LUND UNIVERSITY
School of Economics and Management

Master in Economic Development and Growth

Electricity Prices and Energy Efficiency - a Regression Discontinuity Approach

Mario Györi
eut13mgy@student.lu.se

Abstract: This study analyzes the relationship between electricity prices and energy efficiency in German companies. Economic theory suggests that higher energy prices will lead to higher energy efficiency. This paper tests this hypothesis empirically by analyzing company-level data from Germany. In particular, a special provision of the German Renewable Energy Act (REA) is exploited. According to this provision, some companies are exempted from paying the "REA markup" - a markup charged on the electricity price in order to finance subsidies for renewable energy. Exempted companies pay lower electricity prices and can therefore be used as a counterfactual in a regression discontinuity analysis. The results of the analysis suggest that energy prices have a statistically significant and positive effect on energy efficiency.

Key words: Energy Prices, Energy Efficiency, Regression Discontinuity

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For my parents,

Karin and Helmut Györi

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Abbreviations

ct	Euro cent
DSM	Demand-Side Management
EE	Energy Efficiency
EUR	Euro
FIT	Feed-in-tariff
FOEE	Federal Office of Economics and Export Control (German: *Bundesamt für Wirtschaft und Ausfuhrkontrolle)*
FSO	Federal Statistical Office of Germany (German: *Statistisches Bundesamt)*
Gwh	Gigawatt-hour
IEA	International Energy Agency
Kwh	Kilowatt-hour
RD	Regression Discontinuity
REA	Renewable Energy Act (German: Erneuerbare Energien Gesetz)
SME	Small and Medium sized Enterprise

I.) Introduction

This study examines the relationship between energy prices and energy efficiency in German companies. In particular it addresses the question whether higher energy prices, e.g. induced by an energy tax, can lead to higher energy efficiency. The question is of high policy relevance but has only been investigated very scarcely. This has been mainly due to methodological problems: usually all companies in an economy pay the same market electricity price. This leaves us without a counterfactual to assess the consequences of electricity price changes in a *ceteris paribus* environment.

The present study aims at resolving this problem by adopting an innovative research method: the regression discontinuity design. In particular, the study exploits a provision of the German Renewable Energy Act (REA) according to which some companies pay higher electricity prices than others. Companies which consume more than 10 Gwh of electricity per year and whose electricity costs are higher than15% of value added can apply for an exemption from paying the “REA markup” – a markup charged on the electricity price in order to finance subsidies for renewable energy producers. Exempted companies therefore pay lower electricity prices than their competitors and can be used as a counterfactual in the analysis. The regression discontinuity approach allows us to estimate the “treatment effect” of an REA exemption in a quasi-experimental setting: As the eligibility for exemption depends on arbitrary cutoff points, it can be assumed that companies slightly below the critical threshold and slightly above the critical threshold do not differ systematically from each other in anything besides treatment eligibility. Discontinuities in energy efficiency at the critical threshold can therefore be interpreted as the causal impact of the price differences at this threshold (Imbens & Lemieux 2008).

The results of this study suggest that higher energy prices do indeed lead to higher energy efficiency in German companies. In particular, energy efficiency in companies that were eligible for an REA exemption was on average 1,10% lower than in companies that were not eligible for an exemption. Taking into account that not all eligible companies also applied for an exemption, the Local Average Treatment Effect of an actual exemption was -2.82% (i.e. exempted companies were on average 2.82% less energy efficient than their competitors.

The following paragraphs will summarize the contribution of this study and outline its structure.

<u>IA.) Relevance and Contribution of this Master Thesis</u>

The contribution of this study can be summarized in four main points. First of all, the research question has very high policy relevance. Energy efficiency (EE) is one of the keys to achieve sustainable growth. Today’s developing and emerging market economies have an enormous growth potential and economic growth may help these countries to fight against poverty and to address other pressing social issues. However, previous research has shown that growth is mostly linked to higher energy consumption and, by extension, higher CO2 emissions (Kander, Malanima and Warde 2014). One possibility to achieve desirable growth in an environmentally sustainable fashion is to increase energy efficiency. Therefore we need to know more about energy efficiency, its determinants and policies to promote it.

Secondly, in spite of the policy relevance, the question whether higher energy prices can lead to higher energy efficiency has only been investigated scarcely. Economic theory suggests that under perfectly competitive markets, higher energy prices will lead to higher energy efficiency. An electricity tax might therefore be an easy and economically efficient way to achieve energy efficiency improvements. However, as elaborated in Chapter II, there are also reasons to doubt that the theoretical predictions on energy prices and energy efficiency hold in practice. In order to make informed policy recommendations, it is necessary to examine the issue empirically. However, only very few empirical studies have attempted to examine the relationship between energy prices and energy efficiency before. This study aims at filling this gap.

Third, the study uses an innovative research design that resolves methodological issues that were problematic in previous studies on energy prices and energy efficiency. Using a quasi-experimental research design (Regression Discontinuity), the study comes very close to the experimental ideal, where treatment and control group do not differ in anything but treatment status. This allows us to investigate whether there is a causal relationship between energy prices and energy efficiency. Previous studies on EE policies found correlations between energy prices and energy efficiency but were not able to prove causality between the variables (Jefferson & Fisher Vanden 2004, Hang and Tu 2005).

In general, RD Designs are considered as econometrically superior to OLS regressions, matching estimators or other control strategies, as conclusions on causality can be drawn under relatively weak assumptions (Angrist & Pischke 2008). As a consequence, the method has gained increasing popularity Labor Economics and Development Economics in recent years (see e.g. Angrist and Lavy 1999, Almond et al. 2010, Van der Klaauw 2002). However, to the best of my knowledge, the method has not yet been applied in the fields of Environmental or Energy Economics. One contribution of this study is to illustrate how RD can be used in this context.

Fourth, the study draws on a unique company-level dataset from Germany that has not yet been used in a study on energy efficiency. Company level data is only rarely made available to researchers due to data security concerns. Even anonymized data might allow competitors to draw conclusions on other firm's production patterns or other secret strategies. As a consequence, studies based on company-level micro-data are generally rare. This study draws on data from of the Research Data Centre at the Federal Statistical Office of Germany, which allows researchers to work with company level datasets using a 'controlled teleprocessing of data'. Under this procedure, researchers are not provided with the sensitive datasets, but can send their analysis syntax (e.g. Stata Do-Files) to the research center, where the syntax is applied to the original datasets. The stata outputs are then controlled by an officer of the Federal Statistical Office as well as a representative of the Statistical Office of the *Länder*. Afterwards the results are transmitted to the researchers. One contribution and major difficulty of this Master thesis was to engage in the application for data usage and to coordinate the timely processing of the data with the Federal Statistical Office.

IB.) Structure of the Thesis

Chapter II summarizes the economic theory as well as previous empirical studies on the relationship between energy prices and energy efficiency. Chapter III will provide some institutional background for the RD analysis and discusses the exemption rule to the German Renewable Energy Act which serves as a basis for this study. Chapter IV elaborates on the regression discontinuity method, explains its intuition, assumptions needed and how it can be applied in the context of the German Renewable Energy Act. Chapter V briefly presents the data sources. Chapter VI summarizes the results of the study and presents a number of robustness checks. Chapter VII concludes, discusses possible weaknesses of the study and suggests avenues for future research.

II.) Theory and Litterature Review

This chapter will contextualize this study with respect to the previous literature on energy prices and energy efficiency. To set the stage, section IIA will introduce the concept of energy efficiency and elaborate on its importance for sustainable economic growth. Moreover, it will summarize previous studies on the long run determinants of energy efficiency. Section IIB gives an overview on the available policy options to promote energy efficiency. Given that my study focuses on the relationship between energy prices and energy efficiency, an emphasis is put on price-based measures. Lastly, section IIC summarizes previous studies that have examined the link between energy prices and energy efficiency empirically and elaborates on the econometric difficulties that researchers face when conducting such evaluations.

A.) Energy efficiency – what it is and why it matters

Following Kander, Malanima and Warde (2014), economic energy efficiency (e) shall be defined as the ratio between the value of total production (Y) and energy inputs (E) used in the production of Y:

$$e = \frac{Y}{E} \qquad (1)$$

On the macro level, energy efficiency can hence be computed by dividing GDP (the value of all goods and services produced in an economy) by overall energy use in the economy. On the micro level, the energy efficiency of company i can be expressed as the ratio between the firm's value added (Q_i) and its total energy use (E_i):

$$e_i = \frac{Q_i}{E_i} \qquad (2)$$

The energy efficiency e can be interpreted as the amount of output that can be produced given an amount of energy. Energy intensity (i) is simply the inverse of energy efficiency. It expresses how much energy is needed in order to produce a given amount of output:

$$i_i = \frac{E_i}{Q_i} \qquad (3)$$

There is a broad consensus among academics, international organizations and policy makers that energy efficiency improvements can play a crucial role in the mitigation of climate change (Geller & Attali 2005; Kander, Malanima and Warde 2014; International Energy Agency 2014). Higher energy efficiency allows an economy to produce a certain amount of output at lower environmental costs (or conversely, to produce higher amounts of output without additionally damaging the environment). Energy efficiency improvements are therefore not only needed in highly industrialized countries trying to 'green' their economies; they are also crucial for low and middle income countries that want to put their prospective growth on a sustainable basis. As Birol and Keppler (2000) point out: “Energy efficiency is the critical parameter for policies that aim at reducing energy consumption while maintaining or even boosting economic growth” (457). But how can energy efficiency improvements be achieved? Do they come by themselves? Are policies needed in order to induce them?

In order to answer these questions, it makes sense to ask how efficiency improvements came about in the past. Two major explanations are thinkable: first, our economies might have become less energy intensive due to structural change (e.g. the transition from an industrial to a service economy might have led to lower overall energy intensity). On the other hand, it might also be that technological progress *within* the sectors of the economy has led to efficiency improvements. The question which of both has been the main driver of energy efficiency improvements also has important implications for policy: should policy makers who are keen on promoting energy efficiency gains rather try to accelerate the transition to a service economy or should they set incentives to promote technological change?

