Energy Policy 132 (2019) 978–990

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Absorptive capacity and energy efficiency in manufacturing firms – An empirical analysis in Norway

Mette Talseth Solnørdal*, Sverre Braathen Thyholdt

School of Business and Economics, UiT the Arctic University of Norway, Pb 6050 Langnes, 9037, Tromsø, Norway

ARTICLE INFO

Keywords:
Innovation
Absorptive capacity
Energy efficiency
Manufacturing firms
Community innovation survey

ABSTRACT

Increased energy efficiency (EE) in manufacturing firms is important for confronting climate challenges. However, the information barrier is considered a major restriction on EE innovation. Building on the theory of absorptive capacity and the current EE literature, we argue that this barrier relates to firms' ability to assimilate and exploit information. Thus, this study's objective is to analyse firms' knowledge characteristics as determinants of EE innovation. We perform logit regressions using a Norwegian panel dataset for the period 2010–2014. The results are based on statistical correlations between data points that have potential uncertainties. Still, the main implications from our study are that prior knowledge, in terms of higher educated workforce, knowledge development, in terms of R&D capacity, and external knowledge cooperation, such as cooperation with universities and competitors, increase firms' pursuit of EE innovation. Further, the results also imply that there is an interaction effect between higher educated workforce and collaboration with universities. These results suggest that policy makers should consider firms' ability to assimilate and exploit information. This can be done by providing information according to firms' needs and absorptive capacity, and offering possibilities for firms to increase this capacity.

1. Introduction

Global energy consumption and the emission of greenhouse gases (GHG) are causing climate challenges worldwide. Between 1971 and 2016, the global total final consumption (TFC) of energy grew by a factor of 2.25 (IEA, 2018); if no actions are taken, energy demands are expected to continue rising precipitously, due to economic development, increased access to marketed energy, and population growth (EIA, 2017). Political responses to the urgent need for climate change mitigation and energy efficiency (EE) include, for example, the Paris Agreement (UNFCCC, 2015) and the European 2030 framework for climate and energy (EU, 2014). Since industry is the largest energy-consuming sector globally, accounting for 37% of TFC in 2016 (IEA, 2018), increased industrial EE is considered vital to achieving environmental commitments and ensuring a safe and affordable transition to a sustainable energy system.

EE can be understood as "action taken by firms that has the objective of reducing the amount of energy per unit output" (Costa-Campi et al., 2015 p. 230). Although EE is positively related to manufacturing firms' performance (Fan et al., 2017; Martin et al., 2012; Martínez, 2010; Worrell et al., 2009) and compliance with both social pressure and stricter environmental regulations (Apeaning and Thollander, 2013; Masurel, 2007), firms tend to avoid adopting energy-efficient technologies that are economically and environmentally attractive (Abadie et al., 2012; Anderson and Newell, 2004). Economists refer to this discrepancy between the theoretically optimal and the current level of EE as 'the EE gap' (Jaffe and Stavins, 1994). It is considered a paradox (DeCanio, 1998) that might be explained by market failures, including environmental externalities, lack of information, principal-agent issues, and systematic behavioural biases (Gillingham et al., 2009; Sorrell et al., 2011). Accordingly, energy policies and programmes have been designed to address these market failures (Gillingham and Palmer, 2014; Tanaka, 2011). However, prevailing evidence of the significant unexploited potential for improved industrial EE (Cui and Li, 2015; Lin and Tan, 2016) has raised a call for increased research into the link between EE and innovation. In particular the call address the need for more research regarding which firm characteristics influence EE innovation by innovative firms (Costa-Campi et al., 2015; De Marchi, 2012; Horbach et al., 2012; Hrovatin et al., 2016; Rennings and Rammer, 2009; Trianni et al., 2013b).

