WPS6920

Policy Research Working Paper 6920

Why Has Energy Efficiency Not Scaled-up in the Industrial and Commercial Sectors in Ukraine?

An Empirical Analysis

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June 2014

Abstract

Improvement of energy efficiency is one of the main options to reduce energy demand and to reduce greenhouse gas emissions in Ukraine. However, large-scale deployment of energy efficient technologies has been constrained by several financial, technical, information, behavioral, and institutional barriers. This study assesses these barriers through a survey of 500 industrial and commercial firms throughout Ukraine. The results from the survey were used in a cumulative multi-logit model to understand the importance of the barriers. The analysis shows that financial barriers caused by high upfront costs of energy efficient technologies, higher costs of finance, and higher opportunity costs of energy efficiency investment are key barriers to the adoption of energy efficiency measures in Ukraine. Institutional barriers particularly lack government policies, which also contributes to the slow adoption of energy efficient technologies in the country. The results suggest targeted policy and credit enhancements could help trigger adoption of energy efficient measures. The empirical analysis shows strong inter-linkages among the barriers and finds heterogeneity between industrial and commercial sectors on the realization of the barriers.

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Why Has Energy Efficiency Not Scaled-up in the Industrial and Commercial Sectors in Ukraine? An Empirical Analysis*

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***JEL Classification**:* Q4

***Keywords**:* Energy efficiency, Ukraine, Barriers, Adoption, Discrete choice models, Cumulative Logit Model

Sector: Energy

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* The authors woud like to thank Mook Bangalore, Michael Traux and Mike Toman for very helpful comments and suggestions. We also acknowledge the financial support of the World Bank's Knowledge for Change Program (KCP). The views and interpretations are of authors and should not be attributed to the World Bank Group and the organizations they are affiliated with.

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1. Introduction

The adoption of energy efficiency measures has been touted as a major policy option to curtail energy demand in response to increasing price volatility. Its importance has been further lauded to reduce greenhouse gas (GHG) emissions. The International Energy Agency (IEA) estimates that energy efficiency measures account for the highest potential of the total GHG mitigation required to limit global temperature rise by 2050 to 2°C above pre-industrial levels (IEA, 2012). Many studies that develop marginal abatement cost curves for GHG mitigation show energy efficiency measures entail negative costs (i.e., value of energy savings exceeds investment costs even if GHG mitigation benefits are not accounted for) and therefore these options are interpreted as 'low hanging fruits' for climate mitigation (McKinsey & Company, 2009; ESMAP, 2012; ADB, 1998).

In practice, however, the scale of implementation of such seemingly win-win options is small relative to their apparent economic potential. The rationale for this disparity is that implementation of these options is constrained by financial, institutional, and information barriers (Jaffe and Stavins 1994; Howarth and Sanstad 1995; Sorell et al. 2004; Mundaca et al. 2013). Moreover, the economics of energy efficiency measures is normally evaluated using engineering benefit-cost approaches (e.g., Goldstein et al. 1990; Blumstein and Stoft 1995; Brown et al. 1998; McKinsey & Company 2009; Gillingham and Sweeney 2012) and such an analysis usually omits variables such as opportunity costs (Allcott and Greenstone, 2014). If the costs imposed by barriers are accounted for, energy efficiency measures would be expensive, and firms lose interest to adopt (Anderson and Newell, 2004). The gap between cost efficiency of energy efficiency measures and their implementation is also coined as the "energy efficiency gap" (Blumstein et al., 1980; DeCanio, 1993; Jaffe and Stavins 1994; Sanstad and Howarth, 1994; Schleich, 2009; Sorrell et al., 2004).

A number of studies have attempted, through empirical analysis, to understand the energy efficiency barriers in different countries, economic sectors and energy end-uses (see e.g., Rohdin and Thollander, 2006; Sardianou, 2008; Schleich, 2009). Using semi-structured interviews of the largest 8 non-energy intensive manufacturing firms in Oskarshamn municipality in Sweden that had participated in government sponsored energy audits around 2000, Rohdin and Thollander

(2006) find that cost/risk of production disruption, other priorities not related to energy consumption, information search costs related to energy efficient appliances/devices, higher opportunity costs of investment, lack of sub-metering and split incentives with energy service companies all are barriers to adopt increased energy efficiency. Sardianou (2008) investigates the determinants of industrial decision-making with respect to energy efficiency investments in Greece through a survey of 779 industrial firms around 2005 followed by an empirical analysis using a Probit model. A majority (62%) of firms surveyed reported they did not consider energy saving a first priority although 52% of the sample reported energy saving as a decision criterion when installing new machines or buildings. Fifty-six percent of the sample reported that they would develop an energy conservation policy if a competitor industry had implemented relevant actions; while 70% of firms indicated they were not aware of existing new technologies. Based on a sample of 2,848 German commercial and services sector firms that were surveyed during the 1990s, Schleich (2009) econometrically assesses the relevance of various types of barriers to energy efficiency at the sectoral level and across fifteen sub-sectors. The analysis suggests the lack of information and priority-setting of upper management, who often do not consider energy efficiency as a strategic priority as the main barrier to energy efficiency improvement.

Historically, energy consumption has remained inefficient in Ukraine due to ageing infrastructure and prolonged consumption subsidies (Ogaranko and Hubacek, 2013) These developments have strengthened calls for Ukraine to increase its clean energy base and improve its energy efficiency. The government has indeed enacted several policies to promote the adoption of clean and energy-efficient technologies (Trypolska, 2012) – however, the adoption of energy-efficient technologies remains slow. While barriers to clean energy adoption and options to improve investment have been examined by OECD (2012), to our knowledge, the same analysis has not been done for energy efficiency despite its strategic importance. It is therefore important to investigate the barriers to adoption of energy efficient technologies in the country.

This study aims to empirically examine the energy efficiency barriers in Ukraine in the commercial and industrial establishments. Specifically, the study attempts to examine key questions related to energy efficiency barriers including:

- Size: do larger firms have greater incentives to invest in energy efficiency?
- Energy in total production costs: do energy-intensive firms (i.e., firms with higher share of energy costs in total production costs) have greater incentives to invest in energy efficiency?
- Ownership: are private firms more energy efficient than public firms?
- Employment: are labor-intensive firms less energy efficient than capital-intensive ones?
- Financing: have high upfront capital costs hindered the adoption of energy efficiency technologies?
- Split incentives: are rented spaces where landlords pay energy bills less energy efficient than self-owned spaces?
- Knowledge: is lack of knowledge about energy efficient technologies one of the key barriers?
- Technical barriers: are there any technical barriers preventing scaling-up of energy efficiency measures?
- Existing rules/regulations: have existing rules and regulations helped improve energy efficiency?
- Firm's bureaucracy: have a convoluted and complex internal decision process slowed down adoption of energy efficiency measures?

The study employed a sample survey of 500 commercial/service and industrial establishments throughout the country done in 2012. The data collected were then used in a cumulative Logit model to estimate the importance of the various barriers to the adoption of energy efficiency measures in Ukraine. Our analysis shows financial barriers (e.g., high upfront costs or high costs of financing) are the key factors impeding firms' investments in energy efficiency measures in Ukraine. Knowledge and technical barriers follow this. We find mixed results regarding split incentives, whereby the building is rented and/or jointly owned. Contrary to general intuition, the study does not find evidence to support the energy-intensity hypothesis that assumes energy-intensive firms are more likely to adopt energy efficient technologies compared to non-energy-intensive firms. Instead, firms with higher revenue per unit of energy consumption tend to invest more on energy efficiency improvements. The separation of industrial and commercial firms allow us to introduce heterogeneity among sectors that lead us to

suggest that the commercial sector, which includes the public sector, is less likely to invest in energy efficiency measures in the absence of policy interventions.