Most of the respective studies emphasize that technological progress rather than structural change has been the dominant driver of efficiency improvements. Gales et al. (2007) studied energy efficiency improvements in Sweden, Holland, Italy and Spain over a period of 200 years and find that only 15% of the total reduction in energy intensity has been due to structural change. This finding is also confirmed by Henriques and Kander (2010) who show that the transition to a service economy did not have an impact on energy efficiency in their sample of 13 countries. Mulder and de Groot (2011), Liao, Fan and Wei (2007) and Jefferson and Fisher-Vanden (2004) reach similar conclusions.

My dissertation aims at complementing these historical studies by examining how technological change and energy efficiency improvements can be enhanced and promoted *by policy*. It analyzes whether higher energy prices lead to more energy efficiency in companies and, by extension, whether an energy tax can be an appropriate measure to trigger efficiency improvements.

B.) Policies to promote energy efficiency

The case for introducing policies to promote energy efficiency rests on the assumption that under free markets, investments in energy efficiency will be below the socially optimal level. This potential market failure can be explained by the positive environmental externalities of investments in energy efficiency. In the presence of such externalities, the social benefit of energy efficiency improvements is higher than the private benefit that accrues to the agent making the investment. An intervention of the state may thus be justified in order to correct the sub-optimal marketing outcome.

Gillingham, Newell and Palmer (2009) underline that underinvestment in energy efficiency may not only result from environmental externalities, but also from information problems or capital market failures. Information problems may occur if economic agents are not adequately informed about the potential energy efficiency gains of an investment in a new technology and hence underestimate the benefits of such an investment. Capital market failures occur when economic agents would like to make investments in energy efficiency but are unable to access the needed investment capital. It is important to be aware of these different sources of underinvestment, as the optimal policy responses to address the market failure may differ (e.g. if information problems are at the bottom of underinvestment, a tax on energy may not have any effect on investment decisions while an information campaign might be very beneficial)

In the broadest sense, one can distinguish between **price-based measures** to increase energy efficiency (e.g. an energy tax that is charged on each unit of energy consumed) and **direct measures** to increase energy efficiency (e.g. product standards or information programs). This study will focus on price-based policies and evaluate their effectiveness. However, in order to contextualize the debate, the following paragraphs will also present the functioning of direct measures being a potential alternative to the price-based policies.

Price based policies to promote energy efficiency:

Energy taxes and other price-based policies to promote energy efficiency rest on the assumption that rational agents will decrease their energy use if energy prices rise. Microeconomic theory strongly suggests such a relationship. Following Jefferson and Fisher-Vanden (2004), this can be illustrated in a Cobb-Douglas cost function:

$$C(P_K, P_L, P_E, P_M, Q) = A^{-1}\, P_K^{\alpha_K}\, P_L^{\propto_L}\, P_E^{\alpha_E}\, P_M^{\alpha_M} Q \qquad (4)$$

where A is total factor productivity, P_K is the price of capital, P_L the price of labor, P_E the price of energy and P_M the price of other materials used in production. α_K, α_L , α_E and α_M are the output elasticities of the factors of production and Q is the quantity of output produced. In particular $\alpha_K + \alpha_L + \alpha_E + \alpha_M = 1$ and α_i>0 for all inputs i.

As profit-maximizing companies will minimize costs, the factor demand for energy (E) is given by the first derivative of the cost function with respect to the energy price:

$$E = \frac{\partial\, C(P_K, P_L, P_E, P_M, Q)}{\partial\, P_E} = \frac{\alpha_E\, A^{-1}\, P_K^{\alpha_K}\, P_L^{\propto_L}\, P_E^{\alpha_E}\, P_M^{\alpha_M} Q}{P_E} \qquad (5)$$

As α_E is always smaller than 1 (by definition of the Cobb-Douglas function), it can easily be seen that higher energy prices will lead to lower energy consumption. The relationship can also be expressed in terms of energy intensity i (dividing both sides by Q):

$$\frac{E}{Q} = \frac{\alpha_E\, A^{-1}\, P_K^{\alpha_K}\, P_L^{\propto_L}\, P_E^{\alpha_E}\, P_M^{\alpha_M}}{P_E} \qquad (6)$$

or in terms of energy efficiency (taking the inverse of the expression above):

$$\frac{Q}{E} = \frac{P_E}{\alpha_E \, A^{-1} \, P_K^{\alpha_K} \, P_L^{\propto_L} \, P_E^{\alpha_E} \, P_M^{\alpha_M}} \qquad (7)$$

The cost minimization exercise shows that, according to economic theory, higher energy prices will lead to higher energy efficiency on the company level and as a consequence also in the economy as a whole. This implies that an energy tax can be considered an appropriate measure to promote energy efficiency. The effect may work through two different channels: First, companies will use less energy and more other inputs in order to produce a certain amount of output given a certain technology A. This may happen for example if a company invests in new machinery that requires less energy inputs and more capital and/or labor. Secondly, a change in relative prices will not only lead to higher energy efficiency at a given technology A, but it might also *induce* innovation and technological progress in the field of energy efficiency, as argued by Birol and Keppler (2000). Their argument follows John Hicks (1932) who argued that "... a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind – directed to economising the use of a factor which has become relatively [more] expensive." (Hicks 1932 cited in Birol and Keppler (2000).

It should also be noted that an energy tax has a considerable advantage over other measures to increase energy efficiency (e.g. investment subsidies or product standards) – it allows energy efficiency gains to be made at the lowest possible economic cost. The biggest energy efficiency gains are made by those companies who can afford them at the lowest cost. Smaller adjustments are made by companies for which energy efficiency improvements come at a higher costs. This is why such an energy tax can be considered as the economically most efficient way of promoting energy efficiency. Gillingham, Newell and Palmer (2009) describe energy taxes as the "first-best policy to address the environmental externalities" (25).

However, as Birol and Keppler (2000) point out, it is not clear whether all these theoretical considerations based on the presented microeconomic model also hold in practice. First of all, the model assumes that energy and other inputs are completely substitutable. However, it might be that energy inputs cannot be replaced 1:1 with capital or labor – at least not in the short run. In this case, an energy-efficiency tax would have a smaller effect on energy efficiency than predicted in the model.

Secondly, even if an energy tax leads to energy efficiency improvements, it might be that these improvements are offset by a rebound effect. As Greening, Greene and Difiglio (2000: 389) point out, "gains in the efficiency of energy consumption will result in an effective reduction in the per unit price of energy services. As a result, consumption of energy services should increase (i.e., `rebound' or `take-back'), partially offsetting the impact of the efficiency gain". This would weaken the potential impact of an energy tax.

Direct measures to increase energy efficiency

On the other hand, there are a number of 'direct measures' to increase energy efficiency. Such measures include investment subsidies for investments in energy efficient technologies, product standards that impose certain minimum requirements for the energy efficiency of machinery, information programs to raise awareness about the benefits of investments in energy-efficient technologies etc. Similar to the price-based policies, the direct measures increase the incentives to invest in environmentally-friendly technologies.

However, these measures are only considered to be second best options, as they may allocate the costs of the improvements in an economically inefficient way; consider e.g. a product standard that prohibits the use of a particularly energy-consuming technology. It will be relatively easy to give up this energy-consuming technology for some firms, while other companies can only do so at a very high cost. The latter companies might prefer to make energy-efficiency improvements in another way than giving up the use of the banned product. They might also prefer to pay other companies to make efficiency improvements in their place. However, the product standard will force them to make a specific energy-efficiency improvement – no matter what the cost is. This implies that the energy efficiency gains could be achieved at a lower social cost than under the product standards (Gillingham, Newell and Palmer 2009, Hausman and Joskow 1982).[1]

Under certain circumstances, it may still make sense to use direct measures instead of price-based policies. If the reason for the 'over-use' of energy is not environmental externalities, but e.g. lack of information (companies do not know about the potential benefits of a specific technology) or capital market failures, a product standard or an investment subsidy will be more effective than an energy tax. Previous studies suggest that such barriers may indeed be an important obstacle for investing in energy efficient technologies (see e.g. Rohding, Thollander and Solding 2007). For this reason, the direct measures should only be discarded as 'second best', if we can be sure that the first best policies will have the intended impact. It is therefore crucial to empirically investigate the relation between energy prices and energy efficiency and, consequently, the effectiveness of price-based policies.

C.) Previous Empirical Studies on Energy Efficiency Policies

The following paragraphs will present previous empirical studies related to energy efficiency policies and will elaborate on their contribution as well as their limitations. Moreover, the section will clarify how the present study relates to the previous literature.

[1] Another disadvantage of the direct measures is that they only incentivize investments in energy-saving technologies, but do not promote energy-saving measures at a given technology.

Studies on direct measures / demand side management

Most of the studies on direct measures to increase energy efficiency have examined policies targeted at residential energy consumers. Loughran and Kulick (2004) studied the impact of demand side management (DSM) on energy efficiency in the United States. DSM measures may include information programs for consumers, the provision of low-interest loans for investments in more efficient technologies or even the free installation of such technologies. In order to estimate the impact of the DSM, the authors use panel data on DSM spending by 324 electricity utilities and the corresponding efficiency improvements within their region of activity. Estimating a fixed effects regression, they find that DSM measures do have a statistically significant impact on energy efficiency, but that the magnitude of this effect is small. As a consequence they conclude that energy efficiency improvements by means of DSM come at a high price: The average electricity utility would have to spend \$0.14-\$0.22/kwh in order to achieve a 0.3%-0.4% decrease in electricity sales.

Geller and Attali (2005) study the impact of tax-incentives for investing in residential energy efficiency. Using panel data on tax policy and investments in energy efficiency from 11 IEA member countries, they find that tax-incentives have had a substantial positive impact on energy efficiency. They estimate that a 10 percentage point decrease in the tax price of efficiency investments will lead to a 24 percent increase in overall investments in residential energy efficiency.

Studies on price-based measures

First of all, it should be stated that there are only very few empirical studies on the impact of energy prices or energy taxes on energy efficiency. Studies on this relationship mostly face the problem that there is no variation in energy prices across companies (all companies face the same market price or the same tax), and therefore no counterfactual outcome: We do not know what would have happened if the energy price was higher/lower than the actual price. A number of studies have still tried to address the issue by examining variation in energy prices across regions or by using time-series data containing information on changing energy prices over time.

