Promoting energy efficiency policies over the information barrier

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Abstract

Stakeholders argue that the information barrier is the major obstacle restricting firms from adopting Energy Efficiency Technologies (EETs) in Europe. The present work examines the processes of information gathering as regards to EETs and explores the factors affecting the level of acquired information by EET adopters. Empirical evidence is provided by a data set of Greek manufacturing firms which have adopted EETs. In conclusion, we propose appropriate policy measures able to promote the adoption of EETs by overcoming the information barrier.

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1. Introduction

The promotion of energy efficiency efforts, i.e., the encouragement of means reducing energy consumption without reducing the use of energy-consuming plants and equipment, has a long standing history in the European Union. The energy efficiency policy is very significant for the EU both as a major environmental instrument designed to meet the targets set by the Kyoto Protocol and as a key element in the security of energy supply in the EU. The Green Paper on energy efficiency “Doing More with Less” (Commission, 2005) identified the industries of manufacturing and transport as the potential champions in energy savings among all economic activities. However, and despite policy efforts, the penetration of energy efficiency measures regarding European firms is limited. The most recent pan-European survey of businesses, including SMEs and large enterprises, was carried out by the Observatory of European SMEs in 2006, the final year of the 2000–2006 Action Plan for energy efficiency (Flash Eurobarometer, 2007). This survey revealed that nearly two thirds of SMEs operating in the EU do not even have simple rules or devices for saving energy while only 4% of EU SMEs have a comprehensive system in place for energy efficiency. Even more worrying is the fact that the manufacturing industry is not included among the top three energy-conscious sectors while the transports sector is only third, with the hospitality and healthcare sectors taking the first two places. Such results question, without doubt, the efficiency of energy efficiency policies.

The 2000–2006 Action Plan for energy efficiency identified a number of potential barriers preventing access to and the spread of efficient energy technologies. Lack of or incomplete information hampering the use of cost-effective and energy-efficient technology was among them. In 2005, and following the debate on the Green Paper on energy efficiency (Commission, 2006), the Commission launched a very wide debate complemented by a series of events in order to promote a better understanding of the energy efficiency initiative (Commission, 2006). The Commission
services received approximately 5000 answers from 241 contributions to the debate (31 from NGOs, 66 from Member States and Public Bodies, 106 from industry and the private sector and 38 from private citizens). With regards to the question “How could the community and the Commission in particular, better stimulate European investment in energy efficiency technologies” and on “How could funds spent supporting research in this area be better targeted”, there was a unanimous response that delivered a clear message about the need for sensitization and information. Stakeholders claimed that funds would be better spent on demonstrating and validating the potential of current technology, avoiding the situation in which good solutions stay in closed boxes without delivering results. “Stakeholders need to know that technology exists, is effective and works” (Commission, 2006, p. 3).

The lack of or incomplete information is a real problem especially for smaller businesses lacking the appropriate human capital and scientific expertise to support their decision to adopt energy efficiency technologies. The lack of readily available information and demonstration increases the cost to invest in such technologies due to: increased transaction/search costs making up for lack of human capital; increased uncertainty regarding the investment because of incomplete information or the presence of information asymmetries; and finally due to the risk of lock-in an inappropriate technology when appropriate technologies “stay in closed boxes” or are still emerging and information is not widely available.

Taking into account the aforementioned discussion, our research project develops in two stages. The first stage aims at examining the factors influencing retrieval of information concerning energy efficiency technologies by manufacturing firms and thus addresses issues at the heart of EU’s energy policy. The second stage deals with the distinguishing between readily available and emerging energy efficiency technologies as well as with the examination of the factors affecting information acquisition for each one of these two broad sets of technologies. The empirical results provide direct links to proposals for formulation and implementation of an efficient energy efficiency policy.

The paper is organized as follows: Section 2 reviews the relevant literature and defines the theoretical underpinnings of our research; the Section 3 presents a theoretical approach allowing us to classify decision makers according to their awareness of epidemic and emerging energy efficiency technologies. Based on this, a structural model of adoption is developed. In the same section we present data collection procedures and the statistical description of data. The Section 4 presents the empirical results and the last section concludes the paper, summarizing the research findings and pointing out interesting research questions for future investigation.

2. Theoretical underpinnings

The goal of increasing energy efficiency and of instigating the adoption of energy-efficient technologies (EET) is pursued through the provision of information to prospective adopters (Anderson and Newell, 2004; Kounetas and Tsekousas, 2008). Information provision as a non-price instrument of technology policy is the necessary initial step in the adoption process. Its absence allows limited information adding up to the barrier constraining the adoption of energy efficiency technologies (Blok et al., 2004, p.16).

The role of information prior to adoption has been extensively documented in the economics literature (Arrow, 1996; Feder et al., 1985; Saha et al., 1994). Especially when the energy efficiency paradox is studied, information prior to adoption is related to the existence of market barriers and market failures (DeCani, 1993, 1998; Howarth and Anderson, 1993; Sutherland, 1994; Sanstad and Howarth, 1994) and to an industry’s learning curve which is a meaningful representation of technological change in global energy models (Grubler et al., 1999; Azar and Dowlati, 1999; Read, 2000). Among SMEs, information plays a crucial role for the adoption of energy-efficient technologies (Gillissen et al., 1995; Veltuijzen, 1995; DeGroot et al., 2001). The aforementioned studies reveal that a significant part of the total of available energy-efficient technologies is unknown to prospective adopters and this information gap widens as the size of the firm gets smaller. Thus, the size and other firm-specific characteristics as well as the environment in which firms operate, may contribute to an explanation of the scale of the observed information gap.

Adoption of energy-efficient technologies has been approached through a variety of models including the epidemic, rank, order, stock and supply-side effects paradigms (Karshenas and Stoneman, 1993). The epidemic model is more frequently used when the technology under consideration is mature or not in its infancy (Geroski, 2000). All other models are used for emerging technologies (Morgenstern and Al-Jurf, 1999). The level of information possessed and the way this information is acquired by a decision maker is a critical factor separating these models (indicatively, see Howarth et al., 2000; Morgenstern and Al-Jurf, 1999; Metcalf and Hassett, 1999). In the epidemic model, potential adopters acquire knowledge passively, i.e., by observing without a cost what actual adopters experience. These potential adopters, heterogeneous firms with characteristic information asymmetries (Mansfield, 1989; Geroski, 2000), presume that the primary factor limiting diffusion is lack of information, and that the most important source of information about a new technology is firms which have already adopted it. In the emerging technology model, potential adopters undertake active search for information about new technologies themselves (Lester and McCabe, 1993; Jensen, 1988; Morgenstern, 1996; Morgenstern and Al-Jurf, 1999).

