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KOF Working Papers

Insights into the Determinants of Innovation in Energy Efficiency

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Insights into the Determinants of Innovation in Energy Efficiency^{*†}

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Abstract

Given the increasing interest in understanding (and supporting by means of public policy) innovative activity related to energy efficient technology (EET), I attempt to identify firm-level determinants of innovation and research in this field. A novel dataset of Swiss firms has been assembled by means of a survey in 2009, resulting in more than 2300 observations featuring various indicators of innovative activity and success. Applying standard econometric methodology, I find sizeable differences of the explaining factors of energy efficiency related innovation as compared to overall innovation. In particular, market environment related variables important for overall innovative activity seem to have little explanatory power for EET related innovation, raising the question whether such innovation sufficiently responds to current and potential future demand.

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1 Introduction

This study empirically analyses the factors explaining firms' innovative activities related to energy efficient technologies (EET), focussing both on demand-pull and on technology push (such as human capital and competition) effects. To this aim, a novel dataset of innovative activity in a broad setting of energy-efficient technological applications has been conducted recently (spring 2009) among Swiss firms belonging to both the manufacturing and service sectors. More than 2300 participants returned valid questionnaires (resulting in a response rate of nearly 40%), enabling a number of general insights to issues relevant to corporate management as well as for the academic and political debate.

Technical change and innovative behaviour have been playing a central role in modern growth theory. However, two inherent characteristics of innovations — that the investments required to generate them and their potential benefit are uncertain *ex ante*, and that not all of the benefits of successfully having generated innovations may be appropriable by the firm — make it likely that profit-maximising firms will invest substantially less efforts into generating technological advances than would be socially optimal. If, moreover, progress in a field such as environmental technology has the potential to reduce negative externalities like pollution and greenhouse gas emissions, the problem of a rate of technological progress below a socially desirable level is aggravated even more, giving rise to a “Two Market Failures” problem (Jaffe et al. 2005). Not surprisingly, ecological innovation and its policy implications have become a prominent and complex field of economic investigation.

The question of optimal level of aggregate environmental research activity ultimately is a macroeconomic one, as is the problem of finding an appropriate mix of policy measures to achieve this in the long term (for a formal solution, see Acemoglu et al. 2009). A better understanding at the microeconomic level — about the determinants of environmental innovation activity at the firm or even at the project level, how it relates to overall (i.e. not environment relevant) innovation activity and what its implications in term of efficiency or profitability are — is however necessary for a thorough understanding of how to achieve this macroeconomic goal. This study is a contribution to this type of research, focusing however on specific question of energy related technologies, namely those that enable enterprises and households to reduce their energy inputs for given production or consumption requirements, thus improving energy efficiency.

Concerns about the sustainability of the current patterns of energy use have gained such prominence in recent years (raising awareness about the scarcity of energy sources, price volatility and, last but not least, climate change being the main concerns) that it seems justified to pay particular attention to questions related to energy and energy efficiency from an economist's viewpoint (Popp et al. 2009). Ambitious emission reduction goals for greenhouse gases have been formulated by environmental lobbyists, natural scientists and (increasingly) by governments. There is an overwhelming consensus (at

least among economists) that in order to meet such goals, technological progress in the area of energy generation and consumption needs to be fastened dramatically.

Enabling and (if deemed useful) actively supporting innovation of energy efficient technologies thus becomes a policy priority. A better understanding of the economic environment in which such EET innovations are best brought to success is indispensable if such policy is to be formulated. Of major importance in this context is the idea of *price-induced innovation*, dating back to Hicks (1932, as quoted e.g. by Jaffe et al. 2000) and stating that innovation activity in technologies that allow for substitution in input factors responds to the evolution of relative prices of these factors. Under this hypothesis, implementing policies that persistently increase the price of energy inputs may be feasible to trigger the expected technological improvements in energy efficiency in a long run perspective. Robust empirical analysis of the price-induced innovation hypothesis ideally relies on time-series data and thus is out of reach of this paper (but has been the topic of several other fruitful studies). However, one transmission mechanism by which price-induced innovation would function is by increased demand for energy efficient capital goods by firms and households using energy as an input, which in turn should prompt more pronounced efforts in the development of such technology by firms providing these goods — an effect which the present study can offer some insights on.

My analysis thus attempts to take into account demand-pull determinants (related to the characteristics and size of markets that current and potential providers of such technology operate in) as well as technology-push factors (firms' and industries' intrinsic capabilities to research innovate), and in particular to reveal how these effects differ from determinants of overall innovative activity.

Whereas this study does not cover the topic of determinants of the (broader) concept of eco-innovations, the 2009 survey allowed for firms to inform about their overall innovative behaviour, besides items related to innovations in a vast list of different technologies related to energy efficiency and alternative (renewable) energy generation. Data for average per-employee energy efficiency related R&D investment at the firm level has also been obtained, with some reservations made due to the small number of enterprises actually researching in this field.

The remainder of this paper is organised as follows. Section 2 resumes findings of related (mostly empirical) literature, section 3 presents the data sources alongside with some remarks concerning the construction of variables, section 4 describes the econometric framework and the results, and section 5 concludes.

2 Related Literature

To the best of my knowledge, no empirical study so far has looked at the microeconomic determinants for innovation related to energy efficient technology. This may be attributed not so much to a lack of interest, but rather to the restricted availability of

data (stemming partly from the fact that the topic itself and, in consequence, funding for data collection exercises have received substantial attention only since recently). Related empirical studies may be grouped according to the dimension in which they deviate from the present paper: *macro- or mesoeconomic* studies having industries or countries as their unit of analysis; studies related to *ecological innovation* which is a related but potentially broader technological category than EET; and studies attempting to explain *diffusion* of EET, thus looking at the stage subsequent to actual innovation in the process of technological change. In addition, analyses of the effects of *energy policy* on innovation and of the *profitability or productivity* effects of innovation are worth mentioning here, as they look at EET innovation from a different perspective (or from a different point in the causality chain).

Turning to the *macro- or meso-economic* level, studies explicitly focusing on innovation of energy efficient technologies are Popp (2002) and Verdolini and Galeotti (2009). Both rely on panel data constructed of patent counts and address the issue of induced innovation. The former uses energy efficiency related patent categories as the cross sectional dimension, whereas the latter features cross country data in order to study the geographical and technological channels through which energy-efficient innovation and knowledge disseminate, thus explicitly modelling international technology spillovers. Both studies confirm the importance of demand-pull effects proxied by energy prices as determinants for EET related innovation and suggest furthermore that knowledge stocks (modelled by past research efforts) should be taken into account in the kind of dynamic framework they use.

Testing the induced innovation hypothesis has been the motivation for a number of energy technology related empirical works. Energy efficiency innovation is a phenomenon that ideally lends itself to empirically test for this, since energy prices are universally observed across time and affect economic agents homogeneously, due to the uniform price evolution of energy inputs.¹ Besides this, energy spendings can make up for a large share of production costs of firms in many industries and for expenditure in households. A comprehensive effort is undertaken by Linn (2008), comparing US plant-level energy efficiency data between new entrants and industry incumbents. He finds a significant positive effect (albeit weak in magnitude) for energy prices on the relative efficiency of new plants, supporting the induced innovation hypothesis. Popp et al. (2009, page 29), reviewing other empirical studies addressing the same hypothesis, support this finding of positive and statistically significant induced innovation effects, which are however small in magnitude.

