO_2 through these networks, equivalent to roughly one-third of all CO_2 savings foreseen in the industrial sector to reach Germany's 2020 climate targets (Barckhausen et al. 2018; BMU 2019).

Chapter 1 analyses the causal effect of German energy efficiency networks on energy productivity and CO_2 emissions of its participants, using official plant-level data from the German manufacturing census. In order to estimate this causal effect, I employ a difference-in-differences methodology, comparing participants of a first round of energy efficiency networks in 2009-2014 (treatment group) to a group of plants participating in energy efficiency networks that were initiated after the first round of networks had been completed. The main result of chapter 1 is that energy efficiency networks do not deliver the high energy savings promised by previous analyses. Previous evaluations argued that network participants increase their energy efficiency at two percent per year, or double the speed of the industrial sector as a whole (Jochem et al. 2010; Köwener et al. 2014; Rohde et al. 2015). However, regressions show that energy efficiency improvements triggered by the networks were most likely lower than this threshold. The chapter thus contributes to the literature on the impact evaluation of voluntary environmental management programmes using firm-level data. Such voluntary programmes are well-studied for the U.S. (e.g. Arora and Cason 1995; Khanna and Damon 1999; Vidovic and Khanna 2007; Arimura et al. 2011; Boiral et al. 2018), but less so for European programmes (e.g. Bracke et al. 2008; Kube et al. 2019).

Chapter 2, co-authored with Nils May, turns to the second challenge for decarbonisation, namely the generation of green energy at the lowest possible cost. One of the key technologies for such a low-cost power generation is onshore wind power, which generates electricity at relatively low cost (IRENA 2019). Consequently, the International Energy Agency envisions onshore wind power capacity to more than double within the next ten years globally (IEA 2019a). Onshore wind power is the dominant technology for the production of renewable electricity in Germany, contributing to more than 40 percent of renewable power (AGEB 2019). While the number of installed turbines increased very dynamically in the past two decades, new installations have stalled recently (see Figure 2-1 in section 2.1). One of the reasons for this decline is that a large number of wind projects cannot be built since the construction permit is being contested in court (Fraunhofer IEE 2019).

Minimum distances of wind turbines to nearby settlements are one policy instrument discussed with the aim of increasing social acceptance of wind power (e.g. German Federal Government 2019). Securing local acceptance of wind turbines is crucial for the deployment of wind power (Wüstenhagen et al. 2007): Although support for renewable energy is high in general, wind energy is more controversial than (small-scale) solar photovoltaics (Cashmore et al. 2019). Moreover, onshore wind power requires land and can have negative externalities on local residents (Krekel and Zerrahn 2017). Strict minimum distances have become more popular in recent years, being introduced for example in Poland, Scotland and the German federal state of Bavaria. While such regulation reduces the land area available for new deployment of wind energy, proponents argue that these negative effects on capacity expansion are outweighed because stricter minimum distances would facilitate future growth of wind power by increasing its acceptance.

Chapter 2 evaluates the causal effect of mandatory minimum distances introduced in Bavaria in 2014. Bavaria introduced particularly strict minimum distances equal to around 2,000 meters from nearby settlements. The analysis builds on a newly constructed dataset of German wind power construction permits. We show that this policy led to a strong reduction of permits, translating into a decrease of newly constructed wind turbines of up to 90 percent. This implies that up to 570 megawatts of wind turbines were lost in Bavaria annually. This decrease is in the same order of magnitude as the reduction of land area available for wind turbines. Our findings are robust to a battery of robustness checks.

Chapter 3, co-authored with Karin Arnold, Christa Dufter, Georg Holtz, Serafin von Roon and Jörn C. Richstein, addresses the third challenge of integrating renewable energy into the current energy systems. High shares of wind such as in Germany makes the integration of renewable energy into electricity systems a particular challenge, since integration costs increase with the amount of renewable energy in the grid (Hirth et al. 2015). The traditional paradigm in power systems was that electricity demand is inelastic (Stoft 2002). However, with an increasing share of electricity being produced by intermittent and seasonally varying renewables, more volatile prices provide higher incentives for consumers to adjust their electricity use. From a system perspective, a flexible demand side (or demand response) is an effective measure to maintain grid stability and reduce the need for costly grid expansions or backup generation capacity (Strbac 2008; Eid et al. 2016).

A significant share of the technical and economic potential for demand response lies in industry (Gils 2014). In the energy-intensive industries, technical load reduction potentials for production processes are assumed to be in the range of 2-3 gigawatts in Germany alone (see e.g. Klobasa 2010; Paulus and Borggrefe 2011; Langrock et al. 2015). However, a range of barriers to demand response

exist (O'Connell et al. 2014; Good et al. 2017). Some of these barriers are economic, such as transaction costs, information barriers or the absence of an adequate price signal on electricity markets. However, there are also non-market barriers, such as inertia and bounded rationality.

Chapter 3 analyses the role of demand response aggregators – intermediaries between consumers and energy markets – in addressing some of these challenges. Aggregators may play an important role in facilitating industrial demand response (Burger et al. 2017). Using semi-structured interviews with German demand response aggregators, as well as a wider stakeholder online survey, we examine how aggregators help overcome barriers to industrial demand response. We find that a central role for aggregators is to raise awareness for the potentials of demand response, as well as to support implementation by engaging key actors in industrial companies. Moreover, there is considerable heterogeneity in the kind of services that aggregators offer, many of which create significant economic value. Based on these results, we develop a taxonomy that helps analyse how the different functional roles of aggregators create economic value.

An overarching theme of this dissertation is the question of firm behaviour and organisational change. Good management practices have been shown to improve firm productivity (Bloom and Van Reenen 2010; Bloom et al. 2013). One core predictor for the lack of adoption of good management practices are informational barriers – firms may fail to undertake profitable investments because they are simply unaware of them (Anderson and Newell 2004; Bloom et al. 2013). Chapter 1 assesses whether energy efficiency networks lead to energy productivity gains by disseminating information within and across companies. On the other hand, an informed third party that fills the information gap may also help overcome informational barriers (Gerarden et al. 2017). Consequently, chapter 3 explores how outsourcing energy management to a third party can help overcome barriers to demand response and assist organisational change.

Chapter 1

Do energy efficiency networks save energy? Evidence from German plant-level data*

Abstract

In energy efficiency networks, groups of firms exchange experiences on energy conservation in regular meetings over several years. The companies implement energy efficiency measures in order to reach commonly agreed energy savings and CO_2 reduction goals. Energy efficiency networks exist in several countries, such as Germany, Sweden and China. Existing evaluations of such voluntary regional networks in Germany claim that participants improved energy efficiency at twice the speed of the industry average. Based on comprehensive data from the German manufacturing census, this chapter examines whether participation in energy efficiency networks has a causal impact on energy conservation and CO_2 emissions. I demonstrate that for the average participant there is no evidence of a statistically significant effect on energy productivity or CO_2 emissions due to the network activities. While a small network effect may exist, power calculations show that this effect would be smaller than predicted by the previous literature. However, there is some indication that exporters may have benefitted from the networks by reducing their CO_2 emissions.

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1.1 Introduction

Energy efficiency is often seen as a cost-effective way to reduce greenhouse gas emissions in order to contain global warming (IEA 2018; IPCC 2018). However, there is an "energy efficiency gap" (Jaffe and Stavins 1994), due to a range of market failures and investment barriers such as behavioural anomalies (Gillingham and Palmer 2014). Energy efficiency policies correcting for market failures and underinvestment may therefore play a key role in meeting the 2°C target agreed in the landmark Paris Agreement. A significant share of energy saving opportunities are in the industrial sector, which accounts for almost 30 percent of final energy consumption in Germany and 26 percent in the European Union (AGEB 2016; Lapillonne and Sudries 2016).

Energy efficiency networks are voluntary agreements of companies, targeted at reducing energy consumption in industry. In such networks, 10 to 15 firms from different economic sectors exchange experiences at regular moderated meetings over a period of 3-4 years in order to achieve jointly agreed energy efficiency and CO_2 savings targets (Jochem and Gruber 2007; Köwener et al. 2014; Rohde et al. 2015). The basic mechanism through which energy efficiency networks operate is an information treatment, encouraging investment into energy efficiency by providing companies with the knowledge and skills to effectively reduce energy consumption. Energy efficiency networks are typically regional. They focus on efficiency improvements in cross-sectional technologies (such as lighting or process heat), since participating companies come from different economic sectors with different production technologies (Jochem et al. 2010). Originating from Switzerland, energy efficiency networks now exist in several OECD and large non-OECD countries, such as Germany, Sweden and China (Jochem et al. 2016; Paramonova and Thollander 2016; OECD/IPEEC 2017).

In Germany, energy efficiency networks are one of the major instruments in the national policy mix to improve energy efficiency in industry and reach national climate targets. Together with the main industrial associations, the German government plans to create 500 networks by 2020, half of which had been set up by November 2019 (Barckhausen et al. 2019). These voluntary networks are expected to deliver savings of up to five million tonnes of CO_2 – roughly one-third of all CO_2 savings planned in the industrial sector until 2020 (Barckhausen et al. 2018; BMU 2019). These savings would account for 1/5 of all measures that reduce energy consumption set out in Germany's "National Action Plan on Energy Efficiency" (NAPE), which are necessary to comply with the EU Energy Efficiency Directive (Ringel et al. 2016).

Energy efficiency networks in Germany are generally considered a success in the existing literature. Most studies have looked at the so-called German "pilot networks", which were carried out between

2009 and 2014, before the official adoption of the target of setting up 500 networks. More than 360 companies have participated in 30 of these initial energy efficiency networks. The literature on these networks has focused on bottom-up calculations of energy savings achieved during the networking period, as well as surveys among participating companies (see, e.g., Wohlfarth et al. 2016; Barckhausen et al. 2018; Dütschke et al. 2018). Some of these evaluations conclude that participating companies increased their energy efficiency at around two percent each year, or double the speed of the industrial sector as a whole (Jochem et al. 2010; Köwener et al. 2014; Rohde et al. 2015; Wohlfarth et al. 2016). However, survey evidence also suggests that a large chunk of these energy conservation measures may not have been additional, since the firms would have carried out these measures anyways (e.g. Wohlfarth et al. 2016).

The main contribution of this chapter is that it is the first to use plant-level data in order to uncover whether there is a *causal* relationship between participation in an energy efficiency network and increased energy efficiency, as well as reduced CO_2 emissions. I use two different estimation strategies to explore this causal link. First, I employ a difference-in-differences estimator, comparing the energy productivity and CO_2 emissions of participants of the pilot phase 2009-2014 (treatment group) to a group of plants joining German energy efficiency networks that were initiated after the pilot networks had been completed (post-2014). These latter firms also chose to become part of an efficiency network, but did not receive the treatment until the pilot phase was over. Relative to the average manufacturing firm, this control group is much more similar to the participants of the pilot networks in terms of observables such as average energy consumption or number of employees.

I find no evidence of a statistically significant effect of the energy efficiency networks on either energy productivity or CO_2 emissions for the average plant. Moreover, power calculations show that the network effect – if present – was smaller than predicted by the previous literature. While in some specifications there is a statistically and economically significant effect of the networks on energy productivity and CO_2 emissions, this effect is driven by a few large installations. In the most robust specifications, there is no evidence of an effect of the networks. I provide visual support for the identifying assumption of parallel trends of treatment and control group in the absence of the treatment. Moreover, I test for anticipation effects and do not find evidence of either an increased energy productivity or lower CO_2 emissions prior to the uptake of a network. This lends additional credibility to the identifying assumption.

In order to check the robustness of these results, I employ a semiparametric matching estimator in a second step. This estimator aligns the distribution of observed variables of treatment and control group that are relevant for energy conservation efforts by choosing appropriate comparison units

from the entire manufacturing sector. This reduces the differences between treatment and control group in terms of observables. Moreover, by taking first differences, the estimator accounts for selection on time-invariant plant characteristics, such as organisational structures that favour energy efficiency investments. Results from the matching estimation support the finding of no significant treatment effect due to the network activities. My results are in stark contrast to previous assessments of energy efficiency networks in Germany, and highlight the importance of ex-post policy evaluation.

Finally, I explore heterogeneous treatment effects by taking a closer look at network participants with high exports. I find some indication that high exporters may benefit from energy efficiency networks by reducing their CO_2 emissions. This result may be explained by a better management of exporting firms, which allows exporters to profit more from participating in energy efficiency networks than the average industrial firm. Exporting firms have been found to be more innovative and more productive than domestic non-exporters (Helpman et al. 2004; Yeaple 2005; Aw et al. 2008; Lileeva and Trefler 2010; Atkin et al. 2017). Moreover, exporting may improve management practices (Bloom and Van Reenen 2010), which in turn may have positive spillovers on energy efficiency (Bloom et al. 2010; Martin et al. 2012; Boyd and Curtis 2014). Exporting German manufacturers in particular have been found to be more energy efficient than their non-exporting counterparts (Lutz et al. 2017).

This research contributes to the literature on the impact evaluation of voluntary environmental management programmes using firm-level data. Voluntary agreements to reduce the environmental impacts of production processes have received increasing attention (Segerson and Miceli 1998), with mixed results on their effectiveness. Well-studied voluntary programmes include the U.S. Environmental Protection Agency's 33/50 (Arora and Cason 1995; Khanna and Damon 1999; Gamper-Rabindran 2006; Vidovic and Khanna 2007; Carrión-Flores et al. 2013), as well as the norm for environmental management systems ISO 14001 (e.g. Arimura et al. 2011; see also the comprehensive overview by Boiral et al. 2018). European voluntary programmes such as the EU's Eco Management and Audit Scheme (EMAS), on the other hand, have received considerably less attention (e.g. Bracke et al. 2008). Recently, Kube et al. (2019) find no effect of EMAS on either CO_2 intensity, energy intensity or investments for German manufacturing firms.

The chapter is structured as follows. Section 1.2 explains the concept of energy efficiency networks, as well as the mechanisms through which they are thought to help energy conversation. It also describes the pilot phase of energy efficiency networks in Germany. Section 1.3 outlines two alternative identification strategies used to estimate the treatment effect of energy efficiency networks. Section 1.4 portrays the panel dataset used in this study, discusses the use of energy

productivity as an indicator for energy efficiency, and provides descriptive statistics. Section 1.5 presents the results and discusses the identifying assumptions. Section 1.6 concludes.

1.2 Energy efficiency networks – how they work

Energy efficiency networks (EENs) are an attempt to overcome investment barriers to energy efficiency within companies. EENs work on a voluntary basis, but are often incentivised by existing regulatory and policy frameworks (OECD/IPEEC 2017). The networks are typically regional, meaning that companies from different sectors within one region may join the same network. The cross-sectoral nature of regional energy efficiency networks addresses concerns over sharing sensitive information with potential competitors (Jochem et al. 2010). However, other types of networks also exist. Sectoral networks are made up of different firms from the same sector. Internal company networks, on the other hand, comprise different manufacturing sites of a parent company that join an organisation-wide energy efficiency network.

Figure 1-1 illustrates how energy efficiency networks work.[1] During an initial identification phase (phase 1), profitable energy saving opportunities are identified in an energy audit. Each network participant then commits to a voluntary energy savings goal, as well as a CO_2 reduction goal. The individual goals add up to a joint network target. In the networking phase (phase 2), participants meet at regular moderated meetings for three to four years. Here, they share their experience about the implementation of energy efficiency measures. Moreover, external experts provide input on topics such as energy efficiency technologies, organisational measures like awareness raising among employees, or financing of energy efficiency investments. There are also yearly site visits to monitor progress towards the energy efficiency goal and, at the same time, to allow participants to see efficiency measures implemented in other companies.

Figure 1-1: Phases of energy efficiency networks

Identification phase (5-10 months)	Networking phase (2-4 years)
Identification of profitable energy efficiency investments - Energy audit - Energy savings and CO_2 reduction targets	**Networking activities** - 3-4 network meetings per year - Site inspections - Exchange of experiences - Presentations by external experts

[1] Figure 1-1 is based on the LEEN standard ("Learning energy efficiency networks"), a voluntary quality standard on how to establish and run energy efficiency networks, including a standardised monitoring of the energy savings achieved. LEEN was developed during the 30 "pilot networks" in Germany (Köwener et al. 2014). Other countries have opted for networks running a shorter time period, for example China (OECD/IPEEC 2017).

In order to recover the costs for joining the network from their energy savings, companies participating in energy efficiency networks should have annual energy costs of at least EUR 500,000. The direct costs (fees) for joining a network are between EUR 35,000 and EUR 40,000 for a four-year operating period of a network using the LEEN standard ("Learning energy efficiency networks" – see FN 1). In addition, there are transaction costs such as staff costs for the participation at network meetings (Köwener et al. 2014). However, costs of participation can be much lower when a network does not use the LEEN standard (Jochem et al. 2010).[2]

1.2.1 The pilot phase and the initiative for 500 energy efficiency networks

Between 2009 and 2014, 30 regional networks with 366 participants from 50 different sectors were carried out in Germany. 60 percent of the networks began operating in the year 2010, the rest of the networks started in the years 2009, 2011 and 2012 (see appendix A.1.7.2). Energy efficiency networks were still relatively unknown in Germany when the first networks were set up, and the decision to join a network was voluntary. Consequently, the managers of the 30 pilot networks (energy agencies, industry associations, research institutions or utilities) typically approached companies they knew in order to persuade them to join a network of the treatment group.

There was no direct financial incentive to participate in one of the 30 pilot networks, apart from reduced participation costs. The networks got financial support from the National Climate Initiative of the German environmental ministry to cover parts of the costs of setting up and managing the networks, leading to a reduction of participation costs. Financial support included up to 1/3 of the costs of setting up a network[3], such as project management costs and the costs of the initial energy audit[4]. However, there were no direct payments to companies in the pilot networks, such as financial support for the investment of the implemented energy efficiency measures.

A monitoring of the 30 pilot networks was conducted in Germany, which concluded that its participants achieved an annual energy efficiency improvement of 2.1 percent (Jochem et al. 2010; Köwener et al. 2014; Rohde et al. 2015; Wohlfarth et al. 2016). According to these studies, this is

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[2] In energy efficiency network types not using the LEEN standard, a participation with annual energy costs above EUR 150,000 is also possible (Jochem et al. 2010).

[3] The total project volume was around EUR 9.3 million for the years 2008-2014. Each network could receive up to EUR 8,000 per participating company.

[4] The energy audits at the beginning of phase 1 of the networks were designed such that they comply with the ISO 50001 standard for energy management systems. Following ISO 50001 is voluntary in Germany, yet doing so qualifies energy-intensive companies for exemption from certain energy taxes (Rohde et al. 2015). However, since the standard was only published in 2011, it is not relevant regarding the selection process into energy efficiency networks.

twice the amount of the energy efficiency improvement of the German industry as a whole, which is estimated to have been approximately one percent between 2000 and 2012 (Schlomann et al. 2014).

Following the perceived success of the pilot phase of energy efficiency networks, the German economic ministry (BMWi) signed a letter of intent with several prominent industry associations in 2014 to create 500 energy efficiency networks by 2020. In September 2018, the 200th of these energy efficiency networks was set up. At least 24 of the firms that already participated in the pilot phase – around six percent of firms that were in a network in the first place – chose to join a second network post-2015. Most of these networks are again regional, but there are also some sectoral networks (e.g. in the steel industry), as well as within-company networks. Within-company networks unite several production sites throughout Germany of the same parent company in one network.

1.2.2 Channels linking network activities to energy efficiency investments

Energy efficiency networks typically focus on energy savings from **cross-cutting technologies** such as process heat and process cooling, ventilation or lighting, since these are used in a wide range of industrial sectors (Jochem et al. 2010; Köwener et al. 2014; Rohde et al. 2015). In regional networks, participating companies are from different economic sectors and typically employ very different production technologies. However, the technological focus of energy efficiency networks varies with the network type. In sectoral or within-company networks, there is the option to look more specifically at energy efficiency in commonly used production technologies and hence go beyond mere energy savings from cross-cutting technologies.

Energy efficiency networks are supposed to reduce barriers to energy efficiency investments through a number of channels. First, EENs may help to facilitate organisational change by **overcoming the little priority given to energy efficiency investments** in many firms (Köwener et al. 2014). This is especially true for SMEs (Paramonova et al. 2014). Dütschke et al. (2018) argue that energy efficiency networks act as an "agenda setter" – through the participation in the network energy efficiency becomes a topic of organisational decision-making. Participation in EENs may also raise the awareness of energy conservation potentials within companies and make profitable investment opportunities visible (OECD/IPEEC 2017).

Moreover, EENs may also influence energy conservation through **socio-psychological mechanisms** (Jochem et al. 2010; Stern 1992): The participation of company representatives in a group structure like an energy efficiency network can lead to a higher intrinsic motivation for participants (Köwener et al. 2011). Setting a joint efficiency and CO_2 reduction target in the network may also help the energy managers to elevate the topic of energy-cost reduction to a higher level of

priority in the decision-making structures of their companies and to convince their management to pursue efficiency investments (Jochem and Gruber 2007). Jochem et al. (2007) argue that competition and (positive) peer pressure also play a role. The argument is that setting joint energy efficiency and CO_2 reduction network targets helps to motivate participants to pursue these targets by advancing energy efficiency investments in their companies (Köwener et al. 2011; Rohde et al. 2015). However, evidence from surveys with consulting engineers and network moderators suggests that the joint targets may not be a major driver for energy efficiency improvements (Dütschke et al. 2018).

One major channel through which energy efficiency networks are seen to affect energy conservation is through a **reduction of transaction costs by sharing experiences**. Participants may be able to benefit from their peers' experiences in implementing energy efficiency measures because of the regular meetings and site visits (Köwener et al. 2011). Since network participants can trust each other due to the absence of a commercial interest among network peers, this sharing of experiences may be particularly valuable (Jochem et al. 2010; Köwener et al. 2014). The importance of the networking activities is supported by evidence from surveys among network participants; around three-quarters of participants of the 30 German pilot networks stated that the exchange of experience with other companies was helpful and led to decreased transaction costs (Dütschke et al. 2018; OECD/IPEEC 2017).

Sharing experiences and integrating the knowledge of experts invited to the network meetings may also lead to **reduced information deficits** and may support capacity building. Dütschke et al. (2018 p. 5) argue that the meetings and site visits during the networks work like an "intensive training course", increasing participants' knowledge of energy efficiency solutions. Surveys among network participants confirm that EEN reduce information deficits (Wohlfarth et al. 2016). The availability of reliable information from network peers may also help to **avoid risks and hidden costs** of energy efficiency investments (Paramonova et al. 2014). By replicating energy conservation measures that have already been implemented by their peers, network participants can benefit from the experience others have made (Dütschke et al. 2018).

Finally, **short payback times** are an important barrier for energy efficiency investments in industry (Stede 2017). In some cases, energy managers participating in EENs have been able to change internal investment routines (Jochem et al. 2010). Instead of solely relying on the investment criterion of a short payback time (a measure of risk), they managed to add the investment criterion of internal rate of return. The internal rate of return is often favourable for energy efficiency investments in cross-sectional technologies (Jochem et al. 2014). EENs may therefore lead to a change of decision routines within companies (Dütschke et al. 2018).

In contrast to these very positive assessments of energy efficiency networks, however, there is survey evidence that points to a less optimistic view of the networks. Wohlfarth et al. (2016) interview participants of the pilot networks twice, first before the start of the network, and a second time towards the end of the networks. Participants are asked how important they perceive different barriers to energy efficiency investments. The authors find that the only barrier where the perception changes significantly due to the network participation is the informational barrier "missing information or market overview". Other barriers, such as the little priority given to investing in energy saving opportunities, are not affected.

More significantly, 25 percent of the companies in the energy efficiency networks report that they would have implemented all energy efficiency measures even without having been part of a network. The other 75 percent state that at least "a part" of the measures would not have been implemented without the networks (Wohlfarth et al. 2016 p. 7). In a different survey among companies that took part in one of the networks set up under the initiative to form 500 energy efficiency networks until 2020, 85 percent of the firms report that they would have carried out energy efficiency measures even without participating in a network (dena 2017). Consequently, it is unclear whether energy efficiency networks really lead to additional energy savings.

1.3 Research Design

In line with the potential outcomes framework (Rubin 1974), I estimate the causal effect of membership in a pilot network both on energy productivity (the value of production per unit of total energy consumed in EUR/kWh), as well as on CO_2 emissions of the networking companies. From a climate policy perspective, the question of whether 'energy efficiency networks' are (also) 'CO_2 reduction networks', as well as the amount of CO_2 savings achieved through the networks, are of substantial interest. The German government relies on CO_2 savings generated in energy efficiency networks in order to reach its 2020 climate targets (BMU 2019). Moreover, there is reason to believe that CO_2 savings differ from pure energy efficiency savings, since in some of the networks investments into fuel switching from conventional energy carriers to renewables has been carried out (Köwener et al. 2014). Consequently, total CO_2 savings may be larger than those from a reduction in energy consumption.

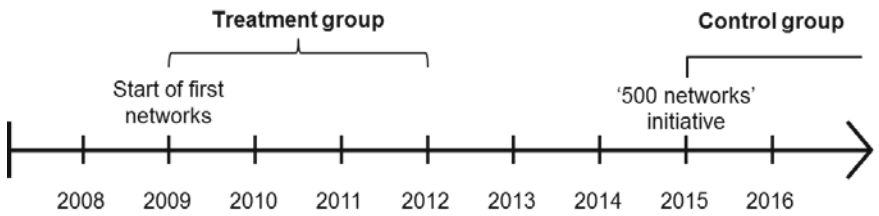
The main challenge to an unbiased estimation of the average treatment effect on the treated (ATT) is the selection mechanism. Since participation in energy efficiency networks is voluntary, companies self-select into the networks. If the factors determining the selection process are systematically related to energy efficiency investments, any naïve estimation of treatment effects comparing firms

in the networks to companies outside of the networks will be biased. I pursue two different identification strategies to overcome this issue. Both estimators rely on different identifying assumptions such as common trends, for which I provide evidence in section 1.5.1.

1.3.1 Difference-in-differences with control group of future network participants

My main specification is a generalised difference-in-differences (DiD) estimation, where network members of the pilot phase ('treated' plants) are compared to a 'control' group of installations joining energy efficiency networks that were initiated at a later point in time. This control group is made up of plants that are part of the initiative to form 500 energy efficiency networks until 2020. The treatment of the two groups does not coincide, since at the time when the first networks were conducted, the networks from the second phase had not yet started (Figure 1-2).

