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Do energy efficiency networks save energy? Evidence from German plant-level data[†]

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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. Existing evaluations of such voluntary regional networks claim that participants improved energy efficiency at twice the speed of the industry average. Based on comprehensive data from the German manufacturing census, this paper shows that this claim is overstated: Likely less than half of energy savings credited to the networks are additional, implying that more than 2.5 million tonnes of CO_2 counted towards national energy efficiency goals would have to be compensated by additional policies. However, although statistically insignificant, estimates of the network effects are still substantial, pointing to 1,400 MWh of energy savings and 600 tonnes of CO_2 reduction for the average participant. These estimates suggest a high cost-effectiveness of energy efficiency networks compared to similar energy efficiency policies, even if actual energy savings are likely lower than previous research suggested.

Keywords: Business networks; energy conservation; organisational learning; policy evaluation; voluntary agreements
JEL codes: D22; Q40; Q51; C50

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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 savings 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-cutting technologies (such as lighting or process heat), since participating companies come from different economic sectors with different production technologies (Jochem et al. 2010; Barckhausen et al. 2019). 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). The importance of networking and sharing best practices among energy directors has also been established in the U.S. Environmental Protection Agency (EPA)'s Energy Star programme (Boyd and Zhang 2013).

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 planned to create 500 networks by 2020, half of which had been set up by November 2019 (Barckhausen et al. 2019). These voluntary networks were evaluated to be on track 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. 2019; 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 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 concluded that participating companies increased their energy efficiency (defined as absolute energy savings compared to a baseline energy consumption) by 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). Moreover, the official monitoring of the 500 networks initiative conducted for the German government found annual savings of 2,824 MWh for the average network participant and concluded that Germany was on track to reach the goal of saving five million tonnes of CO_2 by 2020 (Barckhausen et al. 2019). However, the evaluation counted all energy savings from measures registered under an energy efficiency network as fully additional, not accounting for the fact that some of these measures might have also happened in the absence of the networking activities.

The main contribution of this paper 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 energy conservation, as well as reduced CO_2 emissions. I use a difference-in-differences estimator exploiting the difference in timing between two distinct groups of network participants to explore this causal link. Specifically, I compare the energy consumption 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. In addition to tackling the challenge of self-selection into energy efficiency networks, this estimation strategy leads to a control group that is very similar to the participants of the pilot networks in terms of observables, such as average energy consumption or number of employees. I also provide support for the identifying assumption of parallel trends of treatment and control group in the absence of the treatment with an event study approach.

Point estimates suggest a decrease of energy consumption by 2.2 percent, as well as a reduction of CO_2 emissions by 2.6 percent. This translates into energy savings of around 1,400 MWh for the average network participant, as well as reductions of CO_2 emissions by 600 tonnes. However, these point estimates are not statistically significant, which may well be a function of the limited sample size relative to the (expected) treatment effect. Power calculations, on the other hand, reveal that reductions in energy savings observed for the average participant cannot be fully attributed to the networking activities. Most likely, less than half of the reductions in energy use credited to the energy efficiency networks were additional. My results thus show that previous assessments of energy efficiency networks in Germany overstated their effect, highlighting the importance of ex-post policy evaluation.

Second, I explore heterogeneous treatment effects by taking a closer look at network participants with high exports. 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). Since export shares increase with plant size, I also run a second set of regressions evaluating the treatment effect depending on firm size. Results show that while export share is unlikely to be a determinant of the success of the network activities, larger companies may benefit more from energy efficiency networks by reducing their CO_2 emissions.

Finally, I assess the cost-effectiveness of energy efficiency networks by computing the levelised costs of saved energy (LCSE) and comparing these to other estimates of cost-effectiveness of energy efficiency policies from the literature. Although the effects of energy efficiency networks are smaller than previously thought, the point estimates still suggest a highly cost-effective policy with knowledge acquisition costs between 0.14 and 0.6 cents per kWh, which is an order of magnitude smaller than comparable efficiency policies. Consequently, energy efficiency networks would remain a low-cost instrument when compared to other energy efficiency policies or the cost of generating electricity, even if the true energy savings were lower than the point estimates suggest.

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. More generally, the importance of learning has been established for productivity spillovers and social learning (Conley and Udry 2010; Greenstone et al. 2010).

The paper is structured as follows. Section 2 explains the concept of energy efficiency networks, as well as the mechanisms through which they are thought to help energy conservation. It also describes the pilot phase of energy efficiency networks in Germany. Section 3 outlines the identification strategy used to estimate the treatment effect of energy efficiency networks, and introduces the concept of levelised costs of saved energy. Section 4 portrays the panel dataset used in this study and provides descriptive statistics. Section 5 presents the main results, including an assessment of the identifying assumptions, heterogeneous treatment effects, and cost-effectiveness of energy efficiency networks compared to similar policies. Section 6 discusses explanations and implications of the findings. Section 7 concludes.

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 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 (absolute) 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. The energy managers of the participating plants take part in these physical network meetings (Jochem et al. 2010). Here, they share their experience about the implementation of energy efficiency measures. External experts (consulting engineers) provide input to the networks 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: 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

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). This includes the costs for an extensive energy audit at the beginning of a network of 10 to 12 days (Köwener et al. 2014). In addition, there are transaction costs such as staff costs for the participation at network meetings. However, costs of participation can be much lower when a network does not use the LEEN standard (Jochem et al. 2010).[2]

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.3). 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.

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[1] Figure 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).

[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).

There was no direct financial incentive to participate in one of the 30 pilot networks, apart from reduced participation costs. The networks received 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 (measured in absolute energy savings) of 2.1 percent (Jochem et al. 2010; Köwener et al. 2014; Rohde et al. 2015). According to these studies, this is twice the amount of the energy efficiency improvement of the German industry as a whole, which is estimated to have been approximately one percent annually 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.

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. An evaluation of the 500 networks initiative revealed that almost one-third of the energy efficiency measures targeted lighting (Barckhausen et al. 2019). 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

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[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.

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 influence energy conservation through **socio-psychological mechanisms** (Stern 1992; Jochem et al. 2010): 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 energy savings 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 savings 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 (OECD/IPEEC 2017; Dütschke et al. 2018).

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-cutting 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 were 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 conceivable that not all reductions of energy consumption credited to energy efficiency networks are fully additional. This hypothesis will be tested in the following.

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 consumption, as well as on CO_2 emissions of the networking companies.[5] 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. The next section discusses the identification strategy chosen to overcome this challenge.

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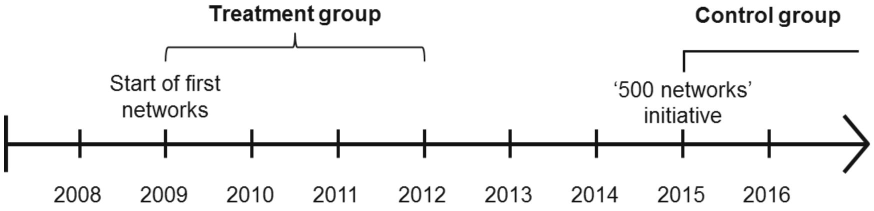
[5] Despite the fact that the name "energy efficiency networks" suggests a relative indicator such as energy intensity, the network targets are set in absolute energy units (MWh and tonnes of CO_2, respectively). Consequently, the dependent variable is also set in absolute units, mirroring the network targets.