The paper is organized as follows. The next section (Section 2) briefly discusses the methodology used to derive the results. Section 3 presents the data used in the analysis, while Section 4 presents preliminary results. The main results are presented in Section 5, and their robustness assessed in Section 6. We offer concluding remarks in Section 7.

2. The methodology

To investigate the hypotheses specified in the introduction and to better understand the barriers to the adoption of cost-effective energy efficiency technologies in Ukraine, we estimate a discrete choice model using the sample of Ukrainian firms that participated in our survey. We choose a discrete choice model to estimate the factors influencing the adoption of energy efficiency measures. We first estimate a binary choice model. The dependent variable is a binary variable with possible values of invested/did not invest in energy efficiency measures in the past five years. The covariate vector includes several factors that in theory facilitate the adoption of energy efficiency measures or keep investments in such measures at bay.

The log-likelihood function of our binary choice model is of the standard type. We look at the log-likelihood function due to convenience, while noting that the natural logarithm of the likelihood function is a monotonic transformation of the likelihood function, and that the log-likelihood function achieves its maximum value at the same point as the likelihood function itself. Let $\mathbf{x_i}$ denote the vector of independent variables and let $\mathbf{y_i}$ denote a dummy that equals 1 if the firm invested in energy efficiency technologies in the past five years and 0 otherwise. An observation is denoted with $\boldsymbol{i}$ and there are $\boldsymbol{N}$ observations:

$$\begin{aligned} \Pr ob\left(Y = y_i\right) &= F\left(\beta' x_i\right), \qquad \text{if } y_i = 1 \\ \Pr ob\left(Y = y_i\right) &= 1 - F\left(\beta' x_i\right), \quad \text{if } y_i = 0. \end{aligned}$$

Where $\boldsymbol{F}$ is the cumulative distribution function associated with either a logit or a probit specification and $\boldsymbol{\beta}$ denotes the parameters estimated. This formulation results in the following log-likelihood function:

$$Ln\ L = \sum_i \left\{ y_i \ln F\left(\beta' x_i\right) + \left(1 - y_i\right) \ln\left(1 - F\left(\beta' x_i\right)\right) \right\}$$

Our covariate vector includes firm revenues, share of energy cost in total production cost, firm privately owned, and several measures of potential barriers to the adoption of energy efficiency measures. Specifically, we use the survey data collected to construct the independent variables capturing the barriers to adoption of energy efficiency measures. The survey section used to collect this data focuses on the perceived barriers to adoption.. The questions of that section in the questionnaire quantify firms' perceived barriers to the adoption of energy efficiency measures. We grouped the barriers into seven categories: financial, split, informational, technical, existing rules and regulation, low energy prices, and firm's bureaucracy. Each category included questions pertaining to specific barriers in the category, where each question asked the respondent answering the questionnaire to quantify the importance of a specific barrier on the scale from 0 (no influence) to 3 (strong influence).

The binary choice model discussed above quantifies the factors that affect firms' decision whether to invest in energy efficiency measures. However, because of the ordinal response of our questionnaire where the response implicitly captures ever-increasing levels of investment in energy efficiency measures, we also employed the ***cumulative logit model***. These models are defined for the probability of having an ordinal response that is less than or equal to the value R, relative to the probability of having a response greater than the value R:

$$\text{logit}\left[\Pr ob\left(y \le R\right) | x\right] = \ln\left[\frac{\Pr ob\left(y \le R\right) | x}{\Pr ob\left(y > R\right) | x}\right] = \beta_{o(R)} - \left(\beta' x\right)$$

Where for an ordinal variable with 7 categories, 6 cumulative logit functions are defined. Each of these cumulative logit functions includes a "cutpoint" (i.e., its own intercept), $\beta_{o(R)}$, but all of the cumulative logit functions share the same set of parameters for the *k* predictors, i.e., $\beta = (\beta_1, ..., \beta_k)$. Note that the number of estimated parameters is significantly lower than that of a multinomial logit model, and is equal to *(R-1)+k*, as opposed to *(R-1)*(k+1)* that are required in a multinomial logit model.

This framework suggests that the following transformation estimates the cumulative probability, denoted $\psi(y \le R \mid x)$, that a given response y is less than or equal to the ordinal category k:

$$\psi(y \le R \mid x) = \frac{\exp\left[\hat{\beta}_{\alpha(R)} - \left(\hat{\beta}_1 x_1 + \ldots + \hat{\beta}_k x_k\right)\right]}{1 + \exp\left[\hat{\beta}_{\alpha(R)} - \left(\hat{\beta}_1 x_1 + \ldots + \hat{\beta}_k x_k\right)\right]}$$

The estimated cumulative probability, denoted $\pi_k(x)$, is just the difference in the estimates' cumulative probability between response category *k* and *(k-1):*

$$\hat{\pi}_k(x) = \hat{\psi}(y \le R \mid x) - \hat{\psi}(y \le R - 1 \mid x)$$

$$\text{where } \hat{\psi}(y \le 0 \mid x) = 0.$$

DeMaris (2004) identified conditions under which linear regression treatment of ordinal response leads to robust analysis. These include more than 5 levels, large sample, and a response distribution that is not highly skewed across the ordinal range. Although once introducing into the calculations missing observations the sample is not too large and our sample does not meet all of these conditions, we elected to keep the linear regression and add it to our analysis. The linear regression treats the ordinal response as a continuous variable, and the estimated results are used to assess the robustness of the estimates of the cumulative Logit model.

3. The survey and data processing

The study employed a sample survey of 500 commercial/service and industrial establishments throughout the country. To map the sample back to an unbiased representation of the survey population we weighted the survey data using the prevalence of different firms in the overall economy for each sample observation.

The respondents rated each barrier on a scale from 0 to 3 based on its perceived influence on the implementation of energy efficiency measures to the firm. If a barrier's influence was strong, it was given 3 points; 2 points were given for considerable influence and 1 point for little influence. If a barrier had no influence, it was given 0 points, and if it was not applicable for a

firm, it was marked as "No answer/Not applicable". The specific questions pertaining to the barriers of each group are included in Table 1 below.

