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

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

Jan Stede*

Abstract: In energy efficiency networks, groups of firms exchange experiences on energy conservation in regular meetings over several years. The companies implement energy efficiency measures in order to reach commonly agreed energy savings and CO₂ reduction goals. Energy efficiency networks exist in several countries, such as Germany, Sweden and China. Existing evaluations of such voluntary regional networks in Germany claim that participants improved energy efficiency at twice the speed of the industry average. Based on comprehensive data from the German manufacturing census, this paper examines whether participation in energy efficiency networks has a causal impact on energy conservation and CO₂ emissions. I employ both a difference-in-differences estimator, using companies that joined energy efficiency networks at a later point in time as a control group, as well as a semiparametric matching estimator. I demonstrate that for the average participant there is no evidence of a statistically significant effect on energy productivity or CO₂ emissions due to the network activities. However, there is some indication that exporters may have benefitted from the networks by reducing their CO₂ emissions.

Keywords: Business networks; voluntary agreements; energy conservation; policy evaluation

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 per cent of final energy consumption in Germany and 26 per cent in the European Union (AGEB, 2016; Lapillonne and Sudries, 2016).

Energy efficiency networks are voluntary agreements of companies, targeted at reducing energy consumption in industry. In such networks, 10 to 15 firms from different economic sectors exchange experiences at regular moderated meetings over a period of 3-4 years in order to achieve jointly agreed energy efficiency and CO₂ savings targets (Jochem and Gruber, 2007; Köwener et al., 2014; Rohde et al., 2015). The basic mechanism through which energy efficiency networks operate is an information treatment, encouraging investment into energy efficiency by providing companies with the knowledge and skills to effectively reduce energy consumption. Energy efficiency networks are typically regional. They focus on efficiency improvements in cross-sectional technologies (such as lighting or process heat), since participating companies come from different economic sectors with different production technologies (Jochem et al., 2010). Originating from Switzerland, energy efficiency networks now exist in several OECD and large non-OECD countries, such as Germany, Sweden and China (Jochem et al., 2016; Paramonova and Thollander, 2016; OECD/IPEEC, 2017).

In Germany, energy efficiency networks are one of the major instruments in the national policy mix to improve energy efficiency in industry and reach national climate targets. Together with the main industrial associations, the German government plans to create 500 networks by 2020, delivering savings of up to five million tonnes of CO₂ through voluntary agreements (Barckhausen et al., 2018; BMU, 2019). These savings would account for 1/5 of all measures that reduce energy consumption set out in Germany’s “National Action Plan on Energy Efficiency” (NAPE), which are necessary to comply with the EU Energy Efficiency Directive (Ringel et al., 2016).

Energy efficiency networks in Germany are generally considered a success in the existing literature. Most studies have looked at the so-called German “pilot networks”, which were carried out between 2009 and 2014, before the official adoption of the target of setting up 500 networks. More than 360 companies have participated in 30 of these initial energy efficiency networks. The literature on these networks has focused on bottom-up calculations of energy savings achieved during the networking period, as well as surveys among participating companies (see, e.g., Wohlfarth et al., 2016; Barckhausen et al., 2018; Dütschke et al., 2018). Some of these evaluations conclude that participating companies increased their energy efficiency at two per cent or double the speed of the industrial sector as a whole (Jochem et al., 2010; Köwener et al., 2014; Rohde et al., 2015). However, survey evidence also suggests that a large chunk of these energy conservation measures may not have been additional, since the firms would have carried out these measures anyways (e.g. Wohlfarth et al., 2016).

The main contribution of this 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 increased energy efficiency, as well as reduced CO₂ emissions. I use two different estimation strategies to explore this causal link. First, I employ a difference-in-differences estimator, comparing the energy productivity and CO₂ emissions of participants of the pilot phase 2009-2014 (treatment group) to a group of plants joining German energy efficiency networks that were initiated after the pilot networks had been completed (post-2014). These latter firms also chose to become part of an efficiency network, but did not receive the treatment until the pilot phase was over. Relative to the average manufacturing firm, this control group is much more similar to the participants of the pilot networks in terms of observables such as average energy consumption or number of employees.

I find no evidence of a statistically significant effect of the energy efficiency networks on either energy productivity or CO₂ emissions for the average plant. While in some specifications there is a statistically and economically significant effect of the networks on energy productivity and CO₂ emissions, this effect is driven by a few large installations. In the most robust specifications, there is no evidence of an effect of the networks. I provide visual support for the identifying assumption of parallel trends of treatment and control group in the absence of the treatment. Moreover, I test for anticipation effects and do not find evidence of either an increased energy productivity or lower CO₂ emissions prior to the uptake of a network. This lends additional credibility to the identifying assumption.

In order to check the robustness of these results, I employ a semiparametric matching estimator in a second step. This estimator aligns the distribution of observed variables of treatment and control group that are relevant for energy conservation efforts by choosing appropriate comparison units from the entire manufacturing sector. This reduces the differences between treatment and control group in terms of observables. Moreover, by taking first differences, the estimator accounts for selection on time-invariant plant characteristics, such as organisational structures that favour energy efficiency investments. Results from the matching estimation support the finding of no significant treatment effect due to the network activities. My results are in stark contrast to previous assessments of energy efficiency networks in Germany, and highlight the importance of ex-post policy evaluation.

Finally, I explore heterogeneous treatment effects by taking a closer look at network participants with high exports. I find some indication that high exporters may benefit from energy efficiency networks by reducing their CO₂ emissions. This result may be explained by a better management of exporting firms, which allows exporters to profit more from participating in energy efficiency networks than the average industrial firm. Exporting firms have been found to be more innovative and more productive than domestic non-exporters (Helpman et al., 2004; Yeaple, 2005; Aw et al., 2008; Lileeva and Trefler, 2010). Moreover, exporting may improve management practices (Bloom and Van Reenen, 2010), which in turn may have positive spillovers on energy efficiency (Bloom et al., 2010; Martin et al., 2012; Boyd and Curtis, 2014). Exporting German manufacturers in particular have been found to be more energy efficient than their non-exporting counterparts (Lutz et al., 2017).

This research contributes to the literature on the impact evaluation of voluntary environmental management programmes using firm-level data. Voluntary agreements to reduce the environmental

impacts of production processes have received increasing attention (Segerson and Miceli, 1998), with mixed results on their effectiveness. Well-studied voluntary programmes include the U.S. Environmental Protection Agency’s 33/50 (Arora and Cason, 1995; Khanna and Damon, 1999; Gamper-Rabindran, 2006; Vidovic and Khanna, 2007; Carrión-Flores et al., 2013), as well as the norm for environmental management systems ISO 14001 (e.g. Arimura et al., 2011; see also the comprehensive overview by Boiral et al., 2018). European voluntary programmes such as the EU’s Eco Management and Audit Scheme (EMAS), on the other hand, have received considerably less attention (e.g. Bracke et al., 2008). Recently, Kube et al. (2019) find no effect of EMAS on either CO₂ intensity, energy intensity or investments for German manufacturing firms.

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 two alternative identification strategies used to estimate the treatment effect of energy efficiency networks. Section 4 portrays the panel dataset used in this study, discusses the use of energy productivity as an indicator for energy efficiency, and provides descriptive statistics. Section 5 presents the results and discusses the identifying assumptions. Section 6 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 energy savings goal, as well as a CO₂ reduction goal. The individual goals add up to a joint network target. In the networking phase (phase 2), participants meet at regular moderated meetings for three to four years. Here, they share their experience about the implementation of energy efficiency measures. Moreover, external experts provide input on topics such as energy efficiency technologies, organisational measures like awareness raising among employees, or financing of energy efficiency investments. There are also yearly site visits to monitor progress towards the energy efficiency goal and, at the same time, to allow participants to see efficiency measures implemented in other companies.

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).

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). In addition, there are transaction costs such as staff costs for the participation at network meetings (Köwener et al., 2014). However, costs of participation can be much lower when a network does not use the LEEN standard (Jochem et al., 2010).²

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 per cent 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.2). Energy efficiency networks were still relatively unknown in Germany when the first networks were set up, and the decision to join a network was voluntary. Consequently, the managers of the 30 pilot networks (energy agencies, industry associations, research institutions or utilities) typically approached companies they knew in order to persuade them to join a network of the treatment group.

There was no direct financial incentive to participate in one of the 30 pilot networks, apart from reduced participation costs. The networks got financial support from the National Climate Initiative of the German environmental ministry to cover parts of the costs of setting up and managing the networks, leading to a reduction of participation costs. Financial support included up to 1/3 of the costs of setting up a network³, such as project management costs and the costs of the initial energy audit⁴. However, there were no direct payments to companies in the pilot networks, such as financial support for the investment of the implemented energy efficiency measures.