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

In order to identify the effect of network participation on energy conservation, I rely on a generalised difference-in-differences (DiD) estimation, where network members of the pilot phase ('treated' plants) are compared to a 'control' group of plants 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 2).

Figure 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.[6] This motivation is likely to be linked to increased energy consumption reduction capacities at the plant 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 4.2). Consequently, companies from the post-2014 networks make a good control group.

I estimate three variants of the unconditional difference-in-differences estimator. Equation (1) is the most basic specification:

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

where the dependent variable is either the log of energy consumption or the log of CO_2 emissions of plant 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 (non-parametric) sector-year interactions that capture intra-industrial

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[6] In principle, treated plants undergo a double selection mechanism. In a first step, there is a selection which networks are set up. In a second step, participants self-select whether to join one of the available networks. The identification strategy addresses only the second selection mechanism. However, the first selection mechanism is not a concern, since the choice of the location of the networks can be viewed as random and, in particular, as independent of the potential future participants. Since the networks were a new concept in Germany at the point of introduction, the focus in the process of determining locations was on finding organisations and managers willing to host such a network. The selection of networks (first selection) therefore does not depend on the second selection mechanism (self-selection of plants). This gives confidence regarding the external validity of my results. I thank an anonymous referee for pointing to the double selection mechanism.

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 consumption and CO_2 emissions of the participating plants.

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

$$y_{it} = \delta \cdot \mathbf{1}\{Network\}_{it} + \mu_i + \tau_t + \gamma_s + \varphi_{st} + \varepsilon_{it}\,, \tag{2}$$

where μ_i is a plant-level fixed effect, controlling for within-plant differences in energy consumption 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. The plant-level fixed effects prevent the estimate of the treatment effect, δ, from being upward biased due to time-invariant unobserved factors at the plant level that affect the level of energy consumption or CO_2 emissions.

In order to increase the precision of the estimates and account for variables that affect firms from the pilot networks and control group differently, for the preferred specification (3), the DiD model is augmented as follows:

$$log(y_{it}) = \delta \cdot \mathbf{1}\{Network\}_{it} + \mu_i + \tau_t + \varphi_{st} + \boldsymbol{X_{it}}\Psi + \varepsilon_{it}\,, \tag{3}$$

where $\boldsymbol{X_{it}}$ contains a set of time-varying control variables[7] at the plant level and Ψ is the corresponding vector of coefficients.

3.2 Cost-effectiveness of energy efficiency networks

Energy efficiency upgrades can be viewed as an upfront investment that delivers energy (cost) savings over time (Gillingham et al. 2018). Determining the cost-effectiveness of an energy efficiency programme, or the cost per kWh of energy saved, is an important parameter of interest to judge the success of an energy efficiency intervention. In the case of energy efficiency networks, these programme costs may be viewed as **knowledge acquisition costs**, i.e. the costs of participating in an energy efficiency network relative to the additional energy savings triggered by the knowledge sharing in the networks.

One way to measure the cost-effectiveness of an energy efficiency investment are the levelised cost of saved energy (LCSE, e.g. Hoffman et al. 2015; Cho et al. 2019). Intuitively, the LCSE compare programme expenditures to the (discounted) present value of future energy savings.[8] The LCSE can be computed by multiplying expenditures with the so-called capital recovery factor (CRF) and dividing by total annual energy savings.

$$LCSE = \frac{Capital\ recovery\ factor * Total\ programme\ expenditures}{Annual\ energy\ savings\ (in\ kWh)} \tag{4}$$

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[7] 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 monetary values such as turnover and value of output.

[8] Alternatively, LCSE may be interpreted as the total programme expenditures, spread in equal payments over the economic lifetime of the energy efficiency measures, and divided by the annual energy saved.

where $Capital\ recovery\ factor = \frac{r*(1+r)^n}{(1+r)^n-1}$;
r: discount rate;
n: average lifetime of the energy efficiency measures.

In theory, investment costs for the energy efficiency measure itself could be added to the computation of the levelised cost of saved energy. In this case, the LCSE could be directly compared to supply-side investments such as the levelised cost of electricity (LCOE). However, information on investment costs for investments of the energy efficiency networks are not publicly available. Moreover, these costs are likely to vary significantly by the type of implemented measure (e.g. new lightning versus more efficient production processes). I therefore focus on the interpretation of LCSE as knowledge acquisition costs.

4 Data

This paper makes use of rich administrative German plant-level data for the period 2003-2014, the AFiD panels[9]. 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 plant-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. 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.3). 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, 695 companies of the control group in models (1) to (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 firm 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

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[9] AFiD is an acronym for *"Amtliche Firmendaten für Deutschland"* ("Official Firm-level Data for Germany").

networks were excluded from the control group.[10] This reduces the size of the control group to 589 companies.

4.1 Descriptive statistics

Table 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. The standardised bias, an indicator to judge the overlap of two groups in a sample, also indicates a very good overlap compared to the manufacturing sector at large (see Figure A-1 in appendix A.2).[11]

Plants 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 13,000 MWh, a turnover[12] of EUR 32.4 million, and 1530 employees. Average energy consumption, turnover and employees of treatment and control group, on the other hand, are roughly five times larger than the average plant in the manufacturing sector. 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: Energy productivity (the value of production per unit of total energy consumed in EUR/kWh) of treatment and control group is less than half as high as that of the manufacturing sector.[13]

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 plants in the control group: Treated plants have a higher turnover (mean of EUR 192 million vs. EUR 172 million) and more employees (7,450 and 5,450 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 plants in the upper tail of the control group's distribution.

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[10] 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 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 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).

[11] Comparing standardised biases is a common procedure to assess the balance of matched samples when matching methods are used. 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).

[12] In this paper, turnover (or revenue) is defined as the income generated by a plant by selling their goods or by providing their services

[13] Energy productivity is a commonly used metric for measuring energy efficiency. It is the inverse of energy intensity, defined by a measure of the value of output per unit of total energy consumed. 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.