Table 1: Specific questions asked to analyze energy efficiency barriers

Financial barriers **High upfront costs**: Are upfront capital costs of energy efficient appliances and devices high? **Lack of capital**: Do financial institutions (Banks and other financial institutions) perceive energy efficiency investment as risky and therefore charge high premium? **Low opportunity costs**: Are there other priorities for capital investment, which can produce high returns? **Low opportunity costs of appliances to be replaced**: Is there any resale value of the replaced appliances, which still has a long operational life? **Long payback period:** Is payback period of efficient appliances/devices too long to discourage their implementation?
Split incentives **Bills paid by landlord:** No incentives for the firm to reduce energy consumption as energy bills are paid by building/facility owners **Split bills:** No incentives for the firm to reduce energy consumption as energy bills are split among the building/facility tenants
Knowledge, information and experience **Metering:** Lack of gas, electric and heat metering **Awareness:** Lack of awareness of the availability and/or benefits of deploying energy efficient processes and devices **Information:** Difficulties with obtaining necessary information **Confidence:** Lack of confidence on energy efficient devices and processes (they do not deliver the services at the level their promoters advocate) **Experience:** Lack of experience in energy efficiency measures
Technical barriers **Skilled personnel:** Lack of skilled personnel to handle the efficient devices and processes **Supplies:** Lack of local supplies for equipment parts and very expensive purchasing from abroad, as well as long lead time to get equipment parts **Reconfiguration:** Installation of energy efficiency measures needs substantial reconfiguration of production process **Malfunction and poor performance:** Higher probability of malfunction or poor performance thereby disrupting production process
Existing Rules and Regulation **Government permits:** Need to obtain government permits to deploy energy efficient devices and processes **Property rights:** Lack of legal protection of property rights **Policy instruments:** Administrative price setting, subsidies and cross subsidies **Government policy:** Lack of effective government policies to facilitate energy efficiency programs **Unofficial payments:** Unofficial payments demanded to receive government permits
Institutional barriers **Decision chain:** Long decision chain on the firm **The future:** Uncertainty about the firm's future **Conflict of interest:** Conflict of interests inside the firm
Economic barriers **Low priority:** Low priority of the firm to reduce energy consumption; energy cost is not a big component of production costs due to low energy prices

To this set of variables, we also introduced variables that capture firm characteristics. These are (i) revenues, (ii) ownership structure (public or private), (iii) share of energy costs to total production costs, (iv) number of employees and (v) facility rented or owned.

Before estimating the binary choice model, we reduced the dimensionality of the model. There are 25 questions assessing the importance of the different barriers to the adoption of energy efficiency measures. In addition, there are 5 variables that capture firms' characteristics. There are another 6 variables when estimating the cumulative logit model. On the other hand, because of missing observations, in some of the runs we ended up with only 98 observations. We had too many variables. We therefore reduced the number of variables/factors using factor analysis tools. Specifically, we used principle-component analysis. [2] While using principle-component analysis we managed to reduce the number of parameters estimated from 36 to about 12, and thus increased precision when estimating the various factors affecting the adoption of energy efficiency measures.

We employ these techniques to aggregate the various independent variables and compute the common factors. The eigenvalue is proportional to the portion of the sum of the squared distances of the points from their multidimensional mean. The principle-component analysis essentially rotates the set of points around their mean in order to align with the principal components. This moves as much of the variance as possible (using an orthogonal transformation) into the first few dimensions. The values in the remaining dimensions tend to be small and may be dropped with minimal loss of information. To this end, we use the rule of thumb that requires the eigenvalue to be greater than 1 for the factor to be included in the empirical analysis. The common factors were then used to aggregate the specific barriers to those mentioned in Section 4 and that are used in the regression analysis. The results of the principle component analysis are depicted in Appendix A.

[2] Principal component analysis employs orthogonal transformation to convert observations of correlated variables (variables that belong to a certain group – e.g., financial barriers) into a set of values of linearly uncorrelated variables that are called principal components. It is used in macroeconomics to aggregate multi-dimension indicators and to clean the noise from observed series in the panel, which is poorly correlated with the rest of the panel (e.g., Avesani et al. 2006, and Forni et al. 2000). It has also being applied to complex dataset, which included multiple indicators, to construct social capital indices (Sabatini, 2005). For more on the asymptotic characteristics of factor analysis, see Bai (2003).

In sum, we substantially reduced the dimensionality of the data (from about 36 to 12 variables). We obtained one common factor with eigenvalue greater than 1 for each of the barriers analyzed bellow, as illustrated in Table 1A to 6A in Appendix A. Using the loading factors we computed the aggregate level explanatory variable and tested the importance of financial (hypothesis *vi*); knowledge (hypothesis *vii*); technical (hypothesis *viii*); whether existing rules and regulations (hypothesis *ix*) serve as barriers to the adoption of energy efficiency measures in Ukraine; the barriers created by the internal structure of the firm (hypothesis *x*); and energy prices (hypothesis *xi*). When assessing the barriers to the adoption of energy efficiency measures, we also included a seventh barrier: energy prices. This set of explanatory variables was then augmented as follows:

1. With variables that capture the size of the firm and are used to test hypothesis *(i)*.
2. To test hypothesis *(ii)* we included in the regression the share of energy cost to the firm relative to total production costs.
3. A dummy variable that equals 1 if the facility is rented and 0 otherwise is used to test the split incentive hypothesis (hypothesis *(iii)*).
4. An ownership dummy that equals one if the firm is privately owned, and zero otherwise (i.e., public or foreign owned), is introduced into the analysis. The parameter is used to evaluate hypothesis *(iv)*.
5. An employment variable is introduced to assess hypothesis *(v)*.

4. The empirical analysis

The key data used in the empirical analysis are summarized in Table 2 – barriers include financial, split, knowledge information and experience, technical, existing rules and regulations, institutional, and economic barriers. Overall, factors are normalized, such that the lowest value assigned to a barrier is zero. When modeling firm characteristics, we have one categorical (total revenues), one dummy variable (private ownership), and one continuous variable (share of energy costs).

Table 2. Data summary

Variable	Obs	Mean	Std. Dev.	Min	Max
Firm characteristics					
Invest	389	0.7609254	0.4270676	0	1
Total revenues	334	2.730539	1.63827	1	8
Share of energy costs	316	11.43358	10.21259	0.3	70
Facility rented	499	1.817635	0.3865323	1	2
Private ownership	491	0.694501	0.4610882	0	1
Employment	233	2.613734	1.375957	0	6
Barriers to the adoption of energy efficiency measures					
Financial barriers	356	6.583883	2.884173	0	14.59367
Split Barriers	382	1.025171	1.562384	0	5.50279
Knowledge barriers	433	3.667689	3.445591	0	12.38596
Technical barriers	420	3.758199	2.553517	0	11.82016
Existing laws and regulation	296	4.832675	2.878283	0	10.71962
Internal institutions	401	0.6719663	0.6634264	0	2.093352
Energy prices	443	0.9006772	1.039524	0	3

We present the Pearson correlation coefficients among the various factors in Table 3. Although principle-component analysis controls for correlation within groups of variables, we wanted to better understand correlation between groups of variables. Some of the correlations suggest we should add an interaction term among the factors, which we do below. But before studying the importance of the interaction terms, we focus on our baseline model, which is without the interaction term.

Table 3. The Pearson correlation coefficient

Column1	Financial barriers	Split Barriers	Knowledge Barriers	Technical Barriers	Existing rules and regulations	Internal institutions	Energy prices
Financial barriers	1.00						
Split Barriers	0.30	1.00					
Knowledge Barriers	0.48	0.57	1.00				
Technical Barriers	0.62	0.29	0.59	1.00			
Existing rules and regulations	0.46	0.56	0.60	0.54	1.00		
Internal institutions	0.46	0.42	0.49	0.50	0.55	1.00	

Energy prices	0.31	0.54	0.57	0.46	0.60	0.52	1.00

We begin with a linear binary model that investigates and evaluates the factors that might impede firms from making any investment in energy efficiency measures. Recall that the dependent variable in our binary model receives a value of 1 if the firm invested in energy efficiency technologies in the past 5 years and 0 otherwise. The parameters estimated are depicted in Table 4, where we depict both the Probit and the Logit model. Although the fit of the models is not very good, the outcome does suggest financial barriers are the key obstacles to the adoption of energy efficiency measures (i.e., we cannot reject hypothesis *vi* at a 5% significant level).