Figure 1-2: Start years of the networks of treatment and control group in the DiD estimator



Comparing the treatment group with a control group that also chose to participate in an energy efficiency network reduces bias from the unconditional DiD estimator. Since both groups voluntarily self-selected to join an energy efficiency network, firms from the pilot networks and the control group are comparable in terms of the (unobserved) motivation to participate in the programme. This motivation is likely to be linked to increased energy consumption reduction capacities at the installation level, such as management structures that favour energy efficiency improvements. Indeed, as the distribution of key (observable) variables shows, the treatment group is much more similar to the control group than to the rest of the German manufacturing sector (see section 1.4.1). Consequently, companies from the post-2014 networks make a good control group.

I estimate three variants of the unconditional difference-in-differences estimator. In the most basic specification, the following equation is estimated:

$$y_{it} = \beta_0 + \beta_1 \omega_i + \delta \cdot \mathbf{1}\{Network\}_{it} + \tau_t + \gamma_s + \varphi_{st} + \varepsilon_{it}\,, \tag{1.1}$$

where the dependent variable is either the (log of) energy productivity or the (log of) CO_2 emissions of installation i in year t. β_1 is a vector of network fixed effects, which control for quality differences

of the 30 different energy efficiency networks ω in the pilot phase. τ_t is a vector of year fixed effects, controlling for the impact of unobserved production shocks such as the effect of the Great Recession on energy efficiency and CO_2 emissions. γ_s contains industry fixed effects for each two-digit industry sector s. φ_{st} are sector-year interactions that capture intra-industrial structural change. β_0 is an intercept. The indicator variable $\mathbf{1}\{Network\}_{it}$ switches from 0 to 1 in the year the energy efficiency network from the pilot phase of firm i starts operating. This makes δ the coefficient of interest, which measures the effect of an energy efficiency network on energy productivity and CO_2 emissions of the participating plants.

In order to increase the precision of the estimates and account for variables that affect firms from the pilot networks and control group differently, the DiD model is augmented to specification (1.2) below:

$$y_{it} = \beta_0 + \beta_1 \omega_i + \delta \cdot \mathbf{1}\{Network\}_{it} + \tau_t + \gamma_s + \varphi_{st} + \boldsymbol{X_{it}}\Psi + \varepsilon_{it}\,, \tag{1.2}$$

where $\boldsymbol{X_{it}}$ contains a set of time-varying control variables at the installation level and Ψ is the corresponding vector of coefficients.

In the third specification, I introduce plant-specific fixed effects:

$$log(y_{it}) = \delta \cdot \mathbf{1}\{Network\}_{it} + \mu_i + \tau_t + \varphi_{st} + \boldsymbol{X_{it}}\Psi + \varepsilon_{it}\,, \tag{1.3}$$

where μ_i is a plant-level fixed effect, controlling for within-plant differences in energy productivity or CO_2 emissions that are constant over time. The reasoning for introducing μ_i is that decisions for energy efficiency investments happen at the plant level. Some of these plants may regularly be investing more into energy efficiency than others, even in the absence of being in a network. The plant-level fixed effects prevent the estimate of the treatment effect, δ, from being upward biased due to such time-invariant unobserved factors, such as organisational structures that favour energy efficiency investments.[5]

1.3.2 Conditional difference-in-differences (DiD) matching estimator

The assumption of parallel trends of the conventional DiD estimator may be implausible if (observable) pre-treatment characteristics that affect the outcome variable are unbalanced between the treated and the untreated (Abadie 2005). More energy-intensive companies, for example, may

[5] More energy-intensive companies have a higher interest to cut back on energy consumption in order to reduce costs. A high motivation to improve energy efficiency can be thought of as organisational structures that favour energy efficiency investments, such as having a member of staff that dedicates part of their time to energy management. Such organisational structures are unlikely to change within a few years and can therefore be seen as constant in the short run.

have a higher incentive to improve energy efficiency because expenditures for energy make up a higher share of production costs. In order to better account for heterogeneity in covariates across treatment and control group, I use the semiparametric matching estimator introduced by Heckman et al. (1998b, 1998a, 1997) as a robustness check. This conditional DiD matching estimator matches on observed company characteristics to select plants from the entire universe of the German manufacturing sector as a control group. As shown by the descriptive statistics below, although treatment and control group in the standard DiD are quite similar in terms of observable variables, some differences remain. The matching estimator accounts for these differences when computing treatment effects. Moreover, by using the time series variation of the panel data, the estimator eliminates bias from temporally-invariant omitted variables. Consequently, it accounts for selection on fixed unobservables (Heckman et al. 1997)

The idea of the conditional DiD matching estimator is to achieve greater overlap in the distribution of the observed covariates in $\boldsymbol{X}$ and make the assumption of parallel trends of the difference-in-differences estimator more credible. The average treatment effect on the treated is estimated with the regression equation

$$\hat{\delta}_{Treat} = \frac{1}{N_1}\sum_{i\in I_1}\left\{\left(y_{it}(1) - y_{it'}(0)\right) - \sum_{k\in I_0} W_{N_0,N_1}(i,k) * \left(y_{kt}(0) - y_{kt'}(0)\right)\right\}, \qquad (1.4)$$

where t' and t denote pre- and post-treatment periods, I_1 is the set of N_1 energy efficiency network participants and I_0 is the set of N_0 non-participants. A nearest neighbour matching algorithm constructs the counterfactual by forming weights W_{N_0,N_1}, which determine how strongly an observation from the control group (N_0) contributes to estimating the treatment effect for the network participants (N_1). Nearest neighbour matching is more suitable for causal inference than the commonly used propensity score matching (King and Nielsen 2019)..

The conditional DiD matching estimator has been widely used in applied econometric research. Fowlie et al. (2012) apply the DiD matching estimator to evaluate a cap-and-trade emissions market in southern California. Petrick and Wagner (2014) and Calel and Dechezleprêtre (2016) use it for an evaluation of the European carbon market.

1.4 Data

This chapter makes use of rich administrative German plant-level data, the AFiD panels[6]. The AFiD panels are official microdata provided by the German research data centres of the Statistical Offices of the Federal States, comprising observations both at the plant and enterprise level from the German industrial sector (Petrick et al. 2011). Using installation-level data allows determining the disaggregated effect of energy efficiency networks on individual plants. For multi-plant companies, this is important since typically not all production sites of a given firm were part of one specific regional network. The AFiD panels contain information on all German manufacturing firms with at least 20 employees (around 43,000 plant-level observations per year), including detailed information on their energy consumption by fuel.[7] Based on these energy inputs, I calculate plant-specific CO_2 emissions using annual fuel-specific emission factors from the German Environment Agency.

I link this data with the full list of plants that took part in the 2009 to 2014 pilot phase of energy efficiency networks. Most of these companies are manufacturers, namely around 290 out of the 366 participants (cf. appendix A.1.7.2). Since the names of these firms are publicly available, they can be matched to the AFiD panels using identifiers like the registration number of the German trade register (*Handelsregisternummer*), as well as the location of the plant. Using this approach, I successfully match 259 companies to the AFiD panel of manufacturing sites. This corresponds to a matching rate of almost 90 percent. Moreover, 489 companies of the control group in models (1.1) to (1.3) (i.e. the companies that have joined networks that started from 2015 onwards) were matched to the AFiD panel. Assuming that the same fraction of companies in the control group is from the manufacturing sector, this means that more than half of the fimrs in the control group was matched to the AFiD panel.

In principle, energy efficiency networks can be regional, sectoral or company networks. As mentioned, all the networks in the pilot phase were regional. In the case of the control group, on the other hand, several sectoral and internal company networks that comprise only of steel companies have been set up since 2015. In order to align the distribution of sectors and the size of the companies in terms of energy consumption between treatment and control group, these networks were excluded from the control group.[8] This reduces the size of the control group of the DiD estimator (section 1.5.1) to 364 companies.

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[6] AFiD is an acronym for *Amtliche Firmendaten für Deutschland* ("Official Firm-level Data for Germany").
[7] CO_2 emissions are calculated using yearly fuel-specific emission factors from the German Environment Agency.
[8] These networks are called ESTA, EnERGY, DIHAG, WVM plus, Elektrostahl and Steel energy+. The exclusion of these networks improves the balance of sectors between treatment and control group. Before excluding the sectoral and

1.4.1 Measurement of energy efficiency and dealing with measurement error

In this chapter, I use energy productivity – defined by the value of output per unit of total energy consumed (EUR/kWh)[9] – as a measurement of energy efficiency for several reasons. Energy productivity (the inverse of energy intensity) is a commonly used metric for measuring energy efficiency. Some of the typical caveats associated with using energy intensity as an indicator for energy efficiency (e.g. Patterson 1996) are alleviated by the research design of this study. First, comparing the development of energy efficiency within firms across time mitigates the issue that energy intensities are often not comparable across industries. Second, year fixed effects and sector-specific trends help to account for external factors such as the impact of the Great Recession on energy efficiency in regression equations (1.1) to (1.3). Finally, a sector-specific price deflator (at the two-digit level), derived from the German National Accounts, is used in order to eliminate time trends from the energy productivity time series by deflating monetary values such as turnover and value of output.

Around two percent of the sample of companies in the manufacturing sector between 2003 and 2014 have very improbable reported values for the reported changes of energy productivity and CO_2 emissions (see Figure A-1-1 in the appendix). While some of the higher variation of energy productivity observed in the data is reasonable, the scale of reported changes for some of the observations is most likely explained by measurement error.[10] Consequently, I use the Mahalanobis distance to identify unusual observations and omit the two percent of observations with the highest distance from the sample.[11] Figure A-1-1 shows how this procedure reduces implausible values for the variables energy productivity and CO_2 emissions.

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company networks, 16 percent of the production sites from the control group had been in the basic metals sector, compared to 6.9 percent in the final sample (Table 1-2). The exclusion of these networks also helps to significantly balance the annual energy consumption between treatment and control group. Without the exclusion of the sectoral and company networks, the mean annual energy consumption in the control group had been 110,000 MWh. This consumption is now down to 76,800 MWh, much closer to the treatment group's mean of 67,400 MWh (see Table 1-1).

[9] The value of output is measured here as the value of production of the goods produced in a specific year targeted for sale, excluding intermediary products *(Absatzproduktionswert)*. Calculating bottom-up energy uses at the product level is not possible with the AFiD data, since a companies' energy consumption in the dataset cannot be attributed directly to the products produced by the same company.

[10] The most extreme of the energy consumption changes reported imply a change in the level of energy productivity by a factor of around 22,000 – this would mean, for example, producing 22,000 cars instead of one with the same amount of energy. This is clearly unrealistic. However, some of the higher variation of energy productivity observed in the data can be explained by an outsourcing of parts of the production chain. If a car manufacturer outsources its paint shop, for example, energy productivity improves although no actual efficiency progress has been made.

[11] The Mahalanobis distance takes into account the covariance among the variables in calculating distances, and allows to consider several variables with different scales. Unlike the standard Euclidean distance, the problems of scale and correlation are therefore not an issue when identifying an outlier using several variables. Here, the Mahalanobis distance is calculated to identify outliers using the variables absolute energy productivity, change of (log) energy productivity over 2008, as well as change of (log) CO_2 emissions over 2008.

1.4.2 Descriptive statistics

Table 1-1 shows the distribution of key variables for treatment and control group, as well as for the whole industrial sector. In terms of the overlap of variables, the firms that have joined energy efficiency networks after the treatment period (post-2015) are much better suited as a control group than the manufacturing sector as a whole. This is also confirmed by comparing pre-treatment trends in the dependent variables (section 1.5.1).

Installations in the energy efficiency networks – both treatment and control group – are very large compared to the industry average. The average production site in the manufacturing sector has a mean annual energy consumption of 13,200 MWh, a turnover of EUR 34 million, and 1550 employees. Moreover, the share of energy costs of total costs is 3.3 percent on average.[12] Average energy consumption, turnover and employees of treatment and control group, on the other hand, are roughly five times larger than the average installation in the manufacturing sector, and the energy cost share is one-third higher (around four percent of total costs). This is consistent with the observation that participation in efficiency networks makes sense only for companies with elevated energy costs. Network participants are also much more energy-intensive: The energy productivity of treatment and control group is only half as high as that of the manufacturing sector.

Compared to the average industrial firm, treatment and control group are very much alike. However, there are some differences. Manufacturing sites in the treatment group are typically larger than installations in the control group[13]: Treated plants have a higher turnover (mean of EUR 180 million vs. EUR 138 million) and more employees (7,300 and 5,000, respectively). In terms of energy consumption and CO_2 emissions, the median of these variables is larger for the pilot networks, while the mean is smaller. This suggests that there are several energy-intensive installations in the upper tail of the control group's distribution.

[12] Information on costs are only available at the firm level in the dataset, not at the plant level. Therefore, the cost figures are included in the descriptive statistics for illustrative purposes, but not used in the regressions.

[13] Since some differences in terms of observables remain between treatment and control group in the DiD estimator, as a robustness check we use nearest neighbour matching to identify a control group and improve the overlap of treatment and control group (see section 1.5.2).

Table 1-1: Distribution of key variables in treatment group and control group

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile	Obs.
Energy consumption [MWh]					
- Pilot networks	67,415 (164,116)	18,815	5,892	48,667	1,256
- Control group	76,799 (228,320)	12,620	3,568	44,970	1,789
- Manufacturing sector	13,229 (93,417)	971	362	3,739	214,215
Energy productivity [€/kWh]					
- Pilot networks	5.32 (6.68)	3.20	1.38	6.58	1,187
- Control group	5.93 (7.55)	3.27	1.23	8.21	1,725
- Manufacturing sector	11.25 (66.33)	5.63	2.70	11.78	205,954
CO_2 emissions[tonnes]					
- Pilot networks	21,417 (48,356)	7,119	2,755	17,832	1,246
- Control group	25,086 (80,305)	4,775	1,480	15,421	1,786
- Manufacturing sector	4,494 (31,037)	398	140	1,523	213,683
Turnover [million €]					
- Pilot networks	179.9 (477)	67.3	23.7	140.7	1,256
- Control group	137.7 (596.1)	44.8	15.9	115.7	1,789
- Manufacturing sector	34.2 (361.4)	6.3	2.7	18.6	214,075
Value of production [million €]					
- Pilot networks	132.1 (224.9)	66.0	24.7	131.0	1,187
- Control group	94.4 (201.9)	41.5	16.5	106.9	1,725
- Manufacturing sector	27.7 (219.5)	5.9	2.6	17.2	205,955
Number of employees					
- Pilot networks	7,283 (13,156)	3,643	1,601	6,812	1,256
- Control group	4,986 (10,702)	2,554	1,168	5,404	1,789
- Manufacturing sector	1,548 (6,167)	600	360	1,313	214,075
Energy cost share [%]					
- Pilot networks	3.9 (5.4)	2.2	1.4	4.1	946
- Control group	4.3 (4.8)	2.7	1.2	5.3	1,257
- Manufacturing sector	3.3 (4.3)	1.9	1.0	3.7	99,318

The statistics are calculated over the treatment period (years 2010-2014). There are 257 manufacturing sites in the pilot networks group, 364 installations in the control group, and an average of 42,843 plants in the manufacturing sector. All variables are at the plant level, except the energy cost share of total costs, which is only available at the firm level, for a subset of the firms that takes part of the Cost Structure Survey *(Kostenstrukturerhebung)*. *Source*: FDZ (2014a), own calculations.

The distribution of firms by sectors of economic activity in Table 1-2 illustrates that firms in energy efficiency networks belong to a wide range of manufacturing sectors. Moreover, the distribution of firms from the different groups over sectors is quite similar. Indeed, the sectoral distributions of treatment and control group are more similar than treatment group and manufacturing sector as a whole.[14]

[14] Looking at absolute differences between sectoral shares, these differences are smaller on average between pilot networks and control group than between pilot networks and the manufacturing sector as a whole.

Table 1-2: Sectors of economic activities

Economic sector *	Pilot networks	Control group	Manufacturing sector
5 Mining of coal and lignite	0.4	0.3	0.1
8 Other mining and quarrying	1.3	1.2	2.3
10 Manufacture of food products	11.6	10.1	11.7
11 Manufacture of beverages	4.5	2.0	1.4
12 Manufacture of tobacco products	0.4	0.6	0.1
13 Manufacture of textiles	1.8	1.0	1.8
16 Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	1.6	1.7	2.9
17 Manufacture of paper and paper products	4.0	3.5	2.2
18 Printing and reproduction of recorded media	2.4	1.7	3.5
19 Manufacture of coke and refined petroleum products	0.4	1.4	0.1
20 Manufacture of chemicals and chemical products	9.3	7.9	3.5
21 Manufacture of basic pharmaceutical products and pharmaceutical preparations	2.5	1.8	0.7
22 Manufacture of rubber and plastic products	9.9	9.0	7.1
23 Manufacture of other non-metallic mineral products	4.3	8.7	7.3
24 Manufacture of basic metals	2.4	6.9	2.4
25 Manufacture of fabricated metal products, except machinery and equipment	10.2	12.0	16.1
26 Manufacture of computer, electronic and optical products	2.7	3.7	3.9
27 Manufacture of electrical equipment	4.7	6.7	4.9
28 Manufacture of machinery and equipment n.e.c.	11.1	14.6	13.6
29 Manufacture of motor vehicles, trailers and semi-trailers	6.0	2.8	3.0
30 Manufacture of other transport equipment	2.1	0.3	0.6
31 Manufacture of furniture	4.1	0.6	2.4
32 Other manufacturing	1.7	1.4	3.6
33 Repair and installation of machinery and equipment	0.6	0.3	3.7

The shares (in percent) are calculated as averages over the years 2003-2014. The industry classification of the years 2003-2008 has been adjusted to the German standard "WZ 2008" in order to allow for a comparison of the industrial sectors over time, using the conversion tables by Dierks et al. (2019) (details in appendix A.1.7.1). There are 257 manufacturing sites in the pilot networks group, 364 installations in the control group, and an average of 42,843 plants in the manufacturing sector. *Source*: FDZ (2014b), own calculations.

* According to the German Classification of Economic Activities, Edition 2008 (WZ 2008).

1.5 Results

1.5.1 DiD with future network control group

Setup and results

Table 1-3 shows the estimation results of the difference-in-differences models for energy productivity (Panel A) and CO_2 emissions (Panel B), with standard errors clustered at the network level.[15] Columns 1 to 3 correspond to the models (1.1) to (1.3) in section 1.3.1, with the dependent variables in levels. Column 1 contains the most basic specification (1.1), i.e. not controlling for any covariates. Column 2 adds a range of covariates, namely sales intensity (the value of production of the goods produced in a specific year targeted for sale divided by the number of employees)[16], the share of turnover generated from exports, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector.[17] Finally, in column 3 – corresponding to model (1.3) – plant-level fixed effects are introduced. In columns 4 through 6, the same models are re-estimated with the dependent variables energy productivity and CO_2 emissions in logs. All specifications in Table 1-3 include year fixed effects, sector fixed effects (i.e. fixed effects for the German WZ industry classification at the two-digit level)[18] and sector-specific trends.

Column 6 – model (1.3) with the dependent variables in logs – is the preferred specification, since the inclusion of plant-level fixed effects controls for unobserved constant factors at the plant level. As energy efficiency changes happen at the plant level, this is the most robust specification. The log specification leads to a percentage interpretation of the coefficients, evaluating changes in energy productivity and CO_2 emissions relative to the size of each plant. Consequently, the log specifications dampens the effect of outliers (with large CO_2 emissions, for example) on the point estimates.

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[15] In the DiD regression, clustering at the network level leads to a total number of 31 clusters (30 networks and one control group). This might potentially lead to a problem with "few" clusters. Although there is no clear-cut definition of when the problem with "few" clusters start, the problem is less severe when clusters are balanced (Cameron and Miller 2015). Here, clusters are relatively balanced since there is a similar number of participating installations in each network.

[16] The variable sales intensity is chosen instead of including the covariates value of production and number of employees individually because these two variables are highly collinear.

[17] The sectors 5, 8, 17, 19, 20, 23, and 24 (cf. Table 1-2) are attributed to the basic materials sector.

[18] The industry classification of the years 2003-2008 has been adjusted to the German standard "WZ 2008" in order to allow for a comparison of the industrial sectors over time, using the conversion tables by Dierks et al. (2019). Details are explained in appendix A.1.7.1. The sector fixed effects drop out when an installation does not change its industry affiliation over time due to the inclusion of plant-level fixed effects in model (1.3).

Table 1-3: Difference-in-differences treatment effects on energy productivity and CO_2 emissions

	Dependent variable in levels			Dependent variable in logs		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent var. energy productivity						
Network	0.400*	0.457**	0.298*	0.0109	0.0224	0.0167
	(0.226)	(0.207)	(0.161)	(0.0248)	(0.0201)	(0.0148)
Observations	6824	6824	6824	6824	6824	6824
R^2 (within-plant)	0.265	0.332	0.164	0.386	0.48	0.38
Panel B: Dependent var. CO_2 emissions						
Network	-3921.4**	-3043.5**	-2466.9**	-0.0329	-0.000518	-0.0101
	(1691.3)	(1310.5)	(935.4)	(0.0342)	(0.0313)	(0.018)
Observations	7101	6801	6801	7101	6801	6801
R^2 (within-plant)	0.186	0.235	0.046	0.238	0.431	0.125
Additional controls	No	Yes	Yes	No	Yes	Yes
Plant-level fixed effects	No	No	Yes	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector-specific trends	Yes	Yes	Yes	Yes	Yes	Yes

Values shown are the coefficients of OLS regressions of the dependent variables on the covariates. Unit of observation is plant-year. Standard errors clustered at the network level in parentheses. Energy productivity is measured in €/kWh. CO_2 emissions are measured in tonnes. Additional control variables include sales intensity (turnover divided by the number of employees), the export share, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector. There are 257 manufacturing sites in the pilot networks group, and 466 installations in the control group. Significance: * p<0.1, ** p<0.05, *** p<0.01. *Source*: FDZ (2014b), own calculations.

As can be seen from Table 1-3, the estimated treatment effects both for energy productivity and for CO_2 emissions are statistically significant in the levels specification (columns 1 to 3). The coefficients in column 3 (specification including plant fixed effects) suggest an increase of energy productivity of 0.3 EUR/kWh (or 5.6 percent relative to the mean of 5.32 EUR/kWh), as well as a reduction of CO_2 emissions by almost 2500 tonnes (minus 11.5 percent) due to the networks.

However, the picture changes when energy productivity and CO_2 emissions are measured in logs (columns 4 to 6). Although the signs are still in the expected direction, all estimated treatment effects are insignificant, both for energy productivity and for CO_2 emissions. The (statistically insignificant) coefficients in the preferred specification in column 6 imply a treatment effect of an increase in energy efficiency of 1.7 percent of the course of the network period, as well as a reduction of CO_2 emissions by one percent.

The insignificance of the estimated treatment effects in the log specification points to an effect of outliers on the point estimates in the levels specifications. Indeed, this hypothesis is confirmed by a re-estimation of the models shown in Table 1-3 excluding the largest companies. I re-estimate all specifications shown in Table 1-3 three times, excluding plants with the one percent highest energy consumption, the 2.5 percent highest energy consumption, and the five percent highest energy consumption, respectively. All coefficients for CO_2 emissions in the levels specification become insignificant. For energy productivity, columns 1 and 2 also become insignificant; only specification (1.3) remains significant at the 10 percent level (detailed results are available from the author on request). This confirms that the significant estimates in the levels specification of in Table 1-3 are probably driven by outliers.

Power calculation

A central question regarding the interpretation of the estimates presented in Table 1-3 is whether the estimates imply a 'null result' (i.e. that energy efficiency networks did not have an effect an energy productivity and CO_2 emissions of participating plants), or whether statistical insignificance is the result of a lack of power. In order to evaluate this question, I compare the results from the preferred specification in column 6 of Table 1-3 to the predictions about the effects of the networks made in the previous literature.

A typical measure to gauge whether an estimate is under-powered is to calculate the minimum detectable effect (MDE, Bloom 1995).[19] The MDE refers to the minimum level of a genuine empirical effect that can be detected under a certain significance level with a chosen likelihood. Conventional levels are a five percent level of statistical significance and 80 percent power (Ioannidis et al. 2017).

This power calculation reveals that the effect of energy efficiency networks on energy productivity is most likely smaller than predicted by the previous literature. Previous studies have claimed that the additional annual increase of energy productivity triggered by a participation in an efficiency network is 1.1 percent (Wohlfarth et al. 2016). Over the course of a four-year network period, this would add up to an increase of energy productivity by almost 4.5 percent. The minimum detectable effect of participation in energy efficiency networks on energy productivity according to column 6 of Table 1-3, on the other hand, is 4.1 percent. The MDE is thus smaller than the predicted effect.

[19] Direct ex-post power calculations, on the other hand, which involve noisily estimated coefficients, are misleading (Hoenig and Heisey 2001).

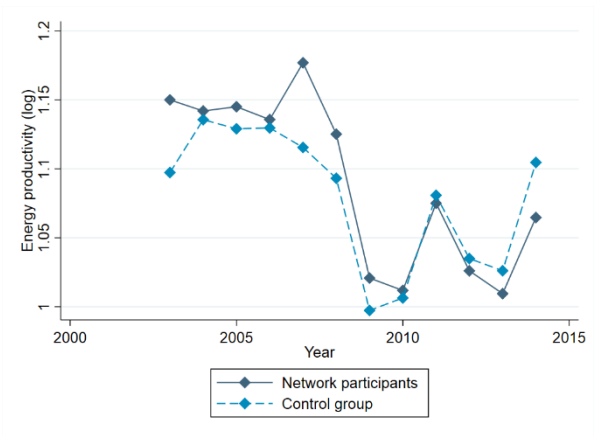
Consequently, a network effect as large as previously predicted should have been detected by the preferred specification with a probability of more than 80 percent.