Table 1: Distribution of key variables

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile	Obs.
Energy consumption [MWh]					
- Pilot networks	62,971 (153,762)	18,386	5,227	47,508	922
- Control group	70,252 (229,865)	12,789	3,875	40,053	2,145
- Manufacturing sector	13,004 (144,090)	952	349	3,630	172,698
CO_2 emissions [tonnes]					
- Pilot networks	22,826 (53,741)	7,620	2,426	18,710	921
- Control group	23,082 (70,909)	5,373	1,658	14,927	2,143
- Manufacturing sector	4,680 (49,827)	403	142	1,535	172,556
Energy productivity [€/kWh]					
- Pilot networks	5.58 (6.12)	3.48	1.73	7.55	877
- Control group	5.79 (8.19)	3.22	1.24	7.24	2,085
- Manufacturing sector	12.11 (77.78)	5.47	2.59	11.32	165,132
CO_2 intensity [tonnes/million €]					
- Pilot networks	353 (1,514)	125	61	244	876
- Control group	303 (527)	135	62	302	2,083
- Manufacturing sector	240 (4,112)	78	37	162	164,990
Turnover [million €]					
- Pilot networks	192 (579)	63.3	24.4	152.1	922
- Control group	171.7 (1001.5)	39.1	14.5	112.2	2,145
- Manufacturing sector	32.4 (353)	5.8	2.5	16.9	172,695
Value of production [million €]					
- Pilot networks	139.1 (299.3)	61.2	24.3	134.4	877
- Control group	160.9 (1627.1)	36.9	14.0	99.2	2,085
- Manufacturing sector	26 (254.8)	5.5	2.4	15.5	165,137
Number of employees					
- Pilot networks	7,450 (13,970)	3,386	1,478	6,764	922
- Control group	5,453 (18,459)	2,350	1,136	4,942	2,145
- Manufacturing sector	1,533 (6,633)	577	335	1,258	172,695

The statistics are calculated over the pre-treatment period (years 2003-2006). There are 257 manufacturing sites in the pilot networks group, 589 plants in the control group, and an average of 42,843 plants in the manufacturing sector. All variables are at the plant level. *Source*: FDZ (2014a), own calculations.

The distribution of firms by sectors of economic activity in Table 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]

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

Table 2: Sectors of economic activities [in %]

Economic sector *	Pilot networks	Control group	Manufacturing sector
5 Mining of coal and lignite	0.4	0.1	0.1
8 Other mining and quarrying	1.3	1.1	2.3
10 Manufacture of food products	11.5	12.3	11.6
11 Manufacture of beverages	4.5	2.5	1.4
12 Manufacture of tobacco products	0.4	0.4	0.1
13 Manufacture of textiles	1.8	2.3	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	1.6	2.9
17 Manufacture of paper and paper products	4.1	4.4	2.2
18 Printing and reproduction of recorded media	2.4	1.9	3.5
19 Manufacture of coke and refined petroleum products	0.4	1.4	0.2
20 Manufacture of chemicals and chemical products	9.2	7.5	3.5
21 Manufacture of basic pharmaceutical products and pharmaceutical preparations	2.5	1.4	0.7
22 Manufacture of rubber and plastic products	9.8	9.3	7.0
23 Manufacture of other non-metallic mineral products	4.2	8.5	7.2
24 Manufacture of basic metals	2.6	6.2	2.4
25 Manufacture of fabricated metal products, except machinery and equipment	10.1	11.0	15.9
26 Manufacture of computer, electronic and optical products	2.7	2.6	3.9
27 Manufacture of electrical equipment	4.7	5.4	4.9
28 Manufacture of machinery and equipment n.e.c.	11.0	13.3	13.6
29 Manufacture of motor vehicles, trailers and semi-trailers	6.2	3.7	3.0
30 Manufacture of other transport equipment	2.0	1.1	0.6
31 Manufacture of furniture	4.1	0.5	2.4
32 Other manufacturing	1.6	0.9	3.6
33 Repair and installation of machinery and equipment	0.9	0.4	4.1

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

The shares 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). There are 257 manufacturing sites in the pilot networks group, 589 plants in the control group, and an average of 42,843 plants in the manufacturing sector. *Source*: FDZ (2014b), own calculations.

4.2 Dealing with measurement error

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 CO2 emissions (see Figure A-2 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.[15] Consequently, I use the Mahalanobis

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[15] 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 (and selling) 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

distance to identify unusual observations and omit the two percent of observations with the highest distance from the sample.[16] Figure A-2 shows how this procedure reduces implausible values for the variables energy productivity and CO_2 emissions.

5 Results

5.1 Causal effect of energy efficiency networks on energy consumption and CO_2 emissions

5.1.1 *Main results*

Table 3 shows the estimation results of the different models for energy consumption (columns 1 to 3) and CO_2 emissions (columns 4 to 6), with standard errors clustered at the network level. Since energy efficiency networks are regional, this ensures that the clustering happens at a suitable regional level.[17] Columns 1 to 3 correspond to the models (1) to (3) in section 3.1, with the dependent variables log energy consumption. Column 1 contains the most basic specification (1), i.e. a simple regression that does not control for any covariates. Column 2 introduces plant-level fixed effects. Column 3 adds several covariates to the fixed effects specification, namely sales intensity (turnover divided by the number of employees)[18], the share of own electricity production of total consumption and the share of turnover generated from exports. In columns 4 through 6, the same models are re-estimated with the dependent variable log CO_2 emissions. All specifications in Table 3 include year fixed effects, sector fixed effects (i.e. fixed effects for the German WZ industry classification at the two-digit level)[19] and sector-specific trends (sector-year interactions).

Columns 3 and 6 depict the preferred specification (model (3)), since the inclusion of plant-level fixed effects controls for unobserved time-invariant factors at the plant level. As energy efficiency changes happen at the plant level, this is the most robust specification. Taking logs of the dependent variables leads to a percentage interpretation of the coefficients, which means changes to energy consumption and CO_2 emissions are evaluated 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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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.

[16] 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.

[17] Clustering at the network level leads to a total number of 186 clusters (30 pilot networks and 156 networks in the control group).

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

[19] 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. The sector fixed effects drop out when a plant does not change its industry affiliation over time due to the inclusion of plant-level fixed effects in model (3).

Table 3: Treatment effects for energy consumption and CO_2 emissions

	Log energy consumption			Log CO_2 emissions		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)
Network	-0.0298 (0.0363)	-0.0212 (0.0238)	-0.0224 (0.0219)	-0.0381 (0.0358)	-0.0273 (0.0220)	-0.0264 (0.0204)
Log sales intensity	-	-	0.110*** (0.0220)	-	-	0.101*** (0.0220)
Electricity production share	-	-	0.0237 (0.0429)	-	-	-0.0199 (0.0399)
Export share	-	-	0.122** (0.0607)	-	-	0.0870 (0.0558)
Observations	9810	9810	9428	9783	9783	9401
R^2 (within-network/ within-plant)	0.494	0.123	0.148	0.480	0.101	0.123
Plant-level fixed effects	No	Yes	Yes	No	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. All specifications include sector-year interactions. Energy consumption is measured in MWh. CO_2 emissions are measured in tonnes. There are 257 manufacturing sites in the pilot networks group and 589 plants 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 3, the negative signs of all estimated treatment effects are in the expected direction. The preferred specifications indicate a reduction of energy consumption by 2.2 percent, as well as a decrease of CO_2 emissions by 2.6 percent, respectively. Although this is a small effect relatively speaking, due to the size of participants it would translate to significant savings in absolute terms: The point estimates suggest a reduction of around 1,400 MWh of energy and 600 tonnes of CO_2 emissions over the course of the network period for the average participant.

None of the point estimates are statistically significant, however. This result is unchanged when I vary the clustering method of the standard errors. Specifically, I re-estimate columns 1-6 clustering at the individual plant level, as well as pooling all control companies into one cluster[20] (reflecting the fact that the networks have not started yet). This somewhat decreases the size of the standard errors, but the point estimates remain insignificant.[21] The results depicted in Table 3 are thus the most conservative specification with respect to the size of the standard errors.