Table 4. The binary model

Column1	Column2	Column3
Variable	**Probit**	**Logit**
Total revenues	0.0258	-0.0380
Share of energy cost	0.0246	0.0529
Private owned	-1.0039	-2.3658
Financial factor	-0.1186**	-0.1892**
Split factor	-0.0203	-0.1294
Knowledge and information factor	0.0040	0.0380
Technical factor	0.2083	0.3800
Existing rules and regulation factor	0.0259	0.0652
Energy prices	0.0902	0.0020
Constant	1.2752***	2.7960*
N	98	98
F	6.1630	6.343536844
Legend: * p<0.10; ** p<0.05; *** p<0.01		

We now present the baseline cumulative logit model, where we try and better understand the factors that guide firms in Ukraine when deciding if and how much to invest in energy efficiency measures. The results are depicted in Table 5, where the cumulative logit model is

depicted in addition to the linear regression model that assumes the investment decisions are a continuous variable. For most of the results we find similar results across the cumulative logit and the linear models, except for the technical barriers, which are significant under the linear model at a 10%, level but not significant under the cumulative logit model. While the F-statistic of the cumulative Logit model is 3028.94, it is less than 100 for the linear model. Thus, in what follows we focus on the cumulative logit model.

Financial Barriers

The analysis suggests financial barriers are the key barriers not only when contemplating whether to make an investment in energy efficiency measures, but also when firms decide how much to invest. While reviewing the literature on energy efficiency barriers in the industrial sector, Worrell (2009) also finds similar results.

Table 5. The baseline model

Column1	Column2	Column3
Variable	**Cumulative Logit**	**Linear**
Log of revenues	2.4257***	1.7974***
Log of energy cost share	0.1728	0.0146
Private owned	-0.4782*	-0.3466*
Log of financial factor	-0.9205**	-0.6200**
Log of split factor	-0.2368	-0.1860
Log of knowledge and information factor	-0.9285	-0.5954
Log of technical factor	1.3632	0.8870*
Log of existing rules and regulation factor	0.2303	0.1157
Log of energy prices	0.4577*	0.3768*
Constant		-0.0494
Cutoff value		
Constant: cut 1	0.5802	
Constant: cut 2	2.8455*	
Constant: cut 3	4.2898**	
Constant: cut 4	5.4113***	
Constant: cut 5	5.6107***	
Constant: cut 6	6.7458***	

Statistics		
N	98	98
F	3028.94	302.96
legend: * p<0.10; ** p<0.05; *** p<0.01		

Moreover, with our dataset, we are able to split the observations into industrial and commercial firms to examine barriers specific to each sector. The barriers are ranked in the industrial sector as follows (we report in parenthesis the rank score that respondents put on the questionnaire): high upfront capital costs that are needed to invest in energy efficient appliances and devices (2.1), lack of capital (1.9), long payback period (1.8), low opportunity costs (1.4) and small monetary value of the replaced appliances (1.2). This ranking is illustrated in Figure 1. Similarly, the commercial firms rank the barriers as follows: high upfront capital costs (1.9), lack of capital (1.8), long payback period (1.5), low opportunity cost (1.4) and small monetary value of the replaced appliances (1.2). Overall, the industrial sector ranks various financial barriers higher, although the differences are not large.

While analyzing conservation tax credits of the early 1980s in the U.S., Carpenter & Chester (1984) found that although 86% of those surveyed knew about the credit, only 35% used it, and of those firms that used it, 94% of investments made into energy efficiency would have been done regardless of the financial incentives (e.g. in the absence of policy). In other words, Carpenter & Chester (1984) do not find the role of financial barriers in inhibiting energy efficiency investments. Our findings contradict those reported in Carpenter & Chester (1984). Our cumulative logit model suggests that at the mean, an increase of 1 in the log of the financial barriers results in an increase of the probability that a firm not invest in energy efficiency measures by 0.92. The linear model finds a similar, yet smaller impact: an increase of 1 in the log of the financial barriers results in the investment variable declining by 0.62.

Split barriers

Split barriers combine two barriers that show the influence of splitting the responsibility of using energy resources with another side: “No incentives for the firm to reduce energy consumption as energy bills are paid by building/facility owners” and “No incentives for the firm

to reduce energy consumption as energy bills are split among the building/facility tenants." Our baseline analysis rejects hypothesis *(iii)*. It rejects the hypothesis that imperfect information yields underinvestment in energy efficiency measures. We return to this hypothesis below, where interaction terms among the various factors are introduced.

Technical barriers, and knowledge and information barriers

Technical barriers are the other major barriers. The installation of energy efficiency measures needs substantial reconfiguration of production processes, and lack of local supplies for equipment parts and very expensive purchasing from abroad are seen as most important technical barriers (1.5). Besides, industrial producers in Ukraine do not trust new devices: they name high probability of their malfunction or poor performance, which can result in disrupting production process as an important barrier (1.1). Commercial firms also report having little experience in energy efficiency measures (the factor having 1 point on average) and say they lack local supplies of equipment parts that are too expensive to purchase from abroad (1.1 on average). Otherwise, respondents of commercial sector did not indicate significant informational or technical barriers. Although the linear regression outcome suggests technical barriers impact adoption of energy efficiency measures, the baseline cumulative Logit model does not hold this claim (i.e., while the linear model cannot reject hypothesis *viii* at a 10% significant level, the cumulative logit model does reject this hypothesis). We also do not find support for information barriers (hypothesis *vii*) under the baseline analysis.

Existing Rules and Regulations

A lack of effective government policies to facilitate energy efficiency programs ranks highest among rules and regulation factors with an average assessment of 2.2 points (Figure 1). Most important rules and regulation barriers for commercial firms are the lack of effective government policies to facilitate energy efficiency programs (1.8), need to obtain government permits to introduce energy efficient devices and processes (1.5), and long decision chain on the firm (1.3). However, once firm characteristics are controlled, existing rules and regulations do not seem to result in large barriers to the adoption of energy efficiency measures. That is, we do not find support for hypothesis *ix*.

Energy Prices

On the other hand, energy prices do play an important role, as predicted by theoretical models and documented in other work that investigated various economies and focused on durable goods (Gillingham et al., 2009) – hypothesis *xi*. Hughes (1991) suggests that the energy sector is very important to Eastern European economies for two reasons: Eastern European countries have higher energy prices than countries with equivalent levels of income but are also some of the most energy intensive economies in the world. Our results suggest that high-energy prices might be affecting firms' demand for cost-effective energy efficiency measures.

