Energy efficiency policies for different firm sizes: challenging current policies with empirical data

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Abstract

Energy efficiency is a simple and often cost-effective way to reduce energy consumption and greenhouse gas emissions. Different policies have been designed to promote the implementation of energy-efficiency measures in industry. It is generally assumed that firms of different size have different means and face different barriers when adopting energy-efficiency measures. Several studies have tried to identify a net effect of firm size and other firm characteristics. However, a detailed understanding beyond linear regression of the general effect of firm size on energy consumption and the adoption of energy efficiency measures is still missing. Also in many policy evaluations (ex-ante as well as ex-post), only average values are used, ignoring differences in firm size of several orders of magnitude. Such a simplistic approach only allows for constrained policy recommendations as it neglects the large diversity that prevails among firms and that dominates firms' adoption decision. Here, we study empirical distributions of firm size and adoption rates and how these interact. We identify general empirical trends by using data from different countries and industry branches. Thus, a more detailed picture of the adoption behaviour of firms of different size is obtained. This is a first step towards a more realistic consideration of diversity among firms in policy design and evaluation methods. The broad empirical trends have consequences for the future design of more effective energy-efficiency policies.

Introduction

Improving energy efficiency is a key strategy in the development towards a more sustainable global energy system (IEA 2011). Increased efficiency is seen as a major option for lowering greenhouse gas emissions by reducing the demand for fossil fuels. It also has the potential to significantly reduce the dependency on energy imports, address the scarcity of energy resources and finally, contribute to improving the competitiveness and productivity of firms. Given these benefits, energy efficiency is at the top of the policy agenda of numerous governments worldwide and is also receiving a lot of attention from researchers and analysts. The International Energy Agency, for example, predicts that global greenhouse gas emissions could be significantly reduced simply by using the currently best available technology (BAT), and additional potentials are available due to new, emerging technologies (IEA 2007).

Thus, the spread or diffusion of energy-efficient technologies (EET) through society is a highly relevant research field. Even the most revolutionary innovations will have no effect on energy demand if they do not find users. It is also a very complex field as numerous and often interrelated factors affect the diffusion of EETs. For policy-makers, however, it is crucial to understand the determinants of diffusion in order to effectively steer or accelerate it where it is too slow from a social optimum perspective.

Several general factors are widely considered to affect the diffusion process. While profitability is probably the most researched innovation characteristic and it is generally accepted that it increases the speed of diffusion (Mansfield 1961; Ray 1988; Stoneman 2002), other characteristics also have a significant impact. For example, it has been shown that the complexity of an innovation is negatively correlated to the speed of diffusion (Kemp, Volpi 2008; Tornatzky, Klein 1982). When looking at the impact of adopter characteristics on diffusion, firm size is the most commonly researched parameter and is generally expected to have a positive impact on the adoption rate. The implication here is that larger firms are more likely to adopt innovations (Davies 1979).

Research on the effect of firm characteristics on the adoption of EET often emphasizes the role of firm size. It is generally accepted that larger firms tend to have higher adoption rates than smaller firms. If, however, intra-firm diffusion is included in this comparison, the picture becomes more complex. Firms also differ in terms of energy intensity, measured as the energy cost share of the firms' turnover. Energy-intensive firms typically focus more on energy efficiency and regard it as an important factor for their competitiveness. On the other hand, energy-intensive firms also typically have access to lower energy tariffs, rendering many EETs less profitable and thus reducing the incentive to adopt them. Further, firms also differ regarding the extent that energy management is integrated into their official routines. If it is officially integrated, the adoption of EETs and searching for new EETs are much more systematic and are given higher priority within the firm, resulting in higher adoption rates. These and many other factors potentially influencing the adoption decision have been analyzed, mainly in terms of case studies and econometric analyses.

The fact that firms differ in the energy consumption is well-established (see, e.g. Stoneman (2002), Schleich (2009), Rohdin et al. (2007) and references therein). Accordingly, policies have been designed for different companies and different industrial segments, particularly for small and medium enterprises and energy intense industry.

The objective of the present paper is to reconsider adoption of EET by companies by particularly taking into account the influence of firm size and energy demand. Some of the results shown in the present paper have qualitatively been discussed in the literature (Saygin et al. (2011) and references therein). Here, we want to go one step further and quantify the degree of heterogeneity among companies and its different origins by a more detailed statistical analysis. Where the fact that companies differ in their energy consumption and adoption decision is well known, we aim at a closer study of this heterogeneity between companies.

The paper is organised as follows. The following section introduces the data sets used for our analysis and reviews some statistical tools and important statistical distributions. The results section will be used to present our main results on the heterogeneity of firms' energy consumption and the influence of two important factors potentially on the adoption decisions, namely payback time and implementation costs, will be studied. We will conclude by pointing out policy implications of the results presented.

Data and Methods

The present section introduces the data we used for the present paper and provides some background on the statistical tools for the analysis to be performed in the results section.