The statistical insignificance of the estimated treatment effects does not imply a 'null result', i.e. that the networks did not have an effect on energy consumption and CO_2 emissions. Instead, the power of the model may simply not be large enough to nail down a small treatment effect, for example due to the limited sample size and imbalance between the number of treated and control plants in the overall sample. Nonetheless, the next section explores what can be said about the predictions from the previous literature of very significant energy savings supposedly triggered by the networks.

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[20] This method might lead to a problem with "few" clusters, since the total number of clusters declines to 31. 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 plants in each network.

[21] Results are available from the author on request.

5.1.2 Power analysis

A central question regarding the interpretation of the estimates presented in Table 3 is how they relate to the predictions made for the effect of the energy efficiency networks. Given the sample at hand, is power sufficiently high in order to detect an effect that could be expected from the networks? One solution to test this is to estimate ex-post the power for detecting an effect size that could be expected from the networks (see McKenzie and Woodruff 2014 for an application to business training programmes).

The effect of energy efficiency networks on their participants' energy consumption is much likely lower than previously expected. Previous evaluations of the pilot networks concluded that participants reduced their energy consumption by 2.1 percent per year (e.g. Wohlfarth et al. 2016).[22] If this effect was fully additional, it would add up to sizeable total energy savings of 8.7 percent over the course of a four-year network. With the preferred model specification presented in the previous section (column 3 of Table 3), such an effect would have been detected at a five percent significance level with a probability of 99 percent. Even assuming that only half of the network savings are additional (as suggested by the "double the industry average" claim), such an effect would have been discovered by the model with a two-thirds probability at the five percent level, and with almost 80 percent likelihood at the ten percent level. Consequently, while the point estimates shown in Table 3 are insignificant, it is very likely that the true energy savings triggered by the networks are smaller than what advocates have argued in the past.

5.1.3 Assessment of identifying assumptions

The main identifying assumption underlying (1) to (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 3 provides visual evidence for the validity of the parallel trends assumption for the pre-treatment period (roughly until 2008) for the dependent variables (log) energy consumption (Panel A), as well as (log) CO_2 emissions (Panel B).

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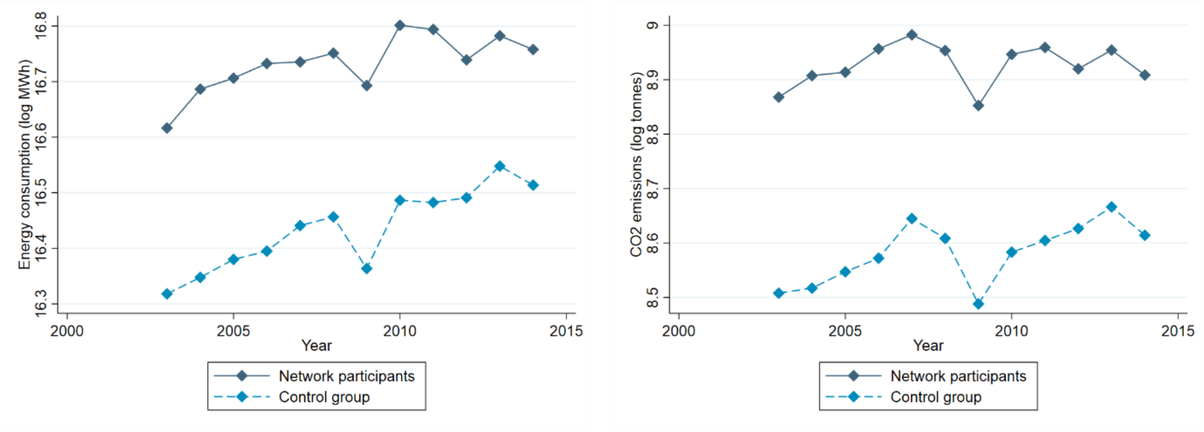
[22] Note that the authors typically call this rate *efficiency* gains. Although this terminology suggests a relative gain (such as an improvement of energy productivity), the underlying numbers are measured in absolute units (megawatt-hours, MWh). Consequently, the annual rate is defined as the reduction of energy consumption relative to a baseline consumption.

Figure 3: Log energy consumption and CO_2 emissions of pilot networks and control group

Panel A: Log energy consumption

Panel B: Log CO_2 emissions



Source: FDZ (2014b), own calculations.

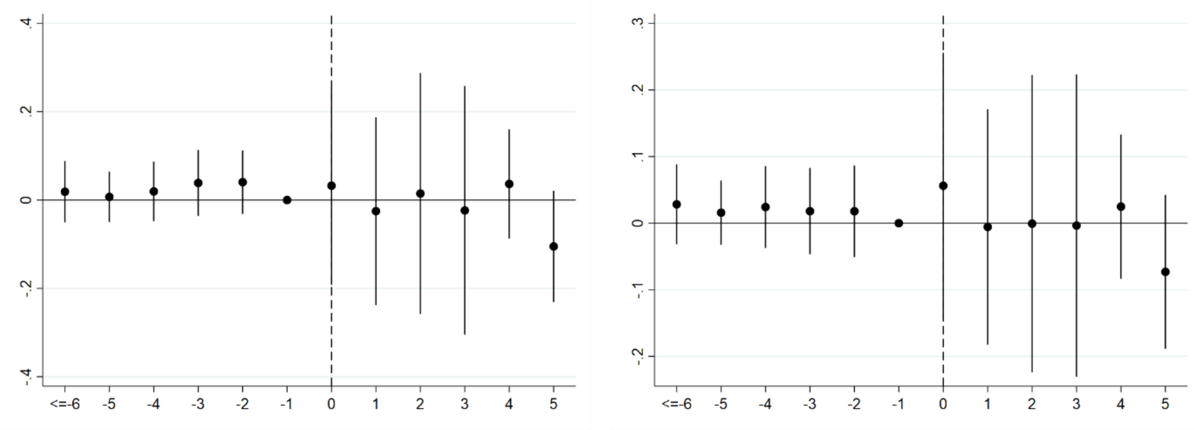
In addition to a visual inspection of Figure 3, I present a more formal test of the identifying assumption with an event study approach. The event study accounts for the fact that networks start at different points in time by regressing dependent variables on yearly treatment effects of the time difference to the start of the network period. It allows to test whether companies are already on an upward trajectory with respect to their energy efficiency when they join a network.

Figure 4 shows that the pseudo-treatment effects in the six years prior to the start of are all insignificant, which provides support for the identifying assumption. Moreover, standard errors are relatively small in the pre-treatment year, and increase significantly for the estimated treatment effect in the network period. This suggests that the networking effect may not be uniform across network participants. Instead, some firms may benefit more from the networks than others, a theory that is explored with the analysis of heterogeneous treatment effects in section 5.2.

Figure 4: Event study regression

Panel A: Log energy consumption

Panel B: Log CO_2 emissions



The event study graphs show yearly treatment effects from OLS regressions of the dependent variables on the covariates. The model includes plant-level fixed effects and sector-year interactions. Additional control variables are sales intensity (turnover divided by the number of employees), as well as the share of own electricity production of total consumption. Standard errors are clustered at the network level. Source: FDZ (2014b), own calculations.