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

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

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

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

the energy efficiency improvement of the German industry as a whole, which is estimated to have been approximately one per cent 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 per cent 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 How energy efficiency networks may help firms to reduce energy consumption

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

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

Moreover, EENs may also influence energy conservation through **socio-psychological mechanisms** (Jochem et al., 2010; Stern, 1992): The participation of company representatives in a group structure like an energy efficiency network can lead to a higher intrinsic motivation for participants (Köwener et al., 2011). Setting a joint efficiency and CO₂ reduction target in the network may also help the energy managers to elevate the topic of energy-cost reduction to a higher level of priority in the decision-making structures of their companies and to convince their management to pursue efficiency investments (Jochem and Gruber, 2007). Jochem et al. (2007) argue that competition and (positive) peer pressure also play a role. The argument is that setting joint energy efficiency and CO₂ reduction network targets helps to motivate participants to pursue these targets by advancing energy efficiency investments in their companies (Köwener et al., 2011; Rohde et al., 2015). However, evidence from surveys with consulting engineers and network moderators suggests that the joint targets may not be a major driver for energy efficiency improvements (Dütschke et al., 2018).

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

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

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

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

More significantly, 25 per cent 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 per cent 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 per cent of the firms report that they would have carried out energy efficiency measures even without participating in a network (dena, 2017). Consequently, it is unclear whether energy efficiency networks really lead to additional energy savings.

3 Research Design

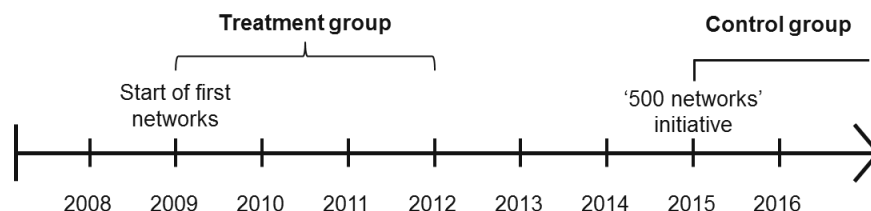
In line with the potential outcomes framework (Rubin, 1974), I estimate the causal effect of membership in a pilot network both on energy productivity (the value of production per unit of total energy consumed in EUR/kWh), as well as on CO₂ emissions of the networking companies. From a climate policy perspective, the question of whether ‘energy efficiency networks’ are (also) ‘CO₂ reduction networks’, as well as the amount of CO₂ savings achieved through the networks, are of substantial interest. The German government relies on CO₂ savings generated in energy efficiency networks in order to reach its 2020 climate targets (BMU, 2019). Moreover, there is reason to believe that CO₂ 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 CO₂ savings may be larger than those from a reduction in energy consumption.

The main challenge to an unbiased estimation of the average treatment effect on the treated (ATT) is the selection mechanism. Since participation in energy efficiency networks is voluntary, companies self-select into the networks. If the factors determining the selection process are systematically related to energy efficiency investments, any naïve estimation of treatment effects comparing firms in the networks to companies outside of the networks will be biased. I pursue two different identification strategies to overcome this issue. Both estimators rely on different identifying assumptions such as common trends, for which I provide evidence in sections 5.1.2 and 5.2.3.

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

My main specification is a generalised difference-in-differences (DiD) estimation, where network members of the pilot phase (‘treated’ plants) are compared to a ‘control’ group of installations joining energy efficiency networks that were initiated at a later point in time. This control group is made up of plants that are part of the initiative to form 500 energy efficiency networks until 2020. The treatment of the two groups does not coincide, since at the time when the first networks were conducted, the networks from the second phase had not yet started (Figure 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. This motivation is likely to be linked to increased energy consumption reduction capacities at the installation level, such as management structures that favour energy efficiency

improvements. Indeed, as the distribution of key (observable) variables shows, the treatment group is much more similar to the control group than to the rest of the German manufacturing sector (see section 4.1). Consequently, companies from the post-2014 networks make a good control group.

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

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

where the dependent variable is either the (log of) energy productivity or the (log of) CO₂ emissions of installation i in year t . β_1 is a vector of network fixed effects, which control for quality differences of the 30 different energy efficiency networks ω in the pilot phase. τ_t is a vector of year fixed effects, controlling for the impact of unobserved production shocks such as the effect of the Great Recession on energy efficiency and CO₂ emissions. γ_s contains industry fixed effects for each two-digit industry sector s . φ_{st} are sector-year interactions that capture intra-industrial structural change. β_0 is an intercept. The indicator variable $\mathbf{1}\{Network\}_{it}$ switches from 0 to 1 in the year the energy efficiency network from the pilot phase of firm i starts operating. This makes δ the coefficient of interest, which measures the effect of an energy efficiency network on energy productivity and CO₂ emissions of the participating plants.

In order to increase the precision of the estimates and account for variables that affect firms from the pilot networks and control group differently, the DiD model is augmented to specification (2) below:

$$y_{it} = \beta_0 + \beta_1 \omega_i + \delta \cdot \mathbf{1}\{Network\}_{it} + \tau_t + \gamma_s + \varphi_{st} + \mathbf{X}_{it} \Psi + \varepsilon_{it}, \quad (2)$$

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

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

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

where μ_i is a plant-level fixed effect, controlling for within-plant differences in energy productivity or CO₂ emissions that are constant over time. The reasoning for introducing μ_i is that decisions for energy efficiency investments happen at the plant level. Some of these plants may regularly be investing more into energy efficiency than others, even in the absence of being in a network. The plant-level fixed effects prevent the estimate of the treatment effect, δ , from being upward biased due to such time-invariant unobserved factors, such as organisational structures that favour energy efficiency investments.⁵

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

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

The assumption of parallel trends of the conventional DiD estimator may be implausible if (observable) pre-treatment characteristics that affect the outcome variable are unbalanced between the treated and the untreated (Abadie, 2005). More energy-intensive companies, for example, may have a higher incentive to improve energy efficiency because expenditures for energy make up a higher share of production costs. In order to better account for heterogeneity in covariates across treatment and control group, I use the semiparametric matching estimator introduced by Heckman et al. (1998b, 1998a, 1997) as a robustness check. This conditional DiD matching estimator matches on observed company characteristics to select plants from the entire universe of the German manufacturing sector as a control group. As shown by the descriptive statistics below, although treatment and control group in the standard DiD are quite similar in terms of observable variables, some differences remain. The matching estimator accounts for these differences when computing treatment effects. Moreover, by using the time series variation of the panel data, the estimator eliminates bias from temporally-invariant omitted variables. Consequently, it accounts for selection on fixed unobservables (Heckman et al., 1997)

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

$$\hat{\delta}_{Treat} = \frac{1}{N_1} \sum_{i \in I_1} \left\{ (y_{it}(1) - y_{it'}(0)) - \sum_{k \in I_0} W_{N_0, N_1}(i, k) * (y_{kt}(0) - y_{kt'}(0)) \right\}, \quad (4)$$

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

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

4 Data

This paper makes use of rich administrative German plant-level data, the AFiD panels⁶. The AFiD panels are official microdata provided by the German research data centres of the Statistical Offices of the Federal States, comprising observations both at the plant and enterprise level from the German industrial sector (Petrick et al., 2011). Using installation-level data allows determining

⁶ AFiD is an acronym for "*Amtliche Firmendaten für Deutschland*" ("Official Firm-level Data for Germany").

the disaggregated effect of energy efficiency networks on individual plants. For multi-plant companies, this is important since typically not all production sites of a given firm were part of one specific regional network. The AFiD panels contain information on all German manufacturing firms with at least 20 employees (around 43,000 plant-level observations per year), including detailed information on their energy consumption by fuel.⁷ Based on these energy inputs, I calculate plant-specific CO₂ 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.2). Since the names of these firms are publicly available, they can be matched to the AFiD panels using identifiers like the registration number of the German trade register (*Handelsregisternummer*), as well as the location of the plant. Using this approach, I successfully match 259 companies to the AFiD panel of manufacturing sites. This corresponds to a matching rate of almost 90 per cent. Moreover, 489 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 firms in the control group was matched to the AFiD panel.