Jefferson and Fisher-Vanden (2004) have examined the driving forces of China's energy intensity decline. They use panel data from 2500 large and medium sized Chinese enterprises over the period 1997-1999 and exploit the fact that energy prices varied across provinces (e.g. because state-set prices were replaced by market prices at different points of time depending on the province). Other explanatory variables, such as ownership regulations or investment in research and development, also varied between provinces or between different companies. This variation allows the authors to estimate a fixed effects regression model that disentangles the respective contribution of price changes, ownership structure and research and development expenditure on energy efficiency. Jefferson and Fisher-Vanden's findings are much in line with the microeconomic theory presented above; higher energy prices are found to be associated with energy efficiency improvements:. The authors conclude: “China’s large and medium-size enterprises exhibit substantial responsiveness to changes in relative prices and to R&D” (ibid. p. 96).

Their research design has both strengths and weaknesses: The fixed effects approach allows the authors to control for time-invariant unobservables which might be correlated with both the explanatory variables and the outcome. Therefore we can be confident that the results are not biased by a omitted third factor and that the observed relationship is indeed causal. However, it should be noted that Jefferson and Fisher-Vanden’s study does not address the possibility of reverse causality. Indeed, it is well thinkable that causality goes the opposite way: higher energy efficiency leads to a lower demand for energy and therefore to lower energy prices (Hung and Tu 2007). Jefferson and Fisher-Vanden do not mention this possible source of bias.

A study by Hang and Tu (2007) also analyzed the relationship between energy prices and energy intensity in China but using macro-level time series data on energy prices and energy efficiency over the period 1985-2004. Similarly as Jefferson and Fisher-Vanden, they estimate regressions with energy intensity as the dependent variable and energy prices, R&D expenditure, and ownership structure as possible explanatory variables. The analysis is carried out for the determinants of overall energy intensity, but also for electricity intensity, oil intensity and coal intensity. Hang and Tu also find a way to address a possible reverse causality problem: Instead of regressing energy intensity on the *current* electricity prices, they regress it on *lagged* electricity prices. Assuming that lagged electricity prices will have an impact on current energy efficiency, but that current energy efficiency cannot have an impact on past electricity prices, this strategy allows the authors to rule out reverse causality. However, unlike Jefferson and Fisher-Vanden, they cannot rule out the possibility that the results are driven by a third, omitted variable (see below).

The authors’ findings can only party confirm the microeconomic theory presented above. The time-series regressions suggest that the own-price elasticities of aggregate energy consumption, oil and coal are indeed negative, i.e. higher energy prices lead to more efficiency. However, in the case of electricity consumption, the authors find a positive-own price elasticity: companies used more electricity per unit of output when the electricity price was high. The paradoxical finding sheds light on another possible problem in terms of the research design: there might be a third (omitted) variable that is associated with both, energy prices and energy intensity. Hang and Tu themselves acknowledge that “electricity demand (Q) in China is highly dependent on such factors as GDP, energy price (P), population (POP), light industry output (M2)”(Hang and Tu 2007: 2958). These factors may be correlated with both electricity prices and electricity intensity and therefore cause a spurious positive correlation between energy prices and energy efficiency.

To sum up, both of the empirical studies which have addressed the issue have difficulties to reveal a *causal* effect running from energy prices to energy efficiency. This problem is related to the fact that they cannot observe companies that pay low electricity prices and companies that pay high electricity prices at the same time and *all else equal*. Therefore it might be that their results are driven by reverse causality (in the case of Jefferson and Fisher-Vanden 2004) or by omitted variables (Hang and Tu 2007). However, knowledge about the direction of causality is crucial in order to make informed policy recommendations on whether an energy tax is an appropriate measure to increase energy efficiency.

The quasi-experimental design of this study attempts to resolve the causality issues; it exploits that very similar companies (those slightly above and slightly below the critical threshold) pay different electricity prices at the same time. This brings the setting very close to the ideal case, where we can observe companies that pay higher electricity prices and others that pay lower electricity prices at the same time and “all else equal”.

III.) The German Renewable Energy Act (REA)

This section will present the German Renewable Energy Act (REA) more in depth. In particular it will focus on the exemption rule of the REA that leads to lower electricity prices for energy-intensive firms. This background information on the legal framework may seem overly detailed but is considered necessary to justify the research design on which this study is based.

A.) History, Aim and Functioning of the REA

The REA was introduced in 2000 and has the aim to promote the production of renewable energy in Germany. Its main component is a feed-in-tariff (FIT): under its FIT scheme, producers of renewable energy are guaranteed predetermined prices for each kilowatt hour of energy they produce. If the market price is below this guaranteed price, the state compensates renewable energy producers for the difference between market price and guaranteed price. The main objective of the REA is to render investments in renewables economically viable and to increase the overall production of 'green' energy (Bode and Groscurth 2006b). Indeed, the REA is considered to be the main reason why Germany was able to substantially increase its renewable energy production over the last decade: while in 2000 only 2.9% of total energy production came from renewables, this share increased to approximately 11% in 2011 (World Bank 2014).

An interesting feature of the REA is that the FIT is not financed through taxes, but through a markup that is charged on the electricity price. In this way, the costs for the promotion of renewables are passed on to the electricity consumers – those who consume more electricity also bear a higher burden in the transition towards a renewable energy future. In this way, the markup supposedly has positive side effects on energy efficiency as it creates incentives for energy saving behavior in households and industry. The exact amount of the markup to be paid per kwh is determined each year by the Ministry of Economics and reflects the overall costs of the FIT scheme[2].

Figure 1 shows how the markup has evolved between the years 2003 and 2014. There was a clear upward trend from 0.41 ct/kwh in 2003 to 6.24 ct/kwh in 2014. In 2008, which is in the focus of this analysis, the REA markup was 1.15 ct/kwh. The increases in the REA markup over time are mainly due to the growth of renewable energy production: with a growing number of producers, the overall costs of the FIT scheme increase and so does the markup required to finance it.

[2] The markup is computed by dividing the costs of the FIT scheme by the number of kilowatt hours of electricity consumed ($Markup\ per\ kwh = \frac{Expenditure\ for\ FITs}{kwhs\ of\ electricity\ consumed}$). As a consequence, the total electricity price is a sum of the market price and the markup ($Price\ per\ kwh = Market\ Price + REA\ Markup$).

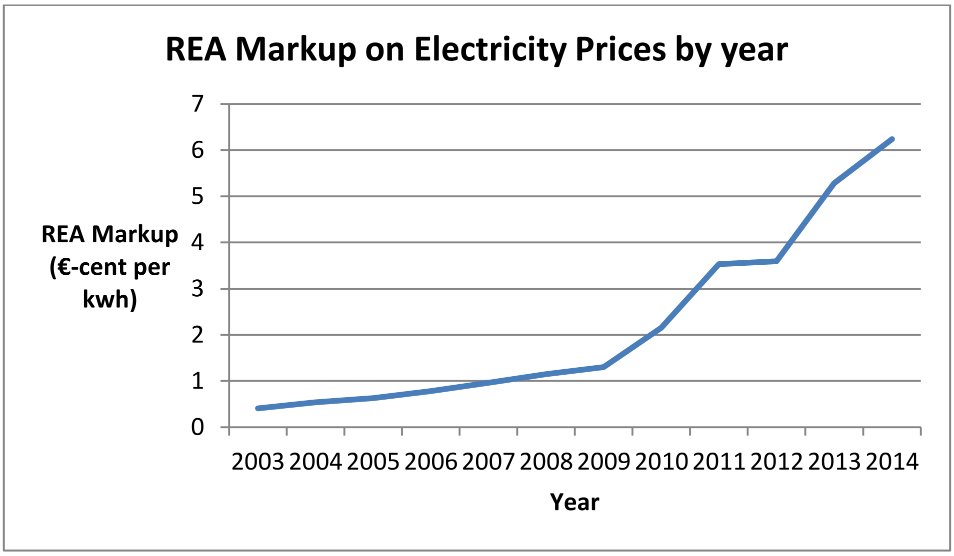

Figure 1: REA Markup on Electricity Prices by year (Source: Statista 2014)

B.) Exemption Rule for energy intensive companies

An interesting feature of the REA is that energy intensive companies are exempted from paying the REA markup. As of 2004, companies whose electricity costs were higher than 15% of value added[3] and whose total energy use was above 10 Gwh per year, were eligible to apply for an exemption from the REA markup at the Federal Office of Economics and Export Control (German: *Bundesamt für Wirtschaft und Ausfuhrkontrolle*). The motivation for the exemption rule is that energy intensive companies might lose international competitiveness if they are obliged to pay the markup and might therefore relocate their production and jobs to other countries (Bundesgesetzblatt 2003).

Companies which fulfill the above-mentioned requirements can apply for an exemption at the German Federal Office of Economics and Export Control (FOEE). In order to prove that they are eligible for an exemption they have to provide certificates about their energy use (to be issued by a Certified Public Accountant of the electricity provider) and about their value added (to be issued by a Certified Public Accountant of the applying company). On the basis of these certificates, the FOEE decides on

[3] Since its introduction in the year 2003, the critical threshold and the application procedure for an exemption have been modified several times: modifications have been introduced in 2004, 2009 and 2012. As the focus of our analysis is the time frame between 2001 and 2008, I focus on the exemption rule's original version and its first modification in 2004.
The most comprehensive reform of the exemption rule occurred in 2012: As of 2012, companies whose electricity costs constituted at least 14% of value added and whose electricity consumption was higher than 1 Gwh per year could apply. The aim of this reform was to make the exemption rule accessible to energy intensive SMEs.

an exemption (Bundesgesetzblatt 2003).[4] [5] If a company is granted exemption by the FOEE, it pays only a small fraction of the regular REA markup, namely 0.05 ct/kwh (as compared to e.g. 1.15 ct/kwh in 2008 or 6.24 ct/kwh in 2014)[6].

Table 1 shows the number of exempted companies over the years. The steady increase in exempted companies reflects mainly two developments. First, modifications of the exemption rule made ever more companies eligible. Secondly, with an increasing REA markup, more companies became eligible for an exemption as they surpassed the critical threshold (electricity costs > 15% of value added).