DATA USED

Large scale data on the adoption of EET by companies is scarce. Here we use two data sets. Both data sets result from energy audits in small- and medium sized firms (SMEs) and contain information on individual energy-efficiency measures that were recommended by the auditors. The smaller data set stems from the evaluation of a governmental incentives program to stimulate energy audits in Germany "Sonderfonds Energieeffizienz in KMU" and is not publicly available. The program has been studied earlier, e.g. by Gruber et al. (2011). The second and larger data set stems from the US Industrial Assessment Center (IAC) (http://iac.rutgers.edu/). The data is publicly available and has been earlier studied, e.g., by Anderson and Newell (2004). We will mainly focus on the latter data set since it is much more comprehensive, i.e. contains more entries, and also states information on adoption of energy efficiency measures. The following table summarises the descriptive statistics of both data sets. The data base further contains a variable named "implementation status", which contains the entries "implemented", "not implemented" or "pending" and is evaluated by phone after the audit has taken place. A project is coded as "implemented" if the implementation has taken place within 24 months after the audit, if not, it is "not implemented".

METHODS

The present section introduces some background methodology that will be used later for analysing the data.

Firm Size Distributions

Firms differ considerably in size. This fact has long been studied and analysed in terms of firms' revenues, number of employees, sales and other measures, see, e.g., Axtell (2001), de Wit (2005), Sutton (1997) and Newman (2005). One main finding is that the distribution of firm sizes is heavy tailed, i.e. large firms occur more frequently than could be expected by localised distributions, say, a normal-distribution.

There is some debate in the literature about the distribution that describes the observed firm sizes best and its origins. This

Table 1. Descriptive statistics of the company data sets and their energy consumption.

Data set and variable	Min	Max	Median	Std. Dev.
German data N = 2670 measures				
Number of employees	1	550	25	59
Annual energy consumption [MWh]	1.66	115,460	460.4	96,414
Annual energy costs [10^3 Euro]	1.606	7,274.7	44.30	904.52
US IAC data N = 114,548 measures				
Number of employees	0	5800	130	193.5
Annual electricity consumption [MWh]	0	1,200,000	3,400.0	25,772.5
Annual energy costs [10^3 USD]	1.0	190,000	295.5	2,516.3

is not the focus of the present paper, but one distribution that provides a good approximation for actual firm sizes is the log-normal distribution

$$P(x) = \frac{1}{x\sqrt{2\pi}\sigma}\exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right] \qquad (1)$$

where x is the random variable under consideration, in our case the firm size measured as number of employees or revenues. The log-normal distribution has two parameters: μ sets the scale and σ determines the distribution's shape. The log-normal distribution can also reproduce power-law tails in firm size distributions, known as Zipf's law (Newman 2005).

In the following, we will use two ways of displaying a distribution function $P(x)$. The complementary cumulative distribution function (CCDF), denoted as $P_c(x)$, and the cumulative distribution function CDF(x) are defined as (Sornette 2000)

$$P_c(x) = \sum_{r\geq x} P(r) \text{ and } \mathrm{CDF}(x) = \sum_{r<x} P(r) \qquad (2)$$

These quantities have two advantages. Firstly, no grouping or binning of the data is necessary as in usual histograms. This is important since the choice of bin widths or class boundaries can have strong impact on the empirical distributions. In contrast to this, both the CDF and CCDF are summed elementwise and thus in principle provide the whole information from every data point. Secondly, both quantities are statistically more stable against outliers. The reason is that the cumulative summation leads to some auto-averaging. Additionally, both quantities have straightforward interpretations: CDF(x) is the probability for values smaller than x and the CCDF $P_c(x)$ is the probability for values in the data larger than or equal to x. Both quantities are shown for the firm size of our data sets measured by the number of employees per firm in figure 1.

We observe similar heavy-tailed distributions of firm size for both the US and German data. This is in agreement with established results on firm size distributions (de Wit 2005). Furthermore, both distributions are similar in shape, the US data is only shifted to larger firm size, i.e. the US data contains larger companies but the distribution has roughly the same statistical properties. The dashed line in the main panel of figure 1 shows additionally a power-law fit of the upper tail of the US data using the methods of (Newman 2005). The fit nicely follows the observed empirical distribution (apart from a simple numerical offset that has been added for better visibility). This power-law tails is actually known as Zipf's law. The validity of this behaviour is not the focus of the present paper but well documented in the literature (see Axtell 2001, deWit 2005, Sornette 2001 and references therein) and has been reproduced here for comparison and completeness.

To summarise, we introduced the CCDF and CDF as statistical tools for displaying and analysing data and confirmed that the data used in the present paper follows known results for empirical firm size distributions, i.e. the data seems representative as far as the statistical distribution of firm sizes is concerned.