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 plants profit from the knowledge acquired by their peers that did participate in energy efficiency networks.[23] In telephone interviews conducted for this paper, 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 excluded 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.

5.2 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 paper, Lutz et al. (2017) show that exporting firms are more energy efficient than their counterparts. Similarly, Richter and Schiersch (2017) find evidence of an "exporter's environmental premium", namely that CO_2 productivity increases with export share.

I test whether exporters profit more from participating in energy efficiency networks than the average firm by calculating treatment effects for varying export shares. Firms in energy efficiency networks generally export more than the average manufacturing firm. While the export share is 18 percent on average in the German manufacturing sector, it is twice as high for network participants (see Table A-2). Around ten percent of all participants of energy efficiency networks have a very high export share of more than 80 percent. These plants are roughly 50 percent larger than the average energy efficiency network participant in terms of key variables such as energy

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[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.

consumption, CO_2 emissions and turnover. Energy productivity, on the other hand, is roughly aligned with the complete treatment group, implying a similar relative importance of energy costs in overall production (Table A-3).

Table 4 shows the interaction effect of regressions of the preferred specification (3) for the variables energy consumption and CO_2 emissions, where the treatment dummy is interacted with a dummy indicating an export share above the respective level. These estimates represent the additional effect of the networks on exporters. All the estimated treatment effects are in the expected direction (negative coefficient), and point estimates are relatively stable for lower export shares. Estimates are only statistically significant for very high export shares (80 and 90 percent for CO_2 emissions, and only 80 percent for energy consumption). Here, the point estimates are comparatively high, around 10 percent of energy consumption and CO_2 emissions savings respectively are estimated.

Table 4: Treatment effects for high exporters

Share of revenue from exports	**(1) 90%**	**(2) 80%**	**(3) 70%**	**(4) 60%**	**(5) 50%**
Panel A: Dependent var. Log energy consumption					
Network	-0.0197	-0.00992	-0.0126	-0.00925	-0.00474
	(0.0224)	(0.0234)	(0.0244)	(0.0256)	(0.0292)
Network × High exporter	-0.0553	-0.107**	-0.0552	-0.0504	-0.0428
	(0.0445)	(0.0502)	(0.0482)	(0.0444)	(0.0408)
Observations	9428	9428	9428	9428	9428
R^2 (within-plant)	0.147	0.148	0.147	0.147	0.147
Panel B: Dependent var. Log CO_2 emissions					
Network	-0.0224	-0.0129	-0.0154	-0.0135	-0.00472
	(0.0231)	(0.0236)	(0.0249)	(0.0252)	(0.0281)
Network × High exporter	-0.0847*	-0.115**	-0.0621	-0.0495	-0.0525
	(0.0440)	(0.0499)	(0.0482)	(0.0435)	(0.0376)
Observations	9401	9401	9401	9401	9401
R^2 (within-plant)	0.122	0.123	0.123	0.122	0.123

Values shown are the coefficients of OLS regressions of the dependent variables on the covariates, with plant-level fixed effects (model (3)). The Network × High exporter interaction yields the treatment effect for companies with an export share above the respective threshold. Standard errors clustered at the network level are in parentheses. All specifications include sector-year interactions. Additional control variables include sales intensity (turnover divided by the number of employees), as well as the share of own electricity production of total consumption. There are 257 manufacturing sites in the pilot networks group and 589 plants in the control group. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. *Source*: FDZ (2014b), own calculations.

As discussed above, export shares increase with firm size. In order to test whether the treatment effect is driven by firm size rather than export status, I repeat the estimations from Table 4 for companies with high turnover. Results are shown in Table 5. In order to compare the estimates for exporters and large companies, the shares for the treatment effects in Table 5 are chosen such that they correspond to the share of the respective exporter category of all treated companies. For example, around four percent of treated companies have export shares of at least 90 percent. Consequently, the treatment effect estimated in column 1 of Table 5 is based on the four percent of treated companies with the highest turnover.

As can be seen from Table 5, treatment effects are statistically significant for CO_2 emissions at least at the ten percent level for all companies within the various groups of the upper 40 percent (and above) of turnover. For energy consumption, on the other hand, only the first treatment effect is statistically significant, albeit with an (unrealistically) high estimated treatment effect.[24] One explanation why for large companies there might be an effect on CO_2 emissions, but not energy consumption, 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.

Table 5: Treatment effects for large companies

Large company percentile	**(1) 0.96**	**(2) 0.89**	**(3) 0.83**	**(4) 0.75**	**(5) 0.61**
Panel A: Dependent var. Log energy consumption					
Network	-0.0120	-0.0167	-0.0110	-0.0159	-0.0164
	(0.0212)	(0.0228)	(0.0234)	(0.0254)	(0.0299)
Network × Large company	-0.224***	-0.0425	-0.0565	-0.0221	-0.0130
	(0.0491)	(0.0497)	(0.0395)	(0.0422)	(0.0372)
Observations	9428	9428	9428	9428	9428
R^2 (within-plant)	0.148	0.147	0.147	0.147	0.147
Panel B: Dependent var. Log CO_2 emissions					
Network	-0.0150	-0.0138	-0.00612	-0.00456	-0.00623
	(0.0213)	(0.0224)	(0.0225)	(0.0233)	(0.0250)
Network × Large company	-0.246***	-0.0958*	-0.101***	-0.0761**	-0.0454*
	(0.0554)	(0.0497)	(0.0362)	(0.0336)	(0.0271)
Observations	9401	9401	9401	9401	9401
R^2 (within-plant)	0.125	0.123	0.124	0.123	0.122

Values shown are the coefficients of OLS regressions of the dependent variables on the covariates, with plant-level fixed effects (model (3)). The Network × Large company interaction yields the treatment effect for companies with turnover above the respective percentile. Standard errors clustered at the network level are in parentheses. All specifications include sector-year interactions. Additional control variables include sales intensity (turnover divided by the number of employees), as well as the share of own electricity production of total consumption. There are 257 manufacturing sites in the pilot networks group and 589 plants in the control group. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. *Source*: FDZ (2014b), own calculations.

5.3 Cost-effectiveness

Although the treatment effect of the energy efficiency is not *statistically* significant, the discussion in section 5.1 has shown that there is likely to be a true underlying effect at least for parts of the networks participants. One important question is how the networking costs compare with the energy savings achieved. In this section, I therefore compute the levelised cost of saved energy (LCSE) under the assumption that the point estimate of the preferred specification equals the true network effect. I then compare this measure of cost-effectiveness to other estimates in the literature.

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[24] Since the estimate of column 1 is based on a very small share (four percent) of the overall treatment group, it is plausible that the estimated treatment effect is confounded by outliers (see discussion in section 4.2).

The levelised costs of saved energy can be interpreted as the total costs for knowledge acquisition within the networks, excluding investment costs. They include the costs of a 10-12 day energy audit at the beginning of a network, costs for the network moderator and the consulting engineers, as well as staff costs of the participants. However, they do not include investment costs for implemented energy efficiency upgrades. I estimate a range of the LCSE by varying the input parameters across two key dimensions. First, I take into account different estimates of the programme costs of energy efficiency networks.[25] Second, I vary the assumed lifetime of energy efficiency investments (between seven and 15 years).