Table 1: Number of Companies exempted from paying the REA markup

Year	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Number of exempted companies	297	327	382	426	507	566	603	734	1720	2098

Source: Information provided by the FOEE (upon an online inquiry)

C.) Importance of the exemption rule for this analysis

The exemption rule of the REA provides us with a quasi-experimental setting in which some companies pay higher electricity prices than others. In other words, we have a "treatment group" of companies which pay the REA markup and a "control group" of companies which do not pay the markup. A comparison of the treatment and control group allows us to draw conclusions on the impact of electricity prices on several environment-related outcome variables (energy efficiency, investments in environmentally friendly technologies). In particular, as substantiated in chapter IV, it is reasonable to assume that variation in treatment status across the critical threshold is as good as random. Companies just below the critical threshold of 10 Gwh will not differ systematically from companies just above the critical threshold. Under this assumption differences between treatment and control group capture the causal effect of the treatment, as the groups should be equal in all characteristics except from treatment status. A regression discontinuity design as described in the next chapter allows us to estimate the size and statistical significance of the treatment effect.

[4] An application for an exemption in year t has to be made in year t-1 and is based on the electricity costs and value added from t-2, e.g. in order to be exempted in year 2008, electricity costs in 2006 have to be higher than 15% of value added in 2006 (Bundesministerium für Wirtschaft und Energie 2014a).

[5] The REA foresees that value added is computed according to the definition of the Federal Statistical Office (FSO); as my analysis also uses FSO data, the data should coincide with the data on which the exemption applications are based (see section IV for more details). (Bundesministerium für Wirtschaft und Energie 2014a)

[6] For the sake of completeness, a minor exception ought to be mentioned: Eligible companies whose electricity costs constitute are below 20% of value added or whose electricity use is below 100 Gwh per year, the exemption is only granted for the amount of electricity that exceeds 10% of the electricity used in the year of application. For all other companies, the whole amount of electricity consumed is exempted. However, the exception does not change the fact that there is a discontinuity in electricity prices around the critical thresholds.

IV.) The Method

This section will present the method that is used in this study: the Regression Discontinuity (RD) design. RD is an innovative quasi-experimental method that can be used to examine causal relationships, even in settings where it is not feasible to conduct a 'field experiment' (Angrist & Pischke 2008). As such, the method has gained increasing popularity in fields such as labor economics, development economics and health economics in recent years. The following paragraphs will present the RD design and elaborate on its strengths and weaknesses in comparison to other econometric approaches. IVA will present the intuition behind the RD design and will mention examples of earlier applications. IVB substantiates how the REA exemption rule can be exploited in an RD context in order to analyze the relationship between energy prices and energy efficiency in German companies. IVC explains how the RD estimation is carried out and IVD elaborates on how the obtained estimates are to be interpreted. Lastly, IVE elaborates on the assumptions that have to hold in order to obtain valid RD estimates and discusses possible threats to the adopted research design.

A.) Regression Discontinuity: The intuition

Regression Discontinuity designs exploit cutoff points that lead to different 'treatments' for individuals/companies at either side of a critical threshold. Often, it can be assumed that individuals slightly below or slightly above the critical thresholds do not differ systematically from each other, but that variation in treatment status is as good as random. If this assumption holds true, different outcomes for individuals slightly below and slightly above the critical threshold, can exclusively be attributed to the differences in treatment status. We can rule out that they are a consequence of "self-selection into treatment", reverse causality or unobserved third factors. In this sense, the RD design mimics an experiment, where observations are randomly assigned into a treatment and a control group. For this reason RD designs are generally considered as econometrically superior to ordinary linear regression models or matching estimators (Imbens&Lemieux 2008). As underlined by Angrist and Pischke (2008), in the latter models the assumption of strict exogeneity[7] is often hard to justify and can never be proven with certainty. RD resolves this problem if variation around a critical threshold is random and – as a consequence - strictly exogeneous.

An example shall illustrate how RD can work in practice: Clark (2009) has used RD in order to examine the impact of school autonomy on students' outcomes in a standardized test. He exploits a UK school reform in the 1980s according to which parents could vote on whether their children's school was continued to be managed by "local education authorities", or whether the school would be

[7] The "strict exogeneity assumption" holds that the conditional mean of the errors in the regression is 0 ($E[\varepsilon|X] = 0$). This implies that the regressors are uncorrelated with the error term and that the estimates are not biased by omitted variables.

given full autonomy. A simple majority was enough to achieve autonomy. Clark exploits the fact that schools slightly below the critical vote share will not differ systematically from schools slightly above the critical vote share of 50%. By assessing whether there was a discontinuity in outcomes across the 50% threshold, he recovers the effect of school autonomy on test outcomes. Clark's approach resolves the important problem of omitted variable bias. More educated parents might tend to send their children to autonomous schools. A mere comparison of autonomous and non-autonomous schools might therefore not recover the true effect of school autonomy on outcomes, but would be biased by the fact that children in autonomous schools grew up in more educated households and might therefore have gotten better grades even without the treatment.

B.) The REA in a Regression Discontinuity Framework

The exemption rule to the REA in Germany provides us with a similar situation: treatment eligibility depends on a critical threshold and it can be assumed that variation in treatment status *around the critical threshold* is as good as random.

In particular, we have a "treatment group" of companies which pay the REA markup and a "control group" of companies which do not pay the markup. A comparison of the treatment and control group allows us to draw conclusions on the impact of electricity prices on energy efficiency and on investments in environmentally-friendly technologies. However, as stated above, it is crucial that treatment and control group did not differ in any systematic manner before being treated (i.e. that treatment assignment is as good as random). This assures that differences between the treatment and control group after the treatment are caused by the treatment and not by omitted variables that are correlated with treatment status.

In the case of the REA exemption rule, it is indeed reasonable to assume that the variation in treatment status around the critical thresholds is as good as random. When we compare companies whose electricity consumption is 9.5 Gwh per year and companies whose electricity consumption is 10.5 Gwh per year, there is no reason to assume that these companies differ systematically in any characteristics except from treatment status. By extension, differences in the characteristics between these firms are very likely due to the treatment. If, for example, investments in energy-saving technologies are significantly higher for companies that are slightly below the critical threshold (let's say companies with an electricity consumption of 9.95 Gwh) than in companies which are slightly above the critical threshold (companies with a consumption of 10.05 Gwh), we can be pretty sure that the variation is due to the 'jump' in electricity prices over the threshold and not due to any other confounding factors.

C.) Implementation of RD

The comparison of treatment and control group can be conducted in a linear regression framework. In order to do so, some more formal notation needs to be introduced. Let D_i indicate the treatment status of company i and c_i its electricity consumption. In particular, if we assumed that treatment switched deterministically at the 10 Gwh threshold, we would have:

$$D_i = \begin{cases} 1 \text{ if } c_i \geq 10\ Gwh \\ 0 \text{ if } c_i < 10\ Gwh, \end{cases} \qquad (8)$$

However, as pointed out in section III, treatment does not only depend on crossing the 10 Gwh threshold. Apart from crossing this threshold, the company must also qualify as energy intensive ($\frac{electricity\ costs}{value\ added} \geq 15\%$), and must submit an application for exemption. As a consequence, it cannot be assumed that treatment switches *deterministically* at 10 Gwh. However, the *probability of treatment* changes at the threshold, as more companies become eligible. Therefore:

$$P\ (D_i = 1|c_i\ ) = \begin{cases} g_1(c_i) \text{ if } c_i \geq 10\ Gwh \\ g_0(c_i) \text{ if } c_i < 10\ Gwh, \end{cases} \qquad (9)$$

where $g_1(c_i) \neq g_0(c_i)$. Equation 8 describes the setting in a "sharp" regression discontinuity design, while the situation in equation 9 is commonly referred to as "fuzzy" regression discontinuity design (Imbens & Lemieux 2008). It should be noted that the fuzzy RD design is a slightly different approach than the sharp RD, but it is an equally valid method to recover a Local Average Treatment Effect (LATE). Although this study employs a fuzzy RD, both estimation strategies shall be described briefly. This shall facilitate the understanding for readers unfamiliar to the estimation of RD equations.

Sharp RD: In a sharp RD, the LATE can be recovered easily by estimating a regression of the form

$$Y_i = \alpha + \beta\ c_i + \rho\ D_i + \varepsilon. \qquad (10)$$

where Y_i is the outcome variable of choice (in our case either energy efficiency or investments into energy efficiency) which is regressed on a constant α, electricity consumption c and a dummy variable D. D indicates whether a company is part of the treatment or the control group (i.e. whether it is above or below the critical threshold). While the regressor c_i controls for a possible linear relation between c and Y (if e.g. companies with higher total energy use are generally more energy efficient) the dummy D captures exclusively whether company i is part of the treatment or the control group. In a sharp RD design, the coefficient ρ would already give us the LATE, i.e. the effect of being part of the treatment group rather than the control group for companies in the neighborhood of the cutoff point.

Fuzzy RD: In a fuzzy RD, estimation of the LATE is conducted in two steps. First, a regression similar to (10) is estimated:

$$Y_i = \alpha + \beta c_i + \rho T_i + \varepsilon. \qquad (11)$$

The only difference to equation 10 is that the dummy indicating *treatment status* (D_i) has been replaced by a dummy T_i which indicates whether a company is *eligible for treatment*:

$$T_i = 1 \; (c_i \geq 10 \; Gwh) \qquad (12)$$

In a second step, ρ needs to be divided by the compliance rate η, i.e. the fraction of eligible companies that do indeed apply for an exemption from paying the REA markup:

$$LATE = \frac{\rho}{\eta} \qquad (13)$$

This division is necessary, as ρ would underestimate the treatment effect, given that for some companies $T_i = 1$, while $D_i = 0$. The division by η corrects for the fact that not all companies with $T_i = 1$ are treated (by definition η ≤ 1) (Angrist & Pischke 2008).[8][9]

Choice of sample for the analysis: As mentioned above, eligibility for an exemption from paying the REA markup depends on two criteria. The company has to consume at least 10 Gwh of electricity each year and the company has to be energy intensive (electricity costs ≥ 15% of value added). For this reason, it makes only sense to estimate equation (11) for all energy intensive companies. Only for these companies energy prices change at the critical threshold of 10 Gwh. For the non-energy-intensive companies, crossing the critical threshold does not have any practical consequences.

It should be noted that although treatment assignment is only assumed to be random for observations close to the critical threshold, the regressions as proposed in equation (11) are commonly estimated in a substantially bigger sample – in our case for companies with overall electricity consumption between 1Gwh and 20 Gwh. This is in order to determine the linear/quadratic relationship by which the two variables under examination are linked to each other. If in addition to this relationship, there is a discontinuity at the critical threshold, we can be confident that this discontinuity is a consequence of the treatment.