The theory of absorptive capacity posits that a firm's innovative performance is influenced by its prior knowledge and its ability to develop new knowledge, through either internal knowledge creation or the inflow of external knowledge (Cohen and Levinthal, 1990;

* Corresponding author.
E-mail addresses: mette.solnordal@uit.no (M.T. Solnørdal), sverre.thyholdt@uit.no (S.B. Thyholdt).

https://doi.org/10.1016/j.enpol.2019.06.069
Received 29 March 2018; Received in revised form 27 June 2019; Accepted 29 June 2019
Available online 02 July 2019

Lichtenthaler, 2009; Sagar and van der Zwaan, 2006; Smith et al., 2005). Newer research, have started to reveal how absorptive capacity, knowledge accumulation capabilities, and cooperation strategies also affect firms' environmental innovativeness (Albort-Morant et al., 2018; Costa-Campi et al., 2017; De Marchi, 2012; De Marchi and Grandinetti, 2013; Horbach et al., 2012, 2013). However, these studies focus on eco-innovations in general, which are rather broadly defined (e.g. Kemp and Pearson, 2007; OECD, 2009). Thus, scholars have argued the need for further classifying various types of eco-innovations (De Marchi, 2012), in order to identify their specific characteristics (Carrillo-Hermosilla et al., 2010; Kemp and Pearson, 2007) and analyse their determinants (Hammar and Löfgren, 2010; Horbach et al., 2012). Following the proposed definition by Costa-Campi et al. (2015 p. 230), we therefore argue that EE innovation is a type of eco-innovation requiring specific academic attention. Indeed, the EE literature indicates that EE innovation in manufacturing firms are positively related to the firms' human resources (Chai and Baudelaire, 2015; Sardianou, 2008), innovativeness (Cagno et al., 2015a; Gerstlberger et al., 2016; Trianni et al., 2013b), and external cooperation (Cagno et al., 2017; Miah et al., 2015; Trianni et al., 2016b). However, these factors have not previously been studied in relation to one another, in terms of their significance, relative importance, and interaction effect. Thus, in this study we aim to fill this gap, using absorptive capacity as a theoretical framework, asking: *What is the relationship between manufacturing firms' absorptive capacity and EE innovation?*

For this analysis, we perform a logit regression using firm-level data from a sample of innovative manufacturing firms in Norway. The self-reported data were collected through the Norwegian Community Innovation Survey (CIS) and the Business Enterprise R&D survey (BERD) for the period 2010–2014. We use R&D investments in EE as a measure of EE innovation. The Norwegian economy is highly dependent on the oil and gas industry (IEA, 2017). As the world looks to diminish reliance on fossil fuels, the government needs to prepare for a future with less dependency on this sector. In this transition, the importance of an innovative and competitive manufacturing industry becomes more pronounced. Concurrently, having ratified the Paris Agreement, Norway faces challenges in seeking to reduce GHG emissions by at least 40% below the 1990 level by 2030 (UNFCCC, 2015). In attaining both objectives increased industrial EE innovation is considered as vital (MPE, 2016), and which requires both governmental and firm-level efforts to maximise the sector's EE potential (IEA, 2017). Given that Norway invests above average and is on par with the EU vision in the knowledge economy (RCN, 2017), we argue that Norway, like other Nordic countries, could be seen as inspirational with respect to how innovation should support competitiveness and green growth; therefore, it is a suitable context to examine our research question.

The paper is structured as follows. Section 2 provides the theoretical background, analytical framework, and hypotheses. Section 3 describes the data, variables, and analysis. Section 4 then presents and discusses the results. In Section 5, we conclude and outline policy implications, the study's limitations, and suggestions for future research.