Measures of Inequality

One goal of the present paper is to highlight the heterogeneity or inequality of companies and their energy consumption as well as adoption behaviour. The present section introduces Lorenz curves as statistical method to display inequality of distribution functions, which will be used later.

Lorenz curves are commonly used to display and quantify inequality or heterogeneity in populations and their distributions. For a given distribution $P(s)$, for example the log-normal distribution given in eq. (1), the coordinates for a Lorenz plot are obtained as (see, e.g., Drăgulescu and Yakovenko (2001))

$$x(r) = \int_0^r P(s)\mathrm{d}s \quad \text{and} \quad y(r) = \frac{\int_0^r sP(s)ds}{\int_0^\infty sP(s)ds} \qquad (3)$$

Lorenz curves are a common tool to display inequality in income distributions and can easily be interpreted as "share x of

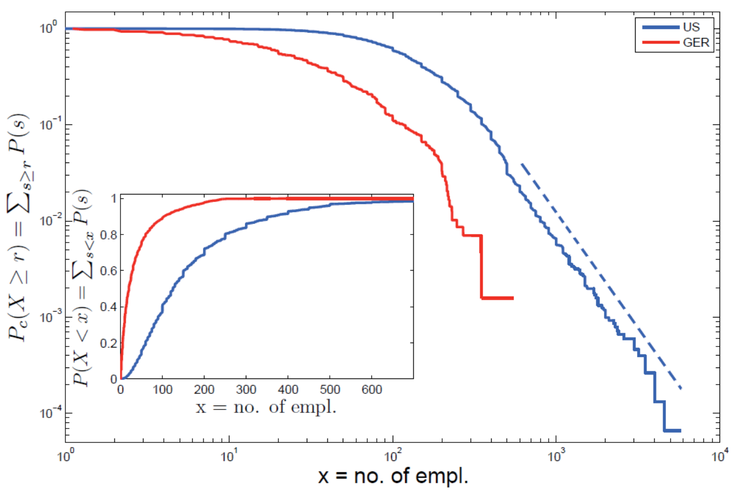

Figure 1. Firm size distribution by employees. Main figure: CCDF for the number of employees per firm. The upper curve shows the US data from IAC, the lower curve shows the German data. Inset: CDF for the number of employees per firm. Lower curve: US data, upper curve: German data. Both data sets contain mainly small and medium enterprises and show similar distribution functions for size. The firms in the US data set are generally larger than in the German data. The dashed line corresponds to a power-law fit of the tail of the US data.

the population has share y of the total income" (Drăgulescu and Yakovenko 2001). Drăgulescu and Yakovenko analytically derived the Lorenz curve formula $y(x) = x + (1 - x) \ln(1 - x)$ for a purely exponential distribution $P(s) = c \exp[-s/T]$ with the scale parameter T and a normalisation constant c. Please note that the scale parameter drops out from the Lorenz curve. This is natural since the Lorenz curve only serves to display inequality and this is independent from scale: a millionaire is poor when everybody else is a billionaire. Only relations matter for inequality, not scale.

If the distribution was uniform, i.e. every s in the data had the same probability of occurrence $P(s)$, the Lorenz curve would be a straight line with unit slope. Lorenz Curves $y(x)$ are also used to define Gini coefficients G

$$G = 1 - 2\int_0^1 y(x)\mathrm{d}x \qquad (4)$$

as simple quantity representing the inequality within an empirical distribution.

Results

The present section contains the results of the present paper. The first part discusses heterogeneity and inequality in firm's energy consumption. The second part will deal with the influence of firm size, payback times and implementation costs on the decision for adopting energy efficiency measures.

HETEROGENEITY IN ENERGY CONSUMPTION

It is natural to assume that the diversity in firm size, recapitulated in the previous section, implies large diversity in firms' energy consumption. Additionally, companies' affiliation to different economic sectors should also add to the inequality in energy consumption. The large heterogeneity of firms in energy consumption is demonstrated in figure 2 where we show the CCDF (main panel) and CDF (inset) of energy consumption per firm measured by their annual energy costs in USD for the US data.

As for company size, we observe that the empirical distribution of annual energy costs in industry is heavy tailed and spans many orders of magnitude. Please note that the data contains only small and medium enterprises. Also shown as in figure 2 is a power-law fit (dashed line) for the upper tail of the energy consumption distribution providing a good fit for more than two orders of magnitude. A horizontal offset of the power-law fit has been added for better visibility. Note the logarithmic scale of the figure, indicating that the fit deviates only by a few per cent. Thus, we have demonstrated that Zipf's law (Axtell 2001, Newman 2005) also holds for energy consumption in industry.