[8] Indeed, the estimation of a fuzzy RD is nothing else than an instrumental variable (IV) estimation, where crossing the 10 Gwh threshold is used as an instrument for treatment. For this reason, ρ can also be seen as the IV's reduced form estimate, while η corresponds to the coefficient from the 1st stage. Equation (13) is the Wald estimator, which recovers the treatment effect by dividing the reduced form by the first stage.

[9] It is also worth mentioning that the sharp RD is only a special case of the fuzzy RD. In particular, in the sharp RD η=1, as treatment is a deterministic function of crossing the critical threshold (i.e. the "compliance rate" is 100%). As a consequence equation (13) becomes: LATE= ρ/η = ρ/1 = ρ

D.) Interpretation of the LATE Estimates – Internal and External Validity

It has to be noted that the estimation by RD yields a "Local Average Treatment Effect" (LATE), rather than an "Average Treatment Effect" (ATE). ATE would be the effect that a treatment (in our case exemption from paying the REA markup), causes on average *across all eligible companies*. The LATE is the average treatment effect for the subgroup of eligible companies *which do apply for an exemption*. In the presence of homogeneous treatment effects (all companies react in the same way), LATE and ATE will be identical and our strategy allows us to determine the average effect for all German companies. However, if treatment effects are heterogeneous, our estimate will only be valid for the subgroup of companies which are eligible <u>and</u> do apply for an exemption.

For this reason RD estimates are considered to have high internal but low external validity. On the one hand, RD allows us to control very well for bias due to confounding factors or reverse causality problems. This is why RD is said to have a high internal validity. On the other hand, the internally valid estimates only hold for a subgroup of the whole population, in our case eligible companies that do apply for an exemption from paying the REA markup and are sufficiently close to the critical threshold. Extrapolating the finding to other companies may be problematic and can only be done under the strong assumption of homogeneous treatment effects. Therefore RD estimates are often blamed for having low external validity (Imbens & Lemieux 2008).

The usefulness of LATE estimates depends very much on the context and the research question. In our specific case, the LATE might even be of higher policy relevance than the ATE. When evaluating the consequences of the REA in Germany, policy makers will care about the extent to which the REA exemption rule has precluded energy efficiency gains *in exempted companies*. This is precisely what the LATE estimates can tell. On the other hand, the LATE will be less useful if we want to estimate e.g. the own price elasticity of electricity. Based on the LATE, we would only be able to obtain an estimate of the elasticity for exempted companies, but not the average elasticity for all companies. An awareness for the limitation of the LATE estimates shall guide the empirical analysis and the interpretation of the results in chapter VI.

E.) Assumptions and Threats

The main assumption needed for a valid RD estimation is that treatment assignment in the neighborhood of the critical threshold is 'as good as random'. If this assumption holds true, treatment status in companies close to the threshold is not correlated with other confounding factors and ρ in equation (11) captures exclusively the effect of the treatment. In general, it is reasonable to make this assumption for companies in a small neighborhood of the critical threshold (see e.g. Angrist & Pischke 2008, Imbens&Lemieux 2008, Almond et.al. 2010, Clark 2009). As argued above, it is unlikely, that the characteristics of a company with $c_i = 9{,}99\ Gwh$ and another company with $c_i = 10{,}01\ Gwh$ are systematically different from each other. Estimating the effect of crossing the 10 Gwh threshold can therefore be considered as similar to comparing energy efficiency in a randomly determined treatment and control group.

However, there are also a number of threats to the assumption that treatment assignment across the critical threshold is as good as random. First, self-selection into treatment might take place if companies are able to manipulate their energy consumption in order to cross the critical threshold of 10 Gwh. For an economist it makes sense to assume such a behavior given the monetary benefits of an exemption from the REA markup. In particular, companies for which energy efficiency improvements come at a high cost might have incentives to 'push' their electricity consumption over the critical threshold. In this case the treatment assignment would no longer be random and our estimates would most likely overestimate the true LATE. A common anticipatory check in RD studies is therefore to assess the histogram of the 'forcing variable'[10], in our case electricity consumption. If there was selection into treatment, the distribution of electricity consumption would feature a peak just above 10 Gwh. Graph 2 shows the histogram of electricity consumption and the kernel density function for all energy intensive companies in our sample.

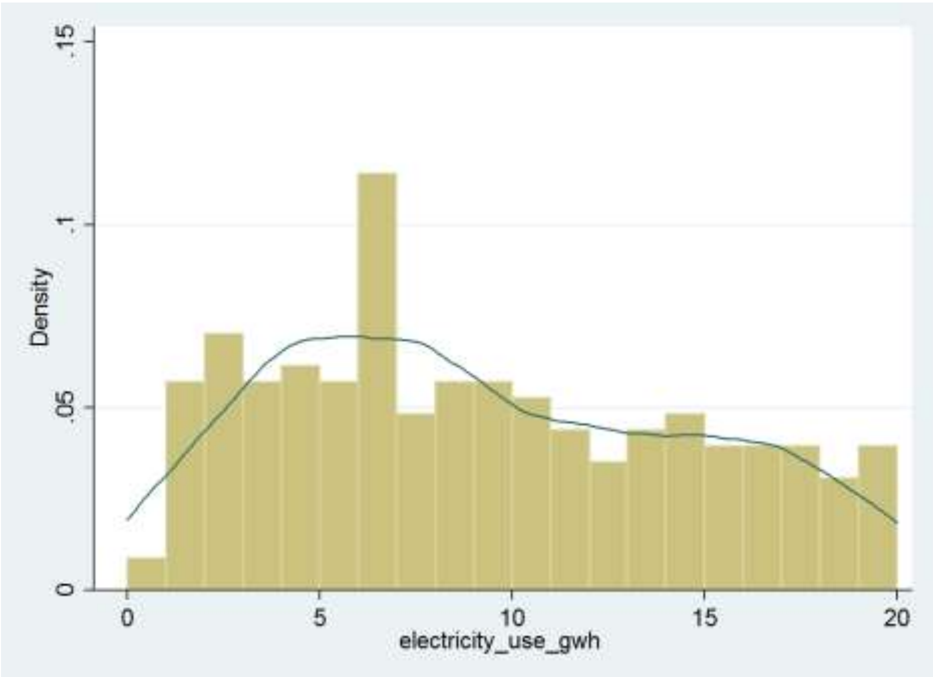

Figure 2: Histogram and Kernel Density Function of Electricity Consumption (Gwh)

The graph does not give reason to assume that our study faces a problem with self-selection into treatment. Rather than featuring a peak above the 10 Gwh cutoff point, the density function decreases around the critical threshold. The number of companies with electricity consumption between 9-10 Gwh is even higher than the number of companies that consume 10-11Gwh. Although the visual

[10] Econometricians refer as forcing variable to the variable which determines treatment eligibility.

inspection of the histogram does not allow us to completely rule out the possibility of self-selection, it shows that it is not a very wide-spread phenomenon.

A second threat to RD estimation is that the explanatory variable and the outcome variable are related to each other in a non-linear (e.g. quadratic or cubic) way. Such non-linearities might be mistaken for discontinuities and ρ would be estimated as significant, even if there is no discontinuity (see Angrist & Pischke 2008 for an extensive discussion of this problem).There are two possibilities in order to check for possible non-linearities. First, a visual inspection of a graph with the outcome variable and the forcing variable can show whether there is a non-linear behavior. Secondly, in addition to equation (11), we can estimate regressions with a more flexible functional form such as

$$Y_i = \alpha + \beta_1 c_i + \beta_2 c_i^2 + \rho T_i + \varepsilon. \qquad (14)$$

If ρ is still significant after controlling for possible quadratic and cubic relationships between the independent and dependent variable, we can be confident that ρ indeed captures a discontinuity. Equations like (14) will be estimated in the empirical analysis in chapter 6.

V The Data

This chapter will present my data sources and will elaborate on the data's coverage and validity. Moreover, it will describe how the variables used in the analysis were obtained and/or computed. Lastly, the chapter provides some summary statistics.

A.) Data Sources

My analysis is based on three datasets which have been provided by the Research Data Centre of the Federal Statistical Office of Germany (FSO). The dataset "Energy Use of Businesses in Mining and Manufacturing Industries"[11] contains information on total energy use as well as total electricity use for the universe of German companies in the mining or manufacturing sector that have more than 20 employees (Forschungsdatenzentrum der Statistischen Ämter des Bundes und der Länder: 2014a). For the year 2008, the dataset contains 37,861 observations. The second dataset used is the FSO's "Cost Structure Survey"[12] (Forschungsdatenzentrum der Statistischen Ämter des Bundes und der Länder: 2014b), which provides information on the companies' sales volume, their number of employees, total costs and information on several other cost-related variables. This data is crucial in order to compute the companies' value added as well as the electricity cost shares (see appendix). Unlike the dataset on Energy Use, the Cost Structure Survey does not capture all German firms but only a random sample of

[11] In German: „Energieverwendung im Bergbau und verarbeitenden Gewerbe"
[12] In German: „Kostenstrukturerhebung"

16,779 observations. The third dataset used for the analysis is the "Survey on Investments in Environmental Protection"[13], which provides information on investments in energy efficiency for a random sample of 6397 companies (Forschungsdatenzentrum der Statistischen Ämter des Bundes und der Länder: 2014c). After merging the dataset with the data on energy use and the cost structure survey, we are left with 4318 companies that can be used to analyze whether *investments* in energy efficiency were indeed lower among exempted companies.

However, the sample size in our regression discontinuity analysis in chapter VI is substantially smaller. As explained in Chapter IVc, the sample should be limited to energy intensive companies (electricity costs ≥ 15% of value added). This leaves us with 539 observations for which information on energy consumption, energy efficiency and value added are available. Out of the 539 companies, 405 had an energy consumption of more than 10 Gwh (Treatment Group), while 134 consumed less than 10 Gwh (Control Group).[14] Moreover, for 201 of the 539 companies, we also have information on the investments in energy efficiency.