2. Conceptual framework and hypotheses

2.1. Background

Manufacturing firms face increasing pressure to play an active role in mitigating climate challenges. EE innovation is one of the main mechanisms that firms can adopt to pursue this objective and both gain and sustain competitive advantage (Porter and Vanderlinde, 1995; Trianni et al., 2013a). However, research has identified numerous economic, organisational, and behavioural barriers to EE innovation in manufacturing firms (Backlund et al., 2012; Cagno et al., 2013; Sorrell et al., 2011). Furthermore, economists recognise several market failures (Gillingham et al., 2009; Rennings, 2000; Sorrell et al., 2011), causing the diffusion of energy-efficient products to be slower than socially optimal (Jaffe and Stavins, 1994). In particular, the significance of information, and the lack of such, before making EE innovation investments decisions is theoretically well documented (Cooremans, 2011; Gillingham and Palmer, 2014; Sorrell et al., 2011) and empirically demonstrated (Cagno et al., 2017; Kounetas et al., 2011; Wohlfarth et al., 2017). These barriers and market failures imply that technology and market factors insufficiently incentivise EE innovation (Gillingham et al., 2009; Rennings, 2000; Sorrell et al., 2011), and highlight the need for energy policies and regulation to achieve social optimal EE innovation. This has driven governments worldwide to implement numerous policies and measures (Abdelaziz et al., 2011; Tanaka, 2011). Voluntary programmes are particularly abundant, with energy information provision and audit consultancies playing a central role (Abadie et al., 2012; Johansson and Thollander, 2018; Kounetas et al., 2011).

Although the need for external information is acknowledged, firms seem to encounter difficulties in assimilating and fully exploiting such information (Apeaning and Thollander, 2013; Johansson and Thollander, 2018; Trianni et al., 2013a). In fact, when studying industrial energy audit programmes, Anderson and Newell (2004) found that firms adopted only about half of audit recommendations. Scholars have also identified a lack of common understanding between governmental and industrial organisations about the most prominent drivers of and barriers to EE (Cagno et al., 2015b), and that policies tend to ignore firms' needs and capabilities (Kounetas et al., 2011). Consequently, this suggest than energy programmes might not be properly designed according to firms' competence levels and needs and address a need for better understanding how firm characteristics influence EE innovations.

2.2. Absorptive capacity and EE innovation in manufacturing firms

In the innovation literature, it is widely recognised that a firm's innovation performance is closely tied to its knowledge accumulation capabilities (Forés and Camisón, 2016; Lööf and Heshmati, 2002; Vinding, 2006). A comprehensive contribution in this regard is the concept of absorptive capacity (Cohen and Levinthal, 1990; Zahra and George, 2002), which concerns the importance of external knowledge for innovation, and posits the ability to evaluate and utilise external knowledge as largely a function of the level of prior related knowledge. Indeed, firms with relevant prior knowledge are likely to better understand information about novel technologies for generating new products, services, and processes (Tsai, 2001), which is relevant for the adoption of EE technologies (Gerstlberger et al., 2016). In addition, a firm can accumulate its knowledge through internal knowledge creation and externally available information (Cohen and Levinthal, 1990; Forés and Camisón, 2016).

Thus, a firm's innovative performance depends on both internal and external knowledge sources (De Marchi and Grandinetti, 2013; Forés and Camisón, 2016). The firm's internal knowledge is embedded within the human capital of individuals and the organisational capital of the business. Human capital comprises the knowledge, skills and abilities residing in and utilised by individuals, whereas organisational capital is the institutionalised knowledge and codified experience residing in and utilised through databases, patents, manuals, structures, systems, and processes (Stefania and Christian, 2015; Subramaniam and Youndt, 2005; Vinding, 2006). Examples of external knowledge can be accessed through different market transactions (Palm and Thollander, 2010). However, the more tacit the knowledge (Leonard and Sensiper, 1998), the greater the need for closer external relationships to transfer the information (Vinding, 2006). In this regard, a firm's absorptive capacity also depends on cooperation strategies and how the knowledge is transferred across organisations (Stefania and Christian, 2015; Subramaniam and Youndt, 2005). Thus, to better understand how to overcome the information barrier and improve energy policies, this paper builds on the theory of absorptive capacity and by analysing firm knowledge characteristics relevant to EE innovation.