Comparing the empirical distribution of firm sizes and energy consumption, one might be led to believe that the heavy tailed distribution of energy consumptions is a trivial consequence of the empirical firm size distribution. This idea could be further strengthen by the seeming similarity of both distributions. However, this can easily be tested by studying *energy consumption per capita* (i.e. per employee) in the different firms. If energy consumption per capita was approximately constant over the different firm sizes, firm size could be used as proxy for energy consumption. We test this hypothesis in figure 3. The left panel of figure 3 shows the energy consumption per capita for all firms from the German data set as a function of firm size (measured as number of employees). We observe that energy consumption per capita is not constant but varies over more than four orders of magnitude (note the logarithmic scale in the left panel of figure 3). In fact, energy consumption per capita appears to follow the heavy-tailed log-normal distribution as the right panel of figure 3 demonstrates.

One might object that different industrial sectors naturally have different per capita energy consumption, but figure 4 will show that the differences between segments are not sufficient to account for the remaining heterogeneity (cf. figure 4 and its discussion). Thus, we conclude that firm size cannot directly be used as proxy for energy consumption. Of course, this fact is not totally new but is already documented in the literature

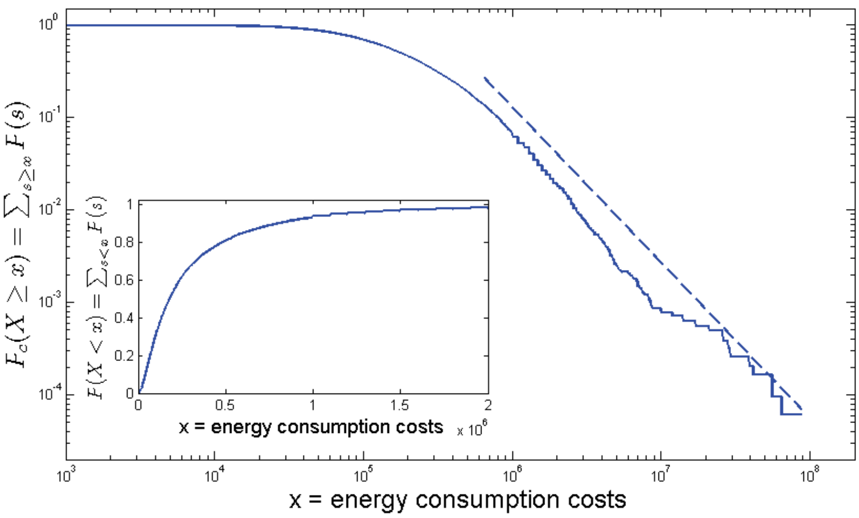

Figure 2. Firm size distribution by annual energy costs. Main panel: CCDF of energy consumption in industry measured as energy costs. The dashed line is a power-law fit for the upper tail of the distribution. Inset: CDF of energy consumption in industry measured as annual energy costs.

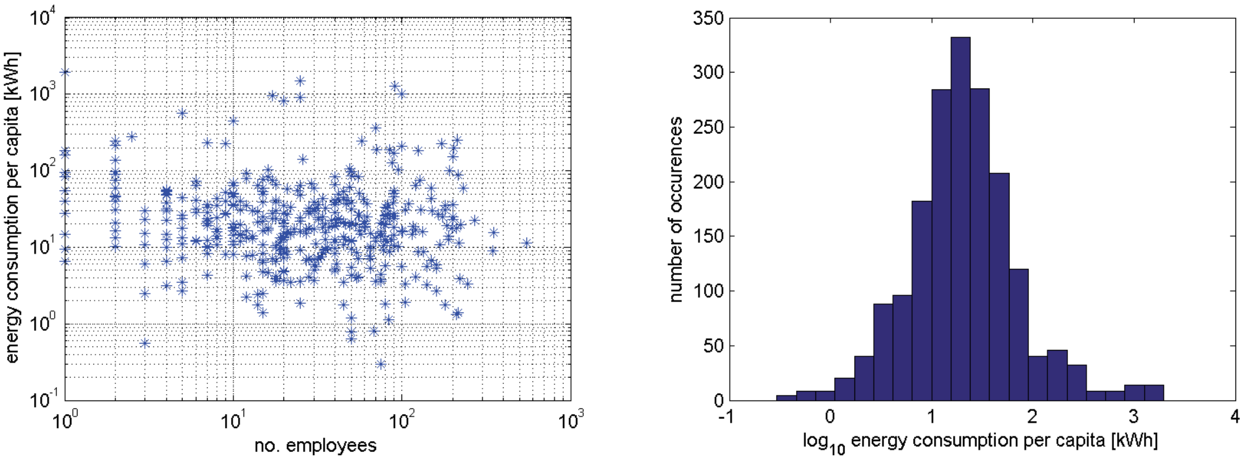

Figure 3. Energy consumption per capita. Left panel: energy consumption per capita for all firms from the German data set as a function of firm size (measured as number of employees).Right panel: Histogram of the logarithm of energy consumptions per capita from the left panel. The distribution appears log-normal since the logarithms of the observable (energy consumption per capita) is normal distributed.