Energy Costs

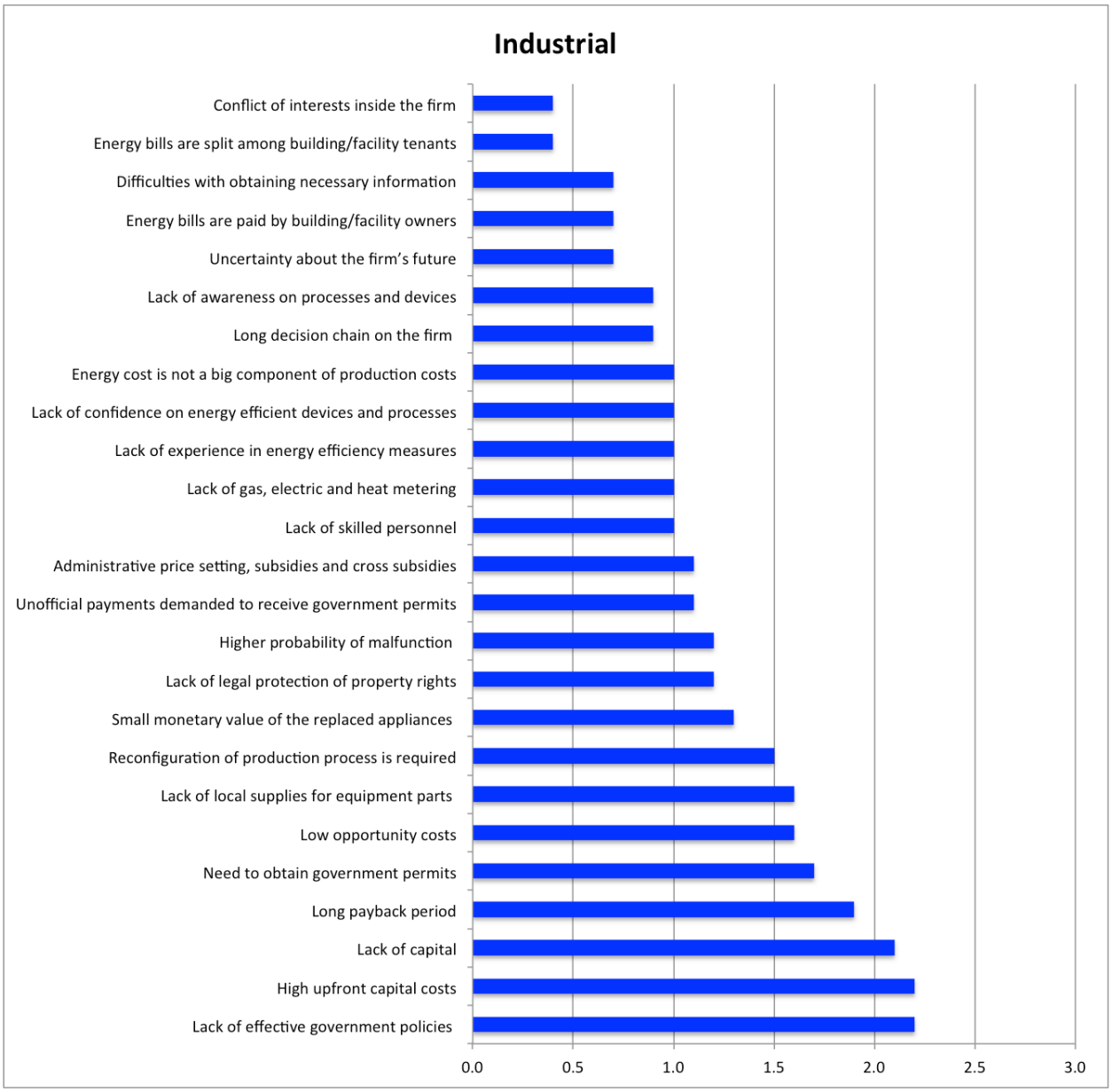
On average, the firms surveyed reveal that they would decrease their energy costs by one-third, if there were no barriers to energy efficiency measures. There is almost no difference between estimates of different sectors. Industrial firms expect to reduce their energy consumption costs by 35.8% on average, and commercial firms say that if not for the barriers, their energy expenditures would be lower by 38.3%.

Firm Revenues

We cannot reject hypothesis *(i)*: size matters. Firms with higher revenues are more likely to invest in energy efficiency measures. In the sample population, industrial firms have more revenues. Further, there is no correlation between firms that earn more revenues and financial barriers (the pairwise correlation coefficient equals -0.04).

Private Ownership

Hypothesis *(ii)* is rejected: Privately owned firms in Ukraine invest less in energy efficiency measures. While in our sample population industrial firms make on average more revenues than commercial firms, relatively more industrial firms are privately owned.


Industrial
Conflict of interests inside the firm
Energy bills are split among building/facility tenants
Difficulties with obtaining necessary information
Energy bills are paid by building/facility owners
Uncertainty about the firm's future
Lack of awareness on processes and devices
Long decision chain on the firm
Energy cost is not a big component of production costs
Lack of confidence on energy efficient devices and processes
Lack of experience in energy efficiency measures
Lack of gas, electric and heat metering
Lack of skilled personnel
Administrative price setting, subsidies and cross subsidies
Unofficial payments demanded to receive government permits
Higher probability of malfunction
Lack of legal protection of property rights
Small monetary value of the replaced appliances
Reconfiguration of production process is required
Lack of local supplies for equipment parts
Low opportunity costs
Need to obtain government permits
Long payback period
Lack of capital
High upfront capital costs
Lack of effective government policies
0.0
0.5
1.0
1.5
2.0
2.5
3.0