Assessment of identifying assumptions

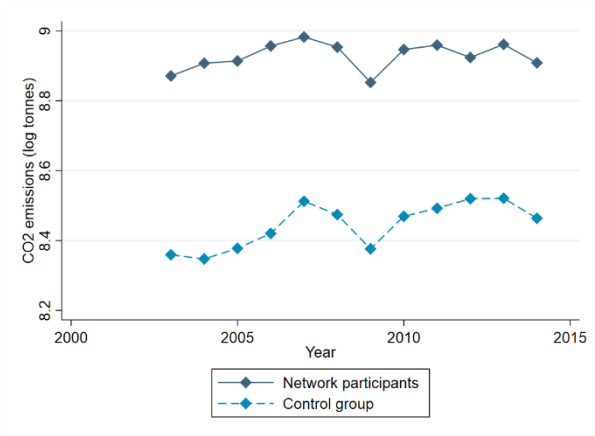
The main identifying assumption underlying (1.1) to (1.3) is that treatment and control group follow common trends. In other words, unobserved factors affecting energy efficiency of companies that are either part of a network or outside of a network are constant over time. Since the parallel trends assumption of the conventional difference-in-differences estimator cannot be tested directly, a common procedure is to look at a graph of pre-treatment trends. Figure 1-3 provides visual evidence for the validity of the parallel trends assumption for the pre-treatment period (until 2008) for the dependent variables (log) energy productivity (Panel A), as well as (log) CO_2 emissions (Panel B).[20]

Figure 1-3: Log energy productivity and CO_2 emissions of pilot networks and control group

Panel A: Log energy productivity



Panel B: Log CO_2 emissions



Source: FDZ (2014b), own calculations.

In addition to a visual inspection of the pre-treatment graphs, I test for anticipation effects.[21] The idea is to test whether companies are already on an upward trajectory with respect to their energy efficiency when they join a network. I estimate three variants of each specification shown in Table 1-3, with up to three pseudo-treatment dummies that indicate a treatment in the years prior to the start of the energy efficiency networks. Of the 72 estimated pseudo-treatment effects[22], only the first lag of CO_2 emissions (in levels) in the plant-level fixed effects model (1.3) is significant at the ten

[20] The development of absolute energy productivity and CO_2 emissions is shown in Figure A-1-2 in the appendix. The parallel trends assumption seems to hold for energy productivity, but not for absolute CO_2 emissions.
[21] The results for the anticipation effects estimation of the plant fixed effects model (1.3) are shown in the appendix (Table A-1-2). The results for the other models are available from the author on request.
[22] For each of the four dependent variables (energy productivity, log energy productivity, CO_2 emissions and log CO_2 emissions), we estimate three different specifications (as in section 1.3.1), each estimated separately with one, two and three lags.

percent level; all other lags are insignificant (see Table A-1-2 in the appendix). This adds confidence to the validity of the common trends assumption.

A second assumption of the DiD estimator is the Stable Unit Treatment Value Assumption (SUTVA). This assumption requires that treatment does not spill over from treated firms to untreated firms (Imbens and Rubin 2015). In general, it is reasonable to assume that knowledge gained in the network meetings should not spill over to non-participating plants in the short run, since companies do not have an interest to share the knowledge gained in energy efficiency networks with their competitors. However, in the case that a parent company owns multiple plants, it cannot be ruled out that non-participating installations profit from the knowledge acquired by their peers that did participate in energy efficiency networks.[23] In telephone interviews conducted for this chapter, managers of energy efficiency networks confirmed that typically all production sites of a company participating in an EEN that are in close geographic proximity to the network also take part in the network and are therefore identified as part of the treatment group. Additionally, in order to rule out potential spillovers within corporations, I exclude from the control group of the post-2015 networks those plants that belong to the same parent company as manufacturers that took part in the pilot networks.

1.5.2 Conditional DiD matching estimator

Setup

Although the control group chosen for the difference-in-differences estimator is much more similar to the firms participating in the pilot energy efficiency networks than the average manufacturing firm in terms of observables, some differences between these groups remain (cf. Table 1-1). In order to improve the overlap of treatment and control group, as a robustness check I use nearest neighbour matching to identify a control group. In contrast to the previous section, for each treated company the conditional DiD matching estimator chooses the closest match out of a rich set of plants from the entire manufacturing sector for the estimation of treatment effects.

The nearest neighbour matching estimator constructs the counterfactual estimate for each treatment case by selecting the m nearest neighbours and setting the weights W_{N_0,N_1} equal to $1/m$ for the selected neighbours, and zero for all other members of the comparison group. In the baseline

[23] If different production sites of a parent company – some of which are part of an energy efficiency network, while others are not – share the same energy manager, for example, the manager could make use of the knowledge gained in the network for the other production sites.

estimations, I estimate treatment effects based on one nearest neighbour matching (1:1), and re-estimate with three nearest neighbours to demonstrate robustness of the results. To mitigate the challenge that the energy efficiency networks start in different years (cf. appendix A.1.7.2), I only include firms in the matching estimation that started between May 2009 and February 2011. Consequently, there is a maximum difference of time spent in a network of 1.5 years within the treatment group.[24]

Since the German manufacturing sector consists of around 43,000 firms, I have a large group of potential nearest neighbours for each treated observation. It is therefore possible to match on several variables without compromising too much on the matching quality. I impose the strictest overlap with respect to industry sector by requiring exact matching on the two-digit industry classification level. The reasoning is that there are unobserved differences, for example in production technology or technological change, that can be thought to be more similar at the sectoral level.[25] Additionally, I match on three continuous variables, namely the 2006-2008 (pre-treatment) averages of energy consumption, energy productivity, and sales intensity.[26] As Fowlie et al. (2012) note, past values of a variable are a good predictor of its value in subsequent periods.

Results

An assessment of the matching quality reveals that the matching procedure strongly reduces the differences between treatment and control group. Figure 3- plots standardised biases for a number of variables (some of which were used in the matching process, others not) before and after the nearest neighbour matching. Comparing standardised biases is a common procedure to assess matching quality. It is better suited to judge the balance of a matched sample than statistical significance testing, since it does not depend on sample size (Imai et al. 2008).[27] Figure 3- shows that the matching significantly reduces the standardised bias between treatment and matched control group for all variables.

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[24] We exclude three networks or 10 percent of the treatment group due to this restriction.

[25] As a robustness check, we impose an exact matching on the three-digit level. This does not change the results qualitatively, but we lose around 15 percent of observations due to an insufficient number of matches or treated companies within one sector on the three-digit level.

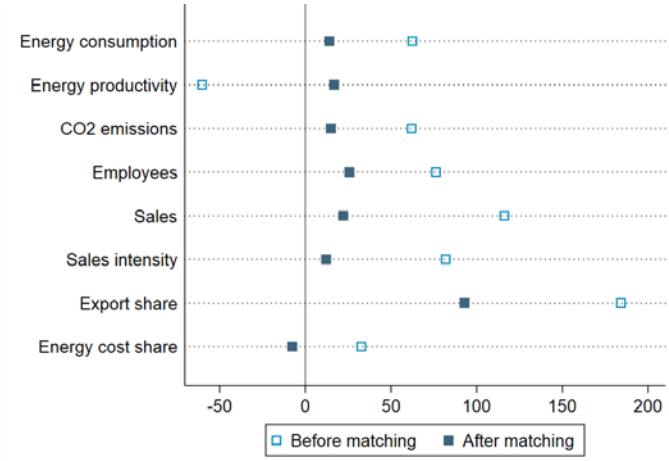
[26] As noted above, the components of the variable sales intensity, namely the variables value of production and number of employees are quite collinear. Using the variable sales intensity (turnover/employee) hence integrates the information of two variables – both of which are an indication of firm size – into one variable that is used for matching.

[27] The standardised bias is defined as $SB = \frac{100(\bar{X}_{Treat} - \bar{X}_{Control})}{\sqrt{(S^2_{Treat} + S^2_{Control})/2}}$, where $\bar{X}_{Treat}$ (S^2_{Treat}) is the mean (variance) of the treatment group, and $\bar{X}_{Control}$ ($S^2_{Control}$) is the mean (variance) of the control group (Rosenbaum and Rubin 1983).

Other indicators for covariate balance also show how the matching algorithm markedly increases the similarity of network companies and the matched control group in terms of observables (see appendix A.1.7.5). Figure A-1-3 plots kernel densities before and after matching for the case of energy consumption, revealing how the overlap improves for the two groups due to the matching process. Table A-1-3 compares the treatment group with the matched control group in terms of the means of several variables, showing that the two groups are similar, although most differences remain statistically significant. Finally, empirical quantile-quantile (Q-Q) plots also show that the matching algorithm results in very similar distribution of key variables for the treated companies and their matched counterparts (Figure A-1-4).

In sum, the matching algorithm significantly improves overlap both for variables included in the matching (e.g. energy consumption, number of employees), as well as for variables *not* explicitly included in the matching, such as energy consumption (e.g. CO_2 emissions, export share, or energy cost share, cf. Figure 1-4). The fact that matching improves overlap among variables that influence energy efficiency but were not used for matching gives confidence that it achieves balance for unobservables related to energy efficiency as well.

Figure 1-4: Standardised biases before and after matching



All variables are at the plant level, except the energy cost share, which is only available at the firm level. *Source:* FDZ (2014a), own calculations.

Table 1-4 gives an overview of the matching results, for one nearest neighbour (Panel A) and three nearest neighbours (Panel B). I compute the average treatment effect on the treated for the variables energy productivity (in levels and logs), as well as CO_2 emissions (in levels and logs). The outcome variables are expressed in the differences between a post-treatment year (either the year 2014 or the year 2013) and the pre-treatment year 2008. I also estimate an average 2013-2014 treatment effect, combing both 2014 and 2013 differences to 2008 in one matching estimation.

Table 1-4: Nearest neighbour matching treatment effects

Year by year comparison (base year 2008)	Energy productivity	Log energy productivity	CO_2 emissions	Log CO_2 emissions
Panel A: One nearest neighbour (1:1)				
2014	-0.312 (0.268)	-0.0112 (0.043)	-1414.1 (1582.9)	0.0305 (0.034)
2013	-0.0686 (0.291)	-0.0391 (0.045)	-493.7 (1459.4)	0.0479 (0.03)
Average 2013-2014	-0.19 (0.198)	-0.0252 (0.031)	-951 (1076.2)	0.0395* (0.022)
Panel B: Three nearest neighbours (1:3)				
2014	-0.161 (0.225)	0.0165 (0.037)	-876.2 (1368.6)	0.00936 (0.025)
2013	-0.153 (0.263)	-0.024 (0.04)	-144.4 (1348.8)	0.0359 (0.023)
Average 2013-2014	-0.157 (0.173)	-0.00391 (0.027)	-508.2 (960.9)	0.0227 (0.017)

Main outcome variables are defined as the difference between 2013 and 2008 or 2014 and 2008. Unit of observation is plant-year. There are 199 treated observation. Control plants are matched from >30,000 plants from the manufacturing sector. Robust Abadie-Imbens (2006, 2011) standard errors in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01. *Source*: FDZ (2014b), own calculations.

The nearest neighbour matching estimator confirms the results of the previous section, namely that no statistically significant effect of joining an energy efficiency network on either energy productivity or CO_2 emissions can be found. As can be seen from Table 1-4, almost all estimated treatment effects are insignificant. The only exception is the combined 2013 and 2014 estimate of the effect on log CO_2 emissions in the specification with one nearest neighbour matching (Panel A), which is significant at the ten percent level. However, the effect becomes insignificant in the three nearest-neighbour matching specification (Panel B).

Assessment of identifying assumptions

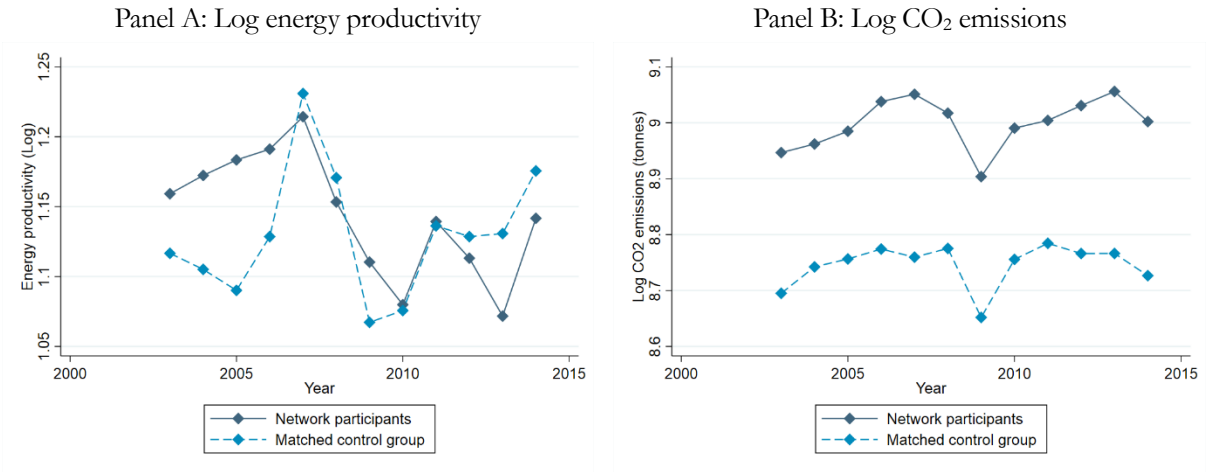
Similar to the common trends assumption of the conventional DiD regression, the conditional DiD matching estimator relies on a version of the unconfoundedness assumption, which is weaker than the conditional independence assumption typically used for matching (Heckman et al. 1998b). It states that, conditional on the covariates X, the counterfactual energy efficiency trends of the firms that are part of the energy efficiency networks must be the same as the trends in the group of the matched control firms. A second identifying assumptions is that matching is performed on a common support $X \in S(X|D = 1)$, with the distributions of covariates in the treatment and control group overlapping. Third, the Stable Unit Treatment Value Assumption is made.

In general, for unconfoundedness to hold in the context of a DiD matching estimator, it is important to have a rich set of variables that are related to the dynamics in the outcome variable (Imbens and Rubin 2015; Smith and Todd 2005). Several of such variables are available in the AFiD panels, and I

use them in the nearest-neighbour matching. For unobserved variables, it is important that they do not vary over time, since the conditional DiD estimator accounts for selection on fixed unobservables and is therefore consistent with a Roy model of self-selection applied to a panel setting (Heckman et al. 1997). It is reasonable to assume that important variables such as the unobserved motivation to reduce energy consumption, or capacities to improve energy efficiency, are constant over the relatively short time horizon of five years of the networking phase.

Figure 1-5 graphs the development of energy productivity and log CO_2 emissions for the treatment group and for the matched control group. A visual assessment of the conditional common trends assumption illustrates that the development of the dependent variable prior to the treatment (pre-2009) is similar. For the variables log energy productivity and CO_2 emissions, the trends are qualitatively similarly in line (appendix A.1.7.6). This gives confidence that the unconfoundedness assumption underlying the conditional DiD matching estimator is fulfilled. Regarding SUTVA, as in the previous section, plants that belong to the same parent company as manufacturers that took part in the pilot networks are excluded from the matched control group, in order to rule out potential spillovers within corporations.

Figure 1-5: Log energy productivity and CO_2 emissions of pilot networks and matched control group



Source: FDZ (2014b), own calculations.

1.5.3 Heterogeneous treatment effects

Although there is no robust evidence for an effect of joining an energy efficiency network for the average participant, there might be subgroups that benefit more from the networking activities than others. One important determinant of whether firms profit from energy efficiency networks are

management structures, which may influence whether energy savings opportunities identified in the networks are realized by making an investment decision into energy efficiency.

Since management quality cannot be observed directly, I use export share as a proxy for management quality. Exporting firms have been found to be more innovative and more productive than domestic non-exporters (Helpman et al. 2004; Yeaple 2005; Aw et al. 2008; Lileeva and Trefler 2010). Moreover, exporting may improve management practices (Bloom and Van Reenen 2010). Good management practices in turn may have positive beneficial spillovers on energy efficiency (Bloom et al. 2010; Martin et al. 2012; Boyd and Curtis 2014). The direct link between exports and energy efficiency has also been studied. For example, accounting for endogeneity through the use of instrumental variables, Roy and Yasar (2015) find that exporting leads to lower fuel consumption relative to electricity use for Indonesian firms. Using the same dataset on German manufacturers as this chapter, Lutz et al. (2017) show that exporting firms are more energy efficient than their counterparts.

I test whether high exporters – defined as plants that make at least 80 percent of their revenue from exports – profit more from participating in energy efficiency networks than the average firm. Firms in energy efficiency networks generally export more than the average manufacturing firm. While the export share is 20 percent on average in the German manufacturing sector, it is about twice as high for network participants (see Table A-1-4). Around 10 percent of all participants of energy efficiency networks are high exporters. These plants are more than 50 percent larger than the average energy efficiency network participant in terms of energy consumption, sales and employees. The share of energy costs of total costs is 5.5 percent for the high exporters, compared to 3.9 percent for the average network participant (Table A-1-5).

Table 1-5 shows the interaction effect of regressions of models (1.1) to (1.3) – the conventional difference-in-differences estimation[28] – for the variables energy productivity and CO_2 emissions, where the treatment dummy is interacted with a "high exporter" dummy.[29] Thus, the estimates represent the additional effect of the networks on high exporters. The only statistically significant effects are the models with the log of CO_2 emissions as the dependent variable (columns 4 to 6 in Panel B). While the estimates in columns 4 and 5 are unrealistically high, column 6 (the preferred specification including plant-level fixed effects) indicates that CO_2 emissions fell by almost 11 percent for high exporters. One explanation why for high exporters there might be an effect on CO_2

[28] Results from the conditional DiD matching estimator are not shown for high exporters, since the number of observations is very low.
[29] For a given firm, this dummy takes on the value of one if exports constitute at least 80 percent of a firm's turnover in at least half of the years.

emissions, but not energy productivity, is the occurrence of fuel switching, i.e. a substitution of the use of "dirty" energy carriers such as coal by less CO_2-intensive energy sources.[30]

Table 1-5: Difference-in-differences treatment effects for high exporters

	Dependent variable in levels			Dependent variable in logs		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent var. Energy productivity						
Network	0.530**	0.501**	0.275*	0.00974	0.00663	0.0206
	(0.217)	(0.212)	(0.154)	(0.0289)	(0.0267)	(0.0169)
Network × High exporter	-1.086	-0.329	0.202	-0.00203	0.131	-0.0372
	(1.158)	(1.014)	(0.649)	(0.151)	(0.143)	(0.0538)
High exporter	1.305**	1.244***		-0.194***	-0.189**	
	(0.519)	(0.396)		(0.0659)	(0.0838)	
Observations	6872	6872	6872	6872	6872	6872
R^2 (within-plant)	0.261	0.331	0.165	0.39	0.482	0.377
Panel B: Dependent var. CO_2 emissions						
Network	-2631.3	-1783.7	-2535.2**	0.0467	0.0678	0.00351
	(1934)	(1447.7)	(1039.6)	(0.0515)	(0.0437)	(0.0203)
Network × High exporter	-10865.6	-10540.3	397.9	-0.676**	-0.560**	-0.113**
	(7599.2)	(6405.7)	(2186.1)	(0.296)	(0.233)	(0.0503)
High exporter	20654.7***	12859.5**		1.162***	0.711***	
	(5799.6)	(5330.4)		(0.272)	(0.221)	
Observations	7149	6849	6849	7149	6849	6849
R^2 (within-plant)	0.19	0.233	0.046	0.265	0.408	0.133

Values shown are the coefficients of OLS regressions of the dependent variables on the covariates. Standard errors clustered at the network level are in parentheses. Energy productivity is measured in €/kWh. CO_2 emissions are measured in tonnes. Additional control variables in columns 2, 3, 5 and 6 include sales intensity (turnover divided by the number of employees), the export share, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector. Columns 3 and 6 include plant-level fixed effects. There are 257 manufacturing sites in the pilot networks group, 27 of which are high exporters, and 466 installations in the control group Significance: * p<0.1, ** p<0.05, *** p<0.01. *Source*: FDZ (2014b), own calculations.

Summing up, in contrast to the average network participant, companies with higher exports may have benefitted from participating in energy efficiency networks by reducing their CO_2 emissions. This gives some support to the hypothesis that better-managed firms may benefit more from participation in energy efficiency networks by better exploiting fuel switching options to reduce their CO_2 emissions.

[30] Regressions of the consumption of different fuels on the variables of column 6 in Table 1-5 indicate a reduction of (CO_2-intensive) electricity consumption for high exporters, and an increase of the consumption of natural gas. However, these results are not statistically significant.

1.6 Conclusion: Do energy efficiency networks deliver?

Energy efficiency networks are a voluntary policy measure aimed at improving energy efficiency and reducing CO_2 emissions that have gained momentum in recent years. This chapter tests for a causal effect of German energy efficiency networks on energy productivity and CO_2 emissions of participating plants. Results show that on average energy efficiency networks affected energy productivity less than predicted by the previous literature. The effects in the most robust specifications of the difference-in-differences estimation are statistically insignificant, and a power calculation reveals that a 'double the industry' effect should have been detected by the model. However, a smaller effect on energy productivity and CO_2 cannot be ruled out. These results are confirmed by a conditional difference-in-differences matching estimator, where the estimated treatment effects are insignificant in all specifications.

There is some indication that good management practices influence whether knowledge gained in the networks translates into changing behaviour at the firm level. Previous studies have found that high export is a proxy for good management, and good management practices in turn lead to higher energy efficiency. This chapter shows that high exporters – defined as treated plants that have a revenue share of at least 80 percent from exports – reduced their CO_2 emissions by around 10 percent. These results suggest that larger, better-managed companies may profit more from participating in energy efficiency networks than the average firm.

There is reason to believe that the network activities were beneficial to at least some of the firms that joined the initial energy efficiency networks. In addition to the significant treatment effect for high exporters, some of the firms (around six percent of firms) that were part of an energy efficiency network decided to continue these activities by joining a second energy efficiency network after the initial one was completed. The most likely explanation for this behaviour is that in these companies' assessment, the initial network did benefit them significantly. It is unlikely that firms would decide to invest significant resources into joining a voluntary programme again, if they did not feel they achieved tangible results in the first network.

On the other hand, there are several reasons why network activities might not have induced larger improvements in energy productivity or CO_2 emissions for the average network participant. First, this article shows that the companies that joined energy efficiency networks are much larger, more energy-intensive and have higher energy costs than the average industrial firm. Consequently, one explanation why network participation may not have had an additional effect is that firms self-selected into networks because they had significantly higher incentives to reduce energy expenditures than other manufacturing companies anyways. The networks then may not have presented an added

value for this particular group of firms. Survey evidence supports this hypothesis: Many participants of energy efficiency networks would have implemented energy efficiency measures even without being part of an energy efficiency network. Second, the group that decided to join a second energy efficiency network is relatively small. Consequently, most firms decided against continuing the network activities after the initial network was completed. Third, a motivation for companies to self-select into energy efficiency networks other than energy conservation may be signalling. Since the names of the companies in German energy efficiency networks are public, joining energy efficiency signals to customers and other stakeholders that a participating company cares about reducing the environmental impact of its production process. Additionally, the rapid expansion of energy efficiency networks in Germany in recent years has largely happened due to a voluntary agreement between the German government and major industrial associations. Thus, a growing number of energy efficiency networks is also a signal to regulators and other stakeholders that industry is willing to reduce energy consumption and CO_2 emissions.

There are several promising avenues for future research. First, mainly very energy-intensive firms with a high absolute energy consumption joined the energy efficiency networks investigated in this chapter. However, it may be that smaller (less energy-intensive) companies profit more from joining an energy efficiency network, for example due to a greater potential for learning. Since German energy efficiency networks are voluntary, they target firms that are already motivated to increase energy efficiency. It may, however, well be that energy efficiency networks are more effective when participants have a lower a-priori interest in energy efficiency.

Second, it is likely that the effect of energy efficiency networks varies with the composition of the networks. All energy efficiency networks investigated in this chapter were regional networks, consisting of companies from different industrial sectors. These companies typically focus on cross-cutting technologies, such as process heat or lighting. Sectoral networks or within-company networks, on the other hand, may very well be more effective at reducing energy consumption of their participants. In these networks, a wider range of energy savings opportunities can be identified by moving beyond cross-sectional technologies to targeting production technologies. One indication that sectoral or within-company networks may be successful is that their number of has been growing in Germany in recent years. Future research may address these questions once sufficient data becomes available for Germany, or by looking at other countries that have introduced energy efficiency networks in the past.

1.7 Appendix

A.1.7.1 Industry reclassification

The German Classification of Economic Activities, Edition 2008 (WZ 2008) is the German equivalent of the international industry classification ISIC Rev. 4. Industrial sectors of the AFiD panels in the years 2003-2008 are classified according to WZ 2003 (the equivalent of ISIC Rev. 3.1), whereas from year 2009 onwards the WZ 2008 is applied. Since there are major discontinuities in the way economic sectors are constructed between WZ 2003 and WZ 2008, a one-to-one mapping between old and new industries is not possible. However, for the purpose of this chapter, the sectors of economic activity need to be comparable over time. Therefore, I convert the WZ 2003 sectors to WZ 2008 based on the assumption that firms do not change their main type of economic activity between the years 2008 and 2009. Based on this assumption, the following three-step procedure is used to map the sectoral affiliation of any firm under WZ 2003 to WZ 2008. First, for all firms that are part of the AFiD panel both in 2008 and in 2009, the WZ 2003 sector of the year 2008 is replaced by the WZ 2008 sector of the year 2009. Second, whenever in any year pre-2008 the WZ 2003 sector of that year equals the WZ 2003 sector of 2008, it is replaced by the same WZ 2008 sector of the year 2009. For all remaining observations, there are either no values for 2008 or 2009 due to panel attrition, or there was a change in the main sector of economic activity prior to 2009. For these cases, the conversion tables developed by Dierks et al. (2019) are used in order to update the WZ 2003 sector to WZ 2008.