The broader concept of *environmental innovation* has been analysed by economists more prominently than energy innovation, perhaps since many environmental issues have gained public attention (and in consequence environmental standards have been intro-

¹At least, prices within the two categories making up for the vast majority of energy inputs in the economy (fossil fuels and electricity) can be expected to exhibit little variation across geography and users at a given point in time.

duced) much earlier than has been the case with energy. Johnstone and Labonne (2006) provide both a recent survey and an empirical investigation, with a specific focus on the effects of public policy frameworks on environmental R&D. In their influential article, Brunnermeier and Cohen (2003) find a positive impact of pollution abatement pressures (as proxied by the corresponding expenditure) on successful patent applications related to ecological technologies. Some recent econometric studies at the firm-level have analysed the effects of Environmental Management Systems (EMS) on the propensity to innovate. Both Wagner (2007) and Horbach (2008) do this for German manufacturing firms. The former uses both patent data and self-reported questionnaire data, while the latter relies on two panel datasets from different sources.

Finally, the main findings of the literature on determinants of overall innovative activity are also of importance here. The broad availability of innovation indicators at the micro level, as exemplified by the CIS (Community Innovation Survey) in European countries, has generated a vast body of empirical studies covering virtually all aspects of innovation. Crépon et al. (1998) provide probably the most systematic operationalisation of an integrated empirical model of innovation that covers the outcomes of R&D, patenting and productivity, and which has been influential to all subsequent research. To resume just some of the most prominent of the important findings of the mentioned study and those who have followed, the firm size effect on innovation is found to be positive (as far as innovation *propensity* is concerned, i.e. when analysing binary indicators of whether a firm is innovative or not), but turns out to be quite ambiguous as for the *intensity* of innovation (when looking at indicators such as R&D expenditure per employees or the share of innovative products in total sales). Stating whether demand-pull factors (emphasised by Schmookler 1966) or technology-push determinants are more important is difficult, as different studies use different sets of variables to accommodate these, reaching mixed conclusions.

3 Data and Construction of Variables

The dataset has been constructed on the basis of the Swiss Enterprise Panel maintained by KOF Swiss Economic Institute at ETH Zürich, using survey response data both from the Energy Technology Survey conducted in 2009, and from the 2008 Innovation Survey. The sample used for both surveys was identical (except for any attrition due to firms dropping out, following an explicit refusal from their part to participate or due to bankruptcy), and can be considered as representative of the private sector of the Swiss economy. Questionnaires were provided in German, French and Italian versions for both surveys mentioned.

3.1 The 2009 Energy Technology Survey

KOF Swiss Economic Institute decided to undertake a survey among Swiss enterprises covering specifically the topic of innovation and diffusion of technologies related to energy efficiency and alternative energy sources in 2009. Over 2000 participants returned valid questionnaires. For the present analysis, which limits itself to technological *innovation* (as opposed to *diffusion*, i.e. application of such technologies by firms which purchase them from other providers), some industries belonging to the service sector have been excluded since they are, due to the nature of their main business activity, highly unlikely to be innovative in the area of energy efficient technology, resulting in a reduced data set of 1577 enterprises. For an overview of the industries retained for this analysis and their respective counts in the dataset, see the first column of table 1. Due to missing data in some of the variables, the number of observations retained for the econometric analysis presented in the next chapter further drops to 1309.

In the questionnaire, the section covering EET innovation asked respondents to specify if they had generated such innovations in the past five years, and if yes, to which technological field(s) those innovations belong, out of a list of 35 specific fields. In addition, questions about the magnitude of their EET related R&D investments (relative to total R&D investments) and sales of energy technology related innovative products or services (relative to total sales) were featured. These latter two allow constructing measures of intensity of both R&D (as an input measure in the innovation chain) and of innovation success (an output measure) related to EET, which are then used to complement the econometric analysis of binary indicators for R&D and innovation in this paper.

Table 1 shows the composition of the data set by industry and size classes as well as the number and percentage of EET innovators for each class. Not surprisingly, fairly large proportions of EET innovators (more than 20%) can be found among manufacturers of electrical and non-electrical machinery, vehicle manufacturers and the energy facilities. A finding also in line with other studies of general or specific innovativeness is that the fraction of innovators is significantly larger among large firms than among small ones (see lower half of table 1). In total, 162 firms are — by their own judgement — innovators in energy efficiency related technologies.

Table 2 provides a brief overview of how often the four different dimensions of innovative activity of interest in this paper — EET innovation, as discussed in the preceding paragraph, being one of them — appear in our data. Nearly two out of three firms (64.7%) turn out to have generated innovations of any kind (including, but not only EET) within the three years up to the date of the survey. Formal R&D activities are conducted by a share of 41.2%. The relative frequencies of innovators in EET and of R&D performers in EET, in comparison, are much smaller (10.3% and 6.3%, respectively), but still sufficient to obtain valuable econometric insights. Consequently, the four dimensions of innovative activity just described make up the (binary) dependent

variables in the econometric models presented in subsection 4.1: INNO_ALL (the firm has generated innovations of any kind), RND_ALL (the firm does research related to any field), INNO_EET (the firm has generated EET related innovations), and RND_EET (the firm does research related to EET).

For purely descriptive purposes, I also list the technological fields featured in the questionnaire and the number of occurrences of each of them in table 3. Electrical engineering clearly is the most prominent of the broader fields here, while building technology and heat generation (two fields with a fairly broad range of applications) exhibit a moderate degree of importance. Transport/vehicles and electricity generation/transmission seem of lesser significance. The latter findings might be due to the fact that (final assembly of) vehicles is of little importance in Switzerland, and that electricity generation and transmission systems (where some large Swiss firms are competitive in the world market) tend to be large-scale applications requiring substantial investment volumes and highly integrated solutions, allowing only a handful of very large corporations to successfully compete.

3.2 Variables

I now turn to the explanatory variables used in the econometric analysis that follows (Table 4 provides a summary of the information given the present subsection).

Basic Firm Characteristics

In line with the widely confirmed empirical finding that larger firms are more likely to undertake research and to generate innovations, the variable LN_EMPL captures firm size, measured as the natural logarithm of the number of full-time equivalent employees. Since innovative activity is also likely to depend on capital intensity, it would be desirable to include this measure in my analysis. However, only a flow measure (i.e. investment) is available in our dataset, as opposed to a true capital stock variable. As including an investment measure might give rise to endogeneity issues, I do not include it in the analysis that follows.²

Further firm characteristics include binary variables indicating whether a firm is held by foreign owners in majority (FOREIGN), and whether it declares itself to be an exporter (EXPORT). Both can in principle be expected to have a positive impact on innovative behaviour, since international involvement of any kind — whether it is by exporting goods to foreign markets or by being in foreign ownership — tends to facilitate access to knowledge, markets and funding, all of which are essential in fostering successful innovation. Human capital intensity within the firm is measured by the proportion of employees having completed higher education (HI_EDU); again, this variable captures

²As a robustness check, all of the estimations that follow have also been calculated in a version that includes the log of total investments divided by employees. Whereas this investment variable was significant in one case (binary indicator for overall R&D), results for the other variables were not affected significantly by including it.

a factor that is essential in the development of new products and processes and thus should positively affect any innovative activity. A preference of the firms' management to use environmentally friendly material inputs in its production process is captured by the variable `ECO_FRIENDLY`, serving as a proxy to a broader commitment by the management to position itself as an environmentally responsible actor. A positive effect, at best, may be expected for innovations related to energy efficiency, but less probably so for overall innovative activity.

The remaining explanatory variables can broadly be categorised into either market or technology related, thus loosely following the distinction made by many previous empirical studies between demand-pull and technology-push factors (see Cohen 1995).

Market Related

This category comprises firms' assessment of the evolution of demand for its products, both retrospectively in the three years up to 2008 (`DEMAND_R`) and as expectations for the current/upcoming three years from 2009 (`DEMAND_F`). Variables expressing how firms perceive the intensity of competition on its product markets, both in their price (`PCOMP`) and non-price (`NPCOMP`) dimensions also enter in this category. Answers to all of these four variables are available on a five-point Likert scale, as specified on the questionnaire.