Due to the high sensitivity of the company level data, the Research Centre of the FSO does not release any of the afore-mentioned datasets to researchers[15]. However, it is possible to apply for data usage under the "controlled teleprocessing of data" (*kontrollierte Datenfernverarbeitung)*. Under this procedure, the data user is provided with an imitative dataset whose structure coincides with the real dataset, but observations and variables are interchanged at random. Based on the fake dataset, the data user can program her syntax (in my case a stata do file) which is then applied to the original datasets by staff of the FSO. Afterwards the stata output is sent back to the data user. It has to be admitted that this procedure involves two major disadvantages: First, the results of the study cannot be reproduced by other scholars, unless they engage in a rather complicated data application process with the FSO. Secondly, the procedure might be slightly more prone to manipulation on behalf of public authorities than other forms of data access. However, given the general reliability of the FSO, it is not assumed that this should be a reason for concern in our case.

In addition to the FSO databases, this study draws on data on electricity prices from Eurostat (2014). This data was necessary to construct the electricity cost share of the companies in our sample. The data provided by Eurostat refers to the average electricity price without taxes charged to medium-sized industrial electricity consumers, i.e. with annual electricity consumption between 500 Mwh and 2000 Mwh.

[13] In German: "Erhebung der Investitionen für den Umweltschutz"

[14] Our treatment group (REA exempted companies) is thus substantially bigger than our control group. However, given the big overall sample size of 539 observations, it is not expected that this leads to problems in terms of statistical power.

[15] Concerns are centered on the possibility of identifying certain companies in the sample and to draw conclusions on their production technologies and other data which could be exploited to the disadvantage of the affected companies.

B.) Major variables

The major explanatory variables used in this study are:

- Total Electricity Consumption (Gwh)
- Electricity Cost Share $= \frac{Electricity\ Costs\ (EUR)}{Value\ Added\ (EUR)}$
- Eligibility Status: A dummy variable indicating whether the company is eligible for an exemption from paying the REA markup

The outcome variables that were examined are:

- Energy Efficiency: $\frac{EUR\ of\ value\ added}{Electricity\ consumption\ (Gwh)} / \frac{EUR\ of\ value\ added}{Electricity\ consumption\ (Kwh)}$
- Investments into energy efficiency (normalized as $\frac{Investments\ in\ Energy\ Efficiency\ (EUR)}{Value\ Added\ (EUR)}$

An in-depth description of how the variables were calculated can be found in the appendix.

C.) Descriptive Statistics

Unfortunately, the possibility of providing summary statistics is limited by the data security requirements of the FSO. Table 2 provides mean values for the variables which are most crucial for our analysis. Minima and Maxima are not provided by the FSO as a matter of principle, as these values might allow a reconstruction of firms' secret production patterns.

Table 2 - Mean Value of Major Variables

Variable	Mean
Value Added	3.36 e(7)
Electricity Use (Gwh)	76.98
Energy Efficiency (Value of Output / kwh)	28.93
Electricity Cost as a Percentage of Value Added	6.24
Investments in Energy Efficiency (Euro)	146977
Investments in Energy Efficiency (Percentage of Value Added)	0.26
Number of observations:	4318

Note: Table includes summary statistics for all companies for which data on value added, electricity consumption and investments in energy efficiency were available for the year 2008.

Source: Own calculations based on Research Data Center of the FSO: 2014a, 2014b, 2014c)

Average value added in the sample is approximately 336 million Euro and mean electricity consumption is 76.98 Gwh per year. The mean energy efficiency is 28.93, which implies that with 1 kwh of electricity, an average firm generated 28.93 EUR of value added. Electricity costs on average only constitute a small percentage of value added (6.24%), implying that the average firm in Germany will not be eligible from an exemption from the REA markup. Lastly, the mean investments in energy efficiency in 2008 amount to 146,977 EUR, which corresponds to 0.26% of value added.

VI.) Results

The results of the empirical analysis suggest that higher electricity prices did indeed lead to higher energy efficiency in German companies. Companies that had to pay the REA markup (and therefore faced higher electricity prices) were more energy efficient than companies that were exempted from paying the markup. A discontinuity at the critical threshold of 10 Gwh is observable in the corresponding graphs and statistically significant in the regression analyses. Robustness Checks as presented in VI B.) provide mixed results with respect to the validity of the estimates. In particular, they give reason to correct the treatment effect estimated in VI a.) downwards. Chapter VI c.) shows that there is no empirical evidence that an REA exemption also leads to lower *investments* into energy efficiency. The following paragraphs will present and interpret the findings.

VI A.) The impact of electricity prices on electricity efficiency

In order to get a first impression of the relationship between energy prices and energy efficiency, it makes sense to analyze a graph of the two variables. Figure3 plots electricity use (x-axis) in German companies against their energy efficiency (y-axis). The blue dots report the average energy efficiency for companies within every 0.25 Gwh interval of electricity consumption (e.g. the first blue dot tot he left refers to the average electricity efficiency for companies with 0-0.25 Gwh of total energy use)[16]. The green and the red line are smooth trends that were fitted to the data on each side of the cutoff point.

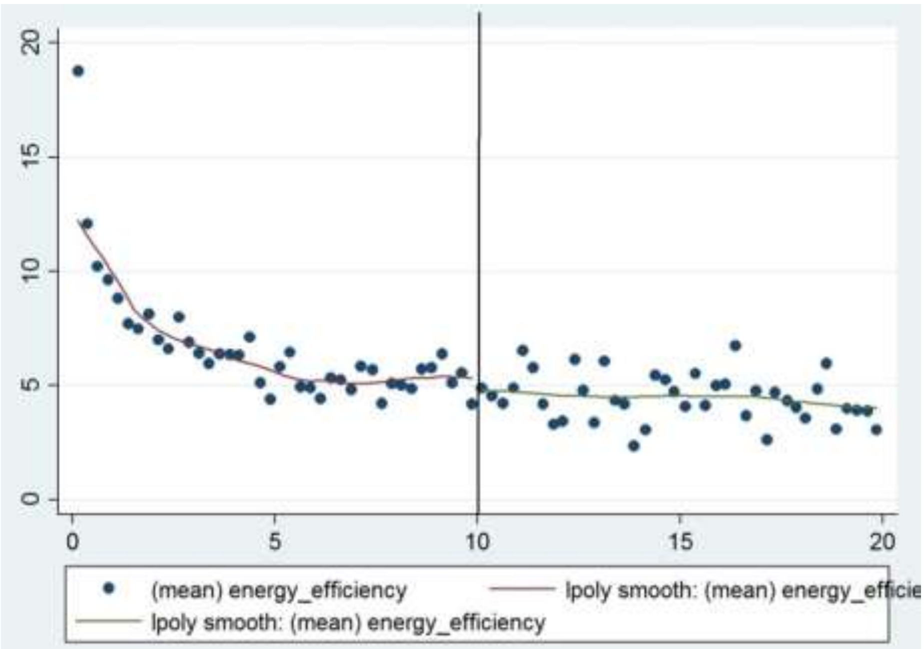

Figure 3: Energy Consumption (Gwh) and Energy Efficiency in German companies (2008) Source: Own calculations based on Research Data Center of the FSO: 2014a, 2014b, 2014c

[16] The graphical examination using such 'bins' and average values is strongly recommended in the literature (Imbens & Lemieux 2008, Angrist & Pischke 2008, Almond et al. 2010). The aim of graphs using intervals is to avoid scatterplots with a confusingly high number of dots.

First of all, the graph shows a negative relationship between energy consumption (gwh) and energy efficiency (EUR/gwh). Secondly, the graph also gives reason to believe that there is a discontinuity at the critical threshold of 10 Gwh. One can observe that energy efficiency slightly below the critical threshold is higher than slightly above the threshold. However, a pure visual inspection of the graph cannot proof whether this is a statistically significant discontinuity or just a manifestation of the negative relationship linking both variables. More certainty can be gained by estimating discontinuity regressions as proposed in chapter IV.

Table 3 presents the results from estimating RD equations as in equation (11):

$$Y_i = \alpha + \beta c_i + \rho T_i + \varepsilon.$$

Table 3: Impact of eligibility status on Energy Efficiency

	Dependent Variable : Electricity Efficiency
Electricity Consumption (Gwh)	-0.00006***
	(0.000016)
Eligibility Status (T)	-0.082***
(T=1 if electr. cons. > 10 Gwh)	(0.018)
Control Variables	No
F-test	0.00***
r2	0.074
Number of observations	539

Note: robust standard errors in parenthesis; statistical significance is denoted by *(10%), **(5%) and ***(1%). The sample consists of all companies that were energy intensive under the REA definition in 2008 (electr. Costs > 15% of value added)

The regression analysis partly confirms the conclusions that were drawn from the visual inspection of figure 3. The results show that there is a statistically significant and negative relationship between electricity consumption and energy efficiency. If electricity consumption grows by 1 Gwh, the average company's energy efficiency decreases by 0.00006 $\frac{Eur\ of\ value\ added}{Kwh}$, or 60 $\frac{Eur\ of\ value\ added}{Gwh}$. In practical terms, this implies that the average company that consumes e.g. 7 Gwh will be able to produce 60 EUR more of value added with each Gwh of electricity used than the average company that consumes 8 Gwh (this relationship should of course not be interpreted as causal. It merely illustrates that companies with a high absolute energy consumption also tend to be less energy efficient).

Second, there is also a statistically significant discontinuity at the critical 10 Gwh threshold. When companies cross the critical threshold, their electricity efficiency decreases on average by 0.082 $\frac{Eur\ of\ value\ added}{Kwh}$, corresponding to 82,000$\frac{Eur\ of\ value\ added}{Gwh}$. It is worth underlining that this effect occurs on top of the general linear trend and that its magnitude is substantially bigger. The average company that increases its energy consumption from e.g. 8.5 to 9.5 Gwh will only experience an energy efficiency loss of 60 $\frac{Eur\ of\ value\ added}{Gwh}$; however if it moves from 9.5 Gwh to 10.5 Gwh, the efficiency decline will be in the order of 82,060 $\frac{Eur\ of\ value\ added}{Gwh}$.

Although statistically significant in model I-III, the effect of crossing the critical threshold is relatively small. Graph 3 indicates that the average level of energy efficiency around the critical threshold is approximately 5 $\frac{Eur\ of\ value\ added}{Kwh}$ or equivalently 5,000,000 $\frac{Eur\ of\ value\ added}{Gwh}$. A jump of 82,000$\frac{Eur\ of\ value\ added}{Gwh}$ at the critical threshold therefore corresponds to a decrease in energy efficiency of approximately 1.64%. The small effect size also explains why the discontinuity does not stand out very prominently in Figure 3.