A.1.7.2 Starting years of the networks in the pilot phase

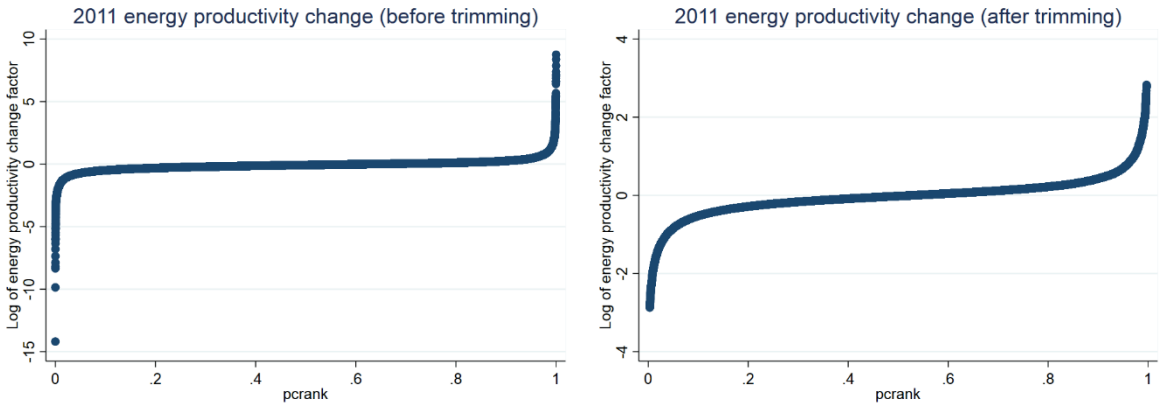
Table A-1-1: Starting years of the companies in the pilot phase

Start year of the network	2009	2010	2011	2012	∑
No. of companies in networks (incl. manufacturing firms)	49	237	84	22	392
No. of companies in networks (excl. non-manufacturing firms)	35	187	56	14	292
No. of companies matched to AFiD panel					256

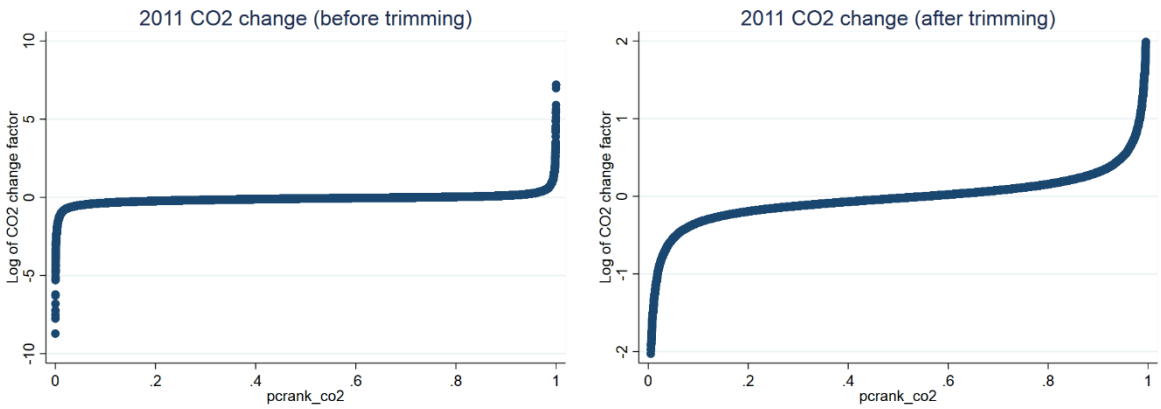
A.1.7.3 Outliers

Figure A-1-1: Change of energy productivity and CO_2 emissions relative to 2008

Panel A: Change of energy productivity prior to the removal of outliers (left) and after their removal (right)



Panel B: Change of CO_2 emissions prior to the removal of outliers (left) and after their removal (right)



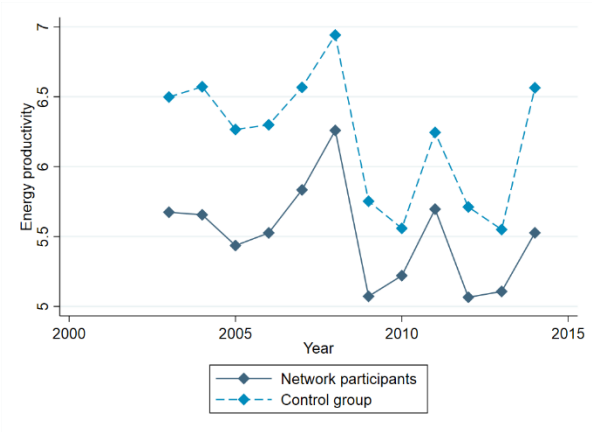
Changes of energy productivity and CO_2 emissions are shown for the year 2011, relative to the pre-treatment year 2008. Due to the logarithmic transformation, a log productivity change of 10 corresponds to a change of energy productivity (CO_2 emissions) by of factor of ~22,000. *Source:* FDZ (2014b), own calculations.

A.1.7.4 Graphs and tables for the DiD estimator

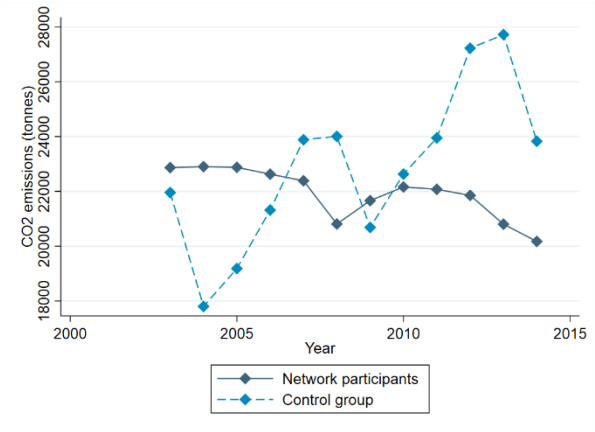
Development of energy productivity and CO_2 emissions

Figure A-1-2: Energy productivity and CO_2 emissions of pilot networks and control group

Panel A: Energy productivity



Panel B: CO_2 emissions



Variables are in levels. *Source:* FDZ (2014b), own calculations.

Anticipation effects

Table A-1-2: Anticipation effects for the difference-in-differences treatment effects

	Dependent variable in levels				Dependent variable in logs			
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent var. Energy productivity								
Ex-post effect	0.298*	0.296	0.266	0.232	0.0167	0.0197	0.0179	0.0207
	(0.161)	(0.185)	(0.189)	(0.182)	(0.0148)	(0.0177)	(0.0193)	(0.0199)
Ex-ante effect (t-1)		-0.00899	-0.0467	-0.0853		0.0144	0.012	0.0153
		(0.154)	(0.167)	(0.164)		(0.0215)	(0.0227)	(0.022)
Ex-ante effect (t-2)			-0.137	-0.18			-0.00837	-0.00478
			(0.115)	(0.135)			(0.018)	(0.0212)
Ex-ante effect (t-3)				-0.143				0.0119
				(0.132)				(0.0206)
Observations	6824	6824	6824	6824	6824	6824	6824	6824
R^2 (within-plant)	0.164	0.164	0.164	0.165	0.38	0.381	0.381	0.381
Panel B: Dependent var. CO_2 emissions								
Ex-post effect	-2466.9**	-3104.5**	-3068.1**	-3171.8**	-0.0101	-0.0131	-0.014	-0.0162
	(935.4)	(1160.9)	(1267.8)	(1456.3)	(0.018)	(0.0209)	(0.0228)	(0.0239)
Ex-ante effect (t-1)		-3029.3*	-2983.0*	-3099.9*		-0.0141	-0.0153	-0.0178
		(1632.4)	(1475.5)	(1568.3)		(0.0185)	(0.0211)	(0.0222)
Ex-ante effect (t-2)			167.6	37.05			-0.0041	-0.00692
			(1765.8)	(2046.1)			(0.017)	(0.0195)
Ex-ante effect (t-3)				-434.2				-0.00937
				(1214.7)				(0.017)
Observations	6801	6801	6801	6801	6801	6801	6801	6801
R^2 (within-plant)	0.046	0.047	0.047	0.047	0.125	0.125	0.125	0.125

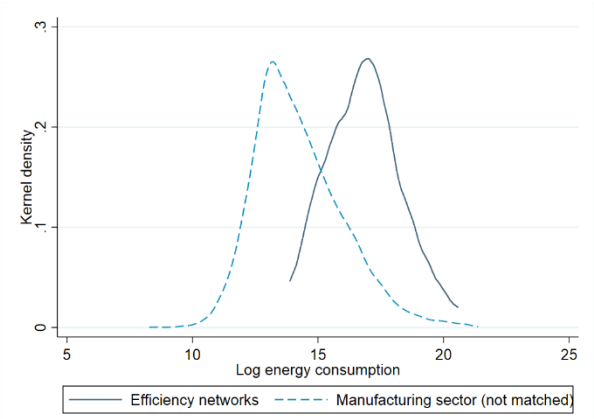
Estimation of different versions of the plant-level fixed effects model (1.3), with and without anticipation effects. Values shown are the coefficients of OLS regressions of the dependent variables on the covariates. Standard errors clustered at the network level are in parentheses. Energy productivity is measured in €/kWh. CO_2 emissions are measured in tonnes. Additional control variables include sales intensity (turnover divided by the number of employees), the export share, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector. Significance: * p<0.1, ** p<0.05, *** p<0.01. *Source*: FDZ (2014b), own calculations.

A.1.7.5 Balance tests for the conditional matching estimator

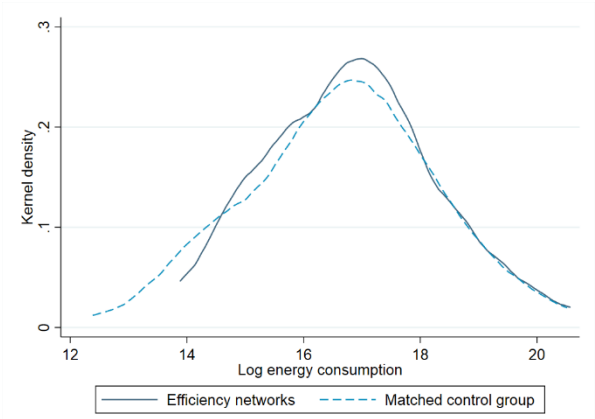
Kernel density of energy consumption

Figure A-1-3: Improvement of balance of energy consumption due to matching

Panel A: Before matching



Panel B: After matching



Panel A shows the kernel density of energy consumption (in logs) of the treatment group versus the entire manufacturing sector (i.e. before matching). Panel B graphs the distribution of energy consumption of the treatment group against the matched control group. *Source:* FDZ (2014b), own calculations.

Mean comparison

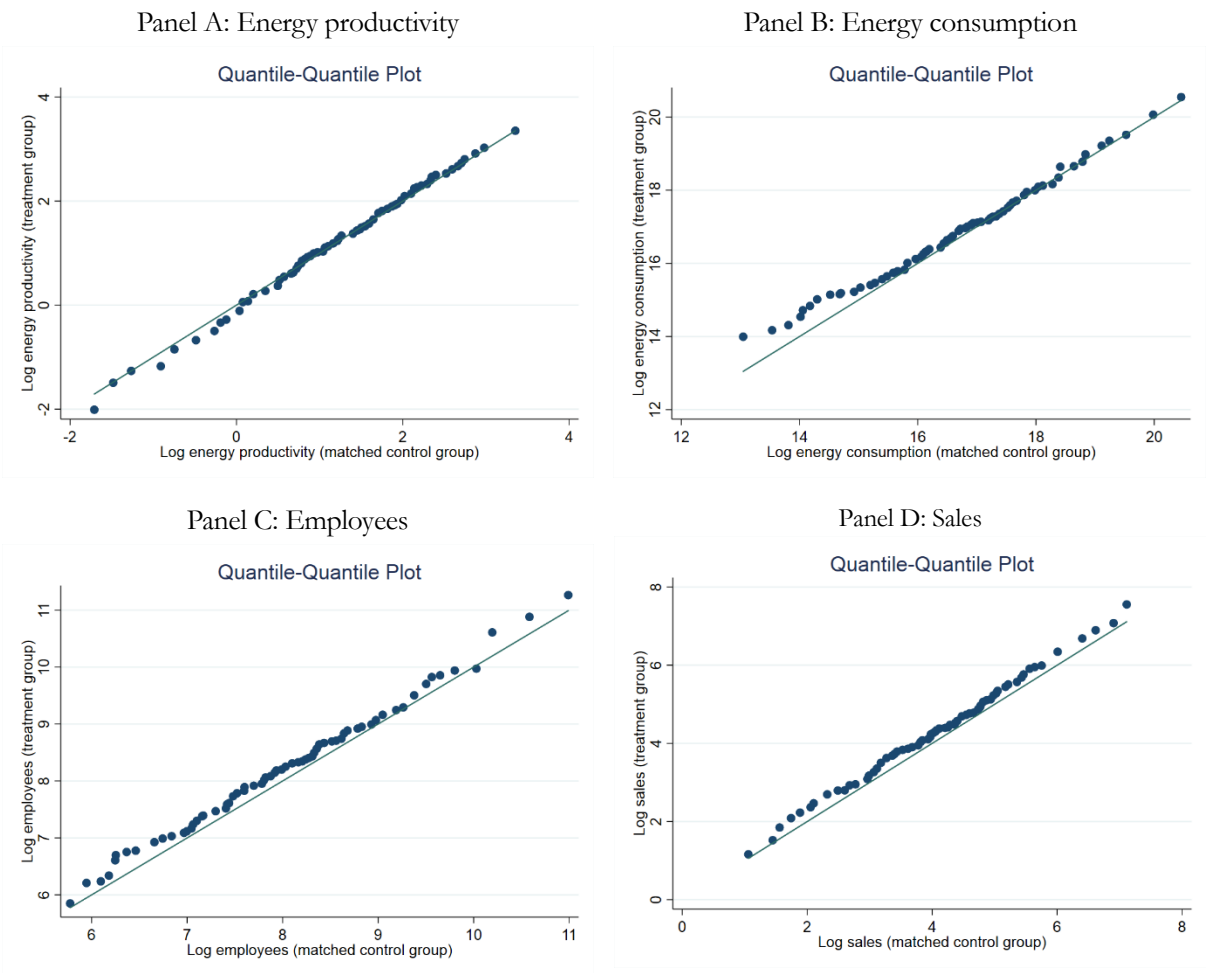
Table A-1-3: Comparison of treatment and matched control group

Variable	Mean networks	Mean matched control	Difference
Energy consumption [MWh]	62,604	58,431	4,173**
Energy productivity [€/kWh]	5.7	5.5	0.18**
CO_2 emissions [tonnes]	22,392	18,603	3,789*
Annual turnover [million €]	190.3	135.9	54.4***
Value of production [million €]	160.0	124.6	35.4**
Number of employees	7,378	6,184	1194**
Sales intensity [thousand €/employee]	22.9	22.2	0.7*
Export share [%]	39.3	33.5	5.8***
Energy cost share [%]	3.6	3.6	-0.1
Observations/plants	199	199	199

All variables are 2008 means. The significance of the difference of the mean of the installations in the pilot networks (treatment group) and the matched control group is tested using a two-sided paired t-test. All variables are at the plant level, except the energy cost share, which is only available at the firm level (reducing the number of observations to 155). * p<0.1, ** p<0.05, *** p<0.01. *Source*: FDZ (2014a), own calculations.

Q-Q plots

Figure A-1-4: Q-Q plots of treatment and matched control group

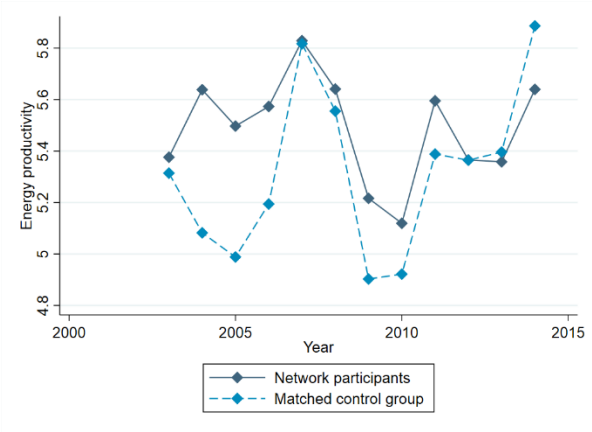


Panels A to D show the 2008 (i.e. pre-treatment) quantile-quantile (Q-Q) plots of several variables for treated and matched control group for the NN(1) matching estimator. All variables are in logs. *Source:* FDZ (2014b), own calculations.

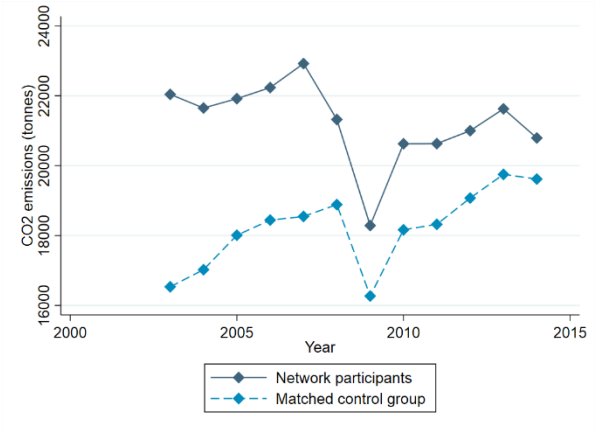
A.1.7.6 Pre-treatment trends for the conditional matching estimator

Figure A-1-5: Energy productivity and CO_2 emissions of pilot networks and matched control group

Panel A: Energy productivity



Panel B: CO_2 emissions



Source: FDZ (2014b), own calculations.

A.1.7.7 Exporters

Export share

Table A-1-4: Distribution of export shares in treatment group and control group

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile
Export share [in %]				
- Pilot networks	39.3 (30.4)	36.6	9.6	63.2
- Control group	36 (29.5)	31.2	7.7	59.3
- Manufacturing sector	20.2 (25.8)	7.1	0.0	35.0

Notes: The export share is measured as the fraction of total revenue generated from exports. The statistics are calculated over the treatment period (years 2010-2014). There are 257 manufacturing sites in the pilot networks group, 364 installations in the control group, and an average of 42,843 plants in the manufacturing sector. *Source*: FDZ (2014b), own calculations.

Descriptive statistics pilot networks vs. high exporters

Table A-1-5: Distribution of key variables for pilot networks and high exporters

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile	Obs.
Energy consumption [MWh]					
- Pilot networks	67,415 (164,116)	18,815	5,892	48,667	1,256
- High exporters	106,089 (164,110)	32,888	15,064	140,522	134
Energy productivity [€/kWh]					
- Pilot networks	5.32 (6.68)	3.20	1.38	6.58	1,187
- High exporters	6.15 (8.06)	3.10	1.06	7.01	129
CO_2 emissions[tonnes]					
- Pilot networks	21,417 (48,356)	7,119	2,755	17,832	1,246
- High exporters	32,889 (43,618)	12,865	5,421	51,496	134
Turnover [million €]					
- Pilot networks	179.9 (477)	67.3	23.7	140.7	1,256
- High exporters	230.8 (291.5)	85.7	52.5	316.4	134
Value of production [million €]					
- Pilot networks	132.1 (224.9)	66.0	24.7	131.0	1,187
- High exporters	221.6 (278.4)	93.7	53.6	308.2	129
Number of employees					
- Pilot networks	7,283 (13,156)	3,643	1,601	6,812	1,256
- High exporters	13,553 (17,412)	4,922	2,434	18,786	134
Energy cost share [%]					
- Pilot networks	3.9 (5.4)	2.2	1.4	4.1	946
- High exporters	5.5 (8.4)	1.9	1.3	4.8	108

Notes: The statistics are calculated over the treatment period (years 2010-2014). There are 257 manufacturing sites in the pilot networks group, 27 of which are high exporters (i.e. at least 80 percent of revenue from exports). All variables are at the plant level, except the energy cost share of total costs, which is only available at the firm level, for a subset of the firms that takes part of the Cost Structure Survey *(Kostenstrukturerhebung)*. *Source*: FDZ (2014a), own calculations.

Chapter 2

Way off: The effect of minimum distance regulation on the deployment of wind power*

Abstract

In order to increase public acceptance of wind power, several countries and regions have introduced mandatory minimum distances of wind turbines to nearby residential areas. Germany's largest federal state Bavaria introduced such separation distances of ten times the height of new wind turbines in 2014. Here, we provide a novel monthly district-level dataset of construction permits for wind turbines constructed in Germany between 2010 and 2018. We use this dataset to evaluate the causal effect of introducing the Bavarian minimum distance regulation on the issuance of construction permits for wind turbines. We find that permits decreased by up to 90 percent. This decrease is in the same order of magnitude as the reduction of land area available for wind turbines. The results are in line with findings indicating that minimum distances do not increase the public acceptance of wind power, but harm the expansion of onshore wind power.

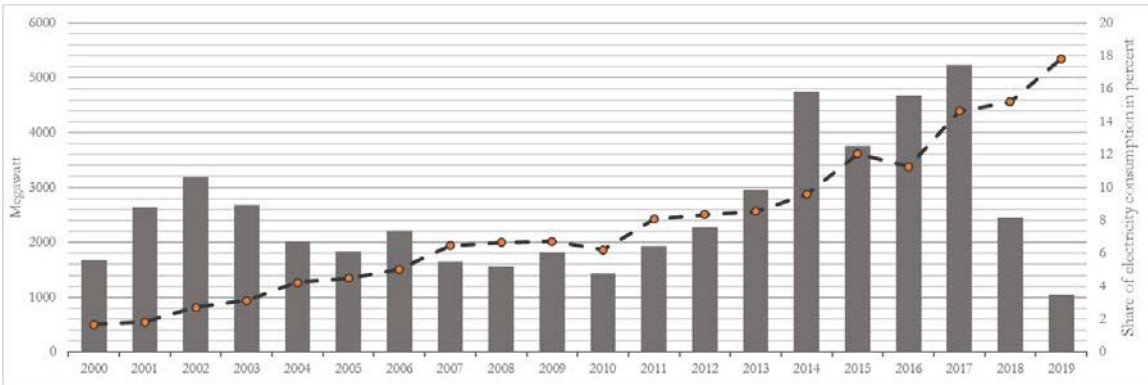
* This chapter is based on joint work with Nils May. We thank Mathias Huebener, Jürgen Quentin, Nolan Ritter, Wolf-Peter Schill and Pascal Vuichard, as well as seminar participants at DIW Berlin, the Hertie School of Governance and the REM-HSG of the University of St. Gallen for helpful comments and suggestions. We also thank Katharina Erdmann and Friedemann Gruner for superb research assistance.

2.1 Introduction

Energy transitions worldwide rely on large amounts of electricity from renewable energy sources to reduce emissions (Chu and Majumdar 2012; IPCC 2018). Renewable energies are needed to replace conventional power plants, as well as to power the decarbonisation in other sectors like transport and industry (Bataille et al. 2018; Mitchell 2016). Consequently, the International Energy Agency expects global electricity demand to grow by more than two percent annually until 2040 (IEA 2019a).

Wind power is a cornerstone of energy transitions in many countries. Onshore wind power generates electricity at relatively low cost due to technological learning and improvements in financing conditions (Egli et al. 2018), as falling auction bids indicate (IRENA 2019). Global onshore wind power capacity is envisioned to more than double within the next ten years (IEA 2019a). In Germany, the share of electricity demand covered by onshore wind has increased steadily in the last two decades (Figure 2-1). Since the introduction of the German renewables support scheme in 2000, it has risen from less than two percent to more than fifteen percent in 2018. While new installations peaked between 2014 and 2017, newly added capacity has plummeted since. One of the reasons for this decline is that a large number of wind projects cannot be built since the construction permit is being contested in court (Fraunhofer IEE 2019).

Figure 2-1: Wind power in Germany



The figure plots the annual onshore wind power additions in Germany (bars, left axis), as well as the respective share of onshore wind power of electricity consumption (dotted line, right axis), based on data from Betreiber-Datenbasis (2019) and the German Federal Ministry for Economic Affairs and Energy (BMWi 2019). Data for 2019 is preliminary.

Although support for renewable energy in general is high, wind energy is more controversial than (small-scale) solar photovoltaics (Cashmore et al. 2019). Onshore wind power requires land and can have negative externalities on local residents (Krekel and Zerrahn 2017). Opposition by residents against new projects may prolong permission processes or prevent installations altogether.

Consequently, securing local acceptance of wind turbines is crucial for the deployment of wind power (Wüstenhagen et al. 2007).

Mandatory minimum distances (or separation distances) between wind turbines and residential areas reduce the land area available for new deployment. However, proponents argue that such negative effects on capacity expansion are outweighed because these policies facilitate future growth of wind power by increasing its acceptance (German Federal Government 2019). In recent years, minimum distance regulation has become more popular: Scotland, Poland and the German federal state of Bavaria introduced separation distances in 2010, 2016 and 2014, respectively. Moreover, the German *Climate Action Programme 2030* includes the intention to introduce such regulation nationally.

While the effects of minimum distance regulation on available land have been assessed before, the actual net effect on new projects is unclear. The lack of suitable data has so far prevented research on this question. The separation distances in Bavaria, for example, directly affect construction permits for wind power plants. On the other hand, the regulation affects new installations of wind turbines (on which data is readily available) only indirectly. However, thus far, there is no comprehensive dataset on building permits for German wind power plants and, as a consequence, no analyses of the direct effect of the Bavarian minimum distance regulation.

We address this gap by evaluating the effect of the minimum distance regulation in Bavaria on the issuance of permits for wind power projects. Wind power plays an essential role in decarbonizing the German energy system, such that the effect of the Bavarian minimum distances has the potential to directly affect the energy transition. Lessons learned from Germany are also relevant for other countries seeking to expand wind power resources.

We assess the Bavarian regulation's effects by creating and analysing a new dataset that comprises information on all permits for German wind turbines that are eventually installed. We combine three distinct datasets and apply statistical inference to identify location, permit date and capacity for all wind turbines installed in Germany between 2010 and 2018. These data can be used to assess the effect of different policies on construction permits for wind turbines in Germany. In this chapter, we evaluate the causal effect of the Bavarian separation distance on the issuance of wind permits.

The results are presented in three steps: First, we introduce our new dataset and information on Bavaria's minimum distance regulation (sections 2.2 and 2.3). Second, we identify the causal effect of the regulation on new permits by comparing developments in the federal state of Bavaria to the rest of Germany (section 2.4). Third, we show how our results relate to federal separation distances,

and discuss in how far minimum distance regulation achieves the goal of increasing socio-political acceptance of onshore wind expansion (sections 2.5 and 2.6).