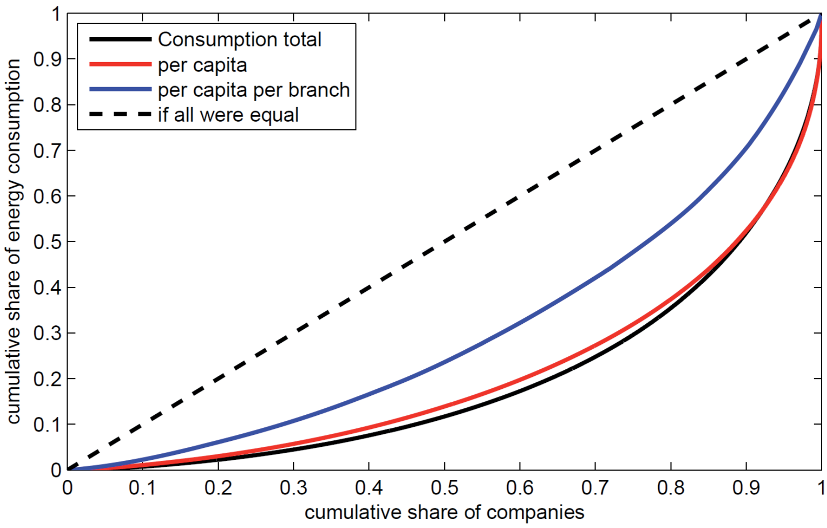

Figure 4. Lorenz curves for energy consumption in industry. Shown are (from bottom to top) the Lorenz curve for total energy consumption (lowest curve), per capita energy consumption (second lowest) and per capita energy consumption per sector/branch (second from top). Also shown is a straight line (dashed top curve) that corresponds to a uniform distribution without any heterogeneity. Lorenz curves are computed as introduced in the method section.

(see, Saygin et al. (2011) and references therein). However, the aim of the present paper is not to only acknowledge this fact but start a more thorough statistical and quantitative analysis of this heterogeneity, as provided in figure 3.

As already mentioned, part of the differences in per capita energy consumption can be attributed to different industrial sectors with their individual production processes. We are now going to analyse the different levels of comparisons already introduced (total energy consumption, per capita energy consumption and pre capita energy consumption per sector) at the same footing. We use the Lorenz plots introduced in the method section to compare the different levels of inequality. The result for the US data is shown in figure 4.

Figure 4 shows Lorenz curves calculated for the US data. The lowest curve corresponds to the distribution of total energy consumptions (cf. figure 2), the second lowest to per capita energy consumption (cf. figure 3) and the third lowest curve corresponds to per capita energy consumption for one industrial sector. Here, companies from commercial printing and lithography have been chosen according to their SIC 2752 (with sample size $N = 1517$). We performed similar analyses for other industrial sectors, such as those producing corrugated and solid fiber boxes (SIC: 2653, sample size $N = 2291$), companies producing plastics (SIC: 3089, with sample size $N = 6271$), as well as producers of motor vehicle parts and accessoires (SIC: 3714, with sample size $N = 2331$). The case of printing and lithography shown in figure 4 actually showed the smallest heterogeneity and has therefore been included in figure 4. Additionally, we display a straight line in figure 4, corresponding to the case of total equality (dashed line in figure 4) for comparison.

Figure 4 demonstrates that neither firm size nor industrial segment are sufficient to account for the heterogeneity in en-

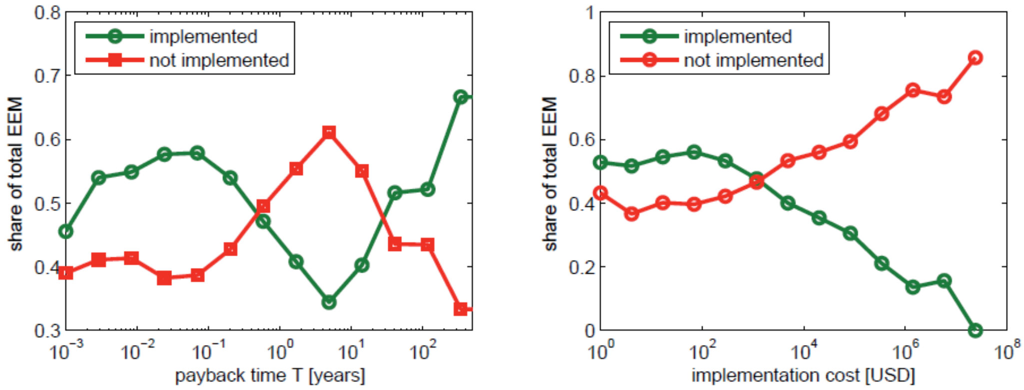

Figure 5. Adoption of energy efficiency measures for differing payback times and implementation cost. Implemented (circles) and not implemented (squares) share of EEMs for different payback times (left panel) and implementation cost (right panel).

ergy consumption in industry. In addition, we computed the Gini coefficints (Gini 1922) for the three curves in figure 4 to quantify the heterogeneity and obtained (bottom-to-top): 30 %, 29 %, 19 %. In order to be able to understand the meaning of these numbers, let us note this inequality in energy consumption per capita is comparable to the income inequality in central european countries, i.e. the Gini Coefficients for income inequality in western European countries are similar. Future analysis could give an overview of quantified heterogeneities in terms of Gini coefficients in energy consumption and look for external factors influencing these as is well-established for income inequality in countries.