In principle, energy efficiency networks can be regional, sectoral or company networks. As mentioned, all the networks in the pilot phase were regional. In the case of the control group, on the other hand, several sectoral and internal company networks that comprise only of steel companies have been set up since 2015. In order to align the distribution of sectors and the size of the companies in terms of energy consumption between treatment and control group, these networks were excluded from the control group.⁸ This reduces the size of the control group of the DiD estimator (section 5.1) to 364 companies.

4.1 Measurement of energy efficiency and dealing with measurement error

In this paper, I use energy productivity – defined by the value of output per unit of total energy consumed (EUR/kWh)⁹ – as a measurement of energy efficiency for several reasons. Energy productivity (the inverse of energy intensity) is a commonly used metric for measuring energy efficiency. Some of the typical caveats associated with using energy intensity as an indicator for energy efficiency (e.g. Patterson, 1996) are alleviated by the research design of this study. First, comparing the development of energy efficiency within firms across time mitigates the issue that

⁷ CO₂ emissions are calculated using yearly fuel-specific emission factors from the German Environment Agency.

⁸ These networks are called ESTA, EnERGY, DIHAG, WVM plus, Elektrostahl and Steel energy+. The exclusion of these networks improves the balance of sectors between treatment and control group. Before excluding the sectoral and company networks, 16 per cent of the production sites from the control group had been in the basic metals sector, compared to 6.9 per cent 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).

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

energy intensities are often not comparable across industries. Second, year fixed effects and sector-specific trends help to account for external factors such as the impact of the Great Recession on energy efficiency in regression equations (1) to (3). Finally, a sector-specific price deflator (at the two-digit level), derived from the German National Accounts, is used in order to eliminate time trends from the energy productivity time series by deflating monetary values such as turnover and value of output.

Around two per cent 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-1 in the appendix). While some of the higher variation of energy productivity observed in the data is reasonable, the scale of reported changes for some of the observations is most likely explained by measurement error.¹⁰ Consequently, I use the Mahalanobis distance to identify unusual observations and omit the two per cent of observations with the highest distance from the sample.¹¹ Figure A-1 shows how this procedure reduces implausible values for the variables energy productivity and CO₂ emissions.

4.2 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. This is also confirmed by comparing pre-treatment trends in the dependent variables (section 5.1.2).

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

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

¹¹ The Mahalanobis distance takes into account the covariance among the variables in calculating distances, and allows to consider several variables with different scales. Unlike the standard Euclidean distance, the problems of scale and correlation are therefore not an issue when identifying an outlier using several variables. Here, the Mahalanobis distance is calculated to identify outliers using the variables absolute energy productivity, change of (log) energy productivity over 2008, as well as change of (log) CO₂ emissions over 2008.

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

Compared to the average industrial firm, treatment and control group are very much alike. However, there are some differences. Manufacturing sites in the treatment group are typically larger than installations in the control group¹³: Treated plants have a higher turnover (mean of EUR 180 million vs. EUR 138 million) and more employees (7,300 and 5,000, respectively). In terms of energy consumption and CO₂ emissions, the median of these variables is larger for the pilot networks, while the mean is smaller. This suggests that there are several energy-intensive installations in the upper tail of the control group's distribution.

Table 1: Distribution of key variables, by treatment status

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile	Obs.
Energy consumption [MWh]					
- Pilot networks	67,415 (164,116)	18,815	5,892	48,667	1,256
- Control group	76,799 (228,320)	12,620	3,568	44,970	1,789
- Manufacturing sector	13,229 (93,417)	971	362	3,739	214,215
Energy productivity [€/kWh]					
- Pilot networks	5.32 (6.68)	3.20	1.38	6.58	1,187
- Control group	5.93 (7.55)	3.27	1.23	8.21	1,725
- Manufacturing sector	11.25 (66.33)	5.63	2.70	11.78	205,954
CO₂ emissions [tonnes]					
- Pilot networks	21,417 (48,356)	7,119	2,755	17,832	1,246
- Control group	25,086 (80,305)	4,775	1,480	15,421	1,786
- Manufacturing sector	4,494 (31,037)	398	140	1,523	213,683
Turnover [million €]					
- Pilot networks	179.9 (477)	67.3	23.7	140.7	1,256
- Control group	137.7 (596.1)	44.8	15.9	115.7	1,789
- Manufacturing sector	34.2 (361.4)	6.3	2.7	18.6	214,075
Value of production [million €]					
- Pilot networks	132.1 (224.9)	66.0	24.7	131.0	1,187
- Control group	94.4 (201.9)	41.5	16.5	106.9	1,725
- Manufacturing sector	27.7 (219.5)	5.9	2.6	17.2	205,955
Number of employees					
- Pilot networks	7,283 (13,156)	3,643	1,601	6,812	1,256
- Control group	4,986 (10,702)	2,554	1,168	5,404	1,789
- Manufacturing sector	1,548 (6,167)	600	360	1,313	214,075
Energy cost share [%]					
- Pilot networks	3.9 (5.4)	2.2	1.4	4.1	946
- Control group	4.3 (4.8)	2.7	1.2	5.3	1,257
- Manufacturing sector	3.3 (4.3)	1.9	1.0	3.7	99,318

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

¹³ Since some differences in terms of observables remain between treatment and control group in the DiD estimator, as a robustness check I use nearest neighbour matching to identify a control group and improve the overlap of treatment and control group (see section 5.2).

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

Table 2: Sectors of economic activities [in %]

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

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

Notes: 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, 364 installations in the control group, and an average of 42,843 plants in the manufacturing sector. *Source:* FDZ (2014b), own calculations.

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

5 Results

5.1 DiD with future network control group

5.1.1 Setup and results

Table 3 shows the estimation results of the difference-in-differences models for energy productivity (Panel A) and CO₂ emissions (Panel B), with standard errors clustered at the network level.¹⁵ Columns 1 to 3 correspond to the models (1) to (3) in section 3.1, with the dependent variables in levels. Column 1 contains the most basic specification (1), i.e. not controlling for any covariates. Column 2 adds a range of covariates, namely sales intensity (the value of production of the goods produced in a specific year targeted for sale divided by the number of employees)¹⁶, the share of turnover generated from exports, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector.¹⁷ Finally, in column 3 – corresponding to model (3) – plant-level fixed effects are introduced. In columns 4 through 6, the same models are re-estimated with the dependent variables energy productivity and CO₂ emissions in logs. 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)¹⁸ and sector-specific trends.

Column 6 – model (3) with the dependent variables in logs – is the preferred specification, since the inclusion of plant-level fixed effects controls for unobserved constant factors at the plant level. As energy efficiency changes happen at the plant level, this is the most robust specification. The log specification leads to a percentage interpretation of the coefficients, evaluating changes in energy productivity and CO₂ emissions relative to the size of each plant. Consequently, the log specifications dampens the effect of outliers (with large CO₂ emissions, for example) on the point estimates.

As can be seen from Table 3, the estimated treatment effects both for energy productivity and for CO₂ emissions are statistically significant in the levels specification (columns 1 to 3). The coefficients in column 3 (specification including plant fixed effects) suggest an increase of energy productivity of 0.3 EUR/kWh (or 5.6 per cent relative to the mean of 5.32 EUR/kWh), as well as a reduction of CO₂ emissions by almost 2500 tonnes (minus 11.5 per cent) due to the networks.

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

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

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

¹⁸ The industry classification of the years 2003-2008 has been adjusted to the German standard “WZ 2008” in order to allow for a comparison of the industrial sectors over time, using the conversion tables by Dierks et al. (2019). Details are explained in appendix A.1. The sector fixed effects drop out when an installation does not change its industry affiliation over time due to the inclusion of plant-level fixed effects in model (3).

Table 3: Difference-in-differences treatment effects for energy productivity and CO₂ emissions

Regressor	Dependent variable in levels			Dependent variable in logs		
	(1)	(2)	(3)	(4)	(5)	(6)
<u>Panel A: Dependent var. energy productivity</u>						
Network	0.400* (0.226)	0.457** (0.207)	0.298* (0.161)	0.0109 (0.0248)	0.0224 (0.0201)	0.0167 (0.0148)
Observations	6824	6824	6824	6824	6824	6824
R ² (within-plant)	0.265	0.332	0.164	0.386	0.48	0.38
<u>Panel B: Dependent var. CO₂ emissions</u>						
Network	-3921.4** (1691.3)	-3043.5** (1310.5)	-2466.9** (935.4)	-0.0329 (0.0342)	-0.000518 (0.0313)	-0.0101 (0.018)
Observations	7101	6801	6801	7101	6801	6801
R ² (within-plant)	0.186	0.235	0.046	0.238	0.431	0.125
Additional controls	No	Yes	Yes	No	Yes	Yes
Plant-level fixed effects	No	No	Yes	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector-specific trends	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Values shown are the coefficients of OLS regressions of the dependent variables on the covariates. Unit of observation is plant-year. Standard errors clustered at the network level in parentheses. Energy productivity is measured in €/kWh. CO₂ emissions are measured in tonnes. Additional control variables include sales intensity (turnover divided by the number of employees), the export share, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector. There are 257 manufacturing sites in the pilot networks group, and 466 installations in the control group. Significance: * p<0.1, ** p<0.05, *** p<0.01. *Source:* FDZ (2014b), own calculations.