2.2 Minimum distance regulation in Bavaria

The federal state Bavaria introduced its minimum distance regulation ("10 H" regulation) to restrict where and what kind of wind turbines could be built. The regulation applies to new building permits for wind turbines. It came into effect in November 2014 (see appendix A.2.8.1 for details on the timing of the introduction and its legal treatment). Subsequently, new permits were only granted for installations that have a distance of ten times the height of the wind turbine to residential areas. The height is measured as the sum of the hub height and the rotor blade length. Since the regulation does not differentiate according to visibility (i.e. a turbine on top of a hill is restricted in the same way as a turbine in a valley), this translates into a distance of almost 2,000 meters in practice (see Table 2-1).

Exemptions exist to the tenfold separation distance in Bavaria. First, local administrations at the municipal level may issue permits without enforcing the regulation when these permits had been filed prior to February 2014. Alternatively, these authorities may introduce exemptions for turbines to also be built at lower distances. Consequently, to be able to identify the effect of the Bavarian 10 H regulation on new installations, it is necessary to differentiate between installations that received their permits under application of the new regulation and those that were still issued under the old regulation (see next section).

2.3 Data

2.3.1 Creating a new wind permit dataset

We create a unique district-level dataset containing monthly permits (in megawatt) of wind turbines installed between 2010 and 2018 in Germany. The permit dataset builds on a combination of three different data sources.

First, the backbone of our analyses is the *Betreiber-Datenbasis*, a private database, in which German wind power plants have been collected since 1988. The *Betreiber-Datenbasis* contains information on the installation date of German wind turbines and their location, as well as technical parameters like capacity, height and rotor blade lengths. It consists of 10,993 plants constructed between 2010 and 2018, with an average power of 2.7 megawatts (MW). The data quality is very high: Aggregate figures

on yearly wind expansion match almost perfectly with the data provided for the German Wind Power Association and the German Engineering Association (Deutsche Windguard 2019).

Second, from the *Anlagenregister*, a public register of renewable energy installations, we retrieve information on construction permit dates for wind turbines in the *Betreiber-Datenbasis*. The *Anlagenregister* is an official publicly accessible database, where all German renewable energy installations between August 2014 and 2019 had to be registered. We merge *Anlagenregister* and *Betreiber-Datenbasis* based on an exact match of the variables' month-year of the construction of the wind turbine, their nominal power, as well as their zip code. This results in a dataset with installation data and technical parameters for all wind turbines, and permit dates for a subset of these installations.[31]

Third, not all permits granted after November 2014 were subject to the 10 H rule, since the law introduced some exceptions (see section 2.2). We identify those permits that did comply with the new regulation by using a range of official documents published by the Bavarian Federal Ministry of Economic Affairs as a response to various parliamentary questions by members of the Bavarian parliament. This allows us to estimate the share of permits after November 2014 granted without an application of the minimum distance regulation.

2.3.2 Construction periods of wind turbines

Despite its official nature, the *Anlagenregister* does not contain all wind turbines constructed in Germany. In both 2013 and 2014, shortly before the Bavarian separation distances (the 10 H regulation) were implemented, around 40 percent of all installations built in Germany were not registered in the *Anlagenregister*. Consequently, the wind permit database we create is based on the *Betreiber-Datenbasis* (which has complete data on all installations), and complemented by information on permit dates from the *Anlagenregister*.

After merging the two databases *Betreiber-Datenbasis* and *Anlagenregister*, we have precise information on the date of construction, but the date that the permits were granted is not available for all plants. For these installations, we approximate the permit date by subtracting typical construction periods from the construction dates. Based on known construction dates, we then derive permit dates for

[31] For the variable month-year of the construction, we allow for a time lag of up to two months between *Betreiber-Datenbasis* and *Anlagenregister*. The reason is that the *Betreiber-Datenbasis* contains the date when the construction of a wind turbine is completed, whereas the *Anlagenregister* contains the commissioning date (i.e. when the installation starts producing electricity). Using this approach, we merge around 60 percent of the *Anlagenregister*'s wind turbines with information on the permit date to the *Betreiber-Datenbasis*.

remaining installations by drawing from the distribution of construction times. We do this in several steps.

First, we define the construction time as the commissioning date minus the permit date for all plants in the *Anlagenregister*. This gives us a distribution of construction periods for German wind power plants. The average construction period is twelve months (see Figure A-2-1 in appendix A.2.8.2). Second, we approximate the missing permit dates in the *Betreiber-Datenbasis* by subtracting from the (known) construction date a random draw of the distribution of construction times.[32] Since almost 99 percent of all wind turbines built after 2010 in Germany have a construction date below four years (cf. Figure A-2-1), we restrict the distributions from which we draw to 48 months in order to exclude extreme (possibly erroneous) observations. Lastly, we aggregate the turbine-specific information on the district level for every month.

The assumption underlying the approximation procedure is that the construction times for the plants for which we do have information on the permit date and the ones where we only have the construction date are similar. We provide evidence for this assumption by showing that the turbines in these two groups are very much alike in terms of height and power: These variables differ between both groups by around two percent (power) and by less than one percent (height) in a typical year (see appendix A.2.8.2).

2.3.3 Descriptive Statistics

Table 2-1 shows that only 7.7 percent of all building permits in the years 2010-2016 were granted to Bavarian wind turbines, although almost one-fourth of all German districts are located in Bavaria. Moreover, the average height of wind turbines of 190 meters in Bavaria implies that the 10 H regulation translates into a separation distance of 1900 meters on average.

[32] Specifically, we draw from two separate yearly distributions, one containing all Bavarian wind turbines, and a second one containing all other German wind turbines. Draws are from yearly distributions of the construction periods, reflecting that the duration of the construction might change over time. However, the construction times for the years 2010-2014 are pooled into a joint distribution, because the number of observations with information on the construction period is low in the individual years.

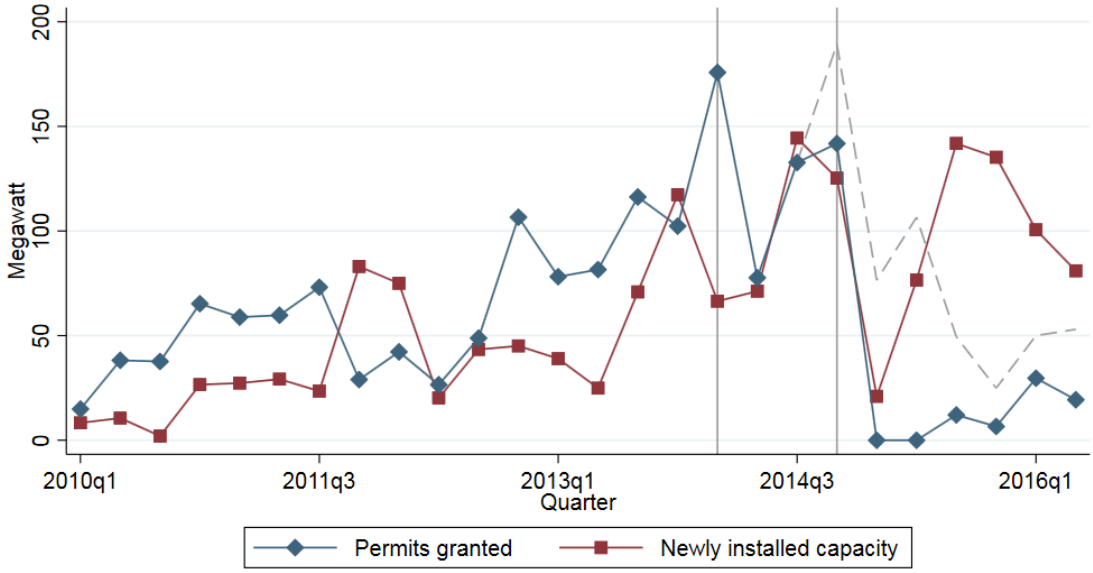
Table 2-1: Descriptive statistics of wind turbines in Bavaria and Germany

	Bavaria	Germany
Number of districts	96	401
Mean district area [km²]	734.8	891.7
Number of wind turbines	760	10,019
Total added wind capacity [MW]	1,986	25,125
Mean power of wind turbines [MW]	2.61	2.70
Mean height of wind turbines [meter]	190	171
Mean number of permits per district [MW/month]	0.25	0.81
Mean construction period [months]	14.9	11.6

The statistics refer to wind turbines from our permit database that received their construction permits between 2010 and 2016. The districts refer to Germany's territorial status as of September 30th, 2019.

Figure 2-2 illustrates the advantage of our new permit dataset. It shows how an analysis based on newly installed wind turbines would be biased. Bavarian construction permits, which are directly affected by the separation distances, declined sharply after November 2014. New installations of wind turbines, on the other hand, actually *increased* after the introduction of mandatory separation distances. Consequently, an analysis of the minimum distance regulation based on installation data would underestimate the effect of the policy.

Figure 2-2: Permits for wind turbines and newly installed wind power capacity in Bavaria



The figure shows the quarterly new construction permits and installations of wind power in Bavaria, as well as the cut-off dates of the introduction of the minimum distance regulation. Permits include the total number of permits (dashed line), or the permits under an application of the Bavarian minimum distance regulation only (blue solid line). The left vertical line marks the cut-off date to file for new permits that are not subject to strict separation distances in February 2014. The right vertical line indicates the introduction of the policy in November 2014. q1 denotes the first quarter for a given year.

2.4 Effect of minimum distances on wind power expansion

2.4.1 Identifying the causal effect

We use a difference-in-differences model to identify the causal effect of the Bavarian separation distances on wind power expansion in Bavaria. The baseline specification is given by

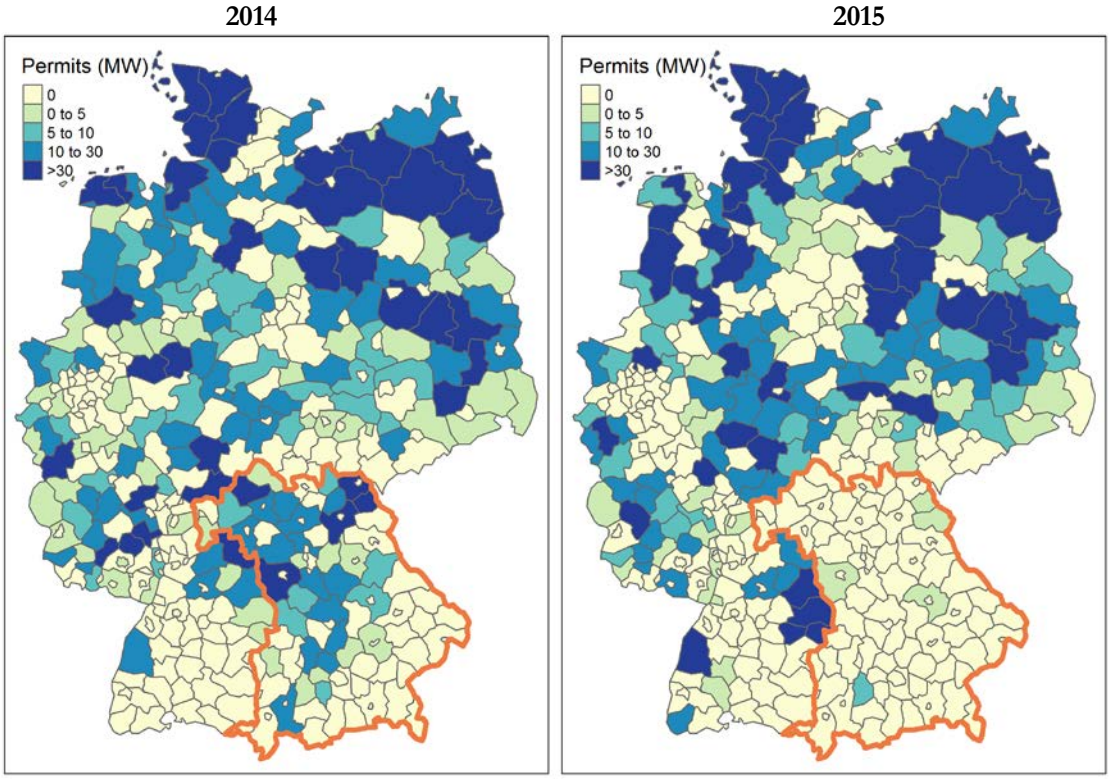
$$q_{i,t}^{Wind} = \delta D_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \tag{2.1}$$

where the dependent variable q is the number of wind turbine permits granted in district i in month t (in MW). μ_i is a district-level fixed effect that controls for those differences in the number of permits between districts that are constant over time. τ_t is a vector of month fixed effects, controlling for the impact of national shocks to the number of permits. Such shocks may include lower costs for building wind turbines over time, as well as changes to the German renewables remuneration regime that affect Bavaria and the rest of Germany similarly. δ is the coefficient of interest, measuring the effect of the 10 H regulation on the number of permits in the average Bavarian district.

2.4.2 Results

The number of wind power permits issued in Bavaria dropped drastically after the minimum distance regulation was introduced. In most Bavarian districts, no permits for wind power plants were issued under the new minimum distance regulation in 2015 (see Figure 2-3). Although there were some minor changes in individual districts in other states as well, on average the other German states did not experience a similar decline.

Figure 2-3: Wind permits before and after the introduction of minimum distances in Bavaria



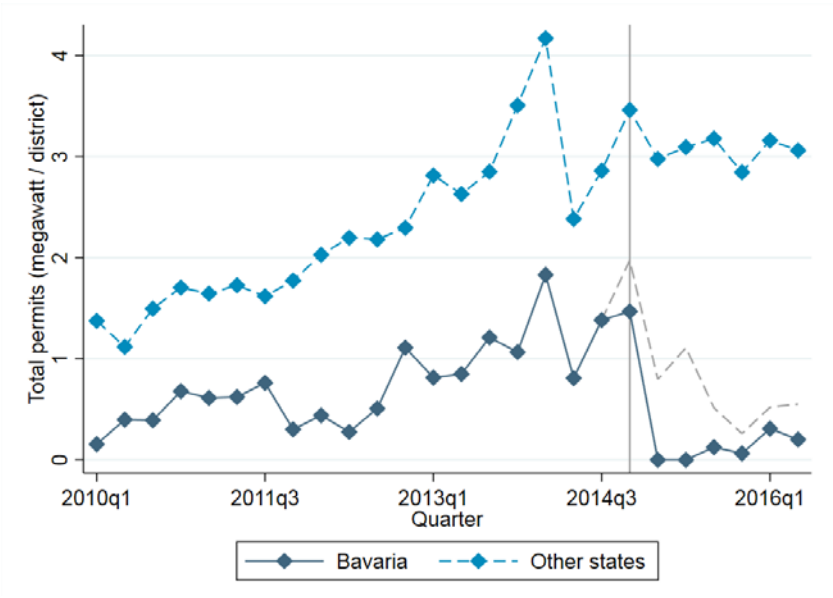
The figure shows the total number of permits for wind turbines (in megawatt) issued in the twelve months before the introduction of minimum distances in Bavaria (left panel), as well as the twelve months after (right panel). Permits in Bavaria (marked by the orange line) include the permits under an application of the Bavarian minimum distance regulation only.

Figure 2-4 illustrates that the number of construction permits issued in Bavaria and the rest of Germany followed a common trend before the introduction of the minimum distance regulation in November 2014. We substantiate this identifying assumption by implementing an event study design in appendix A.2.8.4. The event study approach provides strong support for the identifying assumption, namely that Bavarian permits would have evolved similarly to the rest of Germany, had the minimum distance regulation not been introduced (cf. Figure A-2-2 in the appendix).

The lower level of permits per district in Bavaria visible in Figure 2-4 results from the smaller district areas relative to districts in the rest of Germany (see Table 2-1). Moreover, average wind speeds are lower in Bavaria than in Northern Germany and parts of Central Germany (Deutscher Wetterdienst

2004). However, while the issuance of permits remained stable in Germany after November 2014, their number dropped strongly in Bavaria in the same period. This divergence is even more pronounced when focusing on the permits that were actually granted under the minimum distance regulation (solid line in Figure 2-4).

Figure 2-4: Construction permits for wind power in Bavaria and the rest of Germany



The graph shows the average number of permits for wind turbines (in megawatt) issued quarterly per district. Permits in Bavaria include the total number of permits (dashed line), or the permits under an application of the Bavarian minimum distance regulation only (solid line). q1 denotes the first quarter for a given year.

Our regressions show that the Bavarian regulation drastically reduced the number of construction permits. The regression results are presented in Table 2-2. All coefficients are highly statistically significant. Columns 3 and 6 correspond to the baseline specification (2.1) discussed in the previous section. The results are stable across specifications with different time fixed effects. The model with monthly fixed effects is our preferred specification (columns 3 and 6), since these take up more detailed variation than quarter and annual effects.

For the estimated treatment effects presented in Table 2-2, we also estimate the relative decrease of construction permits in Bavaria. We do this by comparing the point estimates to the number of permits that would be expected had the minimum distance policy not been in place. In other words, the treatment effect is compared to the counterfactual permits that we would expect in the average Bavarian district, had the 10 H regulation not been implemented.

In our baseline specification, we assume that after the introduction of mandatory separation distances, wind turbines built under an exception from the 10 H regulation would not have been built had the strict minimum distance rules been applied. Alternatively, a lower bound of the effect of the regulation can be calculated by assuming that all wind turbines that benefitted from such an exception

would have survived the strict minimum distance rules. Under this alternative assumption, the estimated effect is lower, but remains statistically and economically highly significant.

We present the results from the lower bound estimations in columns 1-3 of Table 2-2). Under the strong assumption that all permits granted under exceptions from the Bavarian 10 H regulation would have also been granted had the regulation been applied, the new mandatory separation distances reduced permits by around 0.34 megawatt (MW) per month per district, i.e. around 396 MW per year in Bavaria. This amounts to a reduction of the number of permits issued in Bavaria by 62 percent because of the introduction of strict minimum distances (column 3 of Table 2-2).

This assumption underestimates the true effect of the Bavarian minimum distances. The separation distances strongly restricted the number of projects able to receive permits, making it unlikely that all of these projects would be in line with the new rules. Consequently, in columns 3-6 of Table 2-2, we re-estimate our models under the more realistic assumption that projects granted a permit without applying the 10 H rule would *not* have received a permit had the 10 H rules been enforced. In other words, we use only Bavarian wind turbines that did receive the permit under the new regulation after November 2014 in our estimation. Here, permits in Bavaria dropped by almost 0.5 MW per district per month (or 90 percent) in our preferred specification (column 6 of Table 2-2). Over the course of a year, this means that (summing over all districts) 571 MW of wind power capacity were not installed in Bavaria. Our results are robust to the estimation of standard errors with an ordinary wild bootstrap procedure instead of the clustering at the state level (cf. appendix A.2.8.3).[33]

[33] Although standard errors need to be clustered at the state level (Abadie et al. 2017), standard errors may be wrong due a low number of clusters (Cameron and Miller 2015). One solution to this is cluster bootstrapping, such as the wild cluster bootstrap. In the case of a small number of treated clusters, however, the wild cluster bootstrap often over-rejects or under-rejects severely (MacKinnon and Webb 2017). Thus, in appendix 0 we compute p values based on the ordinary wild bootstrap (MacKinnon and Webb 2018).

Table 2-2: Effect of minimum distances on wind construction permits in Bavaria

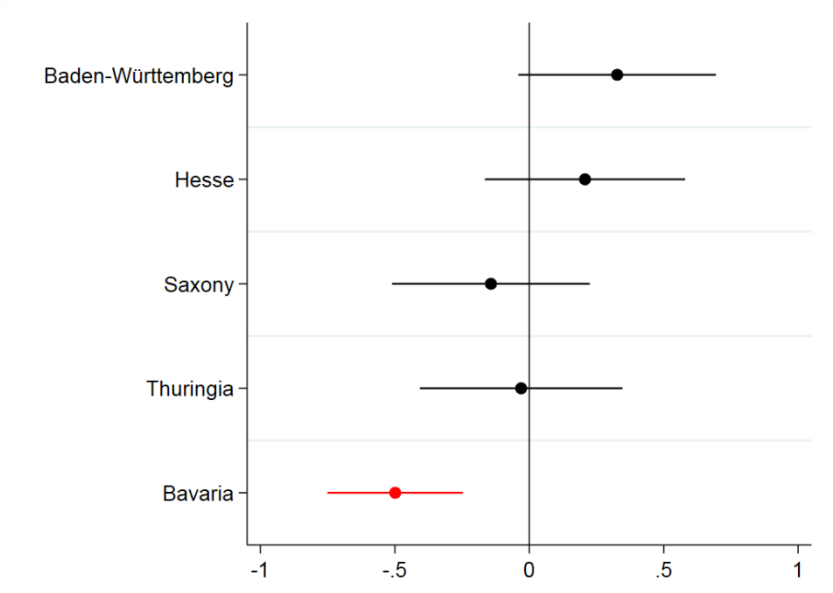
Dependent Variable:	All permits			Permits under minimum distance regulation		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: minimum distance regulation	-0.316*** (0.0809)	-0.326*** (0.0825)	-0.343*** (0.0855)	-0.468*** (0.0812)	-0.477*** (0.0827)	-0.499*** (0.0855)
Change [%]	-57	-59	-62	-84	-86	-90
Observations	31,278	31,278	31,278	31,278	31,278	31,278
Year fixed effects	x			x		
Quarter fixed effects		x			x	
Month fixed effects			x			x

Values shown are the coefficients of fixed effects regressions of monthly construction permits in megawatt at the district level. The percentage decrease of wind turbine permits in Bavaria relative to the counterfactual building permits is also tabulated. Standard errors clustered at the state level are in parentheses. All coefficients remain statistically significant when ordinary wild bootstrap standard errors are used (see appendix A.2.8.3). Significance: * p<0.1, ** p<0.05, *** p<0.01.

2.4.3 Robustness checks

We provide a battery of robustness checks, demonstrating that the main results shown in Table 2-2 hold. First, we run placebo regressions for all the four neighbouring states of Bavaria to demonstrate that our results can be attributed to the introduction of the separation distances. These regressions serve to rule out a general shock to wind expansion that also affected those southern German states, which have similarly mediocre wind speeds as Bavaria. Figure 2-5 visualises the regression results. The regression coefficients are statistically insignificant for all of the neighbouring states. This demonstrates that the change in the number of permits in Bavaria was caused by the introduction of the minimum distance regulation and not by random changes over time that affect states with mediocre wind resources similarly. In other words, no general economic or policy shock that affected the other southern states can explain the observed effect in Bavaria. Moreover, the identified Bavarian coefficient is particularly large when considering that the state is divided into relatively many districts, such that individual districts are small (cf. Table 2-1).

Figure 2-5: Placebo regressions for neighbouring states of Bavaria



The figure compares the coefficients of placebo regressions for the neighbouring states of Bavaria to the baseline specification (Table 2-2, column 6), with standard errors at the 99% significance level.

Second, we demonstrate that our results are robust to possible anticipatory effects. If market participants reacted to the introduction of the 10 H regime by increasingly filing for building permits before the new rules became effective, such anticipatory behaviour would confound our estimates. In order to exclude this possibility, we re-estimate model (2.1), taking into account potential anticipation effects by excluding observations within ±6 months and ±12 months of the introduction of the minimum distance regulation. The estimated relative treatment effect of the separation distances on permits in these specifications is almost identical to the main results in Table 2-2, and the point estimates remain highly statistically significant. This confirms the findings of the baseline specification.

Third, we show that our findings are qualitatively robust to spillover effects. Identification relies on the Stable Unit Treatment Value Assumption (SUTVA), which implies there are no spillovers to the rest of Germany because of the introduction of minimum distances in Bavaria. However, it is conceivable that at least some of the wind projects that were not realised in Bavaria moved to other parts of Germany. This would confound our estimates. Table A-2-5 in appendix A.2.8.5 re-estimates some of the central specifications under the assumption that *all* wind turbines that were not built in Bavaria were immediately constructed elsewhere in the country. Even under this extreme assumption, the relative reduction of wind permits due to the 10 H regulation remains virtually unchanged.

Finally, our results are robust to the approximation procedure of the construction periods. To show this, we re-estimate the models shown in Table 2-2 based on the subset of those plants where we do have information on the construction date from the *Anlagenregister* (see Table A-2-6 in appendix

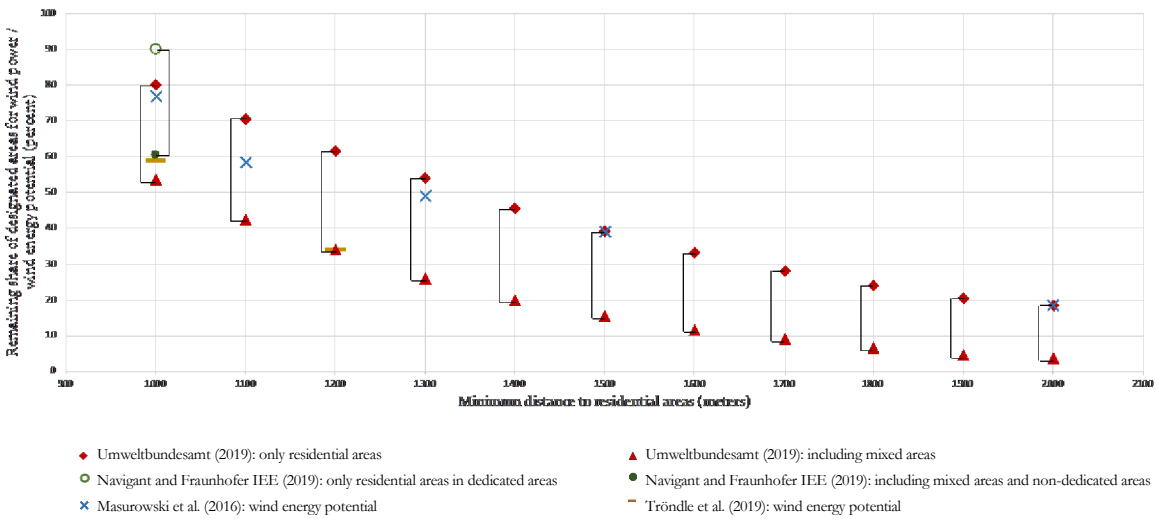
A.2.8.5). The estimated effects of the minimum distance regulations are even stronger in this specification. We therefore rule out that the approximation of permit dates from their construction dates for some of the wind turbines confounds our estimates.

Summing up, our main conclusions remain virtually unchanged under a range of specifications. This provides evidence for the robustness of our results.