Technology Related

Technology (or, technological capacity) related variables can be constructed on the basis of firms' indications as to the relevance of innovation protectability/appropriability measures, knowledge sources, innovation obstacles and -goals.

`TECH_PROT` simply expresses the perceived effectiveness of protection measures against technological imitation by other firms — no matter whether they are of formal (patents, copyrights) or informal (such as secrecy or inherent complexity) nature. Appropriability, thus defined, is generally regarded as providing positive incentives on R&D efforts, as firms are capable of reaping the benefits of their research efforts rather than losing them partly or entirely due to outgoing spillovers. For achieving a socially desirable combination of R&D effort and knowledge dissemination levels across firms, however, appropriability may pose an obstacle rather than a solution by artificially generating monopolistic situations and wasteful duplication of research; an important point made by Spence (1984). A positive effect of this variable on innovation and R&D performance — as I expect to find in the econometric analysis — therefore should not be regarded as unconditionally positive from a perspective of social optimality, even though it might be so from the individual firm's viewpoint.

The importance of two different sources of knowledge is captured by the two variables `KS_CUST`, referring to firms' customers, and `KS_PAT`, referring to patent disclosures.

OBST_MARKET, OBST_FUNDS and OBST_HR reflect whether the firm encountered obstacles in its innovation process that were attributable respectively to marketability risks, (insufficient) external funding and (lack of) dedicated R&D personnel. Finally, GOAL_ENV expresses that generating new environmentally friendly products was an important goal in the firm’s innovation strategy.

Again, these technology related variables are measured on a five-point scale. However, since they were not part of the 2009 survey our dataset stems from and are only available through the 2008 wave of the Swiss Innovation Survey³, I had to rely on using three-digit and four-digit industry average values obtained from the 2008 survey and assigning the corresponding value to each observation in the dataset. This obviously raises some questions about their representativeness, but also brings about certain advantages, to be discussed in the next subsection.

Various Control Variables

Further controls for the regression equations include dummy variables for six industry groups and dummies for the language of the questionnaire submitted to and returned by the respective enterprise (LANG_FR and LANG_IT). The choice of the latter is due to the fact that there might be slight (but empirically noticeable) differences in the interpretations of the notions “Innovation” and “Research and Development” (or any of the notions of concern for the explanatory variables obtained from the survey) across different languages, let alone differing innovative behaviours across the linguistic regions in Switzerland.⁴

3.3 A Note on the Construction of Some Explanatory Variables

The technology related explanatory variables are derived from a previously conducted survey, as mentioned above (the Energy Survey 2009 questionnaire did not contain any such questions). One-to-one matching from responses obtained by the previous survey (Innovation 2008) to observations in the Energy Survey has been rejected, and instead three-digit and four-digit within-industry means for these variables have been calculated and attributed to each observation according to its industry classification. To be more precise, in the main dataset built on the basis of the 2009 survey, each observation has been assigned the mean value of the respective variable calculated over all firms in the 2008 survey belonging to either the same three-digit industry or the same four-digit industry.⁵ Since different economic activities as captured by the NACE classification appear with different frequencies in a given population, and since the number of appear-

³Conducted by KOF Swiss Economic Institute, ETH Zürich

⁴I found that using controls for seven geographical regions instead of the dummies for three languages (which overlap with the regions to a large degree anyway) in the estimation did not result in any effective improvement of coefficient significance or model fit.

⁵The decision criterion for whether to use three-digit or four-digit means was the respective size in terms of number of observations of the corresponding cell: if the number of 2008 survey participants in a three-digit industry exceeded 25, four-digit means were used, otherwise three-digit means.

ances of each activity category in a random sample are random themselves, the size of cells used for calculation of these means varies largely in our data. As both cells that are too small or too large may contribute to measurement error — by inflating random variation induced by individual observations that are not smoothed out by a sufficient number of economically similar observations, and by introducing more economic heterogeneity into a cell — an algorithm was chosen in order to achieve some degree of balance between “too small” and “too large” cells (see footnote 5). Table 10 summarises the frequencies by which certain cell sizes appear as a result of the procedure. While most cells contain between two and twenty observations, roughly a quarter are either smaller (of one single observation) or larger (more than twenty), while the average cell size is 8.8.

As mentioned, relying on such within-industry means is foremost, motivated by data limitations (the overlap between the respondent set of the two surveys is far from perfect). Less evident — but perhaps more important — is the concern that obstacles to innovation (and, to a lesser extent, knowledge sources) are *learned* through innovation: they are perceived more pronouncedly by firms that actively pursue innovation projects, since non-innovators evidently do not get any first-hand experience about them (at least not for obstacles that typically do not come up in the early stages of innovation projects). This phenomenon has been empirically addressed in depth and convincingly confirmed by Baldwin and Lin (2002).⁶ As a consequence, micro-econometric regression exercises using obstacles perceived by individual firms as explanatory variables to predict their innovation outcomes may fail to produce unbiased estimates for the innovation hampering effect of such obstacles, as they suffer from serious endogeneity issues (which may in the worst case produce estimates of a different sign than expected, i.e. positive rather than negative).

Constructing explanatory variables on the basis of within-industry means potentially alleviates this bias by providing average measures stemming from firms similar (in terms of economic activity) to the one in question. Evidently, this procedure gives rise to other problems. If heterogeneity of firms *within* a four-digit industry with respect to these variables is too high, the information content relevant to the individual firm captured by such means might be too little to produce significant estimates. Moreover, it cannot be ruled out that *between-industry* heterogeneity (which I actually need to rely on in order to identify the effects of these variables in the approach chosen) is related to innovative behaviour through other channels than direct causality. In the worst case, this means that the issue of endogeneity is not eliminated but rather shifted to a different level — from the individual firm towards the industry. In particular, industries exhibiting systematically higher innovation propensities (in terms of the proportion of firms innovating) may be expected to consistently yield higher means for some of the ex-

⁶And apparently cannot be neglected in our own data, since for the majority of obstacle categories, innovators consistently report higher scores in the survey than non-innovators, as outlined on pages 66–67 in Arvanitis et al. (2010).

planatory variables in question. Despite all these drawbacks, the use of within-industry means remains my preferred specification, and a number of robustness checks, outlined further in the next section, have actually been carried out to address — at least partly — these concerns. Consequently, only those findings that have been found to be robust to all of these checks (which is the case for the majority of those findings) enter the interpretations of the results that follow.

4 Econometric Framework and Results

As mentioned, the aim of this study is twofold: to identify the factors determining energy efficiency technology (EET) related innovation, and to find out in what respect they differ from the determinants of overall innovative activity as indicated by our data and by previous empirical exercises. Since we capture innovative activity at two different stages of the innovation process — R&D and actual innovations generated — and, at each stage, in two measures (as a binary indicator whether the firm is active at the respective stage, and as an intensity measure for those firms who are active), the following procedure has been chosen. Subsection 4.1 uses binary dependent variable (Probit) models to predict the four outcomes *overall R&D* and *overall innovation* as well as *EET related innovation* and *EET related R&D*:

$$Pr(OUTCOME_i^k = 1) = f^k(\beta_k X_i + \gamma_k F_{j(i)} + \epsilon_{ik}) \quad (1)$$

where i identifies the firm, $k = 1..4$ indexes one of the four outcomes mentioned such that $OUTCOME_i^k$ is one out of RND_ALL_i , RND_EET_i , $INNO_ALL_i$ and $INNO_EET_i$; and where X_i and $F_{j(i)}$, respectively, are the firm-specific and industry specific (for industry j to which firm i belongs) explanatory variables. Admitting the f^k 's to be normal cumulative density functions and the error terms ϵ_{ik} to be distributed normally, the model parameters β_k and γ_k may be consistently estimated by the standard Probit model. Furthermore, assuming cross correlation between the ϵ_{ik} 's (such that $E(\epsilon_{ij}\epsilon_{ik}) \neq 0$ for $j \neq k$), efficient estimates can be obtained by applying a Multivariate Probit model.