However, the picture changes when energy productivity and CO₂ emissions are measured in logs (columns 4 to 6). Although the signs are still in the expected direction, all estimated treatment effects are insignificant, both for energy productivity and for CO₂ emissions. Confidence intervals of the preferred specification in column 6 reveal that with 95 per cent probability, the effect of a participation in energy efficiency networks on energy productivity is lower than 4.7 per cent, and the reduction of CO₂ emissions is smaller than 4.7 per cent.

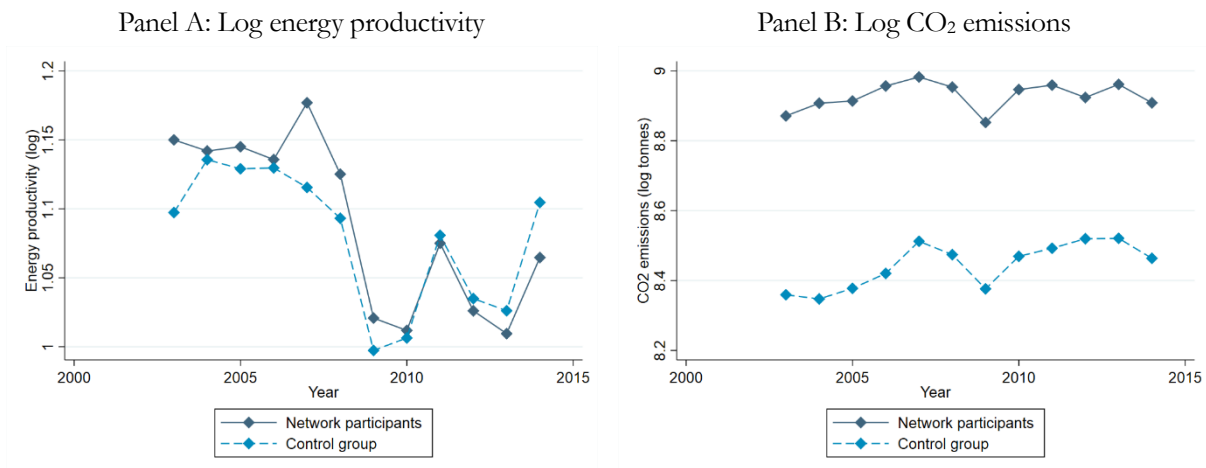
The insignificance of the estimated treatment effects in the log specification points to an effect of outliers on the point estimates in the levels specifications. Indeed, this hypothesis is confirmed by a re-estimation of the models shown in Table 3 excluding the largest companies. I re-estimate all specifications shown in Table 3 three times, excluding plants with the one per cent highest energy consumption, the 2.5 per cent highest energy consumption, and the five per cent highest energy consumption, respectively. All coefficients for CO₂ emissions in the levels specification become insignificant. For energy productivity, columns 1 and 2 also become insignificant; only specification (3) remains significant at the 10 per cent level (detailed results are available from the author on request). This confirms that the significant estimates in the levels specification of in Table 3 are probably driven by outliers.

In sum, while all signs of the DiD models are in the expected direction, no robust statistically significant effect can be found for the average network participant. The estimated treatment effects are insignificant when energy productivity and CO₂ emissions are measured in logs. The effect also vanishes when the largest plants are excluded from the regressions. This suggests that energy efficiency networks may have led to energy productivity improvements and CO₂ savings for some firms, but not on average.

5.1.2 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 (until 2008) for the dependent variables (log) energy productivity (Panel A), as well as (log) CO₂ emissions (Panel B).¹⁹

Figure 3: Development of energy productivity and CO₂ emissions for firms in the pilot networks and the control group of the DiD estimator



Source: FDZ (2014b), own calculations.

In addition to a visual inspection of the pre-treatment graphs, I test for anticipation effects.²⁰ The idea is to test whether companies are already on an upward trajectory with respect to their energy efficiency when they join a network. I estimate three variants of each specification shown in Table 3, with up to three pseudo-treatment dummies that indicate a treatment in the years prior to the start of the energy efficiency networks. Of the 72 estimated pseudo-treatment effects²¹, only the first lag of CO₂ emissions (in levels) in the plant-level fixed effects model (3) is significant at the

¹⁹ The development of absolute energy productivity and CO₂ emissions is shown in Figure A-2 in the appendix. The parallel trends assumption seems to hold for energy productivity, but not for absolute CO₂ emissions.

²⁰ The results for the anticipation effects estimation of the plant fixed effects model (3) are shown in the appendix (Table A-2). The results for the other models are available from the author on request.

²¹ For each of the four dependent variables (energy productivity, log energy productivity, CO₂ emissions and log CO₂ emissions) I estimate three different specifications (as in section 3.1), each estimated separately with one, two and three lags.

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

A second assumption of the DiD estimator is the Stable Unit Treatment Value Assumption (SUTVA). This assumption requires that treatment does not spill over from treated firms to untreated firms (Imbens and Rubin, 2015). In general, it is reasonable to assume that knowledge gained in the network meetings should not spill over to non-participating plants in the short run, since companies do not have an interest to share the knowledge gained in energy efficiency networks with their competitors. However, in the case that a parent company owns multiple plants, it cannot be ruled out that non-participating installations profit from the knowledge acquired by their peers that did participate in energy efficiency networks.²² 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 exclude from the control group of the post-2015 networks those plants that belong to the same parent company as manufacturers that took part in the pilot networks.

5.2 Conditional DiD matching estimator

5.2.1 Setup

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

The nearest neighbour matching estimator constructs the counterfactual estimate for each treatment case by selecting the m nearest neighbours and setting the weights W_{N_0, N_1} equal to $1/m$ for the selected neighbours, and zero for all other members of the comparison group. In the baseline estimations, I estimate treatment effects based on one nearest neighbour matching (1:1), and re-estimate with three nearest neighbours to demonstrate robustness of the results. To mitigate the challenge that the energy efficiency networks start in different years (cf. appendix A.2), I only include firms in the matching estimation that started between May 2009 and February 2011. Consequently, there is a maximum difference of time spent in a network of 1.5 years within the treatment group.²³

Since the German manufacturing sector consists of around 43,000 firms, I have a large group of potential nearest neighbours for each treated observation. It is therefore possible to match on several variables without compromising too much on the matching quality. I impose the strictest

²² 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.

²³ I exclude three networks or 10 per cent of the treatment group due to this restriction.

overlap with respect to industry sector by requiring exact matching on the two-digit industry classification level. The reasoning is that there are unobserved differences, for example in production technology or technological change, that can be thought to be more similar at the sectoral level.²⁴ Additionally, I match on three continuous variables, namely the 2006-2008 (pre-treatment) averages of energy consumption, energy productivity, and sales intensity.²⁵ As Fowlie et al. (2012) note, past values of a variable are a good predictor of its value in subsequent periods.

5.2.2 Results

An assessment of the matching quality reveals that the matching procedure strongly reduces the differences between treatment and control group. Figure 4 plots standardised biases for a number of variables (some of which were used in the matching process, others not) before and after the nearest neighbour matching. Comparing standardised biases is a common procedure to assess matching quality. It is better suited to judge the balance of a matched sample than statistical significance testing, since it does not depend on sample size (Imai et al., 2008).²⁶ Figure 4 shows that the matching significantly reduces the standardised bias between treatment and matched control group for all variables.

Other indicators for covariate balance also show how the matching algorithm markedly increases the similarity of network companies and the matched control group in terms of observables (see appendix A.5). Figure A-3 plots kernel densities before and after matching for the case of energy consumption, revealing how the overlap improves for the two groups due to the matching process. Table A-3 compares the treatment group with the matched control group in terms of the means of several variables, showing that the two groups are similar, although most differences remain statistically significant. Finally, empirical quantile-quantile (Q-Q) plots also show that the matching algorithm results in very similar distribution of key variables for the treated companies and their matched counterparts (Figure A-4).