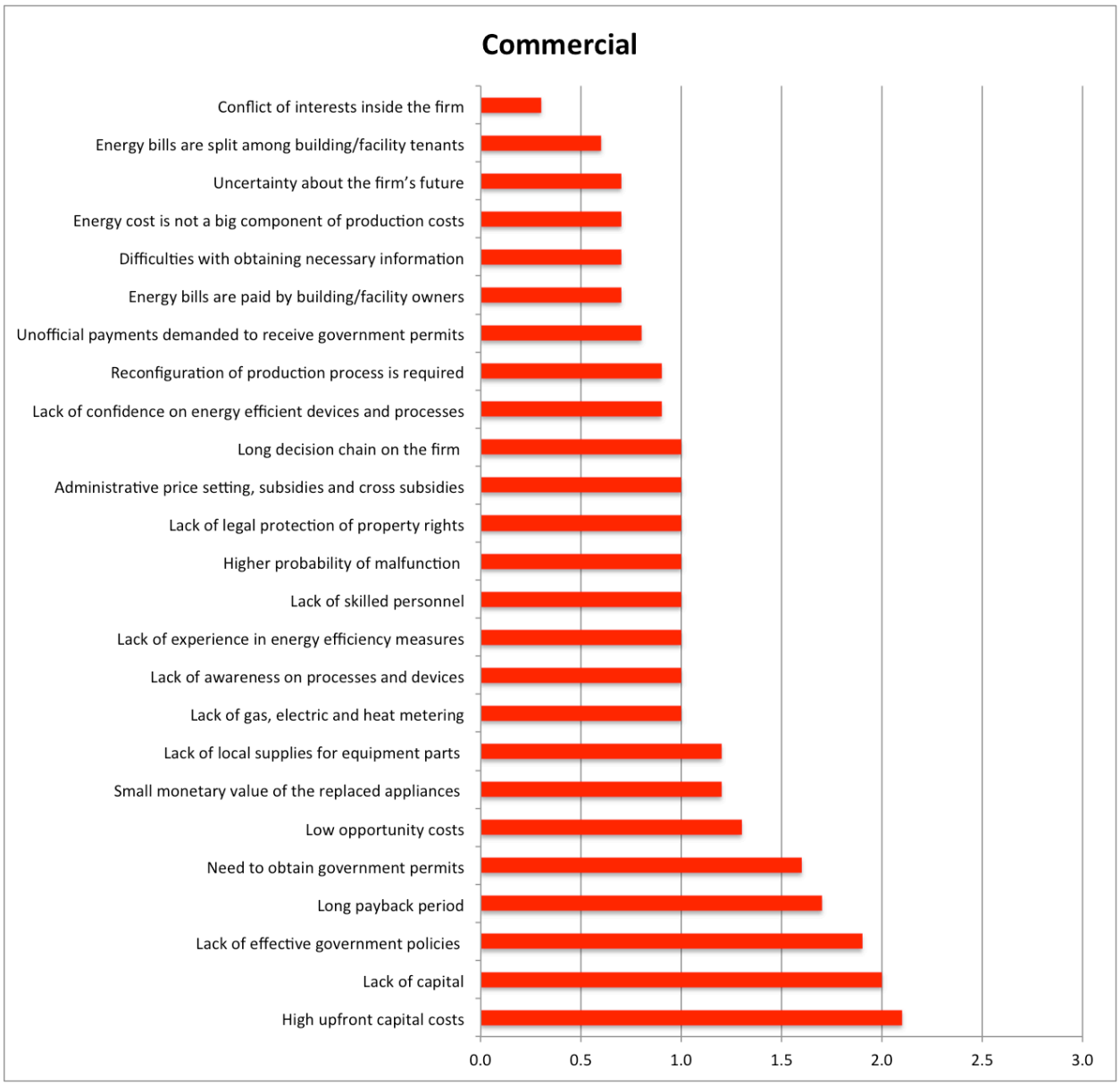


Figure 1. Rating of barriers for energy efficiency by industrial and commercial firms

Industrial/commercial investment levels

While using the cumulative logit model and the estimated cutoff values, we calculated the predicted probability that a firm not invest (0), make a small investment (<20k), make a slightly larger investment (20k-100k), make an average investment (100k-500k), make a larger investment (500k-1M), make a large investment (1M-10M), or make a very large investment

(>10M). We depict the predicted probabilities while separating between industrial and commercial firms. Our analysis suggests that while 24% of commercial firms will not invest in energy efficiency measures, only 15% of industrial firms will not invest. Further, the calculated predicted probabilities suggest that industrial firms are more likely to have larger investments in energy efficiency measures than commercial firms. This conclusion is interesting given that, on average, commercial firms are more energy intensive: while the average share of energy costs in total production costs is slightly larger for commercial firms (19.9% versus 17.7%, respectively), industrial firms are more likely to invest in energy efficiency measures.

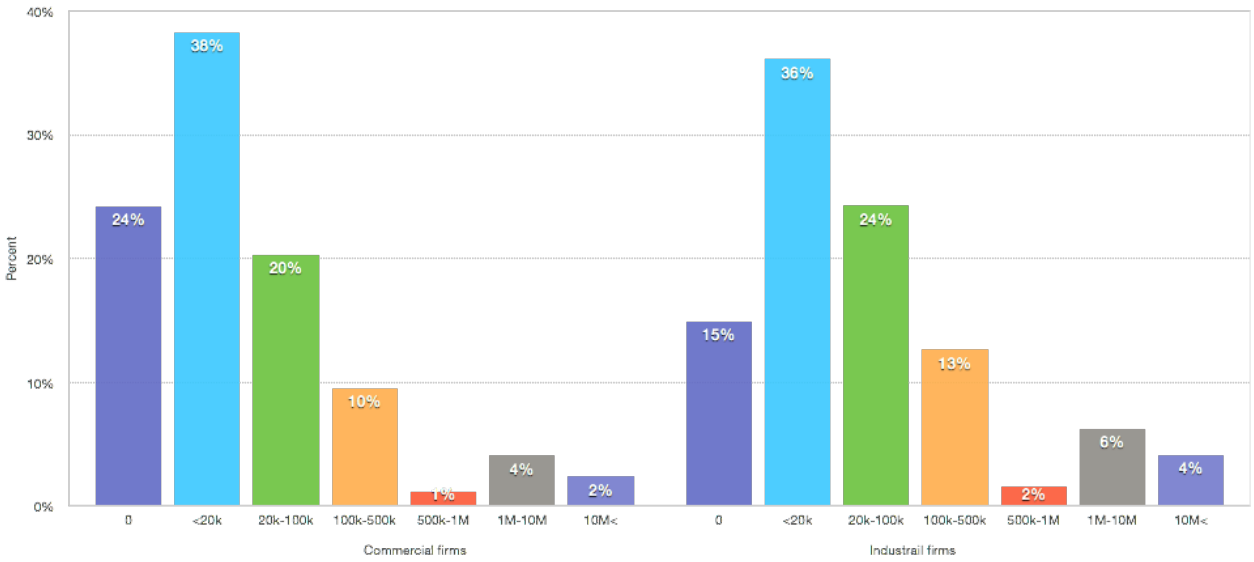


Figure 2. Predicted probabilities of investment using the baseline model

Industrial firms are more likely to be privately owned, while commercial firms are more likely to be publicly owned (Table 6). Our baseline model suggests that, on average, privately owned firms are less likely to invest in energy efficiency measures (Table 5).

Table 6. Ownership

	% private	% public	% foreign	% Total
Commercial	59	38	4	100
Industrial	81	12	7	100

Interactions

How do the various barriers interact? And what is their impact on the adoption of energy efficiency measures? While focusing on the interaction among the various barriers whose correlation coefficient is larger than 0.5, we investigate, for example, the impact of lack of knowledge on firm's perception of technical barriers to the adoption of energy efficiency measures. Although we suspected interaction terms might convey new information, we could not add them to the baseline specification because of data limitations. Therefore, and to investigate the importance of the various interactions, we dropped the private owned firm dummy variable and included an interaction term, one at a time. The various models were estimated assuming a cumulative logit model, and the results are depicted in Appendix B. In Table 7 we present the model that has the greatest explanatory power – its F-Statistic is more than 1,000,000. Introducing other interaction terms resulted in models with substantially lower explanatory power.

Table 7. Baseline model with an interaction of knowledge and technical barriers

Variable	Model I
Log of revenues	2.741325190***
Log of energy cost share	0.130654024
Log of financial factor	-0.915981282***
Log of split factor	-0.235681133
Log of knowledge and information factor	-2.100629047**
Log of technical factor	0.394984634
Log of existing regulation factor	0.200068708
Log of energy cost	0.162249862
Knowledge * technical	0.913821119**
Cutoff parameters omitted	
Statistics	
N	98
F	1.04E+06

Although we do observe some fluctuation in the coefficient values, overall, the significance of firms' revenues and financial barriers is maintained among the various specifications (see Appendix B). Further, as long as we do not introduce an interaction term, which interacts with the financial barriers, the magnitude of the estimated revenue and financial barriers parameters remains relatively stable.

When introducing various interaction terms, one at a time, we get mixed results with respect to split, knowledge and information, and technical barriers. The coefficient of these parameters is significant under some of the specifications modeled in Appendix B but not others.

The introduction of an interaction term between information and technical barriers suggests that less informed firms (higher information barrier) results in firms underestimating the importance of the technical barrier (Table 7). In Appendix B Model VI we also depict a model that shows knowledge affects the impact of split incentives on adoption of energy efficiency measures and reduces the negative impact split incentives have on the amount invested in these measures.