2.5 Minimum distances and land availability

Our main finding of strong negative effects on new permits is in line with model-based estimates of the effect of minimum distances on the land available for wind power. Taking into account the pre-existing regulation, introducing a minimum distance of 1000 meters would reduce the land area by 10 to 47 percent in Germany (see Figure 2-6). This reduction increases to 81 to 96 percent for a distance of 2000 meters. Moreover, the impact of minimum distances on available land varies considerably with the definition of the type of residential areas for which the separation distance holds (Umweltbundesamt 2019). Minimum distances towards individual housing reduce available land considerably more than distances only to larger settlements. For example, a strict definition of a minimum distance of 1000 meters can have effects similar to a less strict definition of 1300 meters (Figure 2-6). Hence, when analysing the effects of minimum distance regulation, it is crucial to specify the reference to which the distance applies.

Figure 2-6: Effect of minimum distance regulation on energy potential and land availability



The figure displays the remaining share of land available for wind power as a function of different minimum distances, based on simulation studies. On the vertical axis, we depict the remaining share of the land dedicated to the construction of wind turbines in regional plans in Germany (Umweltbundesamt 2019; Navigant and Fraunhofer IEE 2019), and the remaining wind energy potential compared to a minimum distance baseline of 800 meters (Masurowski et al. 2016; Tröndle et al. 2019).

2.6 Policies to support public acceptance of wind power

In light of the massive extension plans for onshore wind power in many countries, maintaining and supporting local acceptance of wind power deployment is an important policy goal. However, the academic literature on public acceptance does not support the hypothesis of a significant uptake of public acceptance due to increased separation distances: On the one hand, wind turbines have been shown to exert negative externalities locally, for example on well-being of local residents (Krekel and Zerrahn 2017). Moreover, large accumulations of wind turbines nearby residential nearby residential areas affect acceptance negatively (Ladenburg et al. 2013; Ladenburg and Dahlgaard 2012; Ott and Keil 2017). However, the often-touted not-in-my-backyard (NIMBY) theory has been abandoned by the academic literature for a lack of explanatory power (Wolsink 2012; Zerrahn 2017). There is evidence that negative effects of wind turbines on well-being are transitory and disappear a few years after the installation (Krekel and Zerrahn 2017). In addition, there is no evidence that an increasing proximity to wind turbines exacerbates the negative external effects of wind turbines (Krekel and Zerrahn 2017; Langer et al. 2016, 2018; Rand and Hoen 2017; Hoen et al. 2019; Hübner et al. 2019). This indicates that increasing minimum distances will likely have no effect on the social acceptance of wind power.

One explanation for this paradox is that residents in many countries are already protected from noise, shadowing and visual impairment of wind turbines. In Germany, federal law mandates that project developers need to prove on a case-by-case basis that the effect of noise and other disturbances is limited (Wegner 2017). Consequently, increasing the (implicit) legal separation distances may not improve acceptance significantly. This might also explain why the identified willingness-to-pay for larger minimum distances is low and lies well below the additional costs of reducing the available land area under minimum distance regulation (Drechsler et al. 2017).

Procedural and distributional fairness are important determinants for public acceptance of renewables (Ellis and Ferraro 2016; Zerrahn 2017; Jørgensen et al. 2020). Regarding onshore wind power, one obstacle is that the economic benefits mostly accrue where manufacturers, project developers and related companies are based, rather than where the turbines are located (May and Nilsen 2019). One solution is to address this issue by financially compensating local residents or communities. Denmark and the German state of Mecklenburg Western Pomerania have implemented investment opportunities for residents that live close to the turbines. The German federal state of Brandenburg, on the other hand, has introduced mandatory annual payments to local municipalities (Stede and May 2019). Choice experiments and surveys from Germany, Norway and Switzerland suggest that annual payments to local municipalities are preferred to investment

opportunities for individual residents and can help to increase acceptance for new wind turbines (García et al. 2016; FA Wind 2019; Vuichard et al. 2019).

2.7 Conclusion

Minimum distance regulations between wind turbines and residential areas have been introduced and discussed for many regions and countries around the world, but their causal effects on new wind power projects have not been assessed. Since no comprehensive dataset of wind power permits for Germany existed, research on separation distances so far was limited to descriptive analyses. We address this issue by providing a newly compiled dataset, comprising all permits granted to wind power installations that were installed between 2010 and 2018 in Germany. We use these data to provide causal evidence that minimum distance regulation in the federal state of Bavaria reduced the deployment of wind power by up to 90 percent. This indicates that the increased separation distance not only strongly reduced the land available for wind power deployment, but decreased the number of new installations in the same order of magnitude.

For policymakers, this research shows that separation distances not only reduce land available for wind power deployment, but may translate into drastic reductions of new installations. Possible local exemptions from the regulation were not able to reverse this effect in the case of Bavaria. There is also no evidence that tighter separation distances have a significant effect on public acceptance of wind turbines. Direct payments to local municipalities, on the other hand, address the externalities of wind turbines more directly. Such financial compensation improves public acceptance by allowing the communities that are directly affected to participate in the value added of wind power generation.

For researchers, this chapter has three implications. First, our new dataset on all permits issued for onshore wind power in Germany allows researchers to analyse the effects of various policies that address permission processes rather than installations. This includes, for example, the introduction of environmental regulation, or the opposition by local anti-wind power groups. Second, researchers could look at the introduction of mandatory separation distances in other countries such as Scotland (2010) and Poland (2016), in order to evaluate whether the results of this chapter extend to other jurisdictions. Third, as the number of installations grows, ensuring public acceptance of onshore wind power becomes increasingly important. Therefore, regulatory frameworks are needed that facilitate acceptance without hampering the expansion of wind power. Towards this end, analysing the effects of local investment participation on public acceptance and deployment of wind power is an interesting venue for future research.

2.8 Appendix

A.2.8.1 Timing and legal treatment of the minimum distance regulation – A.2.8.2 Approximation of permit date – A.2.8.3 Bootstrapped standard errors – A.2.8.4 Event study – A.2.8.5 Further robustness checks

A.2.8.1 Timing and legal treatment of the minimum distance regulation

Timeline of introduction. The 10 H regulation came into effect on November 21st, 2014. New permits granted for wind turbines after this date had to adhere to the distance regulation in principle. However, when project developers had filed for permits before February 4th, 2014, a permit could still be granted without considering the 10 H regulation if the decision on the permit was taken until the end of 2015. This also implied that filings that happened in between these dates could be evaluated differently according to the decision date: In case that the filings were still evaluated before November 21st, the old regulation was applied. If decisions were taken by the relevant authority after the cut-off date, the 10 H regulation applied.

Legal treatment. The 10 H regulation is widely discussed and understood as a minimum distance regulation. Legally, the regulation took away the prioritization of wind power in the buildings code. In Germany, wind power is prioritized outside of residential areas and municipalities assign specific areas for wind power deployment. The regulation removed this prioritization. However, individual counties could decide to keep the preferential treatment of wind power in their local planning processes. Permits granted under such exemptions, together with the permits for filings before February 4th, 2014, are reflected in the specifications shown in columns (1-3) in Table 2-2. These estimations rely on the assumption that even in the absence of the exemptions or had the filings been made only later, all permits would also have been granted under the strict application of the 10 H regulation. Thus, these estimates are a lower bound of the effect of the Bavarian minimum distance regulation.

A.2.8.2 Approximation of permit date

Table A-2-1 provides evidence that wind turbines with and without information on the date of the permit are very similar Within the periods from which we use the distributions to approximate the construction date (i.e. 2010-2014, 2015 and 2016), the two variables power and height differ on average by 2.4 percent (power) and 0.8 percent (height). Moreover, we show the overall distribution

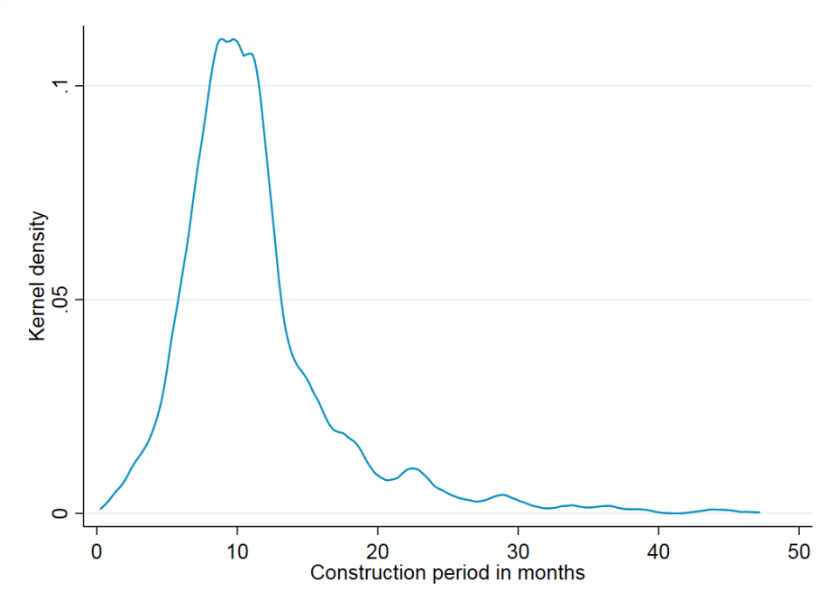
of the construction period in Figure A-2-1, illustrating that the average wind turbine takes one year to build. Figure A-2-1 also illustrates that the vast majority of wind power plants (more than 94 percent) are constructed within less than two years.

Table A-2-1: Comparison of wind turbines with and without information on the date of the building permit

	Turbines with information on the date of the permit			Turbines without information on the date of the permit		
	Power	Height	N	Power	Height	N
2010-2014	2.65	165	1,653	2.52	163	4,429
2010	2.12	138	209	2.23	150	649
2011	2.22	148	107	2.38	155	860
2012	2.81	170	109	2.55	162	1,009
2013	2.73	164	307	2.66	167	1,182
2014	2.77	172	921	2.68	175	729
2015	2.81	182	814	2.81	182	590
2016	3.03	183	1,902	2.96	185	631

The table displays average power (in megawatt) and average height (in meters) by the year in which the building permits were granted.

Figure A-2-1: Distribution of construction periods of wind turbines in Germany



The graph depicts the Kernel density of the construction period of German wind turbines in the years 2010-2017 according to the *Anlagenregister*. The construction period is defined as the number of months elapsed between the issuance of the building permit of a wind turbine and the completion of its construction.

A.2.8.3 Bootstrapped standard errors

Our results are robust to the estimation of standard errors with an ordinary wild bootstrap procedure instead of the clustering at the state level. In general, since the treatment (the minimum distance regulation) is assigned at the federal state level, standard errors need to be clustered at the state level (Abadie et al. 2017). However, as Germany consists of 16 states, there are only few clusters, which means the standard errors may be wrong (Cameron and Miller 2015). One solution to this is cluster bootstrapping, such as the wild cluster bootstrap. In the case of a small number of treated clusters, however, the wild cluster bootstrap often over-rejects or under-rejects severely (MacKinnon and Webb 2017). Thus, we compute p values for the models estimated in Table 2-2 based on the ordinary wild bootstrap (MacKinnon and Webb 2018). The statistical level of significance remains at the one percent level for the preferred specification including all Bavarian wind turbines (column 3 of Table A-2-2). In the preferred specification with only Bavarian wind turbines that received permits under the 10 H regime, the level of significance of the ordinary wild bootstrap is even higher (0.1% level, column 3 of Table A-2-2).

Table A-2-2: Bootstrap standard errors: Effect of minimum distances on wind permits in Bavaria

Dependent Variable:	All permits			Permits under minimum distance regulation		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: Minimum distance regulation	-0.316	-0.326	-0.343	-0.468	-0.477	-0.499
p value – state cluster	0.0014	0.0013	0.0011	0.0000	0.0000	0.0000
p value – ordinary wild bootstrap	0.0080	0.0180	0.0030	0.0000	0.0010	0.0010
Observations	31,278	31,278	31,278	31,278	31,278	31,278
Year fixed effects	x			x		
Quarter fixed effects		x			x	
Month fixed effects			x			x

Values shown are the coefficients and p values of fixed effects regressions of monthly construction permits in megawatt at the district level. P values are clustered at the state level and computed with the ordinary wild bootstrap, respectively. The ordinary wild bootstrap uses 999 replications and Rademacher weights.

A.2.8.4 Event study

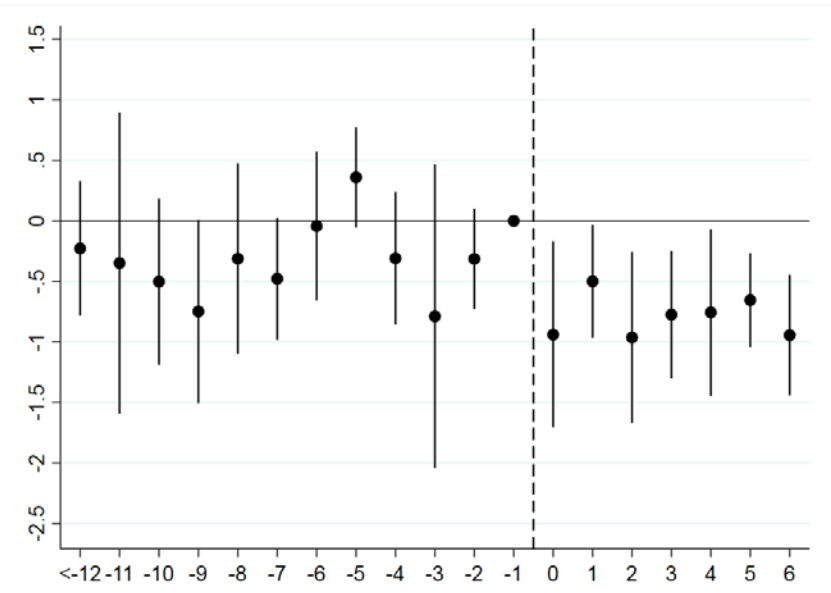
The main identifying assumption underlying the difference-in-differences model is that the number of permits granted in Bavaria and the rest of Germany follow a common trend. A visual inspection of Figure 2-4 supports this hypothesis. Moreover, we implement an event study approach given by

$$q_{i,t}^{Wind} = \sum_{j=-m}^{s} \delta_j D_{i,t+j} + \mu_i + \tau_t + \varepsilon_{i,t} \tag{2.1}$$

where m "leads" and s "lags" of the treatment effect are included instead of the single treatment effect in (2.1).

Figure A-2-2 provides strong evidence for the validity of the main identifying assumption, namely that Bavarian permits would have evolved similarly to the rest of Germany, had the minimum distance regulation not been introduced. The graph shows that there was no statistical difference between the trend of wind permits in Bavaria and the rest of Germany in any of the 12 months before the 10 H rule became effective. After the introduction of the 10 H regime, on the other hand, all interactions of the treatment with time lags to the reform are statistically significant.

Figure A-2-2: Event study: Effect of minimum distances on wind permits in Bavaria



The figure plots coefficient estimates and 99% confidence intervals from an interaction of the reform with indicators on the time difference to the reform (in months). For Bavaria, only permits granted under an application of the minimum distance regulation are included in the regression. The dashed line marks the introduction of the reform in November 2014.

A.2.8.5 Further robustness checks

Anticipation effects

Tables A-2-3 and A-2-4 re-estimate the specifications shown in Table 2-2, excluding observations before and after the introduction of the 10 H rule within a window of six and twelve months, respectively. All coefficients are still highly statistically significant. In our preferred specifications with only Bavarian wind turbines that received permits under the 10 H regulation (column 6 of Tables A-2-3 and A-2-4), the relative effect size is virtually unchanged compared to Table 2-2. In the specification including all Bavarian wind turbines, the effect is even larger, rising to around 70 percent in the robustness checks (column 3 of Tables A-2-3 and A-2-4). This shows that our results are robust to possible anticipation effects.

Table A-2-3: Effect of minimum distances on permits, excluding six months window

Dependent Variable:	All permits			Permits under minimum distance regulation		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: Minimum distance regulation	-0.378***	-0.378***	-0.378***	-0.482***	-0.482***	-0.482***
	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)
Change [%]	-71	-71	-71	-90	-90	-90
Observations	26,466	26,466	26,466	26,466	26,466	26,466
Year fixed effects	x			x		
Quarter fixed effects		x			x	
Month fixed effects			x			x

Values shown are the coefficients of fixed effects regressions of monthly construction permits in megawatt at the district level, excluding observations within a window of six months before and after the introduction of the 10 H rule. The percentage decrease of building permits in Bavaria relative to the counterfactual is also tabulated. Standard errors clustered at the state level are in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table A-2-4: Effect of minimum distances on permits, excluding twelve months window

Dependent Variable:	All permits			Permits under minimum distance regulation		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: Minimum distance regulation	-0.419***	-0.419***	-0.419***	-0.515***	-0.515***	-0.515***
	(0.0958)	(0.0958)	(0.0959)	(0.0958)	(0.0958)	(0.0959)
Change [%]	-71	-71	-71	-88	-88	-88
Observations	21,654	21,654	21,654	21,654	21,654	21,654
Year fixed effects	x			x		
Quarter fixed effects		x			x	
Month fixed effects			x			x

Values shown are the coefficients of fixed effects regressions of monthly construction permits in megawatt at the district level, excluding observations within a window of 12 months before and after the introduction of the 10 H rule. The percentage decrease of building permits in Bavaria relative to the counterfactual is also tabulated. Standard errors clustered at the state level are in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Spillover effects

Table A-2-5 shows that our findings are qualitatively robust to spillover effects. We re-estimate the treatment effects under the assumption that all wind turbines that were not built in Bavaria were immediately constructed elsewhere in the country. The estimation is implemented by reducing the wind permits of all other German states by the amount of permits not issued in Bavaria and re-estimating the models of Table 2-2 based on these reduced permits. As can be seen from Table A-2-5, the point estimates of the treatment effect decrease in this scenario relative to the main specifications in Table 2-2. However, the relative reduction of construction permits in Bavaria remains virtually unchanged (-88 percent in the preferred specification). The reason is that the counterfactual development of Bavarian permits decreases when permits in the rest of Germany are assumed to be lower.

Table A-2-5: Effect of minimum distances on permits, correcting for possible spillover effects

Dependent Variable:	All permits			Permits under minimum distance regulation		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: Minimum distance regulation	-0.222**	-0.229**	-0.235**	-0.328***	-0.332***	-0.342***
	(0.0799)	(0.0813)	(0.0833)	(0.0805)	(0.0819)	(0.0834)
Change [%]	-50	-51	-52	-84	-85	-88
Observations	31,278	31,278	31,278	31,278	31,278	31,278
Year fixed effects	x			x		
Quarter fixed effects		x			x	
Month fixed effects			x			x

Values shown are the coefficients of fixed effects regressions of monthly construction permits in megawatt at the district level. The regressions correct for a hypothetical full spillover, under the extreme assumption that all wind turbines not built in Bavaria were directly built elsewhere in Germany. To implement this, permit data in non-Bavarian districts are reduced by the difference between predicted permits (according to the common trend assumption) and actual permits in Bavaria. The percentage decrease of building permits in Bavaria relative to the counterfactual is also tabulated. Standard errors clustered at the state level are in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Regressions without approximation of permit date

Our regression results also hold when we restrict the sample to only those observations where we have information on both the date of construction and the permit date from the *Anlagenregister*. To show this, we reproduce our results from Table 2-2 using only installations where we have information on both construction date and permit date. The results are qualitatively the same, but the effect of the 10 H regulation is even more pronounced: With this subset of installations, it rises to -78 percent (all permits), and -94 percent (10 H permits only, see columns 3 and 6 of Table A-2-6).

Table A-2-6: Effect of minimum distances on permits, using only turbine data with full information on the construction permit date

Dependent Variable:	All permits			Permits under minimum distance regulation		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: Minimum distance regulation	-0.572***	-0.588***	-0.647***	-0.701***	-0.715***	-0.781***
	(0.0894)	(0.0912)	(0.106)	(0.0894)	(0.0909)	(0.106)
Change [%]	-69	-71	-78	-84	-86	-94
Observations	31,278	31,278	31,278	31,278	31,278	31,278
Year fixed effects	x			x		
Quarter fixed effects		x			x	
Month fixed effects			x			x

For this table, we re-estimate the treatment effects of Table 2-2, using only wind turbine from the *Anlagenregister* that have information on the date of the building permit of the wind turbine. We thus discard all observations with an approximated permit date. Values shown are the coefficients of fixed effects regressions of monthly construction permits in megawatt at the district level. The percentage decrease of building permits in Bavaria relative to the counterfactual is also tabulated. Standard errors clustered at the state level are in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Chapter 3

The role of aggregators in facilitating industrial demand response: Evidence from Germany*

Abstract

Industrial demand response can play an important part in balancing the intermittent production from a growing share of renewable energies in electricity markets. This chapter analyses the role of aggregators – intermediaries between participants and the power markets – in facilitating industrial demand response. Based on the results from semi-structured interviews with German demand response aggregators, as well as a wider stakeholder online survey, we examine the role of aggregators in overcoming barriers to industrial demand response. We find that a central role for aggregators is to raise awareness for the potentials of demand response, as well as to support implementation by engaging key actors in industrial companies. Moreover, we develop a taxonomy that helps analyse how the different functional roles of aggregators create economic value. We find that there is considerable heterogeneity in the kind of services that aggregators offer, many of which do create significant economic value. However, some of the functional roles that aggregators currently fill may become obsolete once market barriers to demand response are reduced or knowledge on demand response becomes more diffused.

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3.1 Introduction

In many countries, the electricity system is currently undergoing substantial changes. The continuously growing share of renewable energies leads to an increase in the number of generation units, while installed capacity per unit decreases. Second, the volatility of electricity generation rises and the traditional paradigm of generation following load is no longer valid. Consequently, a flexible (intentionally responsive) demand side – so-called demand response – gains importance as an effective measure to maintain grid stability and reduce the need for costly grid expansions or backup generation capacity (Strbac 2008; Eid et al. 2016).

Generally, demand response means that electricity consumers change their consumption in response to external signals. These signals can be either price signals from the day-ahead or intraday market, or direct signals from the transmission system operator to activate balancing power (see e.g. Ikäheimo et al. 2010; EC 2013; SEDC 2015). Suppliers of demand response typically offer units that are smaller than traditional generators, and their active participation in electricity markets marks a new territory for many electricity market stakeholders. A large share of the cost-effective demand response potential lies in industry (Gils 2014).

These developments lead to the evolvement of a new actor – the demand response aggregator Different definitions of aggregators exist. In general, aggregators can market both supply side and demand-side units, acting as intermediaries between distributed energy resources (demand response, distributed generation and energy storage) and the power markets. The aggregated pool can be utilised as a single resource, similar to a large conventional power plant. Burger et al. (2017, p. 396) define aggregation as "[…] the act of grouping distinct agents in a power system (i.e. consumers, producers, prosumers, or any mix thereof) to act as a single entity when engaging in power system markets (both wholesale and retail) or selling services to the system operator(s)".

The focus of this chapter is the facilitation of industrial demand response. Therefore, we restrict our analysis to aggregators that market at least some demand response units. This leads to the following definition of demand response aggregators:

An aggregator pools distributed units and markets their generation capacity (generation plants) or demand-side flexibility (electricity consumers) on the spot market, balancing power market and possibly further markets. For this purpose, the aggregator provides recommendations (or control signals) for the units' generation or load profile. Demand response aggregators are aggregators that (also) market demand-side flexibility.

This chapter studies to what extent demand response aggregators help overcome barriers to industrial demand response. A second focus of the chapter is to analyse the activities through which aggregators create long-run economic value. We do so by developing hypotheses regarding functional roles (activities) of aggregators and testing these hypotheses by conducting semi-structured interviews with demand response aggregators, as well as an online survey with different electricity market participants and other stakeholders. We focus on the German market, since Germany is a major industrialised country that has seen a rapidly increasing share of renewable electricity in recent years (Fraunhofer ISE 2019). The interviews and the survey help to understand how demand response aggregators facilitate industrial demand response.

In a next step, we derive a taxonomy mapping six different functional roles that aggregators can assume to a framework of economic value creation by aggregators developed by Burger et al. (2017). We use the taxonomy to evaluate the economic values created by the aggregation of demand response. Finally, we discuss which of the economic value created by the aggregators' functional roles can also be captured by regulatory changes to the market design. Thus, we examine the role of demand response aggregators in today's electricity markets, as well as how this role may evolve in the future.

3.2 Industrial demand response, electricity markets and barriers

3.2.1 Overview of German electricity markets and reserves

The German wholesale electricity market is organised as a so-called energy-only market (EOM).[34] An EOM only remunerates the electricity that is generated, unlike a capacity market, which provides explicit incentives to invest in electricity generation capacities (or demand response). To secure grid stability, the EOM in Germany is supplemented by the balancing energy market and other ancillary services (such as cold start capabilities, voltage control etc.). Furthermore, to guarantee security of supply, there are additional reserves that have not been competitively tendered, which compensate capacities from power plants that have been temporarily shut down, are in cold reserve or are merely on standby.

Electricity is traded on the EOM either in over-the-counter trading, based on bilateral agreements based on various types of products, or on the electricity exchange. The spot market of the electricity

[34] The basis for the market design is the act on the further development of the electricity market („Gesetz zur Weiterentwicklung des Strommarktes (Strommarktgesetz)") of 2016, which can be accessed at https://www.bgbl.de/ (in German).

exchange consists of two markets. First, on the day-ahead market trading takes place within auctions with an hourly resolution until the day before delivery. On the intraday market, electricity can be traded until five minutes before delivery at the latest. In principle, participation to the EOM is open to all actors, and minimum trading volumes are fairly low (0.1 MW on the day-ahead market). However, balancing responsibility in Germany is organised in portfolios, so-called balancing groups ("Bilanzkreise"), which are managed by a balance responsible party (BRP). These actors – often the electricity supplier of a consumer – are responsible for keeping the schedule in balance via matching of production and consumption of all their participating parties and by trading and netting foreseeable imbalances. Balance responsible parties bear imbalance costs for any imbalances resulting from short-term deviations from the schedule. As a result, unless consumers are BRPs themselves[35], the cooperation of the BRP is needed in order to participate in wholesale electricity markets.