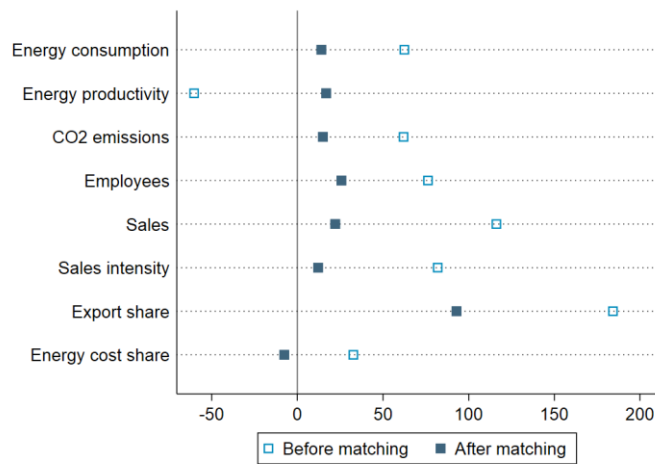
In sum, the matching algorithm significantly improves overlap both for variables included in the matching (e.g. energy consumption, number of employees), as well as for variables *not* explicitly included in the matching, such as energy consumption (e.g. CO₂ emissions, export share, or energy cost share, cf. Figure 4). The fact that matching improves overlap among variables that influence energy efficiency but were not used for matching gives confidence that it achieves balance for unobservables related to energy efficiency as well.

²⁴ As a robustness check, I impose an exact matching on the three-digit level. This does not change the results qualitatively, but I lose around 15 per cent of observations due to an insufficient number of matches or treated companies within one sector on the three-digit level.

²⁵ As noted above, the components of the variable sales intensity, namely the variables value of production and number of employees are quite collinear. Using the variable sales intensity (turnover/employee) hence integrates the information of two variables – both of which are an indication of firm size – into one variable that is used for matching.

²⁶ The standardised bias is defined as $SB = \frac{100(\bar{X}_{Treat} - \bar{X}_{Control})}{\sqrt{(S_{Treat}^2 + S_{Control}^2)/2}}$, where \bar{X}_{Treat} (S_{Treat}^2) is the mean (variance) of the treatment group, and $\bar{X}_{Control}$ ($S_{Control}^2$) is the mean (variance) of the control group (Rosenbaum and Rubin, 1983).

Figure 4: Standardised biases before and after matching



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.

Table 4 gives an overview of the matching results, for one nearest neighbour (Panel A) and three nearest neighbours (Panel B). I compute the average treatment effect on the treated for the variables energy productivity (in levels and logs), as well as CO₂ emissions (in levels and logs). The outcome variables are expressed in the differences between a post-treatment year (either the year 2014 or the year 2013) and the pre-treatment year 2008. I also estimate an average 2013-2014 treatment effect, combining both 2014 and 2013 differences to 2008 in one matching estimation.

Table 4: Nearest neighbour matching treatment effects

Year by year comparison (base year 2008)	Energy productivity	Log energy productivity	CO ₂ emissions	Log CO ₂ emissions
<u>Panel A: One nearest neighbour (1:1)</u>				
2014	-0.312 (0.268)	-0.0112 (0.043)	-1414.1 (1582.9)	0.0305 (0.034)
2013	-0.0686 (0.291)	-0.0391 (0.045)	-493.7 (1459.4)	0.0479 (0.03)
Average 2013-2014	-0.19 (0.198)	-0.0252 (0.031)	-951 (1076.2)	0.0395* (0.022)
<u>Panel B: Three nearest neighbours (1:3)</u>				
2014	-0.161 (0.225)	0.0165 (0.037)	-876.2 (1368.6)	0.00936 (0.025)
2013	-0.153 (0.263)	-0.024 (0.04)	-144.4 (1348.8)	0.0359 (0.023)
Average 2013-2014	-0.157 (0.173)	-0.00391 (0.027)	-508.2 (960.9)	0.0227 (0.017)

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

The nearest neighbour matching estimator confirms the results of the previous section, namely that no statistically significant effect of joining an energy efficiency network on either energy productivity or CO₂ emissions can be found. As can be seen from Table 4, almost all estimated treatment effects are insignificant. The only exception is the combined 2013 and 2014 estimate of the effect on log CO₂ emissions in the specification with one nearest neighbour matching (Panel

A), which is significant at the ten per cent level. However, the effect becomes insignificant in the three nearest-neighbour matching specification (Panel B).

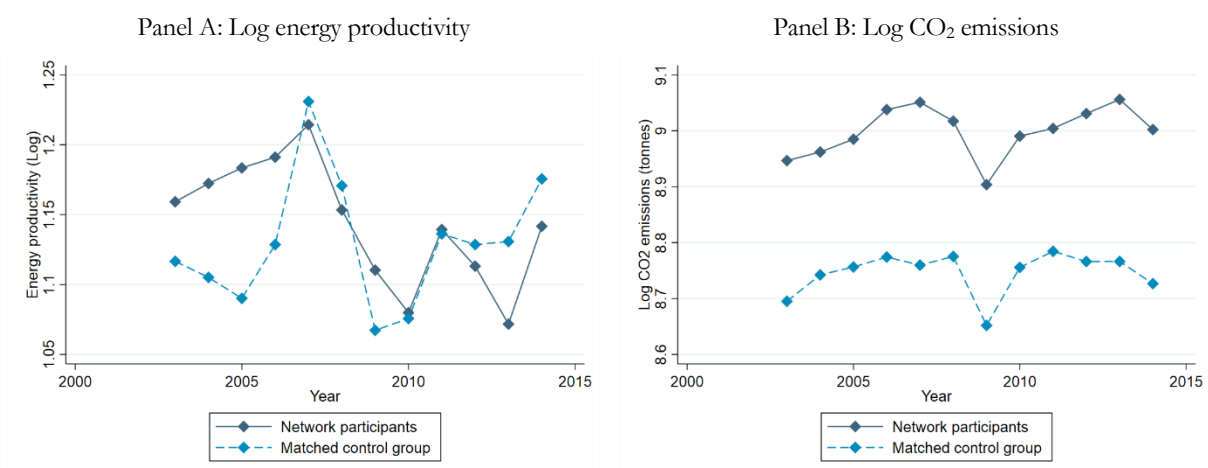
5.2.3 Assessment of identifying assumptions

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

In general, for unconfoundedness to hold in the context of a DiD matching estimator, it is important to have a rich set of variables that are related to the dynamics in the outcome variable (Imbens and Rubin, 2015; Smith and Todd, 2005). Several of such variables are available in the AFiD panels, and I use them in the nearest-neighbour matching. For unobserved variables, it is important that they do not vary over time, since the conditional DiD estimator accounts for selection on fixed unobservables and is therefore consistent with a Roy model of self-selection applied to a panel setting (Heckman et al., 1997). It is reasonable to assume that important variables such as the unobserved motivation to reduce energy consumption, or capacities to improve energy efficiency, are constant over the relatively short time horizon of five years of the networking phase.

Figure 5 graphs the development of energy productivity and log CO₂ emissions for the treatment group and for the matched control group. A visual assessment of the conditional common trends assumption illustrates that the development of the dependent variable prior to the treatment (pre-2009) is similar. For the variables log energy productivity and CO₂ emissions, the trends are qualitatively similarly in line (appendix A.6). This gives confidence that the unconfoundedness assumption underlying the conditional DiD matching estimator is fulfilled. Regarding SUTVA, as in the previous section, plants that belong to the same parent company as manufacturers that took part in the pilot networks are excluded from the matched control group, in order to rule out potential spillovers within corporations.

Figure 5: Development of (log) energy productivity and CO₂ emissions for firms in the pilot networks and the matched control group



Source: FDZ (2014b), own calculations.

5.3 Heterogeneous treatment effects

Although there is no robust evidence for an effect of joining an energy efficiency network for the average participant, there might be subgroups that benefit more from the networking activities than others. One important determinant of whether firms profit from energy efficiency networks are management structures, which may influence whether energy savings opportunities identified in the networks are realized by making an investment decision into energy efficiency.

Since I cannot observe management quality 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.