We also computed the predicted probability, when an interaction between knowledge and technical barriers is introduced into the empirical analysis. Introducing an interaction term skewed the predicted probabilities of the commercial firms' investment patterns toward more investment but yielded less investment for the industrial firms. However, the results still suggest it is more likely to observe investment in energy efficiency measures by industrial firms than commercial firms.

How do the results change when we address the missing data problem? Do we gain information when imputing data or does it just introduce noise and affect the precision of the parameters estimated? The robustness analysis below explores these questions.

5. Robustness

In the main analysis we introduced weights to compensate for potential biases. We now further investigate ways of correcting for the missing data while evaluating the benefits of imputing data. Because of the large portions of data missing, as well as the absence of questions

answered by all respondents that can be used to impute the data, poor results were obtained when using the multiple imputation models.

However, two simple imputations proved useful in further understanding our results. For the first we substituted missing observations pertaining to firms' perception regarding barriers to the adoption of energy efficiency measures with 0, while for the second we substituted it with the mean value. Overall, the results supported our main findings although the size of the parameters estimated did change (see Appendix C).

6. Concluding remarks

This study examines energy efficiency barriers to the industrial and commercial (including public) sectors in Ukraine by conducting a survey of 500 firms throughout the country. The results from the survey are then used in empirical (i.e., Logit and Probit) models to understand the importance of various barriers to the adoption of energy efficiency.

The study finds that financial barriers, such as higher upfront investment costs of energy efficiency technologies, lack of capital and long pay-back period are the strongest barriers to the deployment of energy efficiency technologies in the both industrial and commercial sectors in Ukraine. Lack of effective government policies and existing regulation such as government permits required for the adoption of energy efficiency technologies are other key barriers. Predicted probabilities estimated by our study suggest that industrial firms are more likely to have larger investments than commercial firms despite the fact that the latter have, on average, slightly higher share of energy costs in the total production costs. Our study also suggests that energy price rises would yield more adoption of energy efficiency measures, as would the introduction of credit enhancement instruments.

Although the study suggests policy that reduces upfront costs and risk will result in more adoption of energy efficiency measures in Ukraine, the analysis also suggests heterogeneity among firms and sectors. That is, our analysis finds differences in levels of investment in energy efficiency measures among sectors, with industrial firms investing more. This raises the question whether sectoral heterogeneity be accounted for while designing energy efficiency policy instruments. We plan to further investigate this in future research.

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Appendix A:

In computing the common factor attributed to "financial" barriers to the adoption of energy efficiency measures, we obtained the eigenvalues of the various relevant factors. The analysis suggests we retain only one factor (Table 1A-a). We also obtained the extracted sum of the squared loading (Table 1A-b). We use the loading coefficients to calculate the financial barrier factor that we employ in the empirical analysis. The loading coefficients and eigenvalues enabled us to transition from five variables to one that explains more than 53% of the financial barriers data variability.

Table 1A-a. Principle component analysis of financial barriers

Factor analysis/correlation		Number of obs	356
Method:	Principal-component	Factors retained	1
Rotation:	(unrotated)	Number of parameters	5

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.68267	1.97536	0.5365	0.5365
Factor2	0.70732	0.03498	0.1415	0.678
Factor3	0.67234	0.13459	0.1345	0.8125
Factor4	0.53776	0.13785	0.1076	0.92
Factor5	0.39991	.	0.08	1

LR test: independent vs. saturated chi2(10)= 457.19

Table 1A-b. Factor loading (pattern matrix) and unique variance for financial barriers

Variable	Factor1	Uniqueness
High Up front costs	0.7184	0.484
Lack of Capital	0.7952	0.3677
Low opportunity cost	0.7205	0.4809
Zero or very small monetary value	0.723	0.4773
Long pay back period	0.7018	0.5074

Next, we computed the eigenvalue of the split incentives (Table 2A-a). The eigenvalues suggest one common factor, with the loading factors depicted in Table 2A-b. This resulted in moving from two variables to one, but note that the single factor used explains more than 80% of the variability in the split barriers data.

Table 2A-a. Principle component analysis of split barriers

Factor analysis/correlation		Number of obs	382
Method:	Principal-component	Factors retained	1
Rotation:	(unrotated)	Number of parameters	1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.68226	1.36452	0.8411	0.8411
Factor2	0.31774	.	0.1589	1

LR test:	independent vs. saturated	chi2(10)=	238.34

Table 2A-b. Factor loading (pattern matrix) and unique variance for split barriers

Variable	Factor1	Uniqueness
Energy bills paid by building/facility owner	0.9171	0.1589
Energy bills shared among building/facility owner and firm	0.9171	0.1589

Next, we compute the eigenvalue of the information and knowledge incentives (Table 3A-a). The eigenvalues suggest one common factor, with the loading factors depicted in Table 3A-b. Here we reduced the number of variables in the empirical analysis from five to one, while the the factor chosen explains more than 68% of the variability in the data.

Table 3A-a. Principle component analysis of information and knowledge barriers

Factor analysis/correlation		Number of obs	433

Method:	principal-component	Factors retained	1
Rotation:	(unrotated)	Number of parameters	5

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.41871	2.84219	0.6837	0.6837
Factor2	0.57652	0.13668	0.1153	0.799
Factor3	0.43985	0.08195	0.088	0.887
Factor4	0.35789	0.15086	0.0716	0.9586
Factor5	0.20703.		0.0414	1

LR test:	independent vs. saturated	chi2(10)=	1181.82

Table 3A-b. Factor loading (pattern matrix) and unique variance for split barriers

Variable	Factor1	Uniqueness
No metering	0.7696	0.4077
Lack of awareness	0.8895	0.2088
Difficulty obtaining information	0.8623	0.2564
Lack of confidence in these measures	0.8003	0.3596
Lack of experience	0.8069	0.3489

We computed the eigenvalue of the technical barriers (Table 4A-a). The eigenvalues suggest one common factor, with the loading factors depicted in Table 4A-b. When focusing on the technical barriers, the single factor explains more than 57% of the variability.

Table 4A-a. Principle component analysis of technical barriers

Factor analysis/correlation		Number of obs	420
Method:	principal-component	factors retained	1
Rotation:	(unrotated)	Number of parameters	4

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.31472	1.56538	0.5787	0.5787
Factor2	0.74934	0.2142	0.1873	0.766

Factor3	0.53514	0.13434	0.1338	0.8998
Factor4	0.4008	.	0.1002	1

LR test: independent vs. saturated chi2(10)= 413.15

Table 4A-b. Factor loading (pattern matrix) and unique variance for technical barriers

Variable	Factor1	Uniqueness
Skilled labor	0.7026	0.5064
Expensive imports and lack of domestic supply	0.7938	0.3699
Requires substantial changes to the production process	0.8116	0.3413
High probability of malfunction	0.7296	0.4676

When computing the eigenvalue of questions pertaining rules and regulations (Table 5A-a), we retain one common factor, with the loading factors depicted in Table 5A-b. We used the rule of thumb, that requires the eigenvalue to be greater than 1 for the factor to be included in the empirical analysis. Although the second factor is close to one, its contribution to explaining the variability is much smaller than the first factor (0.5153 versus 0.182). We therefore elected to use only the first factor in our empirical analysis.