The aforementioned theoretical arguments justify why information provision lies at the heart of energy saving policies around the world. Besides the EU’s efforts to increase and enhance the quantity and quality of information provided to prospective adopters of energy-efficient technologies, countries such as the US, Australia, Canada, the UK, Germany, the Netherlands and Denmark, report information dissemination policies as part of their energy policies. The Long-Term Agreements on energy efficiency in the Netherlands: (Nuijen, 1998; Rietbergen et al., 1998)
the Energy Efficiency Best Practice Program in the UK (Miles, 1994), the Agreements on Industrial Energy Efficiency in Denmark (Togeby et al., 1998), the Energy Smart Business Program in Australia (Cooper et al., 1999), the Declaration of German Industry on Global Warming Prevention in Germany (Ramesohl and Kristof, 1999), the Industry Program for Energy Conservation (CIPEC) in Canada (Jago, 1999), and the Green Light Program sponsored by EPA (DeCani, 1998) provide few examples. However, from a strictly technical point of view, these policy interventions provide the information about new technologies without following the rationale of any of the aforementioned models, the epidemic or the emerging technology models. As a result, the policies do not present information regarding best or worst practices of firms that have already adopted energy saving technologies, nor do they follow the principles of information supply suggested by the emerging technology models such as educational workshops and training programs for professionals, advertising, product labeling and energy audits of manufacturing plants (Anderson and Newell, 2004).

In this paper we argue that the firm’s information/knowledge level, regarding the EETs, is non-neutral because it is technology-vintage dependent. Additional elements of heterogeneity are introduced by the firms’ size, age, and sector of economic activity. It should be noted that the definition of the “informed or knowledgeable” EET firm adopted in this paper is also applicable to technologies other than EETs, such as ICTs, waste treatment technologies etc. Additionally, we argue that the absorptive capacity of firms as well as their competencies and capabilities depend upon the nature of the recognized technological opportunities (Cohen and Levinthal, 1989; Malebra and Orsenigo, 1996). Having established that the level of knowledge differs among types of technologies we proceed by determining the factors influencing the capacity of firms to absorb information and knowledge.

3. Information and EET adoption: an empirical implementation

3.1. The Greek incentives schemes for the adoption of energy saving technologies

In Greece, energy saving investment projects undertaken by individual firms are supported by the central or regional authorities. The Greek government has recognized the need to conserve energy in manufacturing and to reduce dangerous emissions in order to meet the criteria of the Kyoto Protocol. In the past two decades, energy policies that aim to promote conservation and induce firms to adopt environment-friendly technologies have been formulated based on (i) the Support Frameworks for Regional and Industrial Development, (ii) the Energy Operational Program (OPE), which was part of the second European Union Support Framework (1994–2000) and (iii) the Operational Program ‘Competitiveness’, which was part of the third European Union Support Framework (2000–2006). Firms submitted their energy efficiency projects and these were assessed by the Directorate of Renewable Energy and Energy Saving in the Ministry of Development and the central services of the Ministry of National Economy. Successful proposals were selected to be supported.

The incentives that have been included in these schemes concern grants for machinery, buildings and other assets, interest rate subsidies, tax-free allowances, favorable tax rates and lower social security contributions. In addition, a significant part of all financial resources of the abovementioned programs was dedicated to information provision and technical support for firms regarding energy conservation and energy consumption reduction issues. Moreover, state authorities attempted to develop and implement activities such as data collection and statistical analysis, participation in the EU Project on Energy Efficiency Indicators and finally the energy auditing and monitoring program through eight intermediary agents and the establishment and operation of 17 energy centers, responsible for the promotion of EU programs. These agents and centers were responsible for the appropriate provision of information concerning energy efficiency projects and for the collection and first assessment of the firms’ applications.

3.2. The sampling framework and the survey process

In order to assemble a sample of EET adopters we used the records provided by the Ministry of Development and the Department of Energy and Natural Resources. The original list contained a total number of 396 firms that had invested in EET. By excluding those firms of the Services sector that implement different energy saving technology, 325 manufacturing firms remain pertinent to our investigation. A further communication with the firms’ managers and chief-engineers indicated that only 298 firms had actually accomplished the transition to energy saving technology and 293 had been granted capital subsidies as an investment incentive for that purpose.

The data related to the purposes of our research is not readily available either from any of the intermediate agents collecting data for the Greek energy policy or from the records kept by central authorities. The latter provided data regarding the EET investments performed only by individual firms. Thus, it was decided to collect additional data by means of a rather extensive questionnaire divided into nine sections and dealing with: the firms’ general, organizational and managerial characteristics, characteristics of the energy conservation technology project they have undertaken, market competition, their strategic orientation, their knowledge and degree of implementation of energy-efficient technologies, their investment behavior, their attitude towards energy saving technologies and towards barriers to invest in energy-efficient technologies, and finally their evaluation of the investment and their potential expectations concerning further investments in energy efficiency projects. The questionnaire was tested, for approximately two months, in a pilot study in the region of Western Greece for further evaluation and improvement. The final questionnaire was addressed to the 298 firms across the country. Only 161 of them agreed to be interviewed with the use of the questionnaire. Face to face interviews took place in the first six months of 2004.
The data derived from the central authorities responsible for supporting EET projects, along with that collected from the aforementioned survey were complemented by firm specific economic and financial data from the business database maintained by the private financial and business information service company called ICAP in Greece. The annual ICAP directories provide key production, employment and financial information from the published balance sheets of nearly all Plc. and Ltd. firms operating in all sectors of economic activity in Greece. From the annual directories of ICAP we matched a database for the firms included in our survey and for the period 1989–2004. The interested reader will find an analytical description of survey process and descriptive outcomes in Kounetas and Tsekouras (2008).

3.3. Modelling and econometric issues

3.3.1. The level and nature of adopters’ information

Let us consider the ith firm (i = 1, 2, . . . , N), which examines the possibility of adopting an energy saving technology. In this process and under the rationality approach, the firm collects information from two distinct sources. The first source corresponds to the available K elements of the epidemic type of information, and is denoted as \( I_e = \{ e_1, e_2, \ldots , e_k \} \). The second source corresponds to the L elements of the emerging technology type of information, and is denoted by the set \( I_m = \{ m_1, m_2, \ldots , m_l \} \). In this way, we define the set of all available information \( I_e \), irrespective of its type, as \( I_0 = \bigcup_{j \in EM} I_j \).