Subsection 4.2 extends this analysis to measures of innovation and R&D intensity (for the case of EET innovativeness only) using a Generalised Tobit (Type 2) selection model to accommodate for potential selectivity, thus following the framework for empirical analysis used by Crépon et al. (1998) with regards to R&D intensity and by Mohnen et al. (2006) with regards to innovation intensity, in order to control for potential selectivity bias:

$$rnd_i^{EET} = \alpha_1 X_i + \eta_i^1 \quad (2)$$

$$innosales_i^{EET} = \alpha_2 X_i + \eta_i^2 \quad (3)$$

where $rndexp_i^{EET}$ and $innosales_i^{EET}$ are the intensity measures used for EET R&D (the logarithm of R&D investments per employee) and innovations (the sales share of EET related innovative products, logistically transformed), which are defined only for those firms conducting such research and having generated such innovations, respectively. Selectivity means that the residuals η_i^{rnd} and $\eta_i^{innosales}$ may be correlated with the respective residuals of the binary outcome equation (1), requiring the Generalised Tobit approach mentioned above for consistent estimation of the parameters α_1 and α_2 .⁷

4.1 Binary Innovation and Research Indicators

Table 5 compares the parameter estimates for determinants of overall R&D to those of EET related R&D, and table 6 does likewise for overall innovations and EET innovations, obtained each from standard Probit estimations. Since the reference period for the indicators considered here overlap (even if not perfectly so), we should not expect a firm to take the respective decisions to engage in any of these four activities independently from each other. A simultaneous estimation procedure, as provided by the Multivariate Probit model, would then provide efficient and thus preferable estimates, and at the same time reveal if cross-correlation among the four equations is present. I report such estimates in table 7.⁸ Since the six estimated correlation coefficients between the four equations are significantly different from zero, cross-correlation is present and therefore the estimates in table 7 are the preferred ones I will refer to in what follows (the qualitative differences to the equation-by-equation estimates being only marginally different, however).

It appears that for a number of variables, primarily those related to basic firm characteristics and demand, the qualitative effect does not change when passing from measures of overall to EET innovativeness, and is in accordance with previous findings in the empirical literature. Firm size, the proportion of employees having completed higher education, evolution of demand (either previous or as expected for the future) and being an exporter all positively affect the probability of both engaging in R&D activities and being innovative. Deviations from this pattern of similarity between overall and EET related innovativeness are EXPORT (which positively affects overall innovations but has no significant effect upon EET innovations), as well as the influence of demand with regards to R&D: overall R&D seems to be affected by (forward looking) demand expectations, whereas only a small and insignificant effect can be found for EET R&D.

As a somewhat puzzling finding, firms that have been contacted by means of a

⁷For concerns of econometric identification and model stability, industry specific explanatory variables are assumed to have no effect upon research and innovation intensity — section 4.2 explains this in more detail.

⁸Based on the `mvprobit` implementation for Stata by Lorenzo Cappellari and Stephen P. Jenkins

French questionnaire report less innovations, regardless of whether overall or EET related innovations are the concern. This result cannot be attributed to differences in economic structure between the linguistic regions, as economic activity has been controlled for using industry dummies.⁹ Without any further investigation, and since there are no comparable studies using language dummies based on Swiss data, currently the only tenable explanation is that speakers of the French language have a narrower understanding of the term “innovation”, which results in them being more reluctant to classify their firms’ new or improved products and processes as innovative. The finding that no statistically significant linguistic difference emerges in our data in the context of R&D — being a notion that brings about less ambiguities in its potential interpretations than “innovations” — supports this explanation. Of more importance for the present study is the finding that this peculiarity in our results for firms belonging to the French speaking language region equally arises for both overall and EET innovations, i.e. no language specific innovation patterns appear when looking at the special case of energy efficient technologies.

Substantial differences between the determinants for overall and for EET related innovativeness appear among the remaining variables. A first insight concerns some explanatory factors related to market environment in a broad sense: non-price competition favours overall but not EET related innovativeness — the effect is negative but not significant for the latter.¹⁰ This positive effect on overall innovativeness is in accordance with existing literature. Risks associated to marketability, on the contrary, have a significantly negative effect on EET innovations only, whereas a slight (significant at the 10% level) positive coefficient results for overall innovations.¹¹ These findings — alongside the result that being an exporter does not increase the probability of innovating in energy efficient technologies — raises concerns that EET innovation, as captured by our survey, does not follow a pattern of *market-orientedness* to the degree that innovative activity and research of other kinds do. This concern will be further addressed in the concluding section.

The informative content provided by two variables related to *innovation protection* — TECH_PROT and KS_CUST — is inconclusive. Patents are deemed an important source of knowledge as far as both overall and EET research and development activities are concerned, as opposed to innovation outcomes (overall or EET), where they do not seem to matter. Somewhat counterintuitive is the significantly negative coefficient of TECH_PROT with regards to both EET R&D and innovation, and the fact that this variable does not turn out significant for overall R&D and innovation, as could have been

⁹Replacing the seven broad industry dummies by dummies for each NACE 2-digit industry (i.e. controlling for economic activity at a more detailed aggregation level) did not change this result.

¹⁰While customers as knowledge source (KS_CUST) exhibits a similar effect, this is not robust to controlling for firm-specific effects and only partly robust to controlling for lagged within-industry average innovation — see subsection 4.3.

¹¹This positive effect disappears when controlling for lagged within-industry average innovation, unlike the negative effect on EET innovations.

expected from earlier studies using this same variable (see, for instance, Arvanitis 2006). A potential explanation is that such protection measures effectively prevent the *imitation* of EET related innovations, resulting in a smaller number of innovating firms (our definition of innovation here includes products and processes that represent imitations of other firms’ pioneering works) than would be the case without such measures in place, but not necessarily resulting in a smaller number of first “pioneering” innovators. As already outlined in section 3, having effective barriers to imitation of innovations cannot be considered a priori good or bad — it means that research and innovation efforts are better appropriable to the first mover, providing a natural incentive to undertake such efforts in the first place. Additionally, since the importance of such measures, as observed in our data, may very well be due to natural (informal) circumstances, which unlike institutional measures (patents, copyrights) cannot be influenced by public policy, I refrain from drawing any policy conclusions in this matter.

A glance at the two variables representing obstacles related to the fundamental resources essential in the innovation process — skilled personnel and funding — reveals only limited evidence that scarcity of any of these would be a serious issue among the EET innovators in our survey. In contrast to overall R&D and innovation, where significantly negative coefficients for OBST_FUNDS appear, lack of external funding is of no significance for EET researchers and innovators. Positive and significant coefficients for OBST_HR appear for overall R&D and for EET innovation; however, there is no clear interpretation for these positive effects¹², and it cannot be ruled out that (in the case of EET innovation) the effect is spurious, as the robustness checks addressing both multicollinearity and within-industry aggregation effects did not confirm it. A prudent policy implication of these findings is that, in order to further strengthen the transformation of our energy system towards more efficiency, measures intended to extend access to external funding to R&D performers and innovators (including direct subsidies) should currently not be the highest priority; or at least they should be complemented by other policy measures, directed for instance at higher rates of diffusion or expanding end-user demand of such technologies.