Table 5A-a. Principle component analysis of existing rules and regulations

Factor analysis/correlation		Number of obs	296
Method:	principal-component	factors retained	1
Rotation:	(unrotated)	Number of parameters	5

Factor	Eigenvalue	Difference	Proportion	Cumulative

Factor1	2.57632	1.66628	0.5153	0.5153
Factor2	0.91004	0.31833	0.182	0.6973
Factor3	0.59171	0.07042	0.1183	0.8156
Factor4	0.52128	0.12064	0.1043	0.9199
Factor5	0.40065	.	0.0801	1

LR test: independent vs. saturated chi2(10)= 363.58

Table 5A-b. Factor loading (pattern matrix) and unique variance for existing rules and regulations

Variable	Factor1	Uniqueness
Government permits required	0.7873	0.3802
Lack of property rights protection	0.7467	0.4425
Administrative price setting	0.7174	0.4853
Government policy not effective	0.5878	0.6544
Unofficial payments demanded	0.7341	0.4612

Finally, we compute the eigenvalue of the internal barriers, i.e., the firms' administration and bureaucratic barriers to the adoption of energy efficiency measures (Table 6A-a). The eigenvalues suggest one common factor, with the loading factors depicted in Table 6A-b. The common factor explains more than 62% of the variability.

Table 6A-a. Principle component analysis of firm's administrative barriers

Factor analysis/correlation		Number of obs	401
Method:	principal-component	factors retained	1
Rotation:	(unrotated)	Number of parameters	3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.88518	1.19138	0.6284	0.6284
Factor2	0.69381	0.27279	0.2313	0.8597
Factor3	0.42101	.	0.1403	1

LR test: independent vs. saturated chi2(10)= 238.16

Table 6A-b. Factor loading (pattern matrix) and unique variance for firm's administrative barriers

Variable	Factor1	Uniqueness
Long decision chains	0.7044	0.5039
Uncertainty about firm's future	0.8139	0.3375
Conflict of interest inside the firm	0.8524	0.2734

Appendix B:

Table 1B. Baseline model with an interaction term

Variable	Model I	Model II	Model III
Log of revenues	2.741325190***	2.182619969***	2.465261230***
Log of energy cost share	0.130654024	0.24513135	0.169066623
Log of financial factor	-0.915981282***	-1.148505292**	-0.969937005**
Log of split factor	-0.235681133	0.176517929	-0.111932736
Log of knowledge and information factor	-2.100629047**	-1.313373421	-0.818492276
Log of technical factor	0.394984634	1.627786066*	1.327466515
Log of existing regulation factor	0.200068708	0.087423073	0.182224142
Log of energy cost	0.162249862	0.743714209**	0.623607336
Knowledge * technical	0.913821119**		
Knowledge * regulation		-0.188530449	
knowledge*energy price			-0.119880911
regulation*technical			
regulation*energy price			

Cutoff parameters omitted			
Statistics			
N	98	91	98
F	1.04E+06	38.62230397	7.65E+03

Variable	Model IV	Model V
Log of revenues	2.100542807***	2.028502915***
Log of energy cost share	0.270295821	0.236193307
Log of financial factor	-1.149360445**	-1.208104546**
Log of split factor	0.180178453	0.400469767*
Log of knowledge and information factor	-1.443025467	-1.398589357
Log of technical factor	1.811733302	1.786825604*
Log of existing regulation factor	0.062758406	0.172567756
Log of energy cost	0.755600114**	1.375906460**
Knowledge * technical		
Knowledge * regulation		
knowledge*energy price		
regulation*technical	-0.058099965	
regulation*energy price		-0.964637983
Cutoff parameters omitted		
Statistics		
N	91	91
F	16.96402005	18.93379284

Variable	Model VI	Model VII
Log of revenues	2.431694291***	2.393070223***
Log of energy cost share	0.19165519	0.320244444
Log of financial factor	-1.018054681**	-1.228787952***
Log of split factor	-3.135320904***	-0.786425154
Log of knowledge and information factor	-1.217403092	-1.417070951
Log of technical factor	1.411140358	1.571963524*
Log of existing regulation factor	0.137219632	-0.131083337
Log of energy cost	0.381446147	0.669916849**
knowledge*split	1.561192111***	
regulation*split		0.723553286
split*energy price		

financial*technical		
Cutoff parameters omitted		
Statistics		
N	98	91
F	1.69E+02	1.32E+02

Variable	Model VIII	Model IX
Log of revenues	2.642495979***	2.708161900***
Log of energy cost share	0.151742152	0.122248513
Log of financial factor	-0.953537008***	-2.322088947***
Log of split factor	-1.590755663***	-0.289456429
Log of knowledge and information factor	-0.807606837	-0.841238136
Log of technical factor	1.15309456	-0.587985858
Log of existing regulation factor	0.113266895	0.33348211
Log of energy cost	0.088761721	0.389469817
knowledge*split		
regulation*split		
split*energy price	1.427506905***	
financial*technical		1.055441141**
Cutoff parameters omitted		
Statistics		
N	98	98
F	55.46015871	2.36E+02

Appendix C:

We began by re-estimating the baseline model presented in Table 4, but now missing data regarding firms' perceived barriers to the adoption were replaced with a zero (Table 1C). The importance of most of the barriers increased by 20% or more relative to the baseline model, but the importance of revenues declined by more than 10%. However, the magnitude of revenues and financial barriers still remained far greater than any of the other barriers estimated.

Table 1C. Replacing missing observations in the data with zeros

Column1	Column2	Column3
Variable	Linear	Ologit
Total revenues	1.6221***	2.1925***
Share of energy cost	0.0527	0.1994
Private owned	-0.3677***	-0.5879**
Financial factor	-0.9723***	-1.5305***
Split factor	-0.0076	0.0565
Knowledge and information factor	-0.6150**	-0.8400***
Technical factor	0.6161**	1.0282**
Existing rules and regulation factor	0.2425	0.2489
Price of energy	0.2823***	0.2155*
Constant	0.8770***	
Cutpoints		
Cutpoint1		-0.8082*
Cutpoint2		1.1169**
Cutpoint3		2.4062***
Cutpoint4		3.2745***
Cutpoint5		3.9332***
Cutpoint6		5.2864***
Statistics		
N	214	214
F	95.0368	15.9024
legend: * p<0.10; ** p<0.05; *** p<0.01		

Next, instead of replacing missing-data with zeros, we replaced them with the mean value (Table 2C). The estimated parameters are similar to those obtained when replacing missing-data with zeros.

When substituting missing-data with either zero or mean of variable, firm's revenues, financial barriers, lack of knowledge and low energy prices are the main factors affecting the adoption of energy efficiency measures.

Table 2C. Replacing missing observations with mean of variable

Column1	Column2	Column3
Variable	Linear	Ologit
Total revenues	1.6088***	2.1656***
Share of energy cost	0.0396	0.1969
Private owned	-0.3308**	-0.5381**
Financial factor	-0.8557***	-1.2845***
Split factor	-0.0358	-0.0460
Knowledge and information factor	-0.6512***	-0.8892***
Technical factor	0.5396*	0.8963**
Existing rules and regulation factor	0.1874	0.1934
Price of energy	0.3082***	0.2566**
Constant	0.9907***	
Cutpoints		
Cutpoint1		-0.8119*
Cutpoint2		1.0992*
Cutpoint3		2.3917***
Cutpoint4		3.2309***
Cutpoint5		3.8991***
Cutpoint6		5.2299***
Statistics		
N	213	213
F	90.7612	21.5872
legend: * p<0.10; ** p<0.05; *** p<0.01		