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

Table 5 shows the interaction effect of regressions of models (1) to (3) – the conventional difference-in-differences estimation²⁷ – for the variables energy productivity and CO₂ emissions, where the treatment dummy is interacted with a “high exporter” dummy.²⁸ Thus, the estimates represent the additional effect of the networks on high exporters. The only statistically significant effects are the models with the log of CO₂ emissions as the dependent variable (columns 4 to 6 in Panel B). While the estimates in columns 4 and 5 are unrealistically high, column 6 (the preferred specification including plant-level fixed effects) indicates that CO₂ emissions fell by almost 11 per cent for high exporters. One explanation why for high exporters there might be an effect on CO₂ emissions, but not energy productivity, is the occurrence of fuel switching, i.e. a substitution of the use of “dirty” energy carriers such as coal by less CO₂-intensive energy sources.²⁹

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

Regressor	Dependent variable in levels			Dependent variable in logs		
	(1)	(2)	(3)	(4)	(5)	(6)
<u>Panel A: Dependent var. Energy productivity</u>						
Network	0.530** (0.217)	0.501** (0.212)	0.275* (0.154)	0.00974 (0.0289)	0.00663 (0.0267)	0.0206 (0.0169)
Network × High exporter	-1.086 (1.158)	-0.329 (1.014)	0.202 (0.649)	-0.00203 (0.151)	0.131 (0.143)	-0.0372 (0.0538)
High exporter	1.305** (0.519)	1.244*** (0.396)		-0.194*** (0.0659)	-0.189** (0.0838)	
Observations	6872	6872	6872	6872	6872	6872
R ² (within-plant)	0.261	0.331	0.165	0.39	0.482	0.377
<u>Panel B: Dependent var. CO₂ emissions</u>						
Network	-2631.3 (1934)	-1783.7 (1447.7)	-2535.2** (1039.6)	0.0467 (0.0515)	0.0678 (0.0437)	0.00351 (0.0203)
Network × High exporter	-10865.6 (7599.2)	-10540.3 (6405.7)	397.9 (2186.1)	-0.676** (0.296)	-0.560** (0.233)	-0.113** (0.0503)
High exporter	20654.7*** (5799.6)	12859.5** (5330.4)		1.162*** (0.272)	0.711*** (0.221)	
Observations	7149	6849	6849	7149	6849	6849
R ² (within-plant)	0.19	0.233	0.046	0.265	0.408	0.133

Notes: Values shown are the coefficients of OLS regressions of the dependent variables on the covariates. Standard errors clustered at the network level are in parentheses. Energy productivity is measured in €/kWh. CO₂ emissions are measured in tonnes. Additional control variables in columns 2, 3, 5 and 6 include sales intensity (turnover divided by the number of employees), the export share, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector. Columns 3 and 6 include plant-level fixed effects. There are 257 manufacturing sites in the pilot networks group, 27 of which are high exporters, and 466 installations in the control group. Significance: * p<0.1, ** p<0.05, *** p<0.01. *Source:* FDZ (2014b), own calculations.

²⁷ Results from the conditional DiD matching estimator are not shown for high exporters, since the number of observations is very low.

²⁸ For a given firm, this dummy takes on the value of one if exports constitute at least 80 per cent of a firm’s turnover in at least half of the years.

²⁹ Regressions of the consumption of different fuels on the variables of column 6 in Table 5 indicate a reduction of (CO₂-intensive) electricity consumption for high exporters, and an increase of the consumption of natural gas. However, these results are not statistically significant.

Summing up, in contrast to the average network participant, companies with higher exports may have benefitted from participating in energy efficiency networks by reducing their CO₂ emissions. This gives some support to the hypothesis that better-managed firms may benefit more from participation in energy efficiency networks by better exploiting fuel switching options to reduce their CO₂ emissions.

6 Conclusion: Do energy efficiency networks deliver?

Energy efficiency networks are a voluntary policy measure aimed at improving energy efficiency and reducing CO₂ emissions that have gained momentum in recent years. This paper tests for a causal effect of German energy efficiency networks on energy productivity and CO₂ emissions of participating plants. Results show that on average energy efficiency networks either did not affect energy productivity and CO₂ emissions at all, or the effect was quite small. The effects in the most robust specifications of the difference-in-differences estimation are statistically insignificant. While for a subset of the different specifications there are statistically significant effects on energy productivity and CO₂ emissions, these are likely driven by a few large plants. Confidence intervals show that for the average participant, participation in a network most likely did not increase energy productivity by more than 4.7 per cent, and reduced CO₂ emissions by less than 4.7 per cent. These results are confirmed by a conditional difference-in-differences matching estimator, where the estimated treatment effects are insignificant in all specifications.

There is, however, some indication that good management practices influence whether knowledge gained in the networks translates into changing behaviour at the firm level. Previous studies have found that high export is a proxy for good management, and good management practices in turn lead to higher energy efficiency. This paper shows that high exporters – defined as treated plants that have a revenue share of at least 80 per cent from exports – reduced their CO₂ emissions by around 10 per cent. These results suggest that larger, better-managed companies may profit more from participating in energy efficiency networks than the average firm.

There are several reasons why network activities might not have induced improvements in energy productivity or CO₂ emissions for the average network participant. First, this article shows that the companies that joined energy efficiency networks are much larger, more energy-intensive and have higher energy costs than the average industrial firm. Consequently, one explanation why network participation may not have had an additional effect is that firms self-selected into networks because they had significantly higher incentives to reduce energy expenditures than other manufacturing companies anyways. The networks then may not have presented an added value for this particular group of firms. Second, a motivation for companies to self-select into energy efficiency networks other than energy conservation may be signalling. Since the names of the companies in German energy efficiency networks are public, joining energy efficiency signals to customers and other stakeholders that a participating company cares about reducing the environmental impact of its production process. Additionally, the rapid expansion of energy efficiency networks in Germany in recent years has largely happened due to a voluntary agreement between the German government and major industrial associations. Thus, a growing number of energy efficiency networks is also a signal to regulators and other stakeholders that industry is willing to reduce energy consumption and CO₂ emissions. Finally, interviews with moderators of energy efficiency networks conducted

for this study have confirmed that typically the network managers approached companies in order to convince them to join an energy efficiency network, not the other way around. Naturally, the network managers approached those companies that they already knew had an interest in improving their energy efficiency. These firms may already have been committed to improving energy efficiency even before joining an energy efficiency network.

On the other hand, there is reason to believe that energy efficiency networks were beneficial at least for some of the firms that joined the energy efficiency networks. First, for the group of high exporters, which are significantly larger than the average network participant, some evidence for a reduction of CO₂ emissions was found. Second, around six per cent of firms that were part of one of the initial networks decided to continue these activities by joining a second energy efficiency network after the initial one was completed. The most likely explanation for this behaviour is that in these companies' assessment, the initial network did benefit them significantly. It is unlikely that firms would decide to invest significant resources into joining a voluntary programme again, if they did not feel they achieved tangible results in the first network.

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. However, it may be that smaller (less energy-intensive) companies profit more from joining an energy efficiency network, for example due to a greater potential for learning. Since German energy efficiency networks are voluntary, they target firms that are already motivated to increase energy efficiency. It may, however, well be that energy efficiency networks are more effective when participants have a lower a-priori interest in energy efficiency.

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

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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. Starting years of the networks in the pilot phase

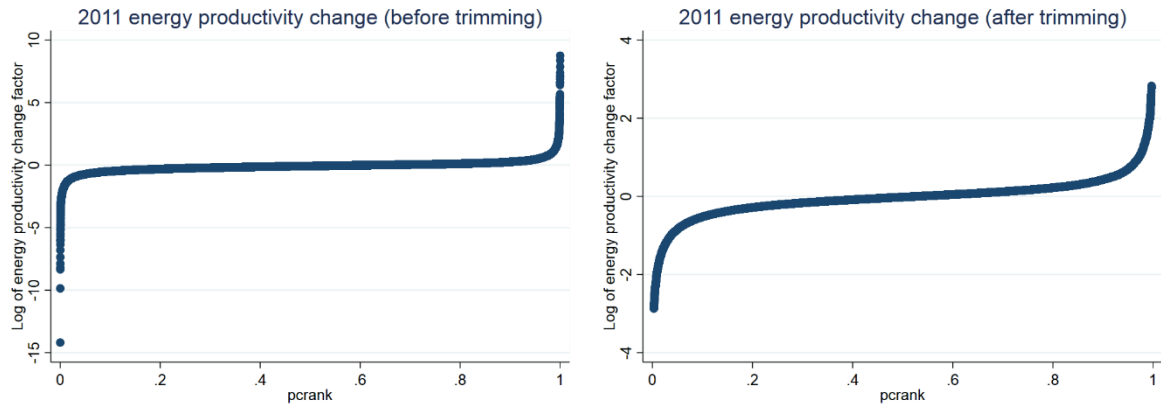
Table A-1: The starting years of the companies in the pilot phase