Results show that the levelised costs of saved energy are very low, even for a relatively small estimated treatment effect of 2.2 percent (column 3 of Table 3). The relatively large energy consumption of treated companies implies that the fixed costs of participating in a network decline relative to the energy savings potential, such that the costs of knowledge acquisition and sharing are low for larger companies. For the mean company, LCSE are below 0.6 euro cents/kWh, which is the upper bound of the estimated range, based on high total programme costs and a low lifetime of energy efficiency measures. Conversely, LCSE would decrease to 0.14 cent/kWh in a scenario of low participation costs and a longer lifetime of the energy efficiency investments of 15 years. This is much lower than estimates of cost-effectiveness of energy efficiency programmes from the literature, as well as the social cost of producing energy.[26]

A comparison of cost-effectiveness estimates across the literature on energy efficiency programmes is complicated by several factors. First, many estimates are not based on randomised control trials (RCTs) or other quasi-experimental methods. Instead, often gross savings are estimated, which include energy savings by programme participants who would also have altered their energy use without the programme being in place (so-called free riders). This study, on the other hand, estimates net savings, i.e. the additional energy savings induced by the networks that would not have happened in the absence of the networking activities. The difference between gross and net savings can be substantial: For a range of energy efficiency programmes, Gillingham et al. (2018) estimate that costs per kWh saved are roughly 50 percent higher for gross savings than for net savings. Second, estimates of cost-effectiveness may be based on a wide range of energy efficiency programmes in different economic sectors. These programmes may range from information programmes to investment subsidies, and may include both commercial and industrial customers, as well as residential customers. This means that some estimates of cost-effectiveness from the literature are purely information costs (as the knowledge acquisition costs calculated for this study), while others include investment costs of the new technologies.

Bearing in mind these caveats, Table 6 shows that the costs for knowledge acquisition from networking in energy efficiency networks are very low compared to other estimates of cost-effectiveness of energy efficiency measures. I group the literature into studies on aggregate energy

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[25] Köwener et al. (2014) that the programme costs for a four-year network period may be up to 40,000 euros. Combining these costs with staff costs (assumed to be of 100,000 Euros/a) for three full-day workshops per year yields an upper bound of annual programme costs of around 11,200 euros. However, two-thirds of network participants state that the total annual costs for the energy efficiency networks are below 5,000 euros (dena 2017). This is chosen as a lower bound for the annual programme costs.

[26] For example, Gillingham et al. (2018) estimate the social cost of electricity generation (including the environmental cost of electricity generation) to be 5.6 (dollar) cents per kWh for the US, based on a wholesale electricity prices of 3.6 cents.

efficiency programmes (comprising a range of programmes, such as information provision or financial incentives), as well as studies on individual interventions. The aggregate studies are either exclusively programmes from the commercial and industrial sector, or include programmes from these sectors. Similar to energy efficiency networks, the *individual* programmes shown in Table 6 focus on information provision (albeit in the residential sector). Allcott (2011), Allcott & Rogers (2014) and Ayres et al. (2013) all study the effect of programmes aiming to trigger behavioural change by providing residential utility customers with feedback about their energy consumption by mail, comparing their energy usage to that of nearby neighbours. Similar to the knowledge acquisition costs of this study, the estimates shown in Table 6 include programme administrator costs only, for example technical assistance such as audits, measurement and verification, or costs of mail to customers in case of behavioural intervention.

The lower bound of the estimate of cost effectiveness of energy efficiency networks is an order of magnitude smaller than the energy efficiency programmes shown in Table 6. This means that energy efficiency networks can be seen as a relatively low-cost policy instrument. This conclusion holds conditional on the point estimate of 2.2 percent energy savings (which is not statistically significant) being the true network effect. Given the large difference to the cost-effectiveness of other programmes, however, energy efficiency networks would remain a cost-effective policy relative to other interventions even if the true effect was significantly lower than the estimated effect.

Table 6: Cost-effectiveness of energy efficiency programmes

Reference	Cost-effectiveness [$Cent/kWh]	Type of savings	Sector	Type of programme
This paper (energy efficiency networks)	0.2 to 0.6[a]	Net	Industry	Information provision
Aggregate programmes				
Arimura et al. (2012)	5[b]	Net	Various	Various (utility ratepayer-funded programmes)
Cho et al. (2019)	2.2	Gross	Commercial & industrial	Various
Gillingham et al. (2018)	2.8	Net	Various	Various (utility ratepayer-funded programmes)
Hoffman et al. (2018)	2.5	Gross	Commercial & industrial	Various (utility ratepayer-funded programmes)
Individual interventions				
Alberini & Towe (2015)	4.5[b]	Net	Buildings	Information provision, investment subsidy
Allcott (2011)	3.31	Net	Buildings	Information provision
Allcott & Rogers (2014)	1.4 to 1.8	Net	Buildings	Information provision
Ayres et al. (2013)	1.8 to 4.9	Net	Buildings	Information provision

[a] The cost-effectiveness of energy efficiency networks is based on the point estimate of 2.2 percent energy savings (column 3 in Table 3). For the range of the estimate, assumptions on programme administrator and participation costs, as well as the average lifetime of the implemented measures are varied. The cost estimate is converted from euros to 2016 US dollars, in order to allow for a comparison with international estimates.

[b] Calculated by Gillingham et al. (2018) based on estimates from the study.

6 Discussion

Several important findings on effect size and cost-effectiveness of energy efficiency networks have emerged from the previous section. These findings are discussed in the following.

First, although no statistically significant effect was found, this does not imply that energy efficiency networks were ineffective. Statistical insignificance is likely to be a function of a lack of statistical power. Although the estimated effect size is plausible, it is small relative to the size of the treatment group. Power calculations show that, given the size of the standard errors, only very high treatment effects could be identified by the model with a reasonable amount of certainty.[27] Given the focus of energy efficiency networks on cross-cutting technologies and relatively little attention to process technologies, such very high energy savings are unlikely. This means that it is plausible that the true (smaller) network effect cannot be detected with (statistical) certainty given the sample size.

Second, it is very likely that a significant share of the network participants did benefit from the networks. One important indicator for this is the high share of participants that continued with the networking after the initial energy efficiency network ended. Although no official numbers exist, interviews with two senior experts on energy efficiency networks held for this paper revealed that the total share of firms that extended the energy efficiency network activities beyond the initial network period is estimated to be above 50 percent. According to the institution that manages the 500 networks initiative, an estimated 30-40 percent of networks continue after the end of the initial period. Moreover, there is a significant share of companies that continue the networking informally, i.e. by self-organising the network activities without relying on a (costly) network manager in a guided networking process.[28] A "null result" (i.e. that none of the participants benefitted at all from the networks) is therefore unlikely.