In addition, we can reasonably argue that \( I_e \cap I_m \equiv \emptyset \). Both sets, \( I_e \) and \( I_m \), are assumed to be closed and fragmented and therefore their union, the \( I_0 \) set, is also closed and fragmented. The meaning of these conditions is that there is no information about energy saving technologies, either already adopted or emerging, that is not contained in the \( I_0 \) set. The ith firm forms its information set \( I_i \) using elements from its epidemic set of information \( I_e (I_{e} \subseteq I_e) \) and from its emerging technology set of information \( I_m (I_{m} \subseteq I_m) \) as \( I_i = \bigcup_{j \in EM} I_{ij} \subseteq I_0 \). The number of information elements that are contained in the set \( I_i \) and come from the sets \( I_{ei} \) and \( I_{mi} \) are denoted by \( n_i(K) \) and \( n_i(L) \), respectively. Of course the relationship \( I_{ij} \subseteq I_{ij} \) holds in any case. Based on the \( I_i \) set, four distinct information states of the ith firm can be defined.

Definition. The information status of the ith firm, which examines the adoption of an energy saving technology, is directly related to its information set \( I_i \).

(i) If \( I_i \equiv \emptyset \) the firm is non-informed in any way.
(ii) If \( I_i \equiv I_0 \) the firm is fully informed.
(iii) If \( I_i \neq \emptyset \) and \( n_i(K) > n_i(L) \) then the firm is informed but its information set is dominated by elements that have an epidemic rather than an emerging technology character. Such being the case the firm is characterized as epidemically informed.
(iv) Finally, if \( I_i \neq \emptyset \) and \( n_i(K) < n_i(L) \) then the firm is also informed but in this case the elements of emerging technology information dominate the corresponding elements of the epidemic character. This is the case of the emerging technology informed firm.

The above definition allows us to formulate the following proposition:

**Proposition.** The ith firm is informed if and only if at least one of the corresponding \( I_{ei} \) and \( I_{mi} \) information sets is non-empty.

Proposition’s proof is straightforward.

At this point we define the following real function

\[
\text{INF} = f(I_i) = \begin{cases} 1 & \text{if } I_i \neq \emptyset \\ 0 & \text{otherwise} \end{cases}
\]

(Equation 1)

Economically speaking, relationship (1) shows that a firm may be considered informed if it possesses any elements of information regardless of its nature. It is evident that shedding light on the nature of this information is quite interesting, especially for policy makers. The approach followed until now allows us to do so. More specifically, we define two additional real functions.

\[
\text{EPIDINF} = g(I_{ei}) = \begin{cases} 1 & \text{if } I_{ei} \neq \emptyset \land n_i(K) > n_i(L) \\ 0 & \text{otherwise} \end{cases}
\]

and

\[
\text{EMRINF} = h(I_{mi}) = \begin{cases} 1 & \text{if } I_{mi} \neq \emptyset \land n_i(K) < n_i(L) \\ 0 & \text{otherwise} \end{cases}
\]

These two real functions describe two different information statuses of the firm. Relationship (2) corresponds to a firm which is essentially informed through the experience which arises from the adoption of energy saving technologies, while relationship (3) involves a firm that acquires information through research into emerging energy saving technologies.

The above analysis can be extended in a straightforward manner under the assumption that the firm is informed epidemiologically, emerging in terms of technology or fully, not only in the case when \( I_i \neq \emptyset \) (i.e. in the case where \( I_{ei} \neq \emptyset \lor I_{mi} \neq \emptyset \)), but also in the case when its level of information exceeds a crucial threshold, let’s say \( I_i \), that is when \( I_i \) is a hyper set of \( I_i \). In other words and in terms of \( n_i(j) (j = K, L) \), one could consider a firm informed in \( n_i(K) > n_i(L) \) and/or \( n_i(L) > n_i(K) \). We should note that this information level threshold, defined either in \( I_i \) terms, or \( n_i(K) \) and \( n_i(L) \) terms, is practically unobservable, and its definition is essentially subjective or arbitrary, although this arbitrary character does not affect our analysis in the sense that the notion of awareness remains stable.

3.3.2. The structural model and the econometric approach

Following the neo-classical theory of the firm, we may consider that a firm decides to acquire or not a specific quantity of information following a decision making process which is quite similar to the case of any other “normal” input. In other words, we argue that each firm evaluates this information-input according to its contribution to firm’s objectives which we can reasonably assume to be summarized in the firm’s profit function. The proposed econometric analysis is not necessarily bound to the neo-classical theoretical framework and can accommodate various theoretical perspectives even in the case
where information is considered to convey knowledge (Foray, 2004, p. 2-3). The level of information acquisition does not coincide with that of a public good or a ‘normal input’. On the contrary, its diffusion depends on many parameters such as appropriability conditions (Malerba and Orsenigo, 1993), the firm’s absorptive capacity (Cohen and Levinthal, 1989), and the firm’s strategic orientation (Hamel and Prahalad, 1983). As a result, the distinction between emerging and epidemic information corresponds to the complex combination of different technological opportunities (Malerba and Orsenigo, 1996) which arise from the existing technology and, also, from the potential technological trajectories regarding EETs. Thus, the notions of the profit function and ‘normal inputs’ are used hereafter only conventionally.

The firm’s decision making process outcome is reflected by the choice of one of the ordered set of the j alternatives of non-informed, informed and fully informed (j = 0, 1, 2). We assume that the firm’s profits are represented by a well-behaved profit function, \( \pi^*_j \), as in the original model for polychotomous ordinal variables presented by Trost and Lee (1984). With case subscripts suppressed, the maximum profits attained by selecting a level of information \( j \), \( \pi^*_j \), are postulated to be linearly associated with exogenous variables:

\[
\pi^*_j = \beta' \mathbf{x} + e_j
\]  

where \( \mathbf{x} \) is a \( (k \times 1) \) vector of exogenous variables, \( \beta \) is a vector of unknown parameters to be estimated, and \( e_j \) is a random error assumed to be identically normally distributed with zero mean and unit variance. \( \pi^*_j \) is unobserved. What is observed is:

\[
\begin{align*}
\pi_0 &= 0 \text{ if } \pi^*_j \leq 0 \Rightarrow \text{EPIDINF} = 0 \text{ and } \text{EMRINF} = 0 \Rightarrow \text{INF} = 0 \Rightarrow \text{non-informed} \\
\pi_1 &= 1 \text{ if } 0 < \pi^*_j \leq \mu \Rightarrow \text{EPIDINF} = 1 \text{ or } \text{RNKINF} = 1 \Rightarrow \text{INF} = 1 \Rightarrow \text{informed in epidemic or in emerging technology type} \\
\pi_2 &= 2 \text{ if } \mu < \pi^*_j \Rightarrow \text{EPIDINF} = 1 \text{ and } \text{RNKINF} = 1 \Rightarrow \text{INF} = 1 \Rightarrow \text{informed in epidemic and in emerging technology type} \\
\end{align*}
\]

which is, in fact, a form of censoring and the \( \mu \) is an unknown parameter to be estimated with \( \beta \). In the theoretical context each firm decides to acquire a level of information which maximizes its profits. The probability that an alternative \( k \) is chosen is \( P_k \) when \( P_k > P_j \forall j (j \neq k) \), where:

\[
P_k = \text{Prob}[\pi_k > \max(\pi_0, \pi_1, \pi_2)]
\]