The control power market comprises three types of reserves: the primary control (PRL), the secondary control (SRL) and the minute reserve (MRL), which vary in terms of their activation time until full power must be provided (30s/5 min/15 min), the provision time (max. 15 min/up to 1h/15 min up to several hours), and various requirements for the bidders such as minimum bid sizes (1 MW/5 MW/5 MW), type of activation (automatic/automatic/manual) and availability requirements.[36] Participation in these reserve markets is limited based on technical criteria. In order to be licensed to provide balancing power, the provider must first undergo a prequalification procedure, in which the suitability of the proposed technical unit (or pool of units) is inspected and tested. For the PRL only a capacity price is paid, i.e. the remuneration is based on the capacity held available. The remuneration of the SRL and the MRL includes both a capacity price component and an energy-related component. Similarly, to the EOM market, cooperation by the BRP is needed to offer flexibility in the control reserves; however, BRPs are obliged by regulation to enable participation in these reserves (StromNZV §26a).

In the context of flexible industrial processes, the directive on switchable loads (AbLaV)[37] is also relevant. Loads contracted under AbLaV can be switched off by the transmission grid operator on very short notification periods in the event of grid congestion in order to reduce the load.[38] As with control power, the loads are contracted through tenders issued by the transmission grid operators.

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[35] Large industrial consumers, for example, sometimes manage their own balancing group.
[36] www.regelleistung.net.
[37] "Verordnung über Vereinbarung zu abschaltbaren Lasten". https://www.gesetze-im-internet.de/ablav_2016/
[38] There are two categories, 350 milliseconds and 15 minutes.

3.2.2 Potential for industrial demand response in Germany

A number of bottom-up studies have estimated that there is a significant potential for demand response in the German industry. A major share lies in the energy-intensive industries, such as aluminium, steel, cement, paper and the chemical industry. Most studies focus on technical potentials, hence neglecting practical and economic aspects. Moreover, flexibility potentials are differentiated between industrial processes and cross-sectional technologies, such as compressed air, lighting, heating and cooling.

For Germany, technical load reduction potentials in the range of 2 GW to 3 GW have been found for production processes in the energy-intensive industry. Potentials for load increase are smaller, ranging between 0.3 GW and 1.3 GW (see e.g. Klobasa 2010; Paulus and Borggrefe 2011; Langrock et al. 2015; Gruber 2017; Steurer 2017). Estimated potentials differ due to different methods and assumptions (Dufter et al. 2017; Müller and Möst 2018). The literature on cross-sectional technologies, on the other hand, is rather scarce, although corresponding demand response potentials are not negligible. Depending on the time of activation, potentials for load reduction vary between 1.2 GW (one hour of activation) and 0.6 GW (several hours of activation). Again, potentials for load increase are smaller, ranging between 1 GW (one hour) and 0.2 MW (four hours, see Gruber 2017; Steurer 2017). Gils (2014) finds demand response potentials for processes and cross-sectional technologies of 4.4 GW and 0.8 GW for load reduction and load increase, respectively.[39]

In sum, load reduction potentials of approximately 3 to 4.4 GW can be assumed for processes and cross-sectional technologies in the German industry. This equals to a demand response potential of 3.8 percent to 5.5 percent of peak load in Germany that could be realised in the short term.[40] This is in line with a review of the potentials for industrial demand response in several Northern European countries by Söder et al. (2018), who find load reduction potentials of 4.7 percent - 7.1 percent of peak load. Note that the actual economic potential of demand response is smaller than the technical potential. The economic potential may vary over time with the system need for flexibility, as well as market and system service prices.

3.2.3 Barriers to industrial demand response

Electricity customers are traditionally used to a constant supply with electricity, which makes demand inelastic (Torriti et al. 2010). While not all technical potential of demand response can be

[39] Considering that technical barriers are disregarded, the potentials appear rather small compared to the studies listed above.
[40] Peak load equals approximately 80 GW in Germany (ÜNB 2018a).

economically leveraged, additional hurdles to exploit the economic potential of demand response exist. Barriers to economic industrial demand response can broadly be categorised into barriers at the firm level (behavioural and/or organisational), informational barriers and barriers related to the market design (or regulatory environment).[41]

On the firm level, the priority of industrial firms is to maintain a good relation with their customers. This means that product quality may not suffer due to demand response and delivery periods must be kept. Consequently, load shedding is typically not an option in industry, but the focus is on shifting demand from one point in time to another (Arnold et al. 2018). Moreover, an important behavioural barrier in the context of demand response is the issue of trust between the provider of demand response (firm) and the buyer (e.g. demand response aggregator, see Good et al. 2017). The issue of trust has several dimensions. Most importantly, industrial clients may be reluctant to share the control of their production processes with another company. Additionally, firms may also be worried to pass on sensitive data. Finally, consumers (both firms and individuals) may be characterised by inertia (reluctance to change behaviour or adapt organisational structures) and bounded rationality (settling for the "good enough"; see Kim and Shcherbakova 2011; Good et al. 2017). This means that firms may not engage in demand response, although it would increase their profits.

Regarding informational barriers, one central problem of including demand response as a resource similar to a generator according to the literature is the difficulty of calculating a baseline consumption (Nolan and O'Malley 2015). This baseline is needed in order to remunerate deviations from the consumption profile that was originally planned. Moreover, ICT infrastructure needs to be installed in order to use units in demand response programmes. This technical equipment is costly (Eid et al. 2016). Third, there are transaction costs associated with collecting and processing demand response market information (Good et al. 2017).

There are a number of barriers to industrial demand response related to market design. First, there are often no rules that (implicitly) consider demand response participation in the provision of different services. In other words, appropriate market structures are missing (Cappers et al. 2013; Koliou et al. 2014). This is a problem in the EU, where there are no homogeneous demand response products over different European countries (Paterakis et al. 2017). To explicitly define the role of an aggregator in providing energy services by demand response is especially important when retailer and balance responsible party are two different entities (Vallés et al. 2016).[42] There are also explicit

[41] For a comprehensive review of barriers, see O'Connell et al. (2014) and Good et al. (2017).

[42] In Germany, units that want to offer flexibility on the balancing power markets had to come to an agreement with the balance responsible party to keep the balance with all other participants until the year 2017. Due du a legislative change in Germany in 2017, balancing responsible parties are now obliged to grant third-party aggregators access to the balancing

barriers to market entry such as minimum bid size to participate in balancing markets (Paterakis et al. 2017).

Second, network tariffs can have an important effect on the incentives for demand response (Vallés et al. 2016). As Perez-Arriaga et. al. (2017) point out, yearly peak demand-related charges (fixed charges) may have detrimental effects. The reason is that deviation from a flat demand profile is penalised, as Richstein and Hosseinioun (2020) confirm in a simulation study. This reduces the revenues that can be achieved for flexibility and makes demand response financially less attractive. In Germany, there are explicit disincentives for demand response due to exemptions from the network tariffs regulation that hinge on high full-load hours demand profiles.[43] Third, on the spot markets (day-ahead and intraday), the level and volatility of electricity prices determine the profitability of demand response. Uncertainty on the number and the duration of high-price periods due to possible changes in the future regulatory environment are an obstacle to investments in demand response (Ländner et al. 2019). This holds for both wholesale markets, as well as control power markets.

3.3 Methodology and hypotheses on the roles of aggregators

3.3.1 Methodology

We use a mix of different qualitative methods (Creswell and Plano Clark 2011) to answer our research questions on the functional roles of aggregators and the barriers to industrial demand response that can be overcome by aggregators. In a first step, we developed hypotheses on the functional roles of aggregators (section 3.3.2). We also carried out a desktop research to identify key stakeholders for our subsequent empirical case study consisting of interviews, an online survey and a stakeholder workshop.

Second, we carried out semi-structured interviews with German demand response aggregators in order to identify the type of economic value aggregators create. We conducted a series of five interviews with aggregators covering a major share of total demand response portfolio of all German aggregators. In order to identify the relevant players, a desk research was carried out in order to identify all German aggregators that market demand response (Table A-3-1 in the Appendix).

power markets (§§ 26a, 27 Abs. 1 Nr. 23 StromNZV, operationalized by Az. BK6-17-046, BNetzA). However, no obligation to provide third-party access to intraday markets exists.

[43] § 19 StromNEV par. 2 on agreed individual (reduced) grid utilisation fees was originally designed to incentivise grid utilisation in off-peak hours. However, when a firm deviates from its usual load pattern due to demand response, the change in the demand profile may result in high penalties that can hardly be compensated by higher revenues from demand response.

Next, the 12 aggregators we identified were contacted to identify their portfolio size. Five interviewees representing more than half of the combined portfolio size marketed by all German aggregators were available for an interview. The interviews lasted 1.5-2h each and were either held in person or by telephone between July and December 2018. The goal was to test the hypotheses we developed, and adapt them where necessary. Moreover, the interviews provided valuable insights in the business models of the different aggregators, such as the kind of markets they serve.

Third, the results of the interviews were discussed in a one-day stakeholder workshop among a broader group of experts consisting of aggregators, as well as stakeholders from industry, utilities, network operators and research. The workshop was complemented by an online survey, using a questionnaire with half-open questions. The survey was sent in advance to participants of the stakeholder workshop with 20 participants, which was held at DIW Berlin on 14 April 2019. 15 of the 20 participants of the workshop (75 percent) took part in the survey, including representatives from three aggregators, four firms that market some of their flexible demand, three network operators, three researchers and consultants, one energy utility and one power exchange.

In a fourth and final step, we develop a taxonomy linking the functional roles of aggregators to the creation of different types of economic value, building on the findings from our interviews and the survey. The taxonomy maps different roles of aggregators that facilitate industrial demand response to different types of economic value created by aggregators (see Burger et al. 2017). The taxonomy is discussed in Section 3.5.

3.3.2 Hypotheses on the functional roles of aggregators

There is a long history of the literature on the roles of aggregators (or retailers[44]) and the value they bring to the electricity market, starting with the discussions between Joskow (2000) and Littlechild (2000) on whether retailer competition is expected to bring economic benefits to electricity markets. Whereas Joskow argued that little is to gain from retail competition, and a regulated pass-through of wholesale prices to consumers would entail lower costs, Littlechild argues that retailers have important roles to play in price formation (especially for forward markets), and in terms of providing value-added services.

Updating the debate to current conditions in electricity markets, Burger et al. (2017) give an overview of the related literature on the value that aggregators (may) provide and identify three categories of economic values. The first group consists of *fundamental* benefits of aggregation, which leads to

[44] Retailers have been ascribed a more active role (similar to the one of aggregators) in earlier literature.

efficiency improvements in the system, regardless of market structure and regulatory imperfections. The second group of economic values comprises *transitory* benefits that may resolve over time with market or technological development. Finally, the last group encompasses the *opportunistic* value of aggregation, resulting from imperfections of market design.

We develop a set of functional roles that demand response aggregators may fulfil in the process of marketing demand-side resources.[45] These (hypothesized) roles were used in the development of the semi-structured questionnaire for the interviews with aggregators. Building on the results of these interviews (Section 3.4), we finally develop a taxonomy in Section 3.5 that maps the set of aggregator roles to the categories of economic values developed by Burger et al. (2017). In the following, the hypothesised functional roles of demand response aggregators are shortly described:

Identification of flexibility potentials

This functional role concerns the identification of flexibility potentials in industrial companies. The hypothesis is that aggregators may help companies identify potentials for demand response flexibility within their organisation.

Realisation of flexibility potentials

This functional role concerns the realisation of flexibility potentials, that is, all activities between the identification of the potential and the first activation and marketing of the resource. This may be installation of ICT infrastructure, (support of) prequalification procedures for reserve power markets, staff training etc.

Automation

This role concerns the automation of providing flexibility measures. In this chapter, we define automation as the automated activation of flexibility options at the industrial site, and not as automated trading. Automation may simply entail sending the customer control signals, but it may also include a fully automated and integrated resource planning, which optimises production under consideration of electricity costs and revenues from providing electricity services. The role of automation may be closely interlinked to the role of participation in electricity market.

Participation in electricity markets, services & provision of related information

[45] Note that these roles need not necessarily be fulfilled by aggregators, but other actors may also perform the same functions.

This function comprises the participation in electricity markets and services by the aggregator on behalf of its customers, as well as the provision of related information (such as prices) to companies. It is often implemented through an automated control of demand-side resources, but could in principle be performed separately (depending on the market structure and regulatory environment).

Provision of risk management products & suitable contracts for companies

Aggregators may also provide risk management products, as well as suitable contracts for industrial companies. This may either be standardised contracts traded on exchanges, or non-standardised contracts tailored to companies, where a residual risk remains with the aggregator. There is a certain overlap to the business model of retailers, where the demand response aggregator is also the energy provider of the industrial client.

Bundling of services

Aggregators may bundle several services and offer those combined services to their clients. These different services could be the participation in several types of electricity markets, but also the co-optimisation of electricity with other energy markets.

The next section discusses empirical findings from the aggregator interviews, as well as the online survey. A ranking of the relative importance of the different functional roles is given in section 3.4.7.

3.4 The functional roles of aggregators: Empirical findings

3.4.1 Identification of demand-side flexibility

The interviews showed that when marketing demand-side flexibility in Germany, the first impulse for the identification of potentials typically comes from the aggregator. In other words, aggregators pro-actively search for and contact new customers, while the reverse seems to be the exception. In doing so, aggregators help to overcome the barrier of companies' inertia to engage with the topic. If aggregators cannot access existing customers from other industries or want to contact additional customers, the industry sector is a first criterion for the selection of the companies to be contacted. The reason is that, based on their understanding of production processes and technologies, aggregators typically have expectations regarding the flexibility potential of companies in a given industrial sector.

There was no consensus among interviewed aggregators if learning takes place, i.e. whether the knowledge gained on the identification of typical demand response potentials can be transferred to

the identification of potentials in other companies within a sector. However, aggregators agreed that the identification of the actual potentials of a company is usually not a big hurdle due to the wide diffusion of energy management systems among industrial customers. Energy management systems simplify the identification of potentials, since all industrial processes with their capacities and energy requirements are already recorded.

Both the interviews and the responses to the questionnaire showed that for an exact determination of potentials that go beyond those of standard processes, a cooperation between the aggregator (knowledge of electricity markets) and the company (knowledge of technical facilities) is necessary. Moreover, the interviews revealed that for the identification of flexibility potentials, the different requirements of the electricity markets and the control power markets (see Section 3.2.1) are decisive. For participation in the control power markets, for example, the short-term controllability of the processes, the ability to perform defined gradients as well as a suitable continuity in the availability of the load are central in order to fulfil the prequalification conditions. The requirements for participation in the electricity markets are lower. Here, however, participation is only worthwhile if a certain amount of energy can be marketed - with any associated effects on the production processes (see Section 3.2.3).

3.4.2 Realisation of potentials

The aggregator interviews revealed the central importance of the aggregator's role of helping to realise demand response potentials. One major result is that the hurdles for the realisation of flexibility potentials are often organisational rather than technical. A main challenge stressed during the interviews is that demand-side flexibility (or sophisticated energy procurement) is typically not reflected in the organisation of (potential) customers.[46] The aggregators saw this as the biggest challenge for the realisation of flexibility potentials.[47]

A large part of the aggregator's work therefore consists of triggering a "change process": Finding the right contact person in the company and convincing them to consider offering demand response. This process includes establishing a first contact within the company with electricity buyers, followed by the energy manager, the technical production manager, and finally management. The interviews revealed that in this process, building trust with a future client is of central importance, and that this process may take several years. For many services, the aggregator has to be granted (automated)

[46] An exception are large companies and power-intensive industries, which often deal with this issue due to their high electricity costs already.
[47] One reason given for this was that the expected revenues from marketing flexibility are currently very low in Germany.

control of processes. Offering demand-side flexibility in core production processes in particular therefore requires good previous experience with automation in peripheral plants. By helping to put the topic of demand side flexibility on the agenda of companies, aggregators contribute to addressing the barrier of a low priority of demand-side flexibility.

The online survey confirmed the major importance of the functional role of realising demand response potentials. Respondents rated this activity as the most important role of aggregators (see section 3.4.7). It includes infrastructure development, support for "change processes", as well as support for prequalification processes. In addition, the survey also showed that most respondents perceived aggregators as an important support in the installation of the ICT infrastructure that is required for marketing of flexibility.

The barrier of a lack of a client's trust to grant the aggregator access to sensitive data of the industrial site, on the other hand, was not confirmed to constitute a major barrier in the online questionnaire. Several respondents mentioned that non-disclosure agreements are a typical solution to this issue.

3.4.3 Automation

The required degree and depth of automation of an activation of flexibility depends on the market where the flexibility is offered. For primary control, secondary control and ABLaV, an automatic activation of flexibility (of the pool offered by the aggregator) by the transmission system operator (TSO) is mandatory. Within the aggregator's pool of dispatchable resources, an automated control of the individual technical units by the aggregator is required for these products.

From a technical point of view, a fully automated control of the client's technical units by the aggregator is typically not a problem. However, the industrial company always has the option (depending on the operating status of the plant) of either (automated) vetoing the activation of flexibility for slower products or declaring a non-availability of units ex-ante. In the event of a veto or deviation by the industrial company, the aggregator must provide back-up capacity to ensure that the flexibility promised to the TSO can be provided.

For participation in the minute reserve and the electricity markets, the level of automation differs between the different aggregators we interviewed. In these markets, direct access by the aggregator to individual technical units of the industrial company is not (legally) required. In these cases, it may be sufficient that the aggregator provides recommendations for the operation of a unit, and the company decides whether to implement these recommendations.

3.4.4 Participation in electricity markets

Aggregators help to overcome market entry barriers by allowing industrial loads to participate in markets that would otherwise be closed to them. Examples of such markets include the reserve markets, which require a minimum bid size and back-up capacity (see Section 3.2.1). However, some aggregators reported that they also have clients that are large enough to engage in all electricity markets themselves, but choose to work with a demand response aggregator. One reason for this is a reduction of costs for participating in markets such as the certified ICT infrastructure in the balancing markets, which aggregators reported to be a costly hurdle for industrial companies.[48] Many of the aggregators we interviewed provide the ICT infrastructure to the client without a fee as part of their service.

As discussed, automation and participation in electricity markets are tightly interlinked. Aggregators take different approaches of trading on spot markets associated with different automation needs. These approaches range from simple threshold strategies to complex models that optimise the use of a pool across different markets. Some aggregators only provide market information, leaving the use of this information to their clients. On the other hand, one of the aggregators interviewed uses a complex optimisation model, which is used to trade continuously in the intraday market on a 24-hour basis, requiring automated call-offs. Here, automation saves substantial resources, since companies would need a 24-hour trading desk to participate in these markets without automated call-offs. Again, the industrial company may always decide to deviate from the schedule provided by the aggregator, thus retaining control of their production processes.

Aggregators thus help to overcome barriers constituted by transaction costs associated with market participation. Another important role of aggregation towards this end is the reduction of the need for backup capacity. This is especially relevant in the case of balancing markets, where there are strict requirements for availability. It is much more costly to fulfil these requirements for an individual industrial company, than for a pool of different loads.[49] Therefore, all the aggregators we interviewed rely on a pool of demand-side resources to reliably deliver demand response by providing redundant capacity when they are selling capacity on the balancing markets.

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[48] Balancing power is seen as "critical infrastructure" (KRITIS) in Germany, and is therefore subject to stricter (more costly) regulation with respect to the security of the IT infrastructure (ÜNB 2018b).

[49] On the German balancing markets, generation or load can only be marketed according to the "N-1"-criterion. This means that out of a pool of resources prequalified for the balancing markets, all but one units can actually be marketed, such that there is back-up capacity in case one of the units does not deliver. In the absence of an aggregator, a company with two flexible units would have to withhold one of them, leading to much higher costs. In a larger pool of an aggregator (large N), on the other hand, the costs of withholding one unit are relatively much smaller.

Again, not all barriers named in the literature seem to be relevant in the context of industrial demand response in Germany. Regarding participation, the difficulty of calculating a baseline consumption was *not* confirmed to constitute a barrier for the cooperation between aggregators and their customers in the interviews. The reason is that balancing responsible parties need to report schedules to the TSO, and are thus already reliant on reports from industrial customers regarding their projected (baseline) consumption.

3.4.5 Provision of hedging

The responses to the online questionnaire showed that uncertainty about future price developments and regulatory changes constitute a barrier to industrial firms' engagement with flexibility issues. However, the potentials of aggregators to overcome this barrier are seen as low, as those issues are beyond the control of the aggregator.

In the interviews, aggregators reported major differences between the types of contracts offered to their clients. On the one extreme, risks and revenues are shared between aggregator and client. On the other hand, some aggregators offer a certain insurance against short-term spot market price risks, for example by guaranteeing minimum revenues from selling flexibility. In some cases, risk management products are also offered for longer time horizons. The aggregator typically asks for an additional premium for these risk management products. For some clients, risk hedging is even more important than the extra revenues from a marketing of flexibility.

When the aggregator is also the energy supplier of its client, it may offer an integrated package of a hedging product (fixed prices of electricity supply), as well as potential revenues from a marketing of demand response. Generally, the more risks the aggregator takes on, the more important it becomes to have a high level of control over the client's production processes.

3.4.6 Bundling of services

The aggregators we interviewed serve a very different set of markets, ranging from only primary control reserve, to a range of electricity and gas markets. While some are only active in marketing the ancillary service balancing power, others focus on the intraday and day-ahead markets. These different activities have implications on the view of whether an aggregator should also be the balance responsible party (BRP), as well as the electricity supplier for its client. Larger industrial companies often manage their own balancing group, and for aggregators only active in the balancing power markets there is no need to be either balance responsible party or supplier. For aggregators with a broader market scope, on the other hand, an integrated role (aggregator, BRP and supplier) is vital,

since it guarantees access to the intraday and day-ahead markets and allows for an integrated optimisation of electricity market activity and the costs for balancing energy.[50]

One major advantage of bundling several services to a client, for example by combining the roles of energy retailer and aggregator marketing industrial demand response, is the reduction of acquisition costs. Since engaging potential customers to market industrial load is a major challenge (see section 3.3.2), reducing acquisition costs by building on trust established in an existing business relationship may be of significant value to the aggregator. Additionally, an integrated portfolio management of electricity and gas markets may also lead to efficiency gains, especially for companies also owning (gas) generation units, or running processes with possible hybrid operation modes.

3.4.7 Ranking of the importance of the different aggregator roles

Building on the interviews, we assess the relative importance of the functions we hypothesized aggregators may fulfil to facilitate demand response. To this end, we used the online survey carried out among participants of the stakeholder workshop (discussed in Section 3.3.1) in order to get a sense how stakeholders from industry, network operators and research value the relative importance of these different functional roles.

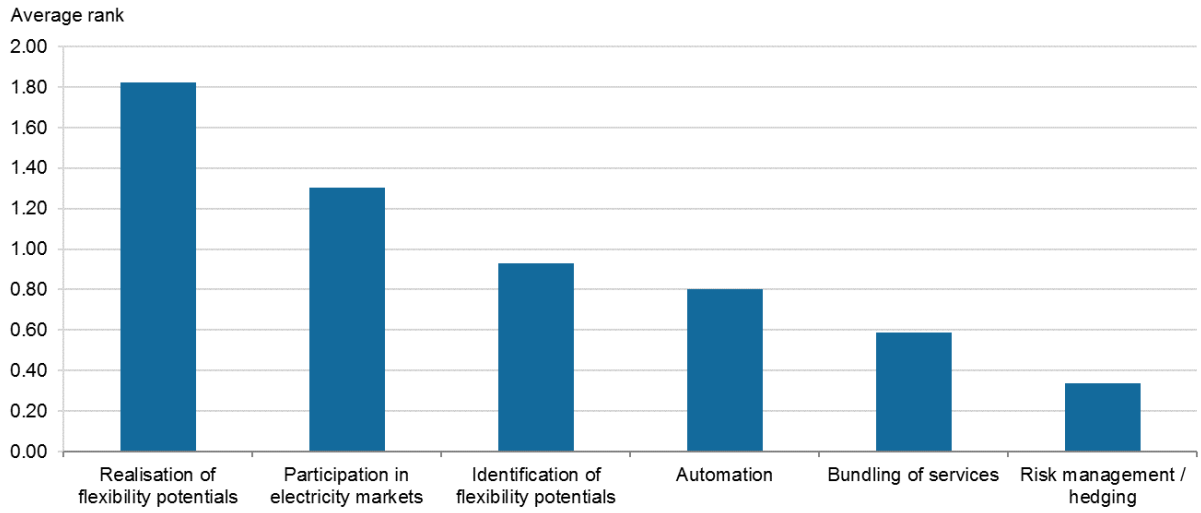
Figure 3-1 graphs the relative importance of the six different functional roles. Participants of the survey were asked to name the three most important roles of aggregators to facilitate demand response. Respondents could choose one of the six roles we hypothesized, or come up with different roles. From these answers, for each role an average rank is calculated, which ranges from a theoretical value of three (if all of the respondents choose that specific role as the most important one) to zero (if none of the respondents names the role).

The realisation of flexible demand resources emerged as the most important function of aggregators (average rank of 1.8), followed by allowing small loads to participate in electricity markets (e.g. in reserve markets) and providing related information (average of 1.3). Consequently, this confirms that processes of organisational change in order to realise and market potentials that are theoretically available are a major function that aggregators perform. Moreover, hurdles to the participation in electricity markets such as minimum size requirements in reserve markets are also an important barrier that is overcome by aggregation. Interestingly, the identification of processes suitable for demand response was considered as less important (average rank of 0.9). This is in line with the

[50] The European Commission has recognised the importance of market access for the demand side. In its 2016 "Winter Package", it calls for a "non-discriminatory access" of the demand side to "all organised markets", including demand response offered through aggregators (EC 2016).

result from the aggregator interviews that identification of flexible demand resources within companies is typically not a major hurdle (Section 3.4.1). Moreover, risk management was deemed to be only of minor importance.

Figure 3-1: Relative importance of the different functional roles of aggregators



The figure plots the responses from our online survey (section 3.3.1) on the relative importance of aggregator roles. For the calculation of average ranks, we assign the values three to one to the functional roles of aggregators that have been named as the most important ones (rank one to three) for every respondent. For every role, we then compute the average rank over all respondents (correcting for multiple answers). The maximum value a role could have is three, which would result if all respondents chose the same role as the most important one.