Third, the network effect is likely to vary by participant. This is plausible given the heterogeneity of participants in terms of sector and plant size, as well as the fact that the quality of network managers and invited experts may vary by network. Section 5.2 presented evidence that the effects of the energy efficiency networks may be higher for larger companies, at least when it comes to CO_2 savings. Moreover, the event study regression (Figure 4) revealed that the standard errors are much larger in the post-treatment period than in the pre-treatment period, which also indicates that some participants may have benefitted more from the networks than others. On the other hand,

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[27] One measure to evaluate the ex-post power of a statistical model is the minimum detectable effect (MDE), which refers to the minimum level of a genuine empirical effect that can be detected under a certain significance level with a chosen likelihood (Bloom 1995). The MDE at conventional levels of a five percent level of statistical significance and 80 percent power (Ioannidis et al. 2017) is a reduction of energy consumption by 6.1 percent over the course of four years.

[28] Information on the share of networks that continue within the official structure was obtained from Steffen Joest, head of office at the *Initiaitve Energieeffizienz-Netzwerke*. While an official estimate of the share of firms that continue to network informally is not available, an estimate of around 25 percent was given by Prof. Eberhard Jochem, who is credited with introducing energy efficiency networks to Germany. The total share of energy efficiency networks that continue their work would thus add up to more than fifty percent.

such possible treatment effect variability also implies that it is less likely for the model to detect an average effect with high statistical certainty.

Fourth, the estimated treatment effects translate into high overall energy savings and low knowledge acquisition costs in energy efficiency networks. For the average network participant, the point estimate of minus 2.2 percent implies an amount of around 1,400 MWh energy saved over the course of the network period. This translates into a cost-effectiveness (expressed in levelised cost of saved energy) of 0.14 to 0.6 cents per kWh. Compared to similar energy efficiency programmes, energy efficiency networks are thus most likely a very low-cost energy efficiency policy.

Finally, the analysis has shown that the true network effect of energy efficiency networks is most likely lower than what advocates have argued. The point estimate of 2.2 percent over the course of four years is much lower than the prediction of an overall reduction of almost 4.5 percent implied by the claim of "double the industry average" savings achieved by the networks. Such a "double the industry" result would have been detected by the model with a probability of almost 80 percent at the 10 percent significance level, and with 66 percent at the five percent level.

Regarding the generalisability of results (external validity), the results from this paper are based on a specific type of network, consisting of comparatively large companies from different economic sectors that meet in regional networks. The central results from this paper can be expected to extend to similar regional networks set up at a later point in time. The main reason to expect such a generalisability is that the pilot networks used a standardised approach to manage the networks (see section 2). Many of the networks in the control group use the same standard, or at least key features of the process, such as an energy audit at the beginning of the networks.

On the other hand, results may not generalise to networks that vary in key parameters such as the network composition (type of firms), as well as firm size. Regarding the type of network, sectoral or within-company networks may address a broader scope of energy efficiency measures, since these can move beyond cross-cutting technologies to focus on technologies used in production processes. Regarding firm size, larger firms may already operate more on the technological frontier, with a lower potential for efficiency improvements. On the other hand, this technological frontier also shifts over time, due to technological progress. Moreover, the results in section 5.1.3 suggest that (within the subset of large companies), the largest plants benefitted relatively more from the networks in terms of CO_2 savings. One explanation is that the largest plants may have more standardised and professional management structure, such as an energy manager with clear responsibilities, who can more easily implement new learnings from the networks.

7 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 paper tests for a causal effect of German energy efficiency networks on energy consumption and CO_2 emissions of participating plants. Estimates from the most robust specification are 2.2 percent energy savings, as well as a reduction of CO_2 emissions of 2.6 percent over the course of four years. While this may be a small effect in relative terms, implied absolute savings are large and economically significant.

The treatment effects translate into a reduction of roughly 1,400 MWh and 600 tonnes of CO_2 for the average network participant. The analysis of heterogeneous treatment effects reveals that relative CO_2 savings may be higher for larger firms. However, the point estimates of the main effects are not statistically significant, likely due to the limited sample size relative to the estimated effect size.

Power calculations reveal that the network effect was most likely lower than proponents previously argued, and probably less than half of energy savings credited to energy efficiency networks are additional. The claim that energy efficiency networks lead to savings twice as high as the industry average is therefore likely exaggerated. Considering that energy efficiency networks mostly focus on cross-cutting technologies (typically lighting), it is plausible that the network effects are limited: Although relative savings from energy efficiency measures targeting cross-cutting technologies may be high, total energy consumption of cross-cutting technologies is only a subset of a company's overall energy consumption. Process technologies, which are responsible for a high share of total energy consumption for many firms in the manufacturing sector, are mostly not a focus of energy efficiency networks, given that firms within one network typically come from different economic sectors.

These results have clear policy implications, namely that energy savings credited to the networks should not be counted as a fully additional contribution to national energy savings targets. Currently, existing evaluations of the networks carried out for the German government regard all measures registered under the efficiency networks as fully additional, and therefore fully credit these energy savings towards the German contribution to the national goal set in the European Energy Efficiency Directive. This research suggests that an adjustment factor should be applied to the savings registered in the energy efficiency networks. Power calculations show that not all energy savings attributed to energy efficiency networks were actually triggered by the networking activities, and most likely less than half of the achieved savings are additional. This would imply that at least half of the total five million tonnes of CO_2 savings envisaged as a contribution under German national energy efficiency policies would have happened in the absence of the networks. Thus, more than 2.5 million tonnes of CO_2 counted towards the EU Energy Efficiency Directive have likely not materialised and would need to be compensated by additional policies.

On the other hand, there are good reasons to believe that the networking activities did benefit at least some of the participants. Most importantly, the share of participants that continued the networking activities (both formally and informally) is estimated to be above fifty percent. It is unlikely that profit-maximising firms would continue investing resources into a voluntary programme that does not benefit them. Additionally, the effect of the networks is likely to differ across participants, as well as across networks, for example due to differences in the quality of the network management or the consulting engineers.

Finally, this paper demonstrates that energy efficiency networks are likely to be a highly cost-effective energy efficiency policy. Assuming the point estimates are correct, I estimate a range of levelised costs of saved energy (LCSE) of the costs of knowledge acquisition between 0.14 to 0.6 cents per kWh saved. This compares favourably to the costs other energy efficiency policies, which are typically an order of magnitude higher. Consequently, energy efficiency networks would remain a low-cost informational policy even if actual savings were not as high as the point estimates suggest. Thus, even if the high expectations of some proponents cannot be fulfilled, on balance energy efficiency networks may still have delivered substantial energy reductions at relatively low cost.

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 paper. 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 if participants have a lower a-priori interest in energy efficiency, as well as potentially a larger distance to the technological frontier. Smaller and less energy-intensive companies may profit more from joining an energy efficiency network due to a greater potential for learning. For networks targeting these companies, it is important that networking costs decrease, since cost-effectiveness will decline if costs are large relative to the energy savings potential of a firm.

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 paper were regional networks focussed on cross-cutting technologies, which consisted of companies from different industrial sectors. 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-cutting technologies to targeting production technologies. One indication that sectoral or within-company networks may be successful is that their number 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.