2.2.1. Prior knowledge and EE innovation

A firm's prior knowledge base is strongly related to its employees and their individual skills (Subramaniam and Youndt, 2005; Vinding, 2006), the latter referring to their level of education, training, and experience (Vega-Jurado et al., 2008). Higher-educated staff seem more receptive to assimilating and transforming available knowledge, leading to greater innovations (Smith et al., 2005; Vinding, 2006) and higher productivity (Haltiwanger et al., 1999). Studies indicate that industries with highly educated employees are less sensitive to barriers to EE investment (Sardianou, 2008), and that competence-enhancing activities positively influence such investments (Cagno et al., 2015a; Svensson and Paramonova, 2017; Trianni et al., 2016a). In other words, companies with highly educated and trained employees seem to have higher levels of absorptive capacity and innovative capabilities, and we predict:

H1. Prior knowledge is positively related to manufacturing firms' EE innovation.

2.2.2. Internal knowledge development and EE innovation

Internal knowledge creation is commonly measured through R&D activities (Arundel and Kemp, 2009; Cohen and Levinthal, 1990), and has traditionally been considered a determinant of absorptive capacity (Vinding, 2006). Internal R&D is an organisational process in which firms access and utilise the knowledge of individual members. These activities not only generate new knowledge but also contribute to developing the firm's innovative capabilities (Grant, 1996; Horbach, 2008).

However, research is inconclusive on the link between internal R&D and EE innovation. Studies in Colombia (Martínez, 2010), Spain (Costa-Campi et al., 2015), and Germany (Horbach et al., 2012), do not provide statistically significant evidence that internal R&D impacts manufacturing firms' investments in EE. However, higher investments in R&D relative to sales (Rennings and Rammer, 2009), strong participation of R&D departments (Rennings et al., 2006), and continuous internal R&D activities (De Marchi, 2012) have all been found to be positively associated with EE. Cagno et al. (2015a) find that firms combining internal R&D with purposive knowledge inflows have lower perceived barriers to efficiency improvements, increase their adoption of available technologies, and improve their EE. Congruently, Martin et al. (2012) contend that firms which have already picked the 'low-hanging fruit' must invest in R&D to further improve their EE. In the light of these research findings, we propose the following hypothesis:

H2. Internal knowledge development is positively related to manufacturing firms' EE innovation.

2.2.3. External knowledge cooperation and EE innovation

Several studies suggest that firms do not consider EE innovation as a part of their core business (Harris et al., 2000; Rudberg et al., 2013; Sardianou, 2008; Sathitbun-anan et al., 2015), and thus not among their core competences (Teece et al., 1997). Consequently, EE is overlooked by management (Harris et al., 2000), employees focus their attention on daily production issues (Sardianou, 2008), and energy-related revenues are neglected (Rudberg et al., 2013; Sathitbun-anan et al., 2015). This findings suggest that firms' are dependent on inflow of external knowledge, and openness to external knowledge sources in order to stimulate their EE innovativeness (Cagno et al., 2015a).

External knowledge can be accessed through written sources such as journals and magazines, conferences, consultants, and cooperation (Palm and Thollander, 2010). However, introducing new innovations might require knowledge that is firm-specific, tacit, and not easily exchanged through market transactions (Grant, 1996; Kogut and Zander, 1992). Under such circumstance, it is found to be more efficient to develop closer relationships and strengthen the information channels (Vinding, 2006). As such, learning networks and strategic alliances provide opportunities to access, and facilitate the transfer of knowledge embedded in other firms (Inkpen and Tsang, 2005; Powell et al., 1996; Sampson, 2007). EE innovative firms are found to jointly develop new projects, and both explore and exploit synergies by using networks (Costa-Campi et al., 2015; Johansson, 2015; Trianni et al., 2013b). Moreover, cooperation may reduce a firm's need for internal R&D (De Marchi, 2012), and lower its transaction costs and risks (Kounetas and Tsekouras, 2008; Venmans, 2014), as well as compensate for internal resource limitations (Trianni et al., 2013b). In light of this research, we propose the following hypothesis:

H3. External knowledge cooperation is positively related to firms' EE innovation.

2.2.4. Interaction effect of knowledge sources of EE