HETEROGENEITY IN ADOPTION DECISIONS

We studied heterogeneity in industrial energy consumption in the previous section and will turn to the decision to implement energy-efficiency measures (EEMs). We will only use the US data for the present section.

Among the many determinants that affect the adoption of EEMs by firms, the EEMs' profitability (e.g. in the form of payback time) and its implementation costs are frequently found to have a major impact on adoption.

Here we compute the ratio of actually implemented EEMs in one category of similar payback times versus the total number of EEMs in the same category. A ratio or share of 0.5 means, that 50 % of the EEMs with similar payback times have been adopted by companies. Figure 5 shows the shares of implemented and not implemented EEMs for different payback times and implementation costs. Where the shares of implemented or not implemented EEMs do not add up to unity, the adoption decision of the remaining EEMs was pending or data was unavailable.

We observe from figure 5, that the likelihood of implementing an EEM decreases with growing payback time and growing implementation cost, as expected. However, even for payback times longer than 10 years the implementation rate does not go to zero. This indicates that some companies adopted irrespective of their payback time and either did not consider payback times or did not decide based on profit maximization. The absolute number of occurrence of this unexpected behaviour is not large and partially this might also be due to the fact, that some companies adopted all of the measures recommended by the auditors. The picture is more straightforward for the effect of implementation cost on the adoption decision. The right panel of figure 5 shows that the rate of adoption steadily decreases with growing implementation costs.[1] Interesting to note and again pointing towards the limitation of simple "profit-maximising" rationality, the adoption rate for EEMs is never larger than 60 % irrespective of the shortness of the payback time or the magnitude of the implementation costs. The results in figure 5 go beyond common linear regression analysis which yields only the sign and magnitude of a relation but not the functional form of the relation between the variables under consideration.

According to neoclassical theory, a rational firm will invest in a project which exhibits positive net present value (NPV). The discount rate used in the NPV calculation should be the return available on other projects of the same risk class and does not depend on the firm's characteristics. Therefore, the decision to invest in an EEM with positive NPV should be independent from firms' characteristics (DeCanio and Watkins, 1998). However, a study by DeCanio and Watkins (1998) on firms' decision to join Green Lights program shows that firms' characteristics, such as number of employees and earnings per share, also influence their decisions.

Here, we chose to study the share of EEMs adopted by firms of different size for varying payback time and implementation cost of the EEM. The results are shown in figure 6.

The left panel of figure 5 shows the share of EEMs adopted by the smallest 10 % of all companies (circles) and the largest 10 % of all companies (squares). These two subsets have been chosen to highlight the effect of firm size. The right panel shows the rate of adoption for the same subsets but as a function of implementation cost. Additionally, both panels show error bars for the different adoption rates. Since the data points in figure 6 are obtained from binning the many individual adoption decisions, the error bars have been computed as Poisson distributed errors, i.e. the uncertainty is given by

1. We used the variable "implementation status" of the IAC database to assess whether an EEM is implemented or not. There is limited time between recommendation and verification of implementation. However, this limited time is not directly an explanation of the fact that only a few projects over $1 million were undertaken. If firms have not decided on the implementation, this is covered by the implementation status "pending" in the IAC database and projects with implementation status "pending" are not included in the figure. A project is defined as "implemented" if the implementation has taken place within 24 months after the audit, if not, it is "not implemented".