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Appendix

A.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 paper, 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.2. Standardised bias of treatment and control group

Figure A-1 shows that the control group starkly improves balance compared to the manufacturing sector for nearly all variables. The only exception is the variable CO_2 intensity (not used in the regression analyses). Here, the standardised bias is lower for the manufacturing sector despite the mean being much further away from that of the treatment group than the control group's mean (cf. Table 1), due to the much larger standard error of the variable in the manufacturing sector than in the control group, which decreases the standardised bias.[29]

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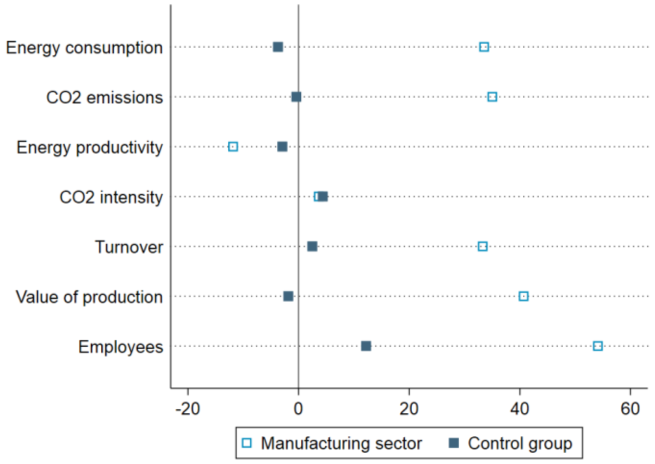
[29] The standardised bias is defined as $SB = \frac{100(\bar{X}_{Treat}-\bar{X}_{Control})}{\sqrt{(S^2_{Treat}+S^2_{Control})/2}}$, where $\bar{X}_{Treat}$ (S^2_{Treat}) is the mean (variance) of the treatment group, and $\bar{X}_{Control}$ ($S^2_{Control}$) is the mean (variance) of the control group (Rosenbaum and Rubin 1985).

Figure A-1: Standardised biases of control group and manufacturing sector



Notes: 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.

A.3. Starting years of the networks in the pilot phase

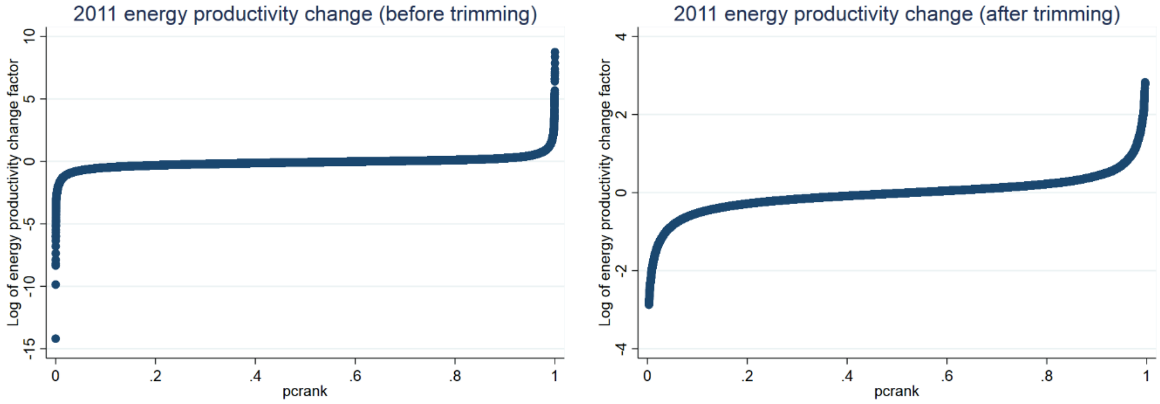
Table A-1: The starting years of the companies in the pilot phase

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

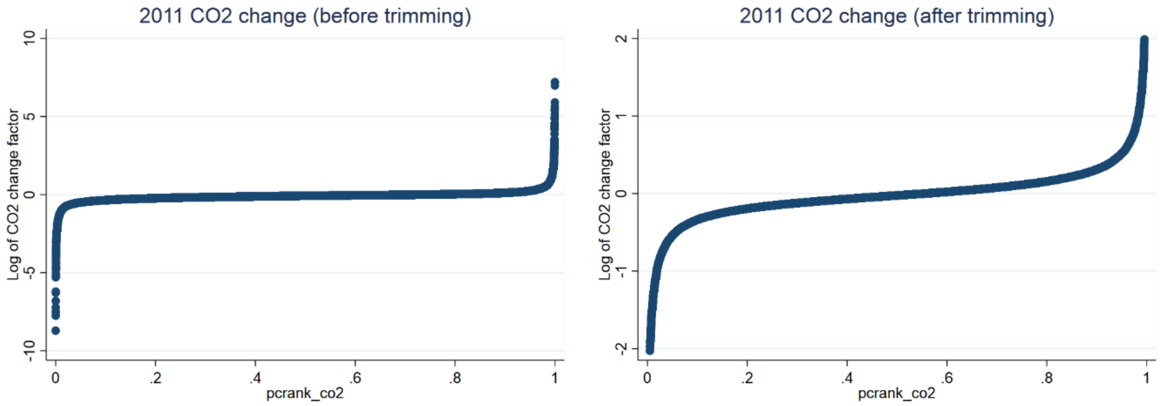
A.4. Outliers

Figure A-2: 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)



Notes: 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.5. Exporters

Export share

Table A-2: Distribution of export share, by treatment status

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile
Export share [in %]				
- Pilot networks	36.6 (28.6)	32.8	12.2	58.3
- Control group	31.6 (27.2)	27.7	5.8	51.3
- Manufacturing sector	17.8 (24.1)	4.5	0.0	30.1

Notes: The export share is measured as the fraction of total revenue generated from exports. The statistics are calculated over the pre-treatment period (years 2003-2006). There are 257 manufacturing sites in the pilot networks group, 589 plants 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-3: Distribution of key variables for pilot networks and exporters

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile	Obs.
Energy consumption [MWh]					
- Pilot networks	62,971 (153,762)	18,386	5,227	47,508	922
- High exporters	98,028 (143,133)	38,466	14,305	141,858	105
CO_2 emissions [tonnes]					
- Pilot networks	22,826 (53,741)	7,620	2,426	18,710	921
- High exporters	33,565 (41,569)	17,239	6,880	48,419	105
Energy productivity [€/kWh]					
- Pilot networks	5.58 (6.12)	3.48	1.73	7.55	877
- High exporters	5.91 (6.38)	2.24	1.20	8.85	105
Turnover [million €]					
- Pilot networks	192 (579)	63.3	24.4	152.1	922
- High exporters	260.3 (397.7)	77.8	55.0	291.4	105
Value of production [million €]					
- Pilot networks	139.1 (299.3)	61.2	24.3	134.4	877
- High exporters	234.6 (384)	81.6	55.7	228.7	105
Number of employees					
- Pilot networks	7,450 (13,970)	3,386	1,478	6,764	922
- High exporters	14,401 (19,169)	4,612	2,663	17,736	105

Notes: High exporters are defined as firms with at least 80 percent export share. The statistics are calculated over the pre-treatment period (years 2003-2006). *Source*: FDZ (2014a), own calculations.