4.2 Intensity Measures for Innovation and Research

Before taking a look at the results of this subsection, some introductory remarks are necessary. First, due to the small number of innovators and R&D performers that actually report how much of their sales are due to EET innovative products (87), or how much R&D investments they devote to EET (80) respectively, the intensity equation estimates should not be expected to be too informative. I present them here mainly in order to examine whether the qualitative findings of the preceding subsection can be

¹²Learning effects in these variables, as already mentioned earlier, might theoretically be strong enough to carry over to the within-industry means used in this analysis, resulting in a spurious (endogenous) effect. Due to data limitations, robustness checks, as outlined in subsection 4.3, only provide inconclusive evidence if this is the case here.

corroborated or, on the contrary, if the qualitative results found here hint to a different interpretations of things.

Second, it should be noted that the selection (first stage) part of the estimates here in some way relates to the preceding subsection. Given the nature of our dataset, EET *innovation* intensity is observed for some (but not for all) firms that declared themselves as EET innovators. By contrast, some positive number of EET *R&D* intensity is observed for all EET researchers and developers present in our dataset (since having EET R&D activities has been defined by a positive value in the corresponding item of the questionnaire). Consequently, the selection equation for innovativeness presented here captures the probability of revealing some nonzero share of innovative sales (which differs from what table 6 reports), whereas the selection equation for R&D measures the same as the corresponding binary outcome equation of the subsection above and therefore perfectly coincides with table 5 (since I use a two-step procedure and the set of explanatory variables is the same).

The intensity measures for EET R&D and innovation constituting the dependent variables in this subsection are: R&D investments attributable to energy efficient technology research, on a per employee basis; and the share of new or enhanced products related to energy technology among the firm's sales. As the former variable is strictly positive for firms undertaking EET R&D, and the latter bounded between zero and 100%, I use logarithmic and logistic transformations, respectively, in order to adjust their domain to the complete set of real numbers.

Table 8 reports estimates for intensity models for both innovativeness and research in energy efficient technologies (in two columns, respectively). The upper panel displays the Generalised Tobit estimates, and is again subdivided in an upper (intensity equation, i.e. second stage) and lower (selection equation, i.e. first stage) part. The lower panel contains ordinary least squares estimates for the intensity stage (and thus ignoring selectivity, which potentially biases these results). As mentioned above, for better comparability with the results from the preceding subsection, estimates reported here are from a two-stage procedure.¹³ The list of explanatory variables for the intensity equation of these estimations is a subset of those used for the selection equation (which are in turn identical to those used in the previous subsection), thus providing for the excluding restrictions that are essential for model identification. The variables excluded from the intensity equation are those derived from the 2008 Innovation Survey plus the language and industry dummies. The choice of these excluded variables is based on purely empirical considerations: block-wise inclusion of any of these variable groups in the intensity stage did not result in any (neither jointly nor individually) statistically significant coefficients there. Interpretations related to the effects of innovation protection, knowledge sources and innovation obstacles upon the intensity of EET R&D or

¹³When estimating the Generalised Tobit model using a maximum likelihood procedure, none of the qualitative findings for either equation change.

innovation are therefore not possible, as no empirical findings can be extracted from our data.

The main findings can be summarised briefly as follows: there seems to be selectivity in the case of EET R&D but not for EET innovation. However, the qualitative results from both intensity equations essentially remain the same if selection is not controlled for. As far as the qualitative results are concerned, none of the coefficients that are statistically significant with regards to intensity are in direct opposition to the findings related to the binary indicators discussed in the preceding subsection, neither for innovativeness nor for R&D.

However, EXPORT now has a significantly positive impact on the share of EET related innovative sales, while I did not find this variable to be of any effect on the fundamental outcome of being an innovator or not. This provides some relief for the lack of market-orientation concern expressed earlier. It could be argued that firms wanting to successfully compete on foreign markets need to have a more specialised product portfolio, which means that many of them will abstain completely from introducing new energy efficient products (thus no effect of EXPORT in the binary estimation is observed), but those exporters who actually do so will be highly specialised in such products and therefore exhibit a large proportion of sales belonging to this product category.

Somewhat surprising are the effects of the perceived degree of competition and demand evolution on R&D and innovation intensity. Non-price competition, despite being of no effect on the binary EET R&D variable, positively affects the magnitude of EET R&D investments among those firms undertaking such research and development. As for EET innovations, the variable for price competition exhibits a positive effect, rather than non-price competition, while so far in this paper (and elsewhere in the empirical literature), out of the two competition variables, the latter has been the one revealing stronger and more significant effects on any innovation indicators.¹⁴ Finally, future demand expectations — rather than previous demand evolution, as in the binary dependent variable model for EET innovations — seem to positively affect the sales success of EET innovators. Reverse causality might be at the root of this last finding, as firms whose new products experience a successful launch on the market will hardly expect their demand to drop in the near future. However, rather than delving too deeply into any speculation about these findings, I deem it more useful to emphasise that they do not fundamentally put into question what has been found in the previous subsection.

¹⁴It can be plausibly expected, however, that fierce price competition induces firms to cut their own energy expenses by promoting innovations for in-house use intended to improve the energy efficiency of their own production. By dropping those EET innovators who declared that they were generating such innovations for in-house use from the sample, the significant effect of PCOMP actually disappeared.

4.3 Robustness Checks

In the preceding sections, a number of potential pitfalls related to the estimation strategy chosen here have already been mentioned briefly. Consequently, this subsection outlines the various robustness checks I have conducted in order to corroborate the results presented earlier. For the sake of brevity, detailed result tables are not included in this paper but can be obtained from the author upon request.

As table 9 indicates, a number of explanatory variables heavily suffer from multicollinearity. The problem seems most serious for the variables constructed on the basis of within-industry means from the 2008 Innovation Survey, and a short glance at the table indicates that correlation coefficients above the value of 0.3 solely appear in conjunction with the four variables TECH_PROT, KS_PAT, OBST_MARKET and OBST_HR. I therefore repeated the binary outcome estimations reported in tables 5 and 6 with each one of these variables omitted once (on a one-by-one basis). In only few instances did this lead to a noteworthy loss of statistical significance in these or in any other variables, and no coefficient which was significant at the 10% or at a more restrictive level in the baseline estimations reversed its sign.¹⁵

The advantages of constructing variables stemming from the 2008 Innovation Survey on the basis of within-industry means have been outlined in the preceding section. Nevertheless, estimations for tables 5 and 6 have been carried out using variables constructed by one-to-one matching of observations between the two surveys. As the sample would dramatically shrink if unmatched respondents for the main survey were just thrown away, dummy variables for nonresponse in the 2008 survey were included as well and the values for the 2008 variables of these observations (where no responses are available) were assigned a standard value of zero in these alternative regressions. The results can be resumed as follows: with two minor exceptions, coefficients for the obstacle variables OBST_MARKET, OBST_FUNDS and OBST_HR tended to be more positive when estimated on individually matched data, which is compatible with the learning hypothesis outlined in the preceding section.¹⁶ The pattern looks similar for the variable TECH_PROT, implying that learning effects may also be present for this variable. As for the two knowledge source variables KS_CUST and KS_PAT, coefficients lost statistical significance in several cases, and in particular came out negative (although not statistically significant) instead of the previously positive outcome of KS_CUST on both overall R&D and Innovation. This loss of significance is not surprising, given that among the respondents of the 2008 Innovation Survey, a considerable number refused to fill in these questions, resulting in an even smaller pool of observations providing ac-

¹⁵ Among the findings worth mentioning are: DEMAND_F ceased to be significant for overall and EET innovations in some instances; OBST_FUNDS lost some significance (in the order of one “star” at most) for overall R&D and innovations; TECH_PROT and KS_PAT mutually depend on each other appearing in the estimation for EET R&D in order to remain significant at the 10% level; and both TECH_PROT and OBST_HR lost some significance (in the order of one “star” at most) for EET innovations.