Start year of the network	2009	2010	2011	2012	Σ
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

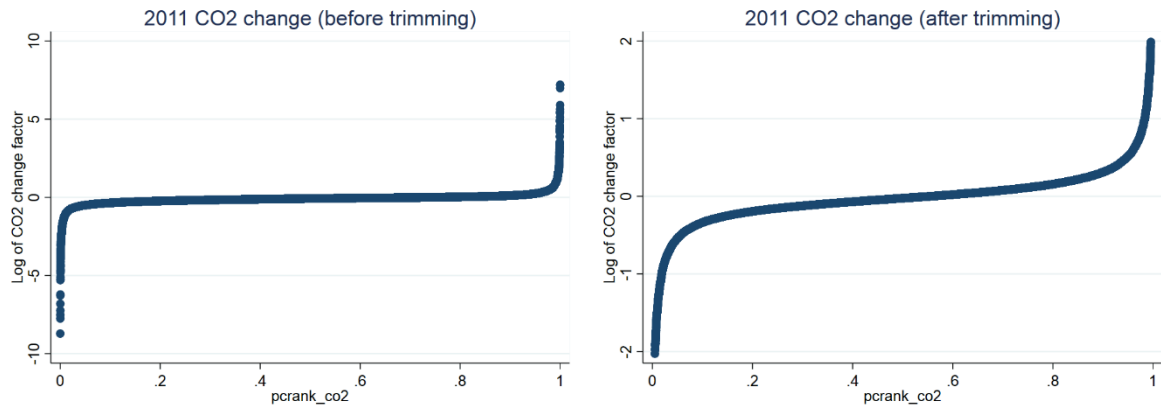
A.3. Outliers

Figure A-1: Change of energy productivity and CO₂ 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 CO₂ emissions prior to the removal of outliers (left) and after their removal (right)

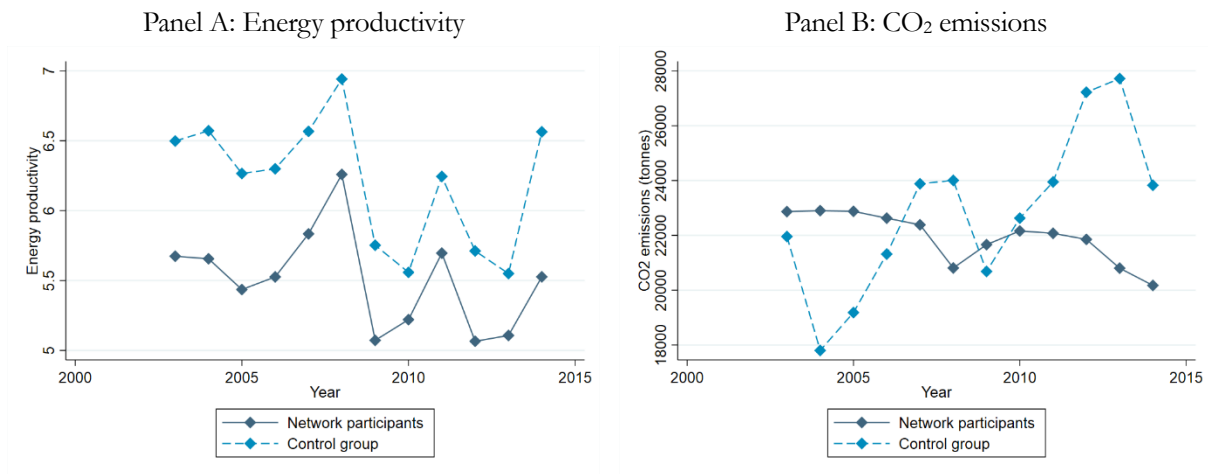


Notes: Changes of energy productivity and CO₂ emissions are shown for the year 2011, relative to the pre-treatment year 2008. Due to the logarithmic transformation, a log productivity change of 10 corresponds to a change of energy productivity (CO₂ emissions) by of factor of ~22,000. *Source:* FDZ (2014b), own calculations.

A.4. Graphs and tables for the DiD estimator

Development of energy productivity and CO₂ emissions

Figure A-2: Development of CO₂ emissions and energy productivity (in levels)



Source: FDZ (2014b), own calculations.

Anticipation effects

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

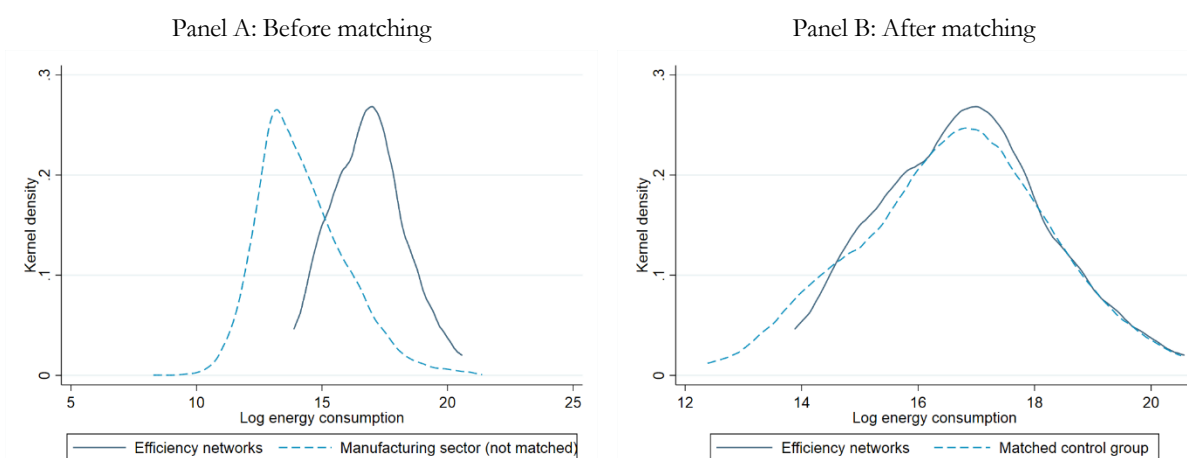
Regressor	Dependent variable in levels				Dependent variable in logs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<u>Panel A: Dependent var. Energy productivity</u>								
Ex-post effect	0.298* (0.161)	0.296 (0.185)	0.266 (0.189)	0.232 (0.182)	0.0167 (0.0148)	0.0197 (0.0177)	0.0179 (0.0193)	0.0207 (0.0199)
Ex-ante effect (t-1)		-0.00899 (0.154)	-0.0467 (0.167)	-0.0853 (0.164)		0.0144 (0.0215)	0.012 (0.0227)	0.0153 (0.022)
Ex-ante effect (t-2)			-0.137 (0.115)	-0.18 (0.135)			-0.00837 (0.018)	-0.00478 (0.0212)
Ex-ante effect (t-3)				-0.143 (0.132)				0.0119 (0.0206)
Observations	6824	6824	6824	6824	6824	6824	6824	6824
R ² (within-plant)	0.164	0.164	0.164	0.165	0.38	0.381	0.381	0.381
<u>Panel B: Dependent var. CO₂ emissions</u>								
Ex-post effect	-2466.9** (935.4)	-3104.5** (1160.9)	-3068.1** (1267.8)	-3171.8** (1456.3)	-0.0101 (0.018)	-0.0131 (0.0209)	-0.014 (0.0228)	-0.0162 (0.0239)
Ex-ante effect (t-1)		-3029.3* (1632.4)	-2983.0* (1475.5)	-3099.9* (1568.3)		-0.0141 (0.0185)	-0.0153 (0.0211)	-0.0178 (0.0222)
Ex-ante effect (t-2)			167.6 (1765.8)	37.05 (2046.1)			-0.0041 (0.017)	-0.00692 (0.0195)
Ex-ante effect (t-3)				-434.2 (1214.7)				-0.00937 (0.017)
Observations	6801	6801	6801	6801	6801	6801	6801	6801
R ² (within-plant)	0.046	0.047	0.047	0.047	0.125	0.125	0.125	0.125

Notes: Estimation of different versions of the plant-level fixed effects model (3), with and without anticipation effects. Values shown are the coefficients of OLS regressions of the dependent variables on the covariates. Standard errors clustered at the network level are in parentheses. Energy productivity is measured in €/kWh. CO₂ emissions are measured in tonnes. Additional control variables include sales intensity (turnover divided by the number of employees), the export share, the share of own electricity production of total consumption, a dummy for investment into environmental protection, as well as a dummy for the basic materials sector. Significance: * p<0.1, ** p<0.05, *** p<0.01. *Source:* FDZ (2014b), own calculations.