3.5 Market design and the economic value of aggregators: Taxonomy and discussion

Although there is considerable heterogeneity in the kind of services that aggregators offer, the functional roles we developed were confirmed as relevant in the interviews. In a next step, we develop a taxonomy that maps aggregator roles to the value categories developed by Burger et al. (2017), introduced in Section 3.3.2 (see Table 3-1 for the subcategories). The goal of the taxonomy is to analyse how aggregators create economic value. Specifically, we discuss whether the functional roles of aggregators are central to their business model, and whether they will remain to be important under an evolving market design. Functional roles that predominantly provide fundamental value will probably also be central to the business model of aggregators in the future. Transitory values, on the other hand, may become less important as the market for demand response matures. Finally, value derived from regulatory imperfections may cede to be of economic value if the regulatory framework is developed further.

The drivers for fundamental value creation are economies of scale and scope, managing uncertainty and price risks and increased competition and potential for innovation (both business and technical) by heterogeneous market actors (Burger et al. 2017). On the other hand, the closing of market information gaps, engaging distributed agents in electricity markets, as well as automation and coordination issues with TSOs and exchanges are only of transitory value. These activities may lose importance if market design improves and behaviours and technologies favouring demand response are widely adopted in the market. Finally, Burger et al. identify several regulatory imperfections (such as group balance responsibility, penalties for non-provision of reserves), which favour the use of aggregators without creating fundamental economic value.

Table 3-1 maps the discussed functional roles to the value categories, based on the discussion in the previous section. It becomes clear that nearly all functional roles bring some fundamental benefits, and are additionally either of transitory value, opportunistic value, or both.

Table 3-1: Taxonomy of functional roles of aggregators and economic value creation

Values	**Fundamental**				**Transitory**			**Opportunistic**
Functional Role	**Economies of scale**	**Economies of scope**	**Managing uncertainty & price risks**	**Competition & innovation**	**Market information gaps**	**Agent engagement & automation**	**Coordination issues (TSO, exchanges)**	
Identification of flexibility potentials	(x)	(x)			x	x		
Realisation of flexibility potentials	x			x		x	x	
Automation	x	x		x		x		
Participation in electricity markets & provision of information	x	x			x	x	x	x
Provision of risk management products & suitable contracts	x		x	x	x		x	
Bundle several services		x		(x)			x	x

The table matches functional roles of aggregators to the categories of value creation developed by Burger et al. (2017).

3.5.1 Identification of demand-side flexibility

On the one hand, this function is important in terms of agent engagement, as previously non-active parties on the power market may become aware via aggregators of the (potential) opportunities of demand-side flexibility. Moreover, industrial companies can benefit from aggregators' know-how on electricity markets. This is an important role, but may prove transitory if demand response becomes more prevalent, e.g. due to higher price volatility on electricity markets. Within the interviews, there were conflicting views on whether experience gained in identifying flexibility potentials can be transferred within and across industries (see Section 3.4.1). It is therefore unclear whether there are significant economies of scale and scope via aggregators for this functional role. Possible reasons that these may not exist is the uniqueness of large industrial processes.

3.5.2 Realisation of potentials

For realisation of flexibility potentials, the interviews revealed that the major value added by aggregators is also agent engagement. Interviewees named the lack of a suitable organisation structure and set-up to realise demand response as a major hurdle (cf. Section 3.4.2) – as demand response gets more profitable and diffused, this hurdle may be reduced and prove to be transitory. Second, aggregators may solve coordination issues with TSOs (and to a lesser degree power exchanges). Examples include the pre-qualification of units, as well as the establishment of certified ICT infrastructure. While this work entails some economies of scale (as pre-qualification procedures and establishing ICT infrastructure are similar over different companies), there is partly a transitory value to it. The reason is that the issue of coordination depends on regulation, as well as the currently limited know-how of companies. Finally, realisation entails some fundamental value connected to innovation and competition regarding ICT infrastructures and business models. Aggregators may compete on technical and organisational innovations. Moreover, there are economies of scale for the installation of ICT infrastructure, such as standardised energy boxes (cf. Burger et al. 2017).

3.5.3 Automation

Automating demand response processes offers several fundamental values, such as economies of scale and scope due to the aggregation of consumers on fewer, larger ICT systems. There are larger economies in the case of central aggregation as opposed to having many aggregators (Burger et al. 2017). Differing automation solutions may also lead to increased competition and innovation between aggregators, in this case with benefits from having many aggregators. The fact that

aggregators typically provide free ICT infrastructure to their clients (Section 3.4.3) reduces transaction cost for the customer.

Part of the value of increased automation that aggregators may bring is in terms of agent engagement, since aggregators are well equipped to spread the knowledge and practice of automating flexibility provision from industrial processes. However, this value is transitory since the interviews revealed that, from a technical point of view, a fully automated control of the client's technical units by the aggregator is typically not a problem. In the long run, therefore, automation may be performed by industry itself.

3.5.4 Participation in electricity markets

The interviews revealed that, although some of the aggregators' clients would in principle be large enough to participate in electricity markets themselves, these companies nevertheless choose to employ the services of an aggregator (cf. Section 3.4.4). One explanation for this behaviour is that participation in electricity markets via aggregators may result in the creation of fundamental value via economies of scale and scope. Reasons for the existence of economies of scale are fixed costs for ICT (for trading), the fulfilment of regulatory requirements and necessary staff (e.g. a 24-hour trading desk for intraday trading). There are also economies of scope, since many of the different electricity markets rely on similar equipment and personnel (see discussion in the section on bundling). In principle, however, this form of aggregation could also be done on a higher level, e.g. by the network operator or power exchanges, who could provide easier access to electricity markets via lower size thresholds or more bidding formats that can reflect the physical properties of demand response units. In other words, a player other than an aggregator could theoretically also fulfil this role.

Our interviews show that aggregators close information gaps by exposing companies to price signals they were not exposed to before. Some aggregators provide simple market information; others go as far as fully automated trading on behalf of their client. With a developing regulatory framework this benefit will be reduced. Aggregators also reduce coordination issues and friction with TSOs and market exchanges by coordinating information exchanges between different market actors (cf. Burger et al. 2017).

In addition to these transitory benefits, part of the value aggregators capture is due to regulatory shortcomings: Limits to market participation by size, penalties on top of marginal costs for failure to perform, balancing responsibilities, as well as the absence of locational price signals all favour large

portfolios rather than individual participation in electricity markets, without increasing the efficiency of the market.

3.5.5 Provision of hedging

The provision of hedging in principle can provide economic value if providers of industrial demand response are risk averse. Hedging provides an efficient means to distribute risks to those willing to bear it or those that have complementary hedging needs, for example inflexible demand that would like to be protected against price peaks. However, suitable hedging products for demand response are not sufficiently standardised or liquidly traded, so market actors may provide new innovative products to hedge demand response (Littlechild 2000). Burger et al. (2017) argue that aggregators can "act as intermediaries between small consumers/producers and volatile markets [and] provide hedging solution to market players", thus filling information gaps and resolving coordination issues between market exchanges and many small players.[51] Moreover, larger portfolios allow for pooling of risks, thus resulting in economies of scale.

In our interviews and the online survey, on the other hand, several participants doubted whether risk management is a role an aggregator has to fill. In the online survey, several participants stated that they do *not* consider risk hedging a fundamental activity of an aggregator. Additionally, some of the aggregators we interviewed do not provide any risk management products for their clients.

There may be several reasons why this role is currently not fulfilled by all aggregators. The possibility to offer risk-management products hinges on whether the aggregator has sufficient capital. The fact that there were several acquisitions of aggregators active in the German market by bigger players with a larger capital base (see Appendix) may mean that more of these players will be able to offer risk management products in the future. Furthermore, currently industrial demand response is mainly provided by overcapacities of current installations. If investment decisions in overcapacities to provide demand response take place, these may have a stronger need to be hedged.

3.5.6 Bundling of services

Bundling several roles, for example combining the roles of energy retailer and aggregator, may lead to the creation of significant fundamental value. The aggregator interviews showed that building trust with customers is difficult and takes several years, i.e. acquisition and transaction costs are high.

[51] Littlechild (2000) already discussed that the improved design of suitable long-term and hedging contracts are an advantage of deregulated retail markets, resulting from increased competition.

This leads to economies of scope at the acquisition stage, e.g. when a retailer with long-running relationship to its client offers additional aggregator services. Further economies of scope may exist at the operation stage, especially if opportunity costs need to be explicitly considered between different energy/electricity markets. This is the case in Germany, where co-optimisation between energy and reserves is not done by the system operator. Bundling services across several markets and industries may also open up the space for further product and service innovation (Burger et al. 2017). There is also some transitory value for the coordination of activities, which may in the future be captured by the system operator (e.g. co-optimisation of energy and reserves).

3.6 Conclusion and policy recommendations

Fundamental changes in electricity markets are leading to a growing importance of utilising (industrial) demand response potentials. Aggregators serve as intermediaries between load and the electricity market, and have therefore received increasing attention in recent years. This chapter investigates how demand response aggregators may overcome barriers to industrial demand response and facilitate the realisation of demand response potentials by bringing them to the market. We develop a set of functional roles that aggregators take up in the market, and investigate which of the different aggregator activities create economic value based on a set of interviews with German demand response aggregators, as well as a survey of market participants and further stakeholders.

We find that demand response aggregators fill six functional roles. Aggregators (1) identify flexibility potentials, and (2) help industrial companies realise them on their premises. Moreover, they (3) automate the activation of flexibility potentials, and (4) participate in electricity markets to market them. Finally, demand response aggregators may provide (5) hedging solutions to stabilise revenues from providing flexibility and (6) bundle several services across electricity and other (energy) markets.

Realising theoretical demand response potentials emerged as the single most important role that aggregators currently have in the German electricity market. One central finding from our interviews is that in Germany demand response aggregators typically approach potential clients (industrial loads) pro-actively and need to persuade companies of marketing flexibility, because demand-side flexibility is often not reflected in the organisation of industrial companies and thus no actor from within the company feels responsible for and has incentives to engage with this topic. Therefore, demand side aggregators play an important role in realising theoretical demand response potential and bringing them to the market. In this process, building trust with a future client – a costly "change process" characterised by high acquisition costs – is a major challenge for the aggregator.

Interestingly, some of the barriers named in the literature on barriers to demand response did *not* emerge as major hurdles in the context of industrial demand response in Germany. First, non-disclosure agreements typically resolve the issue of a lack of a client's trust to grant the aggregator access to sensitive data of the industrial site. Second, the identification of industrial processes that can be used for demand response is usually not a big hurdle due to the wide diffusion of energy management systems among industrial customers. Third, the estimation of a baseline electricity consumption was not a barrier in the context of industrial demand response, since a planned consumption profile has to be reported by industrial loads anyways. This preliminary profile can then serve as a baseline.

With a growing prevalence of demand response, knowledge on how to identify, realise and automate demand response will spread. Consequently, some of the transitory value created by aggregators will decline in importance. In the case of larger industrial loads, for example, clients may become more sophisticated at managing their energy costs in the future, if potential returns become higher due to an increased price volatility or higher price spikes on electricity markets. It is therefore not clear how important demand response aggregators will be in the future for these clients.

However, aggregators also create fundamental value by economies of scale and scope. Examples are providing certified ICT infrastructure for participation in the balancing markets to their clients and serving more consumers on fewer, larger ICT systems, serving different electricity markets with similar technical equipment, as well as saving their clients staff costs, such as for intraday trading. The ICT infrastructure required to participate in balancing markets, for example, is a major hurdle to demand response which aggregators help to overcome.

Aggregators may also create fundamental value by managing uncertainties, as well as increasing competition and innovation. Currently, only some of the German demand response aggregators we interviewed offer hedging products to their clients. The possibility to offer risk-management products hinges on whether the aggregator has sufficient capital. However, this role may become more important in the medium term, since the aggregator interviews showed that risk hedging is more important to some of the clients than the extra revenues from a marketing of flexibility. Currently, however, there is considerable heterogeneity in the kind of services that aggregators offer to their industrial clients.

There are several policy options to facilitate (industrial) demand response that would also render obsolete some of the roles that aggregators currently play. These include lowering size thresholds for participation in balancing markets, as well as introducing multi-part bids, which reflect the physical properties of demand response units. In the current regulatory framework, enabling

companies to participate in electricity markets emerged as the second most important role of aggregators. However, changes in the market design that reduce access barriers, for example by providing a suitable intraday auction platform for industrial loads, would reduce the need for aggregators to participate in these markets on behalf of their clients. It is therefore likely that aggregators will need to progress, as the relative importance of their different functional roles shifts with changing market conditions in an evolving regulatory environment.

3.7 Appendix

Market overview of aggregators in Germany and marketed demand response

We identify 11 German aggregators that market demand response in Germany. We complemented our desk research by a question on demand response aggregators in the online survey, such that we are confident to have identified all major demand response aggregators active on the German market. There were several acquisitions of aggregators in Germany in recent years, such as Entelios (bought by EnerNOC) and REstore (acquired by Centrica). Table A-3-1 gives an overview of German demand response aggregators and the type of electricity markets and reserves they serve.

[Table A-3-1 here]

Table A-3-1 shows that the aggregators interviewed for this study represent a major share of the German aggregator market. We compare the portfolio size of the five demand response aggregators we interviewed to the total portfolio size of demand response and flexible generation marketed in Germany. We find that the five aggregators we interviewed have portfolios of 12.5 GW under management, which includes both generation and demand units. This translates to more than 50 percent of the aggregate portfolio marketed by aggregators in Germany and gives confidence in the conclusions drawn from these interviews.[52]

Several other aspects become apparent when studying Table A-3-1. First, most demand response aggregators offer secondary and tertiary balancing power, as well as intraday optimization. Marketing via the directive on switchable loads (AbLaV) and day-ahead markets are less common. Second, most aggregators serve similar customers, with companies in the basic materials sector and energy-intensive industry the most relevant.[53] Third, demand response aggregators were mostly founded relatively recently. The two exceptions Ørsted and MVV Energie are utilities, which later included demand response aggregation in their business model.

The portfolios of the five interviewed aggregators by far exceed the total amount of demand response prequalified for the reserve markets and for AbLaV. A total of 4.5 GW of demand response were prequalified for the balancing power market (positive and negative) and AbLaV in 2018 (Table A-3-2). Since the same load may be prequalified for different services, the total prequalified demand response capacity is in the range of one GW (amount prequalified for AbLaV) and 4.5 GW (sum of

[52] For the aggregators were we do not have information on their portfolio size, we assume that the amount of demand response and flexible generation under management equals the average of the other aggregators.
[53] However, note that not all aggregators provide information on the type of customer they serve.

balancing markets and AbLaV). Additional loads may be active on day-ahead and intraday markets. However, data on demand response from these markets is not available since bids are submitted anonymously.

There are two reasons why portfolios exceed the amount of prequalified demand response. First, aggregator portfolios include units used for optimization on intraday and day-ahead market, which are not necessarily prequalified for the balancing power markets. Second, the aggregators' portfolios not only include flexible demand, but also generation units. Unfortunately, the share of prequalified demand response by aggregator is not available. At least with respect to the combined demand and generation portfolio, however, the aggregators we interviewed cover a major share of marketed demand response.

Table A-3-2: Prequalified demand response for primary/ secondary/tertiary balancing power and AbLaV

	Positive (load decrease)	**Negative (load increase)**
PRL	80	
SRL	540	660
MRL	880	840
AbLaV	1500	-

Values are in megawatt (MW). *Source*: ÜNB (2018c, 2018d).

Table A-3-1: Portfolio size and markets served by German demand response aggregators

Name	Founded in / headquarter	Portfolio size Germany (DR and generation)	Industrial customers	Primary control	Secondary control	Tertiary control	AbLaV	Intraday	Day-Ahead
Axpo Deutschland	2003 / Düsseldorf und Leipzig	-		x	x	x		x	x
BalancePower	2010 / Munich	-	food industry		x	x			
BayWa r.e. CLENS	2008 / Leipzig	3.300 MW (2019)	primary industry, food industry		x	x		x	x
energy2market	2009 / Leipzig	-		x	x	x	x	x	x
Entelios	2010 / Munich	>1.000 MW (2018)	primary industry, food industry, aerospace	x	x	x	x	x	
GETEC Energie	1996 / Hannover	2.000 MW (2018)	energy intensive industry	x	x	x		x	
MVV Energie	1974 / Mannheim	500 MW (2015)			x	x		x	x
natGAS	2000 / Potsdam	950 MW (2018)	primary industry, food industry, automotive		x	x		x	
Next Kraftwerke	2009 / Cologne	4.909 MW (2018)	different industries	x	x	x	x	x	x
Quadra	2014 / Düsseldorf	-						x	
REstore	2010 / Antwerpen	2.300 MW (2018)	primary industry, food industry	x	planned	planned	x		

Source: Direct communication with the aggregators and company websites.

General Conclusion

This thesis addresses three challenges on the way towards a low-carbon future, namely increasing energy efficiency, the production of renewable electricity, and its integration into energy markets. Chapter 1 identifies the causal effect of energy efficiency networks on energy productivity and CO_2 emissions of participating companies, using plant-level data from the German manufacturing census. Chapter 2 evaluates the effect of strict minimum distance regulation on the expansion of wind power, utilising a newly created district-level dataset of construction permits for German wind turbines. Chapter 3 analyses functional roles of demand response aggregators and their role in driving organisational change, based on semi-structured interviews with German aggregators and a broader stakeholder online survey.

Chapter 1 shows that savings from energy efficiency networks are not as large as anticipated. Energy efficiency networks are one of the core policies for industrial energy efficiency in Germany. In order to help reach Germany's 2020 national GHG emissions target, these networks were supposed to deliver CO_2 savings of five million tonnes, or one-third of the emissions target in the industrial sector. While the previous literature predicted an increase of energy productivity of 4.5 percent over a four-year network period, chapter 1 shows that the effect is most likely smaller than 4.1 percent. The chapter thus illustrates the importance of ex-post policy evaluation of policies such as the energy efficiency networks. Such an impact evaluation is especially challenging for energy efficiency policies, where targets are typically set relative to a counterfactual (or baseline). Estimating this baseline for a policy evaluation is inherently more difficult for energy efficiency policies than for other abatement policies. Consequently, research designs such as the one developed in chapter 1 are required in order to gauge the success of energy efficiency policies.

There are several reasons why the effect of energy efficiency networks on the energy use of participating plants is not as large as suggested by previous research. First, joining energy efficiency networks is voluntary. Chapter 1 shows that energy-intensive firms with high energy costs self-selected into the networks. Even without joining energy efficiency networks, these firms have a significant incentive to reduce energy consumption as much as possible. Participating in an energy

efficiency network may therefore not be a huge additional benefit to such companies. Survey evidence supports this hypothesis: Many participants of energy efficiency networks state that they would have implemented energy efficiency measures even without being part of an energy efficiency network. Second, there may be a signalling motivation for companies to join energy efficiency networks. Participation in a network may be seen as a signal to customers and other stakeholders that a participating company cares about reducing the environmental impact of its production process. This may also signal to regulators that more stringent (compulsory) regulation is not necessary, since industry shows its willingness to reduce energy consumption and CO_2 emissions.

However, there is some evidence that energy efficiency networks did have positive effects for at least some of the participants. First, surveys among participants and anecdotal evidence from some of the participants indicate that some companies were quite enthusiastic about the networks, feeling they did offer an added value. Moreover, a minority of around six percent of plants that were part of one of the initial networks decided to continue these activities by joining a second energy efficiency network after the initial one was completed. It is unlikely that firms would decide to invest resources into joining a voluntary programme again, if they did not feel they achieved tangible results in the first network. Third, there is some indication that good management practices influence whether knowledge gained in the networks translates into changing behaviour at the firm level. Chapter 1 presents evidence that high exporters reduced their CO_2 emissions by around 10 percent. Since exporting is associated with good management practices, this confirms previous findings of a connection between good management practices and the success of energy efficiency measures.

In sum, chapter 1 indicates that at least some plants benefitted from energy efficiency networks. On average, however, savings are smaller than expected, and possibly insignificant. The initial energy efficiency networks can therefore be considered a partial success at best. However, it should be taken into account that energy efficiency networks are only partly funded by the state, and are a relatively low-cost support mechanism for energy efficiency. Consequently, energy efficiency networks may still be a reasonable instrument to support the uptake of energy efficiency measures, even if the initial high expectations of the policy instrument cannot be met.

Chapter 2 shows that strict minimum distances counteract the challenge of expanding the production from renewable energies. By drastically reducing the expansion of wind power, such policies jeopardise climate targets. In comparison to solar PV, onshore wind is more affected by the issue of social acceptance. Therefore, measures to advance acceptance are important, in order to build support for expanding the construction of wind turbines, as well as repowering existing turbines. Strict minimum distances, however, have detrimental consequences for the expansion of wind

power: An evaluation of the federal state of Bavaria's minimum distance regulation showed that increasing separation distances to around 2000 meters from nearby settlements reduced construction permits issued for wind turbines by up to 90 percent. This reduction is in line with model results on the effect of minimum distances on dedicated areas available for wind turbines.

Successful policies to raise acceptance of renewable energies should have a measurable effect on social acceptance, without compromising the expansion of these technologies. Increasingly strict minimum distances violate both of these criteria. First, the evaluation of the Bavarian minimum distance regulation shows that the effect on the expansion of wind turbines was indeed detrimental. Second, there is no evidence that tighter separation distances have a significant positive effect on public acceptance of wind turbines. The main reason for this is that existing minimum distance legislation already protects nearby residents from noise, shadowing and visual impairment of wind turbines in countries like Germany. Strict minimum distances are therefore not a suitable policy to raise acceptance of wind energy.

Alternative policies are better suited to facilitate acceptance without hampering the expansion of wind power. Distributional justice and procedural fairness are important determinants for public acceptance of renewables. Regarding onshore wind projects, the economic benefits often mainly accrue where manufacturers, project developers and related companies are based, rather than where the turbines are located. Therefore, direct payments to local municipalities are a promising alternative to address the externalities of wind turbines more directly. Such financial compensation schemes have been shown to improve public acceptance by allowing the communities that are directly affected to participate in the value added of wind power generation. Denmark, as well as the German federal states of Mecklenburg Western Pomerania and Brandenburg have already implemented similar financial participation schemes.

Chapter 3 demonstrates how demand response aggregators, intermediaries between consumers and energy markets, help integrate renewable electricity into the grid. Aggregators facilitate industrial demand response through a set of functional roles, such as identifying demand response potentials and installing technology for automation. The chapter develops this set of functional roles and sets up a taxonomy linking these roles to the creation of economic value. For example, aggregators create fundamental value through economies of scale and scope, by providing certified ICT infrastructure for participation in the balancing markets to their clients and serving more consumers on fewer, larger ICT systems.

Aggregators help overcome a set of barriers to industrial demand response. Chapter 3 illustrates that a central role for aggregators is to raise awareness for the potentials of demand response, as well as to support implementation by engaging key actors in industrial companies. Realising theoretical demand response potentials is the single most important role that aggregators currently have in the German electricity market. The reason is that companies often do not exploit existing demand response potential, e.g. due to high transaction costs. Moreover, demand-side flexibility is often not reflected in the organisation of industrial companies. In this process, building trust with a future client – a costly "change process" characterised by high acquisition costs – is a major challenge for the aggregator. Therefore, demand side aggregators play an important role in advancing organisational change by realising theoretical demand response potentials and bringing them to the market.

Chapter 3 shows that there is considerable heterogeneity in the kind of services that aggregators offer. Only some of the German demand response aggregators offer hedging products to their clients, for example. The possibility to offer such risk-management products hinges on whether the aggregator has sufficient capital. However, this role may become more important in the medium term, since the interviews revealed that risk hedging is more important to some of the clients than the extra revenues from a marketing of flexibility. Additionally, some of the current aggregator roles may become obsolete once market barriers to demand response are reduced, knowledge on demand response becomes more diffused, or increased price volatility on electricity markets amplify potential returns from demand response. With a growing maturity of demand response markets, knowledge on how to identify, realise and automate demand response will spread among industrial loads. Consequently, some of the transitory value created by aggregators will decline in importance.

Looking forward, there is a continued need to address the three challenges of decarbonisation discussed in this thesis: Successful policies will need to be implemented in order to use energy more efficiently. The use of renewable energies needs to be extended rapidly in all sectors of the economy. And increasing shares of renewable energies will need to be integrated into the existing energy systems. These challenges lead to a myriad of research questions that can be explored by researchers.

Regarding energy efficiency, chapter 1 provides evidence that the dissemination of knowledge in energy efficiency networks may have a positive influence on firm performance, at least if the firms are well-managed. However, the effects from this dissemination are not as large as previously expected. One reason could be that the knowledge gained in regional networks is too general to be of major value to the average firm. This hypothesis can be tested by exploring whether networks focussing more on production technologies than cross-sectional technologies (such as within-

company and sectoral networks) are more successful than regional networks. Another promising avenue for future research is to assess whether mandatory informational policies such as energy audits or the disclosure of carbon emissions have larger effects than voluntary policies such as energy efficiency networks.

Regarding the expansion of renewables, ensuring public acceptance becomes increasingly important as the number of installations grows, especially for onshore wind power. Therefore, regulatory frameworks are needed that facilitate acceptance without hampering the expansion of wind power. Future research could expand on previous work on the determinants of public acceptance of wind power. For example, the question of how to design regulatory frameworks in order to achieve a higher (perceived) procedural fairness during the planning and construction phase of wind turbines deserves the attention of researchers. Moreover, the question of distributional fairness is a promising area for future research. For instance, researchers may analyse the causal effects of local investment participation, such as financial compensation of local municipalities or investment opportunities for nearby residents, on the acceptance of wind power.

Regarding the integration of renewable energies, industrial demand response is one of a set of flexibility options. Here, a key challenge and topic for research is the design of markets that mirror the value of these flexibility options for the energy system. Moreover, as markets mature, the role of aggregators is likely to transition over time. Evaluating this changing role of aggregators and developing adequate regulatory frameworks will thus continue to be relevant. Finally, this thesis has shown that aggregators are agents that drive organisational change by providing information and engaging with motivated individuals within their client organisation. More broadly, third parties such as aggregators may drive organisational change in a number of ways, for example by providing financial support for investments in technologies such as demand response or energy efficiency. Assessing the role of third parties in advancing organisational change therefore remains an important avenue for future research.

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