Moreover, one has to bear in mind that the regressions in table 3 estimate the *effect of becoming eligible* for an exemption on energy efficiency, not the *treatment effect* of being exempted. As elaborated in chapter IVc.), the treatment effect of an exemption can be estimated by dividing the estimates from table 3 by the compliance rate η. If treatment status can be observed in the dataset, it is very straightforward to compute η as the ratio $\frac{Treated\ Observations}{Eligible\ Observations}$ (see e.g. Almond et al. 2010, Imbens & Lemieux 2008). However, the datasets used for this analysis only contain information on eligibility status, not on whether a company actually was treated (i.e. exempted from paying the REA markup). As a consequence the compliance rate had to be calculated using an additional source of information; as mentioned in chapter III, the German Federal Office of Economics and Export Control (FOEE) annually publishes a list with the names of all exempted companies. The number of treated companies was inferred from this list. Together with the information on eligible companies from the FSO datasets, η was computed as

$$\eta = \frac{Treated\ Observations}{Eligible\ Observations} = \frac{352}{919} = 0.383 \qquad (16)$$

It has to be admitted that this way of computing η is less reliable than estimating η from the dataset of analysis. In particular, my way of calculation does not allow the estimation of standard errors for η. As a consequence I am also not able to conclude whether the LATE estimates computed below are statistically significant or not. Therefore the estimation of the (local) Average Treatment Effect on the

Treated should rather be considered as a “back-of-the-envelop-calculation” and not a reliable statistical analysis. Bearing these limitations in mind, the LATE can be estimated as (see equation (14)):

$$LATE = \frac{\rho}{\eta} = \frac{82{,}000\ EUR/Gwh}{0.383} = 214{,}085\ \frac{EUR\ of\ value\ added}{Gwh} \qquad (17)$$

The LATE estimates can be interpreted as the average effect that an REA exemption caused in companies that were eligible <u>and</u> applied for an exemption from paying the REA markup (put differently, in companies that were *affected* by the exemption rule. In the econometric literature this group of observations is commonly referred to as ‘compliers’). In particular, this LATE estimate implies that energy efficiency in actually exempted companies was approximately 4.28% lower than in non-exempted companies.

VI B.) Robustness Checks – Energy Prices and Energy Efficiency

A number of robustness checks can be conducted in order to test whether the electricity efficiency decrease at the 10 Gwh threshold is indeed a consequence of the REA markup and not a spurious relationship.

First, it makes sense to verify whether the statistical significance and the magnitude of the estimated treatment effect depend on the specification of the regression model. Table 4 therefore presents a number of alternative regression models that allow us to check the robustness of the results described above. Column I serves as a benchmark and restates the results of the basic model as proposed in table 3. In Column II, additional control variables were included. Column III introduces a quadratic term in order to control for possible non-linearities (the estimated model is: $Y_i = \alpha + \beta_1 c_i + \beta_2 c_i^2 + \rho T_i + \varepsilon$). Columns IV and V present a robustness check that is conducted in most RD analyses: model I is estimated using only observations in a small neighborhood of the critical threshold (a so-called ‘discontinuity sample’). In column IV, the sample is restricted to companies whose electricity use lies between 5 and 15 Gwh. In column V, only companies with electricity consumption between 7 and 13 Gwh are considered.

Table 4: Alternative specifications of the regression model

	Dependent Variable : Electricity Efficiency				
	Full Sample			Discontinuity Samples	
				+/- 5	+/- 3
	I	II	III	IV	V
Electricity Consumption	-0.00006***	-0.00028***	-0.00029***	-0.076	-0.014
(Gwh)	(0.000016)	(0.000028)	(0.0000365)	(0.0093)	(0.021)
Eligibility Status (T)	-0.082***	-0.077***	-0.054***	0.070	0.072
(=1 if electr. cons.> 10 Gwh)	(0.018)	(0.017)	(0.017)	(0.056)	(0.072)
(Electricity Consumption)^2			6.89 e(-8)***		
			(9.65 e(-9))		
Control Variables	No	Yes	No	No	No
F-test	0.00***	0.00***	0.00***	0.39	0.54
Adjusted r2	0.074	0.21	0.16	0.015	0.019
Number of observations	539	539	539	127	67

Note: robust standard errors in parenthesis; statistical significance is denoted by *(10%), **(5%) and ***(1%)

The control variables included in Model II are: the company's value added, its own electricity production (Gwh), sales of electricity (Gwh), total consumption of coal (kwh) and total consumption of gas (kwh)

The sample consists of all companies that were energy intensive under the REA definition in 2008
(electr. Costs > 15% of value added)

Column II shows that adding control variables increases the goodness of fit of the model (r2), but does not substantially change the magnitude and significance of the coefficient on T. The estimated treatment effect is only slightly smaller: -0.077 as compared to -0.082 in model I. This result confirms the validity of the regression discontinuity estimations. As pointed out by Imbens & Lemieux (2008), the estimated coefficient in an RD model should not change if additional controls are included. If treatment assignment around the critical threshold is indeed as good as random, treatment and control observations will not differ systematically from each other around the cutoff point. As a consequence the inclusion of additional controls will not influence the estimated treatment effect.

Column III presents the regression results controlling for a quadratic relationship between energy consumption and energy efficiency by including the square of electricity consumption as a regressor. The results show that even with this specification, there is a statistically significant discontinuity at the cutoff point. This implies that the discontinuity that was detected in models I and II is not just an artifact of a quadratic relationship. However, the effect of crossing the critical threshold is now estimated to be substantially smaller: -0.054 as compared to -0.082. Moreover the r2 of the model increases from 7.4% to 16% and the standard errors are slightly smaller than in Model I. This gives reason to assume that energy consumption and energy efficiency are indeed linked by a non-linear relationship and that Model I might overestimate the treatment effect. To be on the safe side, it makes sense to correct the treatment effects that were presented in table 3 downwards. Based on model III, the average effect of becoming eligible for an exemption is an energy efficiency decrease of 54,000 $\frac{Eur\ of\ value\ added}{Gwh}$. As to the companies that are actually exempted: A back-of-the-envelope calculation as presented above would yield a LATE of approximately 141,000 $\frac{Eur\ of\ value\ added}{Gwh}$ i.e. companies that are REA exempted were on average 2.82 % less energy efficient than their competitors who paid the markup.

A further robustness check consists of running the discontinuity regressions in a very small neighborhood of the critical threshold, the so-called discontinuity sample. Columns IV and V show that both, the coefficient on electricity consumption and the coefficient on the dummy indicating treatment eligibility become statistically insignificant. The coefficient on the eligibility also changes sign and becomes positive. The results cast doubt on the robustness of my findings. However, it also has to be acknowledged that our discontinuity samples consist of only very few observations (127 and 67 respectively). The insignificant estimates might therefore also be a consequence of low statistical power.

Two more robustness checks are left to the appendix and shall only be briefly summarized here. First, I estimated models as in table 3, but replaced the outcome variable electricity efficiency with *gas efficiency*. As gas prices are not affected by the exemption rule to the REA markup, gas efficiency should not change at the critical threshold. Indeed, the dummy on eligibility status is not significant in these models. A last check consisted of 'misplacing' the eligibility dummy to thresholds of electricity consumption that should not have any practical implications for energy efficiency. The results of this robustness check were mixed; when the eligibility dummy was misplaced to 8 Gwh it was still significant. When misplaced to 12 Gwh it was not. An in-depth discussion of the findings and the detailed regression tables are presented in the appendix.

All in all, the robustness checks provide mixed results regarding the validity of the estimates presented in table 3. While some checks are encouraging and corroborate the findings, others cast doubt on the validity of the adopted research design. It is important to bear these doubts in mind; in particular, there is strong evidence that electricity consumption and electricity efficiency are linked to each other in a non-linear way. Therefore I have corrected the estimates presented in VIa downwards – the findings presented in the introduction and conclusion correspond to those based on the quadratic model (column III of table 4).

VI C.) The impact of electricity prices on investments into energy efficiency

After estimating the impact of the REA exemption rule on energy efficiency, it makes sense to ask how the energy efficiency differences came about. Data on Investments in Energy Efficiency can be used in order to examine whether companies that had to pay the REA markup also invested more in energy efficiency. Microeconomic theory would predict such a pattern as companies paying higher electricity prices have higher incentives to invest in efficiency improvements (see chapter II B). Table 5 presents the corresponding discontinuity regressions. Column I-III of the table correspond to models I-III in table 4 (classical RD model, RD model with controls, model with quadratic functional form). As the sample of energy-intensive companies for which we have data on investments is very small (201), it was not possible to estimate these regressions in a discontinuity sample of +/- 3 or +/- 5.

Table 5: Impact of eligibility status on Investments in Energy Efficiency

	Dependent Variable : Investments in Energy Efficiency		
	I	II	III
Electricity Consumption (Gwh)	-4.15 e(-6)	-4.27 e(-6)	-1.4 e(-6)
	(3.83 e(-6))	(7.57 e(-6))	(2.72 e(-10)
Eligibility Status (T)	-0.0013	-0.0008	-0.001
(=1 if electr. cons.> 10 Gwh)	(0.0097)	(0.01)	(0.0007)
$(\text{Electricity Consumption})^2$			1.85 e(-10)
			(6.32 e(-10)
Control Variables	No	Yes	No
F-test	0.53	0.98	0.34
r2	0.006	0.008	0.001
Number of observations	201	201	201

Note: robust standard errors in parenthesis; statistical significance is denoted by *(10%), **(5%) and ***(1%)
The control variables included in Model II are: The company's value added, own electricity production (Gwh), sales of electricity (Gwh), total consumption of coal (kwh) and total consumption of gas (kwh)

The results in table 5 do not suggest that there is a statistically significant relationship between energy prices and investments into energy efficiency. In all three estimated models, neither the coefficients on total electricity consumption nor the coefficient on the discontinuity-dummy are estimated to be significant. Moreover, I conducted F-tests to test for the joint significance of the estimated models. The null hypothesis (all coefficients are equal to 0) could not be rejected in any of the three models. Moreover, the low r^2 indicates that the estimated models do not describe the distribution of our data very well. All in all, it can be concluded that there is no evidence that an REA exemption (and as a consequence lower electricity prices) leads to lower investments into energy efficiency.