¹⁶ The two exceptions are OBST_MARKET for overall innovation and OBST_HR for EET innovation, which both lose their statistically significant (at the 10% level) effect, while remaining positive in sign.

tual information for this exercise and inflating the associated estimated standard errors. This effect is even more pronounced for GOAL_ENV, being based on a question only the innovating firms in the 2008 Innovation Survey were asked to answer.

The preceding section also briefly addressed concerns that potential endogeneity due to learning effects in the variables for innovation protection, knowledge sources and obstacles might be shifted from the (firm specific) individual level to the industry level by the approach I have chosen, rather than alleviating it: industries with a priori higher propensities to research and/or to innovate may have mean values (for these explanatory variables) which systematically differ due to the larger proportion of responses plagued by learning effects. One possibility to obtain some insights about the magnitude of this effect is to include the proportion of 2008 innovators — which is equivalent to the mean value of the binary variable for whether firms were innovators or not at the time of that survey — as controls in my regressions. I conducted this kind of check for the estimations in tables 5 and 6, including both the proportions of product and of process innovators of the 2008 survey in the list of explanatory variables.¹⁷ The effect on the estimates of introducing these controls is stronger with respect to overall R&D and overall innovation (in both models, the significance category of four explanatory variables was affected) than it is for EET R&D (where KS_PAT turns out slightly more significant) and EET innovation (with no changes in significance categories). I thus conclude that the loss of significance of some explanatory variables, following the introduction of these controls, is more likely due to high correlation of the controls with the dependent variables (that is, of within-industry average lagged innovation with current innovation and current R&D) rather than due to spuriousness of these explanatory variables.¹⁸ Again, in any case, the interpretations here are based on individual observed coefficients only whose significance is not affected by this check.

5 Implications and Conclusion

Empirical comparison of the determinants for research and development (R&D) and innovation related to energy efficient technology (EET), on the one hand, to those related to overall technological progress on the other hand, has provided several insights about the innovative behaviour of Swiss firms. While a number of fundamental firm characteristics, such as firm size, human capital intensity or foreign ownership, do not seem to differ much in their impact on the two sets of innovative activity, some notable differences among other variables have been found. They can be summarised by the three broadly defined concepts of *market-orientedness*, *innovation protection* and *productive inputs* in the innovation process.

¹⁷The distinction between product and process innovators is sensible here, since some of the explanatory variables in question, in particular KS_CUST and OBST_MARKET, are likely to be affected by learning effects if the firm is a product innovator, but not so if it is a (pure) process innovator.

¹⁸This assumption is further supported by the fact that the controls turn out statistically significant only in the estimations with current overall innovations and R&D as the dependent variables.

Perhaps the most pronounced finding of this paper is related to *market-orientedness*, or a lack thereof when it comes to R&D and innovation in EET, exemplified by the absence of statistically significant effects of exports and competition and the presence of marketability related risks in my estimations concerned with this specific subgroup of innovations. There are a number of potential explanations why this finding might be related to the very nature of innovation in energy efficient technologies:

- The entrepreneurial success of EET innovation — which is, after all, what firms are furthestmost concerned with — is largely dependent on the cyclical evolution of fundamentals in the world economy: the crude oil price drop coming into effect shortly before the date of our survey, ending a several year-long period of oil price hikes, might have temporarily lessened the chances of generating profits from EET innovations. However, this claim conflicts with the finding that many EET improvements in our dataset are related to efficiency in the use of electricity rather than fossil fuels, and electricity prices in most world regions — in contrast to those for most fossil fuels — have been less volatile in the recent past and are widely expected to increase in the near future.
- New products characterised by improved energy efficiency, by their very nature, require less customer interaction than innovations of most other types, as there is little room for customisation. Consequently, it should not come as a surprise to see fewer indications of market-orientedness for this specific group of innovations than for others in our data.
- There may be motives other than immediate market success for firms to innovate in EET: reputational gains; accessing funds from public or private institutions supporting such innovations; innovating for internal use. However, as far as the last one of these motives is concerned, excluding all EET innovators declaring to innovate for in-house use from the sample should partly remove those effects, which is not the case in our data.

While all of these explanations would imply that there is not too much to worry about this finding, none of them seems completely satisfactory. A further complication to deeper analysis of the reasons is that we do not dispose about project-level data for energy efficient innovations — all of our indicators are aggregated at the firm or industry levels. Given the current state of information, it is certainly prudent for policymakers to carefully observe if any of the concerns related to missing market-orientedness manifests itself in other data sources or in individual cases. Potentially meaningful indications may be obtained by comparing the failure rate of such research projects, once initiated, related to EET; the commercial success of such projects; or the specific difficulties in exporting energy efficient technology.

The implications provided by variables related to *innovation protection* are, as already mentioned, less clear-cut — technology protection measures, where they are per-

ceived as being effective, have a somewhat dampening effect on the innovation propensity in EET. However, the broad definition of this variable (it measures all kinds of informal protection measures, in addition to formal legal protection by patents) and the fact that it is not overly robust does not allow us to derive too much interpretation from this finding.

Somehow more optimistic, as far as policy is concerned, are the findings that two essential productive *inputs* in the innovation process — funding and human resources — do not seem to be limiting factors in the innovation process with regards to energy efficient technology. Moreover, demand for energy technology — exemplified both by past demand evolution and future demand expectations — at various instances have statistically significant positive effects upon R&D as well as innovation related to EET. This is substantial (if not sufficient) microeconomic evidence that demand-induced innovation may constitute an important transmission channel through which both market prices and energy policy can positively affect the pace of technological change. Price signals induced by current or expected scarcity of energy sources, or by CO₂ pricing as an outcome of implicit or explicit public policy measures, can thus be expected to be effective in helping to transform the economy into a less energy intensive one in the long run. It is thus reasonable to stress the finding — also put forward by recent theoretical literature, see Acemoglu et al. (2009), for instance — that the optimal design of energy policy should combine direct support for R&D by public and private bodies with measures putting an explicit price on non-renewable energy consumption, or more concretely, the CO₂ emissions associated with it.

6 References

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7 Appendix

Table 1: Composition of Data Set by Industry and Size Class

Industry (NACE)	Number of firms	Percentage of firms (%)	Number of EET innovating firms	Percentage of EET innovating firms (% within industry)
Food, beverage, tobacco (15, 16)	98	6.2	1	1.0
Textiles (17)	24	1.5	2	8.3
Clothing, leather (18, 19)	10	0.6	0	0.0
Wood processing (20)	37	2.3	2	5.4
Paper (21)	25	1.6	2	8.0
Printing (22)	68	4.3	0	0.0
Chemicals (23, 24)	85	5.4	5	5.9
Plastics, rubber (25)	52	3.3	4	7.7
Glass, stone, clay (26)	41	2.6	0	0.0
Metal (27)	31	2.0	4	12.9
Metal working (28)	167	10.6	14	8.4
Machinery (29)	194	12.3	43	22.2
Electrical machinery (31)	58	3.7	19	32.8
Electronics, instruments (30, 32, 331-334)	126	8.0	23	18.3
Watches (335)	40	2.5	1	2.5
Vehicles (34, 35)	22	1.4	6	27.3
Other manufacturing (36, 37)	37	2.3	1	2.7
Energy, water (40, 41)	49	3.1	14	28.6
Construction (45)	203	12.9	4	2.0
Computer services (72, 73)	50	3.2	8	16.0
Business services (74)	149	9.4	8	5.4
Telecommunication (64)	11	0.7	1	9.1
Total	1577	100.0	162	10.3

Size class (number of employees)	Number of firms	Percentage of firms (%)	Number of EET innovating firms	Percentage of EET innovating firms (% within industry)
Small (< 50)	720	45.7	40	5.6
Medium (50 – 250)	617	39.1	72	11.7
Large (\geq 250)	240	15.2	50	20.8
Total	1577	100.0	162	10.3