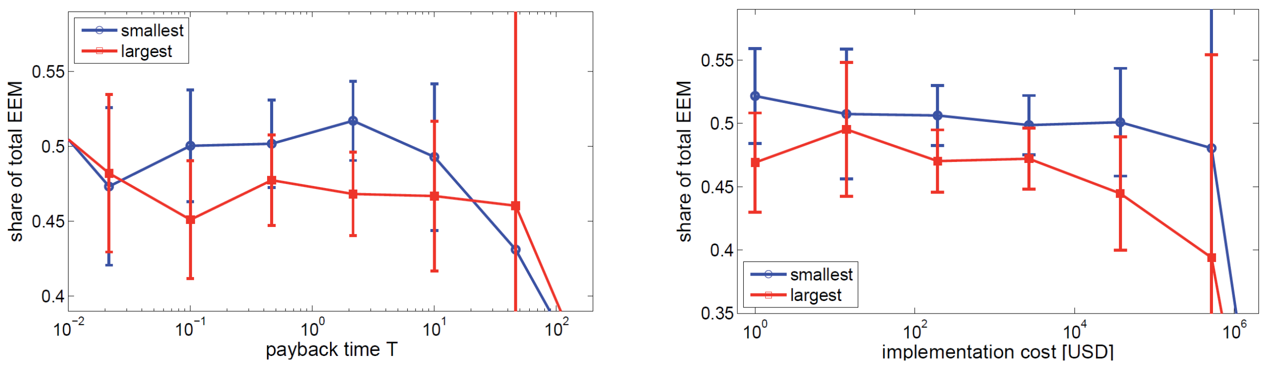

Figure 6. Effect of firm size on adoption decision. Share of implemented EEMs for 10 % smallest (circles) and 10% largest companies (squares) for differing payback times (left panel) and implementation cost (right panel). The error bars are explained in the main text.

$$\Delta n_i = \sqrt{n_i} \qquad (5)$$

where n_i is the number of data points in an individual bin. The error is very large for EEMs with very long payback time (longer than 10 years) since only a small number of EEMs fall into that class. The same is true for EEMs with very high implementation costs (right panel of figure 6). However, for the bulk of the distribution of EEMs, i.e. for the majority of actual adoption decisions with payback times between one month and a few years and implementation costs between 100 and 10,000 USD, the error in adoption rate is smaller or comparable to difference in adoption rate. We performed similar analysis with different bin widths and different shares of firm size, e.g., the largest and smallest quarter of all firms, but the results remained unaffected. Studying a larger share of companies (e.g. 25 %) implies a larger sample and therefore a smaller error, but at the same time the difference to observe between the smallest and largest subset of companies also turns smaller. The difference in adoption rate was typically slightly smaller or comparable to the error for the bulk of the distributions. Thus, the firm size seems to have an effect on the adoption decision when comparing the largest and smallest firms, but the effect is not much larger than the measurement error and we cannot be certain. Interestingly, the effect seems to be opposite of what is typically expected. For both varying payback times and implementation costs the smaller firms actually implement a larger share EEMs than the largest firms.

Discussion and Policy Implications

We empirically analysed and quantified different sources and degrees of heterogeneity in industrial energy consumption. We draw on data from the US energy audit program IAC and the German audit program "special fund for energy efficiency in SMEs". Where the qualitative picture was well-established (firms differ largely in the structure of their energy consumption), we found statistical laws and could quantify the degree of heterogeneity using Lorenz curves and Gini coefficients.

We found a huge degree of heterogeneity among firms' energy consumption. Even when correcting for firm size, by taking into account the number of employees per firm, the resulting specific energy consumption per capita varies substantially across firms. Taking the industrial sector into account did reduce heterogeneity considerably, but still, a substantial level of heterogeneity remains even within the individual sectors. While the industrial sectors considered are already very narrow (SIC at the 4-digit level), grouping firms by type of product could result in more homogenous groups, particularly when the production output is used as reference instead of the number of employees. This however would reduce sample size and faces methodological difficulties since many firms produce a product mix rather than a single product.

The huge variety of firms' energy consumption illustrated in our analysis, needs also to be taken into account for policy design as well as for policy analysis. Policy impact assessments (ex-ante as well as ex-post) often calculate the impact in terms of energy savings and the related costs as average values for the entire sample of firms. Such neglect of the fact that firms' energy consumption is very heterogeneous restricts potential policy recommendations. Allowing for different classes of firms with similar energy consumption, would be a first step to consider heterogeneity in such analyses and, thus, be more explicit about the impact of policies. While a program might be cost-effective for the average firm, this might not be the case for all firms. E.g. for firms with lower energy consumption the administrative costs might be higher than saved energy costs. In a second step, considering the entire distribution of firms' energy consumption would allow to identifying the "break even" firm, for which a program is cost-effective. Similarly, policy design can account for heterogeneity and improve cost-effectiveness of programs, by including threshold levels for program participation. From a different perspective, policies could focus on firms with highest energy consumption per employee within a given industrial sector, e.g. by treating the sickest patient first and most intensively instead of treating all patients similarly.

Furthermore, the analysis shows that the adoption rate increases with shorter payback time and lower implementation costs. While this result is expected and generally in line with the recent literature, the fact that even for EEMs with zero implementation costs and payback periods of less than a month, adoption rates are not significantly above 50 % is rather astonishing. These measures are known to the firm, they should be technically applicable as well as cost-effective. Quite fundamental other reasons must be behind the non-adoption of such a high share of measures. While this "energy-efficiency gap" has been widely researched in the past (see e.g. Jaffee and

Stavins 1994), the data set used in our analysis allows a more quantitative estimation of this gap. The analysis of the adoption rate further gives some indication that smaller firms tend to adopt a higher share of the recommended EEMs. This is somewhat contradictory to the general understanding that smaller firms face higher barriers such as access to capital for financing, internal know-how and staff (Gruber and Brand 1991). Possible reasons might be that decision processes in larger firms are more complex or simply that larger firms received a higher number of recommendations. Anderson and Newell (2004) analysed the same data set as presented in figure 6, using multivariate regression analysis. They did not receive a significant result for the variable firm size (in terms of number of employees). As a potential reason, they mention the relatively small range of firm sizes, which results from the fact that the program is addressed SMEs. Certainly, further data and research on the effect of firm size on the adoption of EEMs is required to allow more robust conclusions and policy recommendations.