A.5. Balance tests for the conditional matching estimator

Kernel density of energy consumption

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



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

Mean comparison

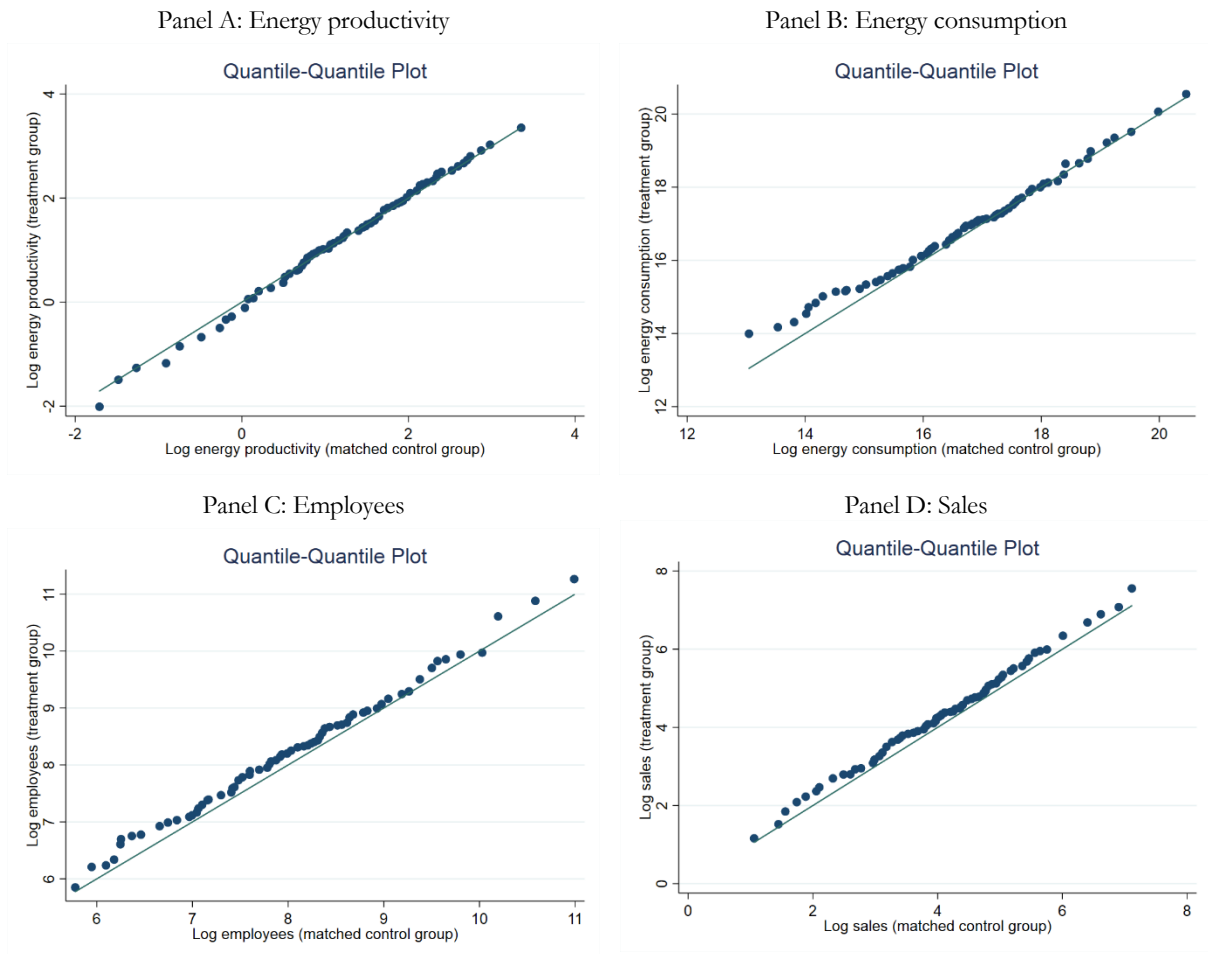
Table A-3: Comparison of the means of treatment and matched control group

Variable	Mean networks	Mean matched control	Difference
Energy consumption [MWh]	62,604	58,431	4,173**
Energy productivity [€/kWh]	5.7	5.5	0.18**
CO ₂ emissions [tonnes]	22,392	18,603	3,789*
Annual turnover [million €]	190.3	135.9	54.4***
Value of production [million €]	160.0	124.6	35.4**
Number of employees	7,378	6,184	1194**
Sales intensity [thousand €/employee]	22.9	22.2	0.7*
Export share [%]	39.3	33.5	5.8***
Energy cost share [%]	3.6	3.6	-0.1
Observations/plants	199	199	199

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

Q-Q plots

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

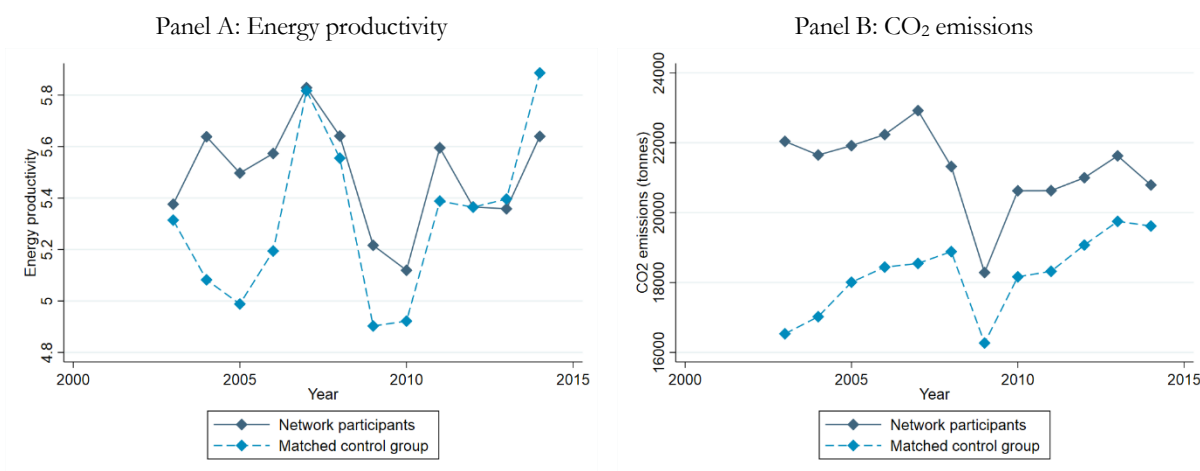


Notes: Panels A to D show the 2008 (i.e. pre-treatment) quantile-quantile (Q-Q) plots of several variables for treated and matched control group for the NN(1) matching estimator. All variables are in logs.

Source: FDZ (2014b), own calculations.

A.6. Pre-treatment trends for the conditional matching estimator

Figure A-5: Development of energy productivity and CO₂ emissions for firms in the pilot networks and the matched control group



Source: FDZ (2014b), own calculations.

A.7. Exporters

Export share

Table A-4: Distribution of export share, by treatment status

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

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

Descriptive statistics pilot networks vs. high exporters

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

Variable	Mean (standard deviation)	Median	Lower quartile	Upper quartile	Obs.
Energy consumption [MWh]					
- Pilot networks	67,415 (164,116)	18,815	5,892	48,667	1,256
- High exporters	106,089 (164,110)	32,888	15,064	140,522	134
Energy productivity [€/kWh]					
- Pilot networks	5.32 (6.68)	3.20	1.38	6.58	1,187
- High exporters	6.15 (8.06)	3.10	1.06	7.01	129
CO₂ emissions [tonnes]					
- Pilot networks	21,417 (48,356)	7,119	2,755	17,832	1,246
- High exporters	32,889 (43,618)	12,865	5,421	51,496	134
Turnover [million €]					
- Pilot networks	179.9 (477)	67.3	23.7	140.7	1,256
- High exporters	230.8 (291.5)	85.7	52.5	316.4	134
Value of production [million €]					
- Pilot networks	132.1 (224.9)	66.0	24.7	131.0	1,187
- High exporters	221.6 (278.4)	93.7	53.6	308.2	129
Number of employees					
- Pilot networks	7,283 (13,156)	3,643	1,601	6,812	1,256
- High exporters	13,553 (17,412)	4,922	2,434	18,786	134
Energy cost share [%]					
- Pilot networks	3.9 (5.4)	2.2	1.4	4.1	946
- High exporters	5.5 (8.4)	1.9	1.3	4.8	108

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