This result comes as a surprise as microeconomic theory suggests that higher energy prices lead to higher investments into energy efficiency. Moreover, the regression models presented above show that electricity prices had a positive impact on energy efficiency. How is it possible that companies that pay higher electricity prices become more energy efficient but do not invest into energy efficiency improvements?

One possibility is that companies make efficiency improvements at a given input mix by using their resources more efficiently. Companies that pay higher electricity prices might e.g. optimize the running time of their machinery so that less energy is consumed. This would lead to higher energy efficiency without making efficiency investments. In the production function presented in Chapter II ($\frac{Q}{E} = \frac{P_E}{\alpha_E\, A^{-1}\, P_K^{\alpha_K}\, P_L^{\propto_L}\, P_E^{\alpha_E}\, P_M^{\alpha_M}}$), such a pattern would be reflected in an increasing A and as a consequence higher energy efficiency $\frac{Q}{E}$. Another possibility is that there was an effect on efficiency investments, but that the regressions in table 5 were not able to detect it because of low statistical power[17]. Problems with low statistical typically arise if the sample size and/or the treatment effect are small. In our case, the sample for the analysis of efficiency investments consists of merely 201 observations. Moreover, it can be conjectured that, as a consequence of the small REA markup in 2008 (1.15 ct./kwh), the resulting effect on investments was also small. Therefore we cannot rule out that the absence of significant results in table 5 is a consequence of low statistical power.

[17] Statistical power is the probability of correctly rejecting Ho, if Ho is false. If statistical power is low, we run the risk of not rejecting Ho, even though it is falls (i.e. concluding that there is no effect, even if there is one). For an in depth discussion, see Moher, Dulberg and Wells (1994)

VII.) Conclusion

This study provided evidence that higher energy prices have lead to higher energy efficiency in German manufacturing companies. The case study of the German Renewable Energy Act showed that energy efficiency in companies that were exempted from paying the REA markup was on average 2.82% lower than in companies that paid the markup (given a markup of 1.15 ct/kwh which corresponded to 13.54% of the average electricity price in 2008).

It has to be noted that the estimated treatment effect holds for energy intensive companies that were eligible and applied for an exemption from the REA markup and were sufficiently close to the critical threshold of 10 Gwh. It can be expected that the estimates have a *high internal validity* for this specific group of companies. However, an extrapolation of the finding to companies with substantially higher/lower overall energy consumption is problematic and can only be done under the strong assumption of homogeneous treatment effects (see chapter IV). As in any regression discontinuity estimation, the *external validity of the finding is therefore limited*.

In spite of the limited external validity, the finding has two important policy implications. First, it can be stated that the exemption rule to the German Renewable Energy Act has led to energy efficiency losses. Exempted companies would have produced in a more energy efficient way if they had not been exempted from the REA markup. Secondly, the results suggest that an energy tax can be an effective measure to promote energy efficiency improvements. Although the REA markup is not conceived as an energy tax, it has essentially the same effect. It can be conjectured that an energy tax might also have a positive impact on energy efficiency in developing countries and emerging market economies. This study is not in a position to prove this, but gives at least reason to assume that a tax on industrial energy consumption (possibly in exchange for other tax alleviations) might facilitate a more sustainable development in these countries. An interesting avenue for future research would be to evaluate the impact of an energy tax in a developing country context.

Lastly, the study can be seen as an example of how counterfactual thinking and quasi-experimental research designs can be used in environmental and energy economics. As Ferraro (2009) points out, "[s]ome have argued that environmental policy is different from other social policy fields, and thus attempting to establish causality through identification of counterfactual outcomes is quixotic" (2009: 75). This study provides a counterexample to this claim and illustrates the advantages of using counterfactual thinking in environmental economics. Identifying other situations where environmental policies can be evaluated using a counterfactual might be a promising avenue for future research. Most importantly, such studies would contribute to building an evidence base for more successful environmental policies in the future.

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Appendix 1 – Calculation of the Variables used in the Analysis

Explanatory variables: The most important explanatory variables for the regression discontinuity analysis are 1.) Total electricity consumption and 2.) Electricity cost share. These are the "forcing variables" determining whether a company will be part of the treatment or of the control group (i.e. whether they it is exempted from paying the REA markup or not). Data on total electricity consumption (kwh) was obtained from the FSO dataset on "Energy use in manufacturing and mining companies.

The electricity cost share is not part of any of the FSO datasets, but can be computed as:

$$Electricity\ Cost\ Share = \frac{Electricity\ Costs}{Value\ Added}$$

As the FSO does not provide data on total electricity costs, but only on total electricity consumption, the electricity costs were computed using the Eurostat (2014) database on electricity prices (electricity costs = "Total electricity consumption (kwh) x Electricity Price (kwh)"). Value added was computed using the data from the cost structure survey, following the official definition of value added of the FSO (Statisitisches Bundesamt 2007)[18]:

$$\begin{aligned}&Value\ Added = \\ &Total\ Sales + Change\ in\ inventory + \ Value\ of\ self\ produced\ assets\ that\ were\ activated\ in\ the\ business\ year - \\ &Consumption\ of\ raw\ materials\ and\ other\ operating\ supplies - Costs\ for\ hired\ labor - \\ &costs\ for\ repairs\ and\ maintenance\end{aligned}$$

Based on the estimations of value added and electricity costs, it was then possible to compute the electricity cost share of the companies according to the formula presented above.

Moreover, dummy variables were created in order to indicate whether a company's electricity cost share and overall electricity use were above the critical threshold which allows them to apply for an exemption from paying the REA markup: The dummy "eligibility status" takes on the value 1 if a company is eligible for an exemption from paying the REA markup (i.e. if its electricitcy cost share is at least 15% and its electricity consumption is at least 10 Gwh)

Outcome Variables: The outcome variables to be examined are 1.) electricity efficiency in 2008 and 2.) investments in energy efficiency in 2008. Using the definition of value added that was presented above, electricity efficiency was computed as:

$$Electricity\ Efficiency = \frac{Value\ Added}{Electricity\ Consumption\ (kwh)}\ .$$

Electricity efficiency changes between 2001 and 2008 were simply computed as the difference between electricity efficiency in 2008 and electricity efficiency in 2001. The third outcome variable, investments in energy efficiency, was also obtained from the FSO datasets, which provide information on the volume of energy efficiency investments in Euro. The problem with this measure is that the investment volume will always increase with company size. In order to control for this, I normalized the investment measure by value added:

[18] Companies applying for an exemption from the REA markup have to base their application on this definition. We can thus assume that the data used in the application process is coherent with the data used in this analysis.

$$Normalized\ Energy\ Efficiency\ Investments = \frac{Energy\ Investments\ (EUR)}{Value\ Added}$$ [19]

[19] For the sake of simplicity, the rest of the paper will refer to this normalized measure as „Energy Efficiency Investments“. Total efficiency investments will be referred to as “Energy Efficiency Investments in Euro”.

Appendix 2 – Robustness Checks

Table 6 presents a further robustness check. It consists in running the same regression model as in table 3, but to replace the outcome variable with a covariate that should not be affected by the critical threshold. In particular, I check whether *gas efficiency* changes at the cutoff point. Gas efficiency is therefore regressed on electricity consumption (Gwh) and on a dummy indicating whether a company was eligible for an exemption from the markup. The regression results are presented in table 6.

Table 6: Robustness Check - Impact of crossing the critical threshold on gas efficiency

	Dependent Variable : Gas Efficiency
Electricity Consumption (Gwh)	-7450.94
	-8305.87
Eligibility Status (T)	-1.15 e(7)
(T=1 if electr. cons. > 10 Gwh)	(1.11 e(7))
Control Variables	No
F-test	0.31
r2	0.006
Number of observations	398

Note: standard errors in parenthesis; statistical significance is denoted by *(10%), **(5%) and ***(1%)

Indeed, the results are encouraging. While crossing the critical threshold has a statistically significant and negative effect on electricity efficiency, gas efficiency is not affected by crossing the critical threshold. The estimated coefficient on "eligibility status" is negative but not statistically significant.

A further robustness check is to 'misplace' the dummy variable that indicates treatment eligibility to an arbitrary cutoff point which should not have any practical implications for electricity efficiency. In particular, I created dummy variables indicating whether a company's electricitiy consumption was above or below 8 Gwh / 12 Gwh. Crossing these thresholds should not have any consequences for electricity efficiency, as electricity prices do not change at these cutoff points. Table 7(presents the corresponding regression results (column I refers to the model where the dummy was 'misplaced' to 8 Gwh and column II refers to the model where the dummy is misplaced to 12 Gwh).

Table 7: Robustness Check - 'Misplace' the Discontinuity to 8 Gwh / 12 Gwh

	Dependent Variable : Electricity Efficiency	
	I	II
Electricity Consumption (Gwh)	-0.0000617***	-0.0000551***
	(0.0000159)	(0.0000167)
Eligibility Status (T)	-0.087***	- omitted -
(Model I: T=1 if electr. cons. > 8 Gwh	-0.019	(due to collinearity)
Model II: T=1 if electr. cons. > 12 Gwh		
F-test	0	0.001
r2	0.07	0.028
Number of observations	539	539

Note: standard errors in parenthesis; statistical significance is denoted by *(10%), **(5%) and ***(1%)

The results of the second robustness check cast doubt on the validity of the research design and the results that were presented in part A of this chapter. Model I suggests that there is a statistically significant discontinuity in energy efficiency at the 8 Gwh threshold. In particular, the estimated coefficient is -0.087 and consequently even higher than the treatment effect estimated above. Model II is more encouraging. If we misplace the dummy indicating treatment eligibility to 12 Gwh, Stata omits the dummy due to multicollinearity. This implies that the dummy cannot add additional information to the model and that crossing the 12 Gwh threshold does not have practical implications for the companies in my sample. However, why is the dummy on eligibility significant if misplaced to 8 Gwh? Different explanations are possible. First, it might be that the discontinuity found in VIA is spurious and just a manifestation of the generally negative relationship between energy use (Gwh) and energy efficiency. In this case my findings would not be valid. Another possibility is that the dummy on the 8 Gwh threshold partly captures the discontinuity at the 10 Gwh threshold. Lastly, it might be that some companies whose energy use is between 8 Gwh and 10 Gwh tried to decrease their energy efficiency in order to cross the critical threshold at some point in the future. Such a behavior could also lead to a significant dummy at the 8 Gwh threshold.