Generally, heterogeneity in specific energy consumption per capita (corrected for industrial sector) entails either a very diverse product output within this sector or reveals differences in energy efficiency on the firm level. While these effects cannot be disentangled in our data set, without using firm groups based on products, it is very likely that both effects play a role. Due to this uncertainty, specific energy consumption values on the level of industrial sectors that are related to the number of employees do not provide a sufficient basis for the application of mandatory benchmarks. However, they might provide a first indicative comparison of a firm's energy efficiency in comparison to other firms in the same sector and thus justify an energy audit.

Generally, conducting similar analyses using a larger data sample that also includes large firms could provide further insights on the role of firm size.

References

Anderson, S.T. and Newell, R.G., 2004. Information programs for technology adoption: the case of energy-efficiency audits, Resource and Energy Economics 26 (2004) 27 - 50.

Axtell, R., 2001. Zipf Distribution of U.S. Firm Sizes. Science, 293: 1818–1820.

Davies, S. 1979. The diffusion of process innovations, Cambridge: Cambridge University Press.

de Wit, G., 2005. Firm size distributions: an overview of steady-state distributions resulting from firm dynamics models. International Journal of Industrial Organization 23 (5–6), 423–445.

DeCanio, Stephen J., Watkins, William E., 1998. Investment in Energy Efficiency: Do the Characteristics of Firms Matter?, Review of Economics and Statistics 1998 80:1, 95-107.

Drăgulescu, A. and Yakovenko, V.M., 2001. Evidence for the exponential distribution of income in the USA. The European Physical Journal B 20 (4), 585-589.

Gini, C., 1922. Indici di concentrazione e di dipendenza, Biblioteca delli'economista 20 (1922) 77.

Gruber, E.; Brand, M. (1991): Promoting energy conservation in small and medium-sized companies. Energy Policy, 19 (3), pp. 279-287.

Gruber, E., Fleiter, T., Mai, M.., Frahm, B.-J., 2011. Efficiency of an energy audit programme for SMEs in Germany - results of an evaluation study, European Council for an Energy-Efficient Economy - ECEEE, Paris: ECEEE 2011 Summer Study: 6-11 June 2011, Stockholm: ECEEE, 2011.

IEA (2007): Tracking industrial energy efficiency and CO 2 emissions, Paris: International Energy Agency (IEA).

IEA (2011): World energy outlook 2011, Paris: International Energy Agency.

Jaffe, A.B.; Stavins, R.N., 1994. The energy-efficiency gap – What does it mean? In: Energy Policy, 22 (10), pp. 804-810.

Kemp, R.; Volpi, M. (2008): The diffusion of clean technologies: a review with suggestions for future diffusion analysis. Journal of Cleaner Production, 16 (1), p. S14-S21.

Mansfield, E., 1961. Technical change and the rate of imitations. In: Econometrica, 29 (4), pp. 741-766.

Newman, M., 2005. Power Laws, Pareto Distributions and Zipf's law. Contemporary Physics, 46: 323–351. URL http://arxiv.org/PS_cache/cond-mat/pdf/0412/0412004v3.pdf.

Ray, G.F. (1988): Full circle: the diffusion of technology. Research Policy, 18, pp. 1-18.

Rohdin, P.; Thollander, P.; Solding, P. (2007): Barriers to and drivers for energy efficiency in the Swedish foundry industry. In: Energy Policy, 35 (1), pp. 672-677.

Saygin, D., Worrell, E., Patel, M.K., Gielen, D.J., 2011. Benchmarking the energy use of energy-intensive industries in industrialized and in developing countries. Energy 36 (2011), 6661 - 6673.

Schleich, J., 2009. Barriers to energy efficiency: a comparison across the German commercial and services sector. In: Ecological Economics, 68 (7), pp. 2150-2159.

Sornette, D., 2000. Critical Phenomena in Natural Sciences. Springer, Berlin.

Stoneman, P., 2002. The economics of technological diffusion, Oxford: Blackwell Publishers.

Sutton, J., 1997. Gibrat's legacy. Journal of Economic Literature 35 (1), 40–59.

Tornatzky, L.G., Klein, K.J., 1982. Innovation characteristics and innovation adoption-implementation: a meta-analysis of findings. In: IEEE Transactions on Engineering Management, 29 (1), pp. 28-45.

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