Table 2: Number of Innovators and R&D Performers in Sample

	Variable	Frequency	Relative Frequency (%)
Overall innovators	INNO_ALL	1021	64.7
Overall R&D performers	RND_ALL	650	41.2
EET innovators	INNO_EET	162	10.3
EET R&D performers	RND_EET	100	6.3
Total		1577	100.0

Table 3: Occurrences of EET Related Technology Fields in Dataset

Technology Field	Occurrences (firms researching in this field)	Relative occurrence (to total number of firms researching in EET, %)
Electrical engineering	118	72.8
Electric motors	60	37.0
IT related	34	21.0
Consumer electronics	14	8.6
Process technology components	60	37.0
Process technology systems	53	32.7
Fuel cells	13	8.0
Turbines	13	8.0
Transport and vehicles	51	31.5
Engines/traction systems	27	16.7
Vehicle bodies	10	6.2
Hydrogen based engine	7	4.3
Electricity based engine	28	17.3
Traffic management systems	6	3.7
Building technology	86	53.1
Insulation	35	21.6
Lightning	42	25.9
Heating	52	32.1
Cooling/shadowing	38	23.5
Air conditioning	37	22.8
Electricity generation/transmission	53	32.7
Photovoltaics	32	19.8
Electricity from biomass	16	9.9
Wind power	16	9.9
CC using biomass	11	6.8
CC using fossil fuels	12	7.4
Decentralised CC	6	3.7
Hydroelectric	17	10.5
Fossil fuel power	7	4.3
Nuclear power	9	5.6
HVDC transmission	4	2.5
Superconductors	1	0.6
Heat generation and transmission	71	43.8
Solar heat	29	17.9
Heat from biomass	14	8.6
Geothermal	8	4.9
Heat pumps	26	16.0
Waste heat recovery	37	22.8
District heating	12	7.4
Carbon Capturing and Storage	4	2.5
Total	162	100.0

Table 4: Definition of Explanatory Variables

Variable	Description	Type	Source
LN_EMPL	Firm size (natural logarithm of the number of full-time equivalent employees)	continuous	
FOREIGN	Firm is held by foreign owners in majority	binary	
EXPORT	Firm is an exporter	binary	
HLEDU	Human capital intensity (proportion of employees having completed higher education)	continuous (0–100%)	Energy 2009
ECO_FRIENDLY	Preference of the firms' management to use environmentally friendly material inputs in its production process	5-point Likert	
DEMAND_R	Assessment of the evolution of demand for products (retrospectively in the three years up to 2008)	5-point Likert	
DEMAND_F	Assessment of the evolution of demand for products (upcoming in the three years from 2009 onwards)	5-point Likert	Energy 2009
PCOMP	Perceived intensity of competition (in prices)	5-point Likert	
NPCOMP	Perceived intensity of competition (non-price dimensions)	5-point Likert	
TECH_PROT	Perceived effectiveness of protection measures against technological imitation by other firms, both formal (patents, copyrights) or informal (secrecy or inherent complexity etc.)	5-point Likert	
GOAL_ENV	Importance of generating new environmentally friendly products in the firm's innovation strategy	5-point Likert	
KS_CUST	Importance of firm's customers as knowledge source	5-point Likert	Inno. 2008
KS_PAT	Importance of patent disclosures as knowledge source	5-point Likert	
OBST_MARKET	Importance of marketability risks as an obstacle to innovation	5-point Likert	
OBST_FUND	Importance of (insufficient) external funding as an obstacle to innovation	5-point Likert	
OBST_HR	Importance of (lack of) dedicated R&D personnel as an obstacle to innovation	5-point Likert	
<i>(Reference group; omitted)</i>	Questionnaire language: German		
LANG_FR	Questionnaire language: French	dummies	Energy 2009
LANG_IT	Questionnaire language: Italian		
Industry dummies	Industry (six categories)	dummies	Energy 2009

Table 5: Results of Binary Outcome Estimations — Firms' Decisions to Conduct R&D

	RND_ALL	RND_EET
(Intercept)	-4.1407*** (-6.90)	-4.5367*** (-5.01)
LN_EMPL	0.2443*** (7.53)	0.1518*** (3.09)
FOREIGN	-0.1435 (-1.21)	0.0015 (0.01)
HLEDU	0.0135*** (5.58)	0.0142*** (4.03)
EXPORT	0.7566*** (7.54)	0.4769** (2.26)
ECO_FRIENDLY	0.0020 (0.05)	0.0102 (0.15)
DEMAND_R	-0.0008 (-0.02)	0.1287 (1.57)
DEMAND_F	0.1593*** (3.25)	0.0926 (1.24)
PCOMP	0.0049 (0.11)	0.0261 (0.36)
NPCOMP	0.1006** (2.21)	-0.0967 (-1.29)
LANG_FR	0.0951 (0.81)	-0.3799 (-1.57)
LANG_IT	-0.0490 (-0.23)	-0.1822 (-0.50)
GOAL_ENV	0.1097 (1.49)	0.3287*** (2.87)
TECH_PROT	0.0682 (0.66)	-0.3390* (-1.96)
KS_CUST	0.1789* (1.75)	-0.0888 (-0.55)
KS_PAT	0.2167* (1.72)	0.3844* (1.94)
OBST_MARKET	0.1138 (1.12)	-0.1761 (-0.97)
OBST_FUNDS	-0.2647*** (-2.65)	0.1757 (1.08)
OBST_HR	0.1961** (2.14)	-0.0445 (-0.29)
Industry Dummies	Yes	Yes
N	1309	1309
Maximised log-L	-644.7	-223.8
Null log-L	-890.6	-298.4

z-Values in brackets. Stars denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels respectively.

Dependent Variables: R&D Activities related to any Technology (RND_ALL) or related to Energy Efficient Technologies (RND_EET)

Table 6: Results of Binary Outcome Estimations — Firms' Innovation Outcomes

	INNO_ALL	INNO_EET
(Intercept)	-3.0545*** (-5.45)	-3.8448*** (-4.97)
LN_EMPL	0.1955*** (6.12)	0.1536*** (3.87)
FOREIGN	-0.1672 (-1.35)	-0.0105 (-0.07)
HLEDU	0.0068*** (2.88)	0.0118*** (4.08)
EXPORT	0.3995*** (4.19)	0.0781 (0.54)
ECO_FRIENDLY	0.1081*** (2.80)	0.0996* (1.87)
DEMAND_R	0.1421*** (2.96)	0.2093*** (3.09)
DEMAND_F	0.0805* (1.67)	0.1023* (1.66)
PCOMP	0.0322 (0.77)	-0.0160 (-0.28)
NPCOMP	0.1401*** (3.22)	-0.0875 (-1.46)
LANG_FR	-0.5821*** (-5.34)	-0.5694*** (-2.92)
LANG_IT	-0.1741 (-0.89)	-0.3337 (-1.06)
GOAL_ENV	-0.0061 (-0.09)	0.3225*** (3.52)
TECH_PROT	0.0023 (0.02)	-0.2797** (-2.01)
KS_CUST	0.2786*** (2.80)	0.0793 (0.61)
KS_PAT	-0.0622 (-0.51)	0.1454 (0.89)
OBST_MARKET	0.1777* (1.73)	-0.3802** (-2.56)
OBST_FUNDS	-0.1974** (-2.04)	0.0292 (0.22)
OBST_HR	0.0215 (0.24)	0.2170* (1.68)
Industry Dummies	Yes	Yes
N	1309	1309
Maximised log-L	-696.5	-357.2
Null log-L	-839.1	-451.5

z-Values in brackets. Stars denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels respectively.