Due to the fact that the sample includes firms which acquire epidemic and emerging technology type information, selectivity bias can be introduced. Selectivity bias may be corrected by adding a selection mechanism (Green, 1997):

\[
\begin{align*}
0^* &= \mathbf{a}' \mathbf{z} + u \\
\theta &= \begin{cases} 
1 & \text{if } 0^* > 0 \\
0 & \text{if } 0^* \leq 0
\end{cases}
\end{align*}
\]  

and

\[
\text{Prob}(\theta = 1) = \Phi(\mathbf{a}' \mathbf{z})
\]

\[
\text{Prob}(\theta = 0) = 1 - \Phi(\mathbf{a}' \mathbf{z})
\]

where \( 0^* \) are the unobservable profits by the \( i \)th firm from acquiring epidemic instead of emerging technology type information, \( \mathbf{z} \) is a set of exogenous variables, \( \Phi(\cdot) \) is the cumulative distribution function for a standard normal variable and \( u \sim N(0, 1) \). Let \( \theta = 1 \) if the firm acquires emerging information and \( 0 \) otherwise. The model described in Eqs. (7a) and (7b) is a univariate probit model and \( \pi_0 \) is observed if and only if \( \theta = 1 \). Eq. (1) may be respecified as a sample selection problem (Heckman, 1979):

\[
E[\pi|x, \theta^* > 0] = \beta' \mathbf{x} + E[\mathbf{e}|x, \theta^* > 0]
\]

If \( e \) and \( u \) are bivariate normally distributed\(^1\) with correlation coefficient \( \rho \), then Eq. (8) becomes:

\[
E[\mathbf{e}|x, \theta^* > 0] = E[\mathbf{e}|x, u = -\mathbf{a}' \mathbf{z}] = \rho \lambda
\]

where \( \lambda \) is defined as the ratio of the density and the cumulative distribution function for a standard normal variable:

\[
\lambda = \frac{\phi(-\mathbf{a}' \mathbf{z})}{\Phi(\mathbf{a}' \mathbf{z})}
\]

Eq. (4) for emerging informed firms becomes

\[
\pi^*_j = \beta' \mathbf{x} + \rho \lambda + e_j
\]

This may be estimated if a consistent estimate of \( \lambda \) is obtained. Consistent estimates of \( \lambda \) are obtained by estimating the ordinary probit in Eq. (7) for all sample observations to compute consistent estimates of \( \mathbf{a} \) that are used in Eq. (10) to estimate \( \lambda \). Eq. (11) is then estimated using the subsample of emerging informed EET adopters as an ordered probit model by replacing \( \lambda \) with the consistent estimates derived by Eq. (10). The selectivity bias test is then equivalent to a t-test of the null hypothesis that \( \rho \) equals to zero. A more analytical approach of the estimation techniques can be found in Greene (1997) and Maddala (1983).

3.4. Variables definition

3.4.1. The definition of the information level regarding EET

In order to build quantitative measures of information acquisition we followed a multi-stage process based on a simple mathematical model presented in the previous Sec-

\(^1\) Following Bera et al. (1984) we test the null hypothesis that the error terms are not bivariate normally distributed. The null hypothesis is not rejected. The statistical methodology, the code in Limdep 9.0, the relevant dataset and the estimated values of the used criterion are available by the authors upon request.
tion 3.3. In this section we attempt to discuss the intuition behind the mathematical model. First, we construct a variable (hereinafter denoted as the INF variable) which separates the EETs’ adopters into prior informed and prior non-informed. The interviewed managers of the firms were asked directly to rank their prior information level about emerging and epidemic EETs in a scale of one to five. In the next step the average of the distribution of responses of all firms was calculated for the epidemic and emerging EETs separately. If the epidemic rank of a firm exceeded the epidemic average of all firms, the firm was characterized as informed. In all other cases it was characterized as non-informed. The same procedure was followed for emerging technologies. Furthermore, the classification which resulted from this procedure was filtered by asking the managers, who were characterized as informed in the previous stage, to record at least two epidemic and/or emerging EETs. This question allowed us to test the agent’s perception of the notion of epidemic and emerging EETs. If the interviewed manager failed to acknowledge at least two epidemic and/or emerging technologies, the firm was characterized as non-informed. Hence, the dichotomous variable INF takes the value of 1 if the manager’s rank exceeds the average of the epidemic or emerging general ranking and if, at the same time, he or she can record at least two epidemic or emerging EETs. On the contrary, the INF variable takes the value of 0, that is, the firm is considered not to be informed when the two above mentioned conditions do not hold simultaneously.

At a second stage we constructed the variables depicting the level of prior information that the firms may possess for the epidemic and emerging technology correspondingly. In the remaining of this paper these variables will be referred to as EPIDINF and EMRINF for epidemic and emerging technologies correspondingly. More specifically the managers of the firms that were characterized as informed at the first stage were asked to rank their information level on a scale from one to three, for five broad categories of information for both epidemic and emerging technologies. More specifically, the five broad categories of information are: (i) Investment Cost and Funding Opportunities, (ii) Technical Characteristics of Equipment, (iii) Competition and Best Practices, (iv) Environmental Regulation and Social Pressure and (v) Flexibility and Adjustment of the firm in terms of the EETs embodiment.

Thus, in the second part phase of the interview, each firm ranked on a scale from one to three, the extent of its information regarding 17 investment characteristics of epidemic EETs which in turn comprise the aforementioned five broad categories. For each firm the average score was calculated and then normalized by dividing it with the standard deviation of each firm’s scores distribution. The next step was to calculate the range of variation, that is the difference between the maximum and the minimum of the normalized average scores, and two limits were set, taking into account that the scale of ranking is three degrees. More specifically, the lower limit that corresponds to inadequately epidemic informed firms is the product of the range of variation multiplied by one third (1/3) while the upper limit, that in turn corresponds to adequately epidemic informed firms is the product of the range of variation multiplied by two thirds (2/3). Thus, if a firm’s score is lower than or equal to the lower limit, this firm is characterized as insufficiently informed (EPIDINF = 0). If, on the other hand, a firm’s score lies between the two limits it is characterized as sufficiently informed (EPIDINF = 1) and finally if it is above the upper limit it is characterized as fully informed (EPIDINF = 2). The exact same procedure is followed in the case where the firms are grouped with respect to their level of information for the emerging technologies. Hence the insufficiently informed firms correspond to EMRINF = 0, the sufficiently informed ones to EMRINF = 1 and finally the fully informed firms correspond to EMRINF = 2. Basic descriptive statistics of the used dependent variables are presented in the upper part of Table 2.

3.4.2. The definition of explanatory variables

The vector of factors that determine the level of information possessed by the adopters of new technologies (the x vector of the above equations), is classified into the following four categories: First, factors that are associated with the firm’s attitude towards the research and development process (Gillissen, 1995; Anderson and Newell, 2004) and the introduction of energy saving innovations. Such variables are, (RDP), (RDP), (FINFORM), (INNOV), and (INNOVC) are defined analytically in Table 2. Secondly, factors that are associated with the behavior of the firm towards investments (DeGroot et al., 2001), captured by the variables (PINV), (PINV), (FUTINV), (FUTINV) of Table 1. It must be noted here that the variable (WILINVEED) captures a combined effect of the two above factors since it is defined as a dummy variable which takes the value of 1 if the firm has implemented an additional energy saving technology through an investment project and of 0 if it has not. Thirdly, factors related to the technical support the firm has and the opportunity it has to derive information relevant to energy saving technologies. Such factors are captured by the variables (ECOP) (Gillissen, 1995; DeGroot et al., 2001), (INFTYPE) and (LOC) in Table 2. Finally, factors related to the issue of the principal agent, (DGOVORG) and (DECINV), to the customer oriented technologies (DeGroot et al., 2001), captured by the variable (EXT), and to the firm’s size and its relation to investment (SIZE) (DeGroot et al., 2001). Basic descriptive statistics of the used explanatory variables are presented in the lower part of Table 2.

4. Results and discussion

This section presents the empirical results of our research project in two stages. First the factors determining the level of information that adopters of energy saving technologies obtain are isolated, irrespective of the character of the information itself. In other words we present the results fitting the empirical Eq. (1). Secondly, we identify the set of determinants which specify the level of information that adopters of EET possess when the information is distinguished into epidemic or emerging technology. As a result, three models are presented that describe (a) the
probability that a firm will be informed or non-informed, (b) the probability that a firm will be non-informed, informed or fully informed regarding emerging energy saving technologies and (c) the probability that a firm will be non-informed, informed or fully informed regarding existing and already used energy saving technologies.

Table 1
Variables Definition.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>INF</td>
<td>A dummy variable that takes the value of 1 if the firm is informed about energy saving technologies and 0 otherwise</td>
</tr>
<tr>
<td>EMRINF</td>
<td>Three levels of emerging information: Not informed (0), merely or partial informed and full informed (2)</td>
</tr>
<tr>
<td>EPIDINF</td>
<td>Three levels of epidemic information: Not informed (0), merely or partial informed and fully informed (2)</td>
</tr>
</tbody>
</table>

Explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>RDD</td>
<td>A dummy variable that takes the value of 1 if the firm has an R&amp;D department and 0 otherwise</td>
</tr>
<tr>
<td>RDP</td>
<td>Firm’s R&amp;D department employees</td>
</tr>
<tr>
<td>ECOP</td>
<td>A dummy variable that takes the value of 1 if the firm is cooperating with an external energy efficiency expert and 0 if it is otherwise</td>
</tr>
<tr>
<td>FINFORM</td>
<td>A dummy variable that takes the value of 1 if firm’s has at least one internal energy efficiency expert who works on energy efficiency issues and 0 if it is otherwise</td>
</tr>
<tr>
<td>INNOVD</td>
<td>A dummy variable that takes the value of 1 if the firm has introduced an innovative procedure during the 3 years period before the EET adoption and 0 otherwise</td>
</tr>
<tr>
<td>FUTINV</td>
<td>A dummy variable that takes the value of 1 if the firm undertook an investment project, not related to EET, in a 2 year time-horizon after the EET adoption and 0 otherwise</td>
</tr>
<tr>
<td>PINV</td>
<td>A dummy variable that takes the value of 1 if the firm realized an investment project, not related to EET, in the last 3 years before the EET adoption, and 0 otherwise</td>
</tr>
<tr>
<td>EXT</td>
<td>A dummy variable that takes the value of 1 if the firm exports, after the EET adoption, at least one fourth of its production to foreign markets and 0 otherwise</td>
</tr>
<tr>
<td>INFTYPE</td>
<td>A dichotomous variable which takes the value of 1 if the firm acquires information mainly through the specialized technical support energy efficiency agencies which operate in the context of the second and third European Union Support Framework and imply no direct cost and 0 otherwise</td>
</tr>
<tr>
<td>SIZE</td>
<td>Firm’s size captured by the number of employees</td>
</tr>
<tr>
<td>WILINVEED</td>
<td>A dummy variable that takes the value of 1 if the firm undertook an additional EET project in a 2 years time-horizon after the EET adoption and 0 if it is otherwise</td>
</tr>
<tr>
<td>LOC</td>
<td>A dummy variable that takes the value of 1 if the industry is established in the greater Athens area and 0 otherwise</td>
</tr>
<tr>
<td>FUTINVC</td>
<td>Firm’s investments costs, not in EET, in a 2 year time-horizon after the EET adoption</td>
</tr>
<tr>
<td>PINVC</td>
<td>Firm’s investment costs, not in EET, during the last 3 years before the EET adoption</td>
</tr>
<tr>
<td>INNOVC</td>
<td>Firm’s innovation costs during the last 3 years before the EET adoption</td>
</tr>
<tr>
<td>DGOVORG</td>
<td>A dummy variable that takes the value of 1 if firm’s business decisions are taken by managers and 0 otherwise</td>
</tr>
<tr>
<td>DECINV</td>
<td>A dummy variable that takes the value of 1 if firm’s investment decisions are taken by managers and 0 if it is otherwise</td>
</tr>
</tbody>
</table>

Table 2
Descriptive statistics of the used variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Variable</th>
<th>Mean (%)</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>INF</td>
<td>0.1553%</td>
<td>0.363</td>
<td>0.000</td>
<td>1.000</td>
<td>EPIDINF</td>
<td>0:18.00</td>
<td>1:35.40</td>
<td>2:46.60</td>
<td></td>
</tr>
<tr>
<td>EMRINF</td>
<td>0.2610%</td>
<td>0.440</td>
<td>0.000</td>
<td>2.000</td>
<td>FINFORM</td>
<td>0:29.82%</td>
<td>1:30.18%</td>
<td>2:42.20%</td>
<td></td>
</tr>
<tr>
<td>SIZE</td>
<td>0.402</td>
<td>0.514</td>
<td>0.008</td>
<td>3.100</td>
<td>LOC</td>
<td>0:69.61</td>
<td>1:30.39</td>
<td>1:70.18%</td>
<td></td>
</tr>
<tr>
<td>FUTINV</td>
<td>0.3790%</td>
<td>0.486</td>
<td>0.000</td>
<td>1.000</td>
<td>DGOVORG</td>
<td>0:55.30</td>
<td>1:44.70</td>
<td>1:77.00</td>
<td></td>
</tr>
<tr>
<td>PINV</td>
<td>0.1060 %</td>
<td>0.498</td>
<td>0.000</td>
<td>1.000</td>
<td>INNOVD</td>
<td>0:10.60</td>
<td>1:89.40</td>
<td>1:77.00</td>
<td></td>
</tr>
<tr>
<td>INFTYPE</td>
<td>0.8450%</td>
<td>0.361</td>
<td>0.000</td>
<td>1.000</td>
<td>WILINVEED</td>
<td>0:63.57</td>
<td>1:36.46</td>
<td>1:36.46</td>
<td></td>
</tr>
</tbody>
</table>

* Percentages are reported for dummy variables.
The search for the best empirical model was guided by two criteria. First, we searched for a meaningful and informed, as mentioned in the above discussion, set of explanatory variables among the available financial and economic variables, transformations of variables or interactions among variables. Secondly, we looked for the models with the best econometric properties among alternative models. This implied that variables with no statistically significant results have been included in our final model, since this is also an important finding, ensuring, however, that they do not unfavorably affect the statistical power of the model. Separate tests examining the null hypothesis that individual coefficients are zero, and a joint test of the null hypothesis that all the parameters associated with the explanatory variables are equal to zero have been carried out. Specification test analysis involved a test for homoscedasticity (Greene, 1997, p. 890), and a test for the omission of certain variables. Omission of a significant variable, in the context of a binary, dichotomous choice model, implies that even if the omitted variable is uncorrelated with the dependent variable, the coefficient of the included variables will be inconsistent (Yatchew and Griliches, 1984). A goodness-of-fit measure usually reported as McFadden’s pseudo-$R^2$ measure, or rho-square ($\rho^2$) (Maddala, 1983), as well as the percentage of correctly predicted cases are also computed.

### 4.1. Determinants of the firms’ level of information about EE technologies

The first research question was examined using a probit model which depicts the distinction between informed and non-informed adopters as they are reflected by the dependent dichotomous variable ($INF$). This probit model is also used to ‘forecast’ whether a randomly drawn adopter of EE technologies is informed in any of the two ways in question or not and its estimates are used to ‘correct’ the ordered probit models that explore the second major research question of the present paper.

Maximum likelihood coefficient estimates and their standard errors for this probit model are presented in the left-hand part of Table 3. The chi-square test rejects the null hypothesis that all coefficients of the explanatory variables are equal to zero. The model correctly predicts 89.44% of the cases (144 out of 161). In the same table, marginal effects are presented only for statistically significant variables since the notion of marginal effects is meaningless for variables that are not statistically significant. Five out of the nine explanatory variables included are found to be statistically significant at the 5% level, while two more are statistically significant at the 10% level. No significant effects on the level of information are identified for the variables that reflect the existence or non-existence of R&D activities ($RDD$), as well as the investment behaviour of the firm as this is reflected in the 3-year period before the EET adoption ($PINV$) and the investment projects which may have been realized in the 2-year period after the EET adoption ($FUTINV$). Thus, one could argue that the knowledge which may be accumulated either by the R&D activities or by investment experience in projects that are not related to EET is not transformed to information about the energy efficiency investments, at least in a straightforward manner, (Bougheas, 2004). As expected, the firm’s size ($SIZE$), exerts a positive and statistically significant effect on the probability that a firm is informed. On the contrary, the variable defined as the ratio of the investment expenditure to the size of the firm was not found to be statistically significant. Using a simple nested model test, it was decided to exclude the variable from the list of explanatory variables. Thus, we can argue that it is the absolute size of the firm and not the relative magnitude of the investment project with respect to the firm’s size which plays a crucial role in relation to the probability that a firm is informed. This result is in accordance to the arguments of the present paper.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient estimates</th>
<th>Marginal effects</th>
<th>Variables</th>
<th>Coefficient estimates</th>
<th>Marginal effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.439 (0.505)</td>
<td>–</td>
<td>EXT</td>
<td>1.211 (0.447)**</td>
<td>-0.661</td>
</tr>
<tr>
<td> </td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RDD</td>
<td>-0.299 (0.393)</td>
<td>–</td>
<td>FINFORM</td>
<td>0.638 (0.372)**</td>
<td>-0.816</td>
</tr>
<tr>
<td> </td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECOP</td>
<td>1.468 (0.483)**</td>
<td>=0.769</td>
<td>SIZE</td>
<td>2.631 (1.322)**</td>
<td>-0.614</td>
</tr>
<tr>
<td> </td>
<td></td>
<td>=1.986</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td> </td>
<td></td>
<td>$Ch=0.217$</td>
<td>SIZE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INNOV</td>
<td>-1.270 (0.433)**</td>
<td>=0.993 $Ch=-0.106$</td>
<td>FUTINV</td>
<td>-1.184 (0.648)**</td>
<td>-0.992</td>
</tr>
<tr>
<td> </td>
<td></td>
<td>$Ch=0.384$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PINV</td>
<td>0.577 (0.394)</td>
<td>–</td>
<td>WILINVEED</td>
<td>1.129 (0.498)**</td>
<td>-0.661</td>
</tr>
<tr>
<td> </td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood = –37.895</td>
<td>Restricted log-likelihood = –69.513</td>
<td>$X^2 = 63.237$</td>
<td>Pseudo-$R^2 = 0.354$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Numbers in parentheses are the asymptotic standard errors.
- **, *, and *** denotes statistical significance at 5%, 10% and 1% respectively.
- $Ch$ denotes the difference between the “=1” and “=0” cases.
ment that small firms face heavy barriers regarding the adoption of EET due to information restrictions that are caused by their size or in other words by their limited available resources (Kim, 1999). Thus, the low adoption rates of EET among European SMEs, as presented in the introductory section of this work, should be sought outside the conventional scale measures.

The probability that a firm is characterized as informed is positively affected both by the orientation of firms to foreign markets as it is captured by the (EXT) variable and by the fact that the firm realized an additional EET investment project in the 2-year period after the adoption of the EET (WILINVEED). In addition, as expected, the effect of the firm’s cooperation with a specialized agency which provides technical support concerning investment projects in EE technologies (ECOP), and of the (FINFORM) variable, is positive and statistically significant, which reflects the spending of the firm’s human resources on procedures that may improve energy efficiency. The positive influence of the firm’s exporting activities may be interpreted in a dual way. First, firms that have penetrated foreign markets have more sources of information since they act in an international environment, and secondly they have to deal with high-pressure rivalry from both their competitors and the requirements of their major customers, which is combined with the firm’s desire to avoid being locked out of future tendering processes or markets (Tsekouras and Skuras, 2005).

On the other hand, according to our empirical findings, negative influence is exerted by the variable (INNOVD) which depicts the introduction of a product or process innovation in the production procedure in the last 3 years before the adoption of the EET. This empirical result is in accordance with a significant part of the relative literature, which considers the fact that the introduction of an innovation process absorbs financial or intangible resources from the firm, and increases the uncertainty the firm faces (see for instance Aizenman and Marion, 1993; Bell and Campa, 1997; Lensink et al., 2005). Considering that information seeking is a resources consuming process and that the adoption of a new technology leads to increased uncertainty and firms are risk-neutral, the abovementioned relationship is rather easily interpretable (Leahy and Whited, 1996).

At this point we should note that several other variables that were included as explanatory variables were not only found to be statistically not significant, but also their inclusion resulted in the deterioration of the percentage of correctly predicted cases. These variables include a set of a firm’s specific financial indices, the perception of competition, dummy variables that allow us to disentangle industry-specific effects, the firm’s age, location and time elapsed between the realisation of the energy efficiency investment project and the year 2004 when the survey took place.

4.2. Determinants of the different types of information

In order to determine the factors identifying an EET adopter as emerging technology informed or as epidemiologically informed, two ordered probit models have been estimated. For the first model, the dependent variable is (EMRINF) and depicts the different levels of information that the firm possesses before and during the adoption of the EE technology process, regarding only emerging EET. For the second model, the dependent variable is (EPIDINF) which depicts the level of information that the firms possessed at the time they decided to adopt an existing EET that had already been adopted by another firm before them. We estimated these two ordinal probit models on the subsample of 134 EET adopters only after correcting for selectivity bias using the estimates of the previous probit model. Maximum likelihood estimated coefficients, their corresponding asymptotic standard errors, the chi-square statistic, the pseudo-$R^2$ goodness of fit measure and the percentage of the correctly predicted cases are shown in Table 4.

The chi-square test is highly significant and the corresponding goodness-of-fit pseudo-$R^2$ measure indicates a quite satisfactory fit. The emerging technology information model correctly predicts 58.39% of the cases and the corresponding epidemic information model 54.66% of the cases. The t-value for the selectivity coefficient ($\rho$) indicates the presence of selectivity bias for emerging technology informed firms. The opposite holds for the epidemiologically informed firms. Therefore the subsample limited to informed adopters is not a random sample since it concerns the acquired emerging technology information. The models’ parameter estimates indicate the direction of the effect of each one of the eleven explanatory variables (RDD, ECOP, FUTINV, SIZE, PINV, FINFORM, WILINVEED, LOC, DECINV, DGOVORG, INNOVD) on the information level probabilities (non-informed, informed, fully informed), but do not directly represent the actual probability change. Estimation of the marginal effects of the explanatory variables on the probability of ranking a firm according to the information level it possesses (Table 4) represents the probability changes. For continuous explanatory variables the marginal effects show the percentage change in the probability that the firm will choose to acquire the specific level of information given a marginal change in the variable. For the dummy explanatory variables the marginal effects are analyzed as discrete or relative changes when the respective dummy takes its two different values, 0 and 1 respectively (Greene, 1997).

According to the empirical results, the variables (ECOP), (WILINVEED) and (PINV) were found to exert a positive influence on the probability that a firm is informed regarding both types of information, i.e., emerging and epidemic. As it was expected, the cooperation of the firm with a specialized energy efficiency consultant, as captured by the variable (ECOP), was found to exert positive influence on the possession of either an emerging technology or epidemic type of information. The same holds for the variable (WILINVEED), which captures the fact that a firm undertook an additional EE investment project in the 2-year period after the initial adoption. The finding regarding the (PINV) dummy variable is quite interesting, according to which, the accumulated knowledge that is generated from the realization of an investment project in the recent past increases the current information status of the firm and thus increases the probabilities
Table 4  
Maximum likelihood estimates and marginal effects of the ordinal probit models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Emerging information: dependent variable EMRINF</th>
<th>Epidemic information: dependent variable EPIDINF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient estimates (standard errors)</td>
<td>Coefficient estimates (standard errors)</td>
</tr>
<tr>
<td></td>
<td>Marginal effects Emerging informed</td>
<td>Marginal effects Fully emerging informed</td>
</tr>
<tr>
<td></td>
<td>Non-emerging informed</td>
<td>Emerging informed</td>
</tr>
<tr>
<td>Constant</td>
<td>0.128 (0.607)</td>
<td>0.043 (0.492)</td>
</tr>
<tr>
<td>RDD</td>
<td>-0.090 (0.240)</td>
<td>-</td>
</tr>
<tr>
<td>ECOP</td>
<td>1.142 (0.247)**</td>
<td>0.829 (0.254)**</td>
</tr>
<tr>
<td>FUTINV</td>
<td>-0.600 (0.254)*</td>
<td>-0.313 (0.291)</td>
</tr>
<tr>
<td>SIZE</td>
<td>0.315 (0.442)</td>
<td>0.649 (0.302)*</td>
</tr>
<tr>
<td>PINV</td>
<td>0.789 (0.240)**</td>
<td>0.602 (0.225)**</td>
</tr>
<tr>
<td>FINFORM</td>
<td>0.379 (0.247)</td>
<td>0.455 (0.238)**</td>
</tr>
<tr>
<td>WILINVEED</td>
<td>1.130 (0.449)*</td>
<td>0.642 (0.299)*</td>
</tr>
<tr>
<td>LOC</td>
<td>0.599 (0.247)*</td>
<td>0.389 (0.266)</td>
</tr>
<tr>
<td>DECINV</td>
<td>-0.374 (0.393)</td>
<td>-0.608 (0.310)**</td>
</tr>
<tr>
<td>DGOVORG</td>
<td>-0.045 (0.214)</td>
<td>0.164 (0.169)</td>
</tr>
<tr>
<td>INNOVD</td>
<td>-0.578 (0.502)</td>
<td>-0.306 (0.248)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>1.413 (0.312)*</td>
<td>1.224 (0.158)*</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.754 (0.177)*</td>
<td>0.662 (0.719)</td>
</tr>
<tr>
<td>Log-likelihood = -137.934</td>
<td>Restricted</td>
<td>Log-likelihood = -134.493</td>
</tr>
<tr>
<td>Pseudo-$R^2$ = 0.205</td>
<td>log-likelihood = -173.674</td>
<td>$X^2 = 71.479$</td>
</tr>
</tbody>
</table>

- Numbers in parentheses are the asymptotic standard errors.
- *, **, and *** denotes statistical significance at 5%, 10% and 1% respectively.
- Ch denotes the difference between the “=1” and “=0” cases.
that a firm should be informed regardless of the type of information.

Four out of the eleven explanatory variables in the ordinal probit models were found not to have a statistically significant influence on the probability that a firm is characterized as non-informed, informed or fully informed according to an emerging or epidemic technology type of information. In particular, we refer to the existence or non-existence of R&D activities (RDD), and the introduction of any innovation other than EET in the firm's operations in the period just before the adoption of the EET which is captured by the (INNOVD) variable. In addition, the firm's internal organization structure was found to exert no significant effects that may lead to non-optimal decisions, mainly due to the principal agent type of information problems. This is depicted in the (DGOVORG) variable. The result regarding the (RDD) variable is consistent with the corresponding effect which we identified in the simple probit model, as already discussed in the previous section. The uncertainty which is associated with the introduction of any kind of innovation captured by the (INNOVD) variable does not affect the decision of a firm to acquire information of either an emerging technology or an epidemic type, concerning the specific EET. The specific finding does not confirm the argument that a firm may not undertake an energy efficiency investment project or adopt an energy efficiency innovation process, and thus it does not actively search for any type of relative information, because its ‘risk stock’ has been exhausted by the introduction of innovation processes in technologies that are not related to energy efficiency (Leahy and Whited, 1996; Anderson and Newell, 2004).

If a firm is established in the greater Athens area (LOC), the probability that it will be informed about an emerging technology type of information is positively higher. Apparently, this finding is related to the number of available sources of information, especially in the case of emerging EET, as well as to fact that the corresponding cost increases depending on the distance between the firm and the source of information. On the other hand, the probabilities that a firm is informed about EET regarding the emerging technology type of information are negatively affected by the (FUTINV) dummy variable which depicts the fact that the firm realized other kind of investments, apart from an energy efficiency project, in the 2-year period after the EET adoption (FUTINV). The direction of the effect of the (FUTINV) variable reveals that in the case of the EET that is in maturity, an issue of the attitude against risk arises. The probability that the firm is informed decreases when managers, and not the owners or the principal share-holders of the firm, are responsible for evaluating investments. In other words, the certainty equivalence of managers is smaller than that of the firm’s owners. This finding may also be interpreted in a principal – agent framework from which observability and jurisdiction aspects are generated. The statistically non significant influence of the (LOC) and (FUTINV) variables, especially when they are compared with the corresponding influence of the same variables on the probabilities that a firm is informed about an emerging technology type of information, depicts the different relative scarcity and consequently the acquisition cost of the two types of information.

5. Conclusions and policy implications

The information barrier is like a wall that does not allow a firm to view a wider EET landscape. Adopting EETs presumes that firms are familiar with the EET world, can evaluate the costs and benefits of adoption and can reduce its risk. Our analysis revealed that the basic building block of this information wall is the “resource constraints”. Resource constraints emerge in various forms. The positive effect of a firm’s size on the probability that the firm is informed in general or specifically informed about epidemic type technologies reveals the absolute advantage of larger firms. This advantage is rooted in a firm’s financial capacity, and in the capability of its human resources to collect, screen and evaluate information. However, the advantage connected to size is relative. When the firm is engaged in activities that demand high quality human capital resources, such as R&D or simply innovation activities, its effective size is reduced. In other words, when other activ-
ities which are vital for a firm’s survival and growth, such as innovation, compete with the activities concerning the adoption of EETs for the firm’s same resources, then the availability of resources to be assigned to the adoption and introduction of EETs is condensed. We should, therefore, be aware that when the knowledge base of a firm is extended by, for example R&D activities, the knowledge base related to EETs is not equally enhanced. On the contrary, the firm’s knowledge base regarding EETs may be reduced because quality human capital is re-directed to other activities. Our argument is also supported by evidence indicating that when resources are directly or indirectly offered to the firms, the progress of EETs adoption is smoothed due to higher information acquisition. As a result, the probability that a firm is informed increases when this firm gets free technical support from specialized agencies, has accumulated its own expertise or is in close proximity to other firms and exploits spillover effects.

Evidence provided in this work supports the argument that the level of information or knowledge acquired by a firm is technology specific. The technology vintage is the key factor determining the heterogeneity underlying the level of knowledge among firms. In this direction, the definition of the informed firm allowed us to test the heterogeneity induced by technology vintages.

The conclusions of the present case study are relevant to policy makers and have implications for the design and implementation of energy efficient policies. The current policy framework exposed in the introductory section of this paper targets directly at the heart of the information barrier policy issue. It attempts to smooth the constraints holding firms from overcoming the information hurdle. The provision of traditional policy tools such as direct capital subsidies intend to flatten the levels imposed by financial constraints and combat the absolute disadvantage necessitated by smallness. Concurrently, the operation of technical support centers allows relatively constrained firms to substitute their own resources by freely available information and advice. The same function is undertaken by demonstration projects. Our results indicate that both activities should be geographically targeted at places where spillover effects are maximized.

Gaining higher levels of information may be supported by modern flexibly tailored combinations of assistance using complex multi-instrument sets of support to business development efforts. Flexible instruments refer to the whole range of assistance extended beyond the conventional capital subsidy approach and including activities aiming to search for and contract short term specialized personnel, visit demonstration projects or specialized exhibitions or facilitate cooperation with specialized agencies, research centers and institutions. Such aid reduces search costs as well as adjustment costs after the technology is adopted. Tailored combinations may allow assistance to be differentiated according to various criteria. For example, our analysis revealed that firms which have undertaken an investment in the past have a higher level of information concerning epidemic and/or emerging technologies. Such firms are more constrained due to their past investments and therefore in need of assistance. It should be mentioned that such tailored combinations may require the coordination of activities among policies.

Firms employ resources in order to increase their production capacity, introduce innovations, adopt ICTs and acquire competences within a globalized business environment. Thus, energy efficiency policy should be coordinated with regional policies providing infrastructure and/or direct financial support to businesses, with policies fostering innovation and ICTs and policies promoting environmental friendly business operation. To some extent synergies have been developed among these policies but a closer coordination at local/regional level will maximize the advantage of local knowledge in tailoring integrated activities for energy saving as well as innovation and environmental protection.

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References