Dependent Variables: Innovation outcomes related to any Technology (INNO_ALL) or related to Energy Efficient Technologies (INNO_EET)

Table 7: Results of Tetrivariate Probit Estimations

Same models as in tables 5 and 6, estimated simultaneously				
	RND_ALL	RND_EET	INNO_ALL	INNO_EET
(Intercept)	-4.0588*** (-6.79)	-4.3922*** (-4.81)	-2.9808*** (-5.39)	-3.9641*** (-5.27)
LN_EMPL	0.2407*** (7.42)	0.1658*** (3.39)	0.1879*** (6.01)	0.1684*** (4.38)
FOREIGN	-0.1299 (-1.09)	-0.0093 (-0.06)	-0.1538 (-1.25)	-0.0263 (-0.19)
HLEDU	0.0136*** (5.65)	0.0114*** (3.24)	0.0070*** (3.00)	0.0112*** (4.10)
EXPORT	0.7439*** (7.44)	0.3984* (1.87)	0.4068*** (4.34)	0.0010 (0.01)
ECO_FRIENDLY	-0.0104 (-0.26)	0.0317 (0.50)	0.1003*** (2.65)	0.1010** (2.06)
DEMAND_R	0.0126 (0.26)	0.1663** (2.01)	0.1448*** (3.05)	0.2036*** (3.13)
DEMAND_F	0.1524*** (3.12)	0.1098 (1.49)	0.0750 (1.58)	0.1093* (1.86)
PCOMP	0.0042 (0.10)	0.0028 (0.04)	0.0345 (0.83)	-0.0202 (-0.37)
NPCOMP	0.1060** (2.32)	-0.0952 (-1.34)	0.1463*** (3.38)	-0.0894 (-1.60)
LANG_FR	0.0725 (0.61)	-0.4002 (-1.64)	-0.5705*** (-5.18)	-0.5604*** (-3.10)
LANG_IT	-0.0659 (-0.32)	-0.1987 (-0.57)	-0.1745 (-0.93)	-0.3569 (-1.12)
GOAL_ENV	0.1250* (1.68)	0.2331** (2.01)	0.0053 (0.08)	0.2772*** (3.14)
TECH_PROT	0.0566 (0.54)	-0.2924* (-1.69)	-0.0089 (-0.09)	-0.3108** (-2.28)
KS_CUST	0.1685* (1.65)	-0.0561 (-0.34)	0.2834*** (2.88)	0.0880 (0.72)
KS_PAT	0.2232* (1.73)	0.3838** (1.98)	-0.0661 (-0.55)	0.1603 (1.03)
OBST_MARKET	0.1139 (1.13)	-0.1834 (-0.98)	0.1717* (1.71)	-0.3283** (-2.33)
OBST_FUNDS	-0.2541** (-2.55)	0.0351 (0.22)	-0.2021** (-2.11)	-0.0222 (-0.18)
OBST_HR	0.1548* (1.70)	0.0456 (0.29)	0.0099 (0.11)	0.3042** (2.48)
Industry Dummies	Yes	Yes	Yes	Yes
No. of obs. (total)	1309			
LR chi2	662.6			
p-Value	0.0000			
<i>Estimated cross-equation correlation coefficients:</i>				
ρ_{21}	0.5125*** (7.24)			
ρ_{31}	0.5080*** (12.03)			
ρ_{41}	0.3855*** (6.83)			
ρ_{32}	0.2672*** (3.83)			
ρ_{42}	0.7673*** (21.46)			
ρ_{43}	0.2360*** (3.58)			

z-Values in brackets. Stars denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels respectively.

Table 8: Results of Generalised Tobit Estimations

	rnd^{EET}		$innosales^{EET}$	
	<i>Intensity Equation</i>			
(Intercept)	13.4596***	(4.84)	-4.2584*	(-1.96)
LN_EMPL	-0.2459	(-1.51)	-0.1819	(-1.32)
FOREIGN	0.6162	(1.29)	-0.0163	(-0.04)
HLEDU	-0.0083	(-0.77)	-0.0037	(-0.39)
EXPORT	0.6159	(0.76)	1.3406***	(2.66)
ECO_FRIENDLY	0.1609	(0.73)	0.0851	(0.45)
DEMAND_R	-0.0014	(0.00)	-0.1508	(-0.54)
DEMAND_F	-0.2070	(-0.86)	0.4492**	(2.15)
PCOMP	-0.1690	(-0.73)	0.4371**	(2.24)
NPCOMP	0.6673***	(3.28)	-0.1088	(-0.62)
invMillsRatio	-1.2400**	(-2.18)	0.0699	(0.17)
	<i>Selection Equation</i>			
(Intercept)	-4.5367***	(-4.90)	-5.5545***	(-5.95)
LN_EMPL	0.1518***	(3.10)	0.1304***	(2.71)
FOREIGN	0.0015	(0.01)	-0.0062	(-0.04)
HLEDU	0.0142***	(4.02)	0.0099***	(2.80)
EXPORT	0.4769**	(2.25)	0.0430	(0.24)
ECO_FRIENDLY	0.0102	(0.15)	-0.0159	(-0.25)
DEMAND_R	0.1287	(1.55)	0.1994**	(2.39)
DEMAND_F	0.0926	(1.24)	0.1927***	(2.59)
PCOMP	0.0261	(0.36)	0.0372	(0.53)
NPCOMP	-0.0967	(-1.32)	0.0722	(1.02)
LANG_FR	-0.3799	(-1.58)	-0.5115**	(-2.05)
LANG_IT	-0.1822	(-0.50)	-0.3907	(-0.94)
GOAL_ENV	0.3287***	(2.83)	0.4299***	(3.80)
TECH_PROT	-0.3390*	(-1.94)	-0.3494**	(-2.07)
KS_CUST	-0.0888	(-0.55)	0.1060	(0.69)
KS_PAT	0.3844*	(1.92)	0.0565	(0.27)
OBST_MARKET	-0.1761	(-0.95)	-0.3647*	(-1.88)
OBST_FUNDS	0.1757	(1.07)	0.0844	(0.51)
OBST_HR	-0.0445	(-0.28)	0.2774*	(1.70)
Industry Dummies	Yes		Yes	
sigma	2.0286		1.5695	
rho	-0.6113		0.0446	
N(total)	1309		1309	
N(uncensored)	79		86	
Adj. R2	0.1708		0.0767	

Comparison Model:

<i>Intensity Equation Estimated without Controlling for Selection</i>				
(Intercept)	8.8116***	(4.62)	-3.9971**	(-2.45)
LN_EMPL	-0.0973	(-0.63)	-0.1918	(-1.45)
FOREIGN	0.6127	(1.23)	-0.0094	(-0.02)
HLEDU	0.0017	(0.16)	-0.0043	(-0.46)
EXPORT	1.3484*	(1.70)	1.3351**	(2.49)
ECO_FRIENDLY	0.1298	(0.56)	0.0904	(0.46)
DEMAND_R	0.1175	(0.39)	-0.1661	(-0.59)
DEMAND_F	-0.0274	(-0.12)	0.4384**	(2.07)
PCOMP	-0.1263	(-0.52)	0.4377**	(2.11)
NPCOMP	0.6806***	(3.23)	-0.1142	(-0.62)
N	79		86	
Adj. R2	0.1286		0.0886	
P(F).value	0.0266		0.0618	

z-Values in brackets. Stars denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels respectively.

Dependent variables: logarithm of firm's EET related R&D investments per employee (left); logistic transformation of the firm's sales share of new or enhanced products related to EET (right).

Table 10: Size Distribution of (Number of Valid Observations in each) Modified 4-Digit Industry Cells Used for Calculation of Innovation Survey 2008 Variables

Number of Valid Observations in each Cell	Number of Cells
1	53
2-3	74
4-5	51
6-10	71
11-20	91
21-100	51
Total	391
Mean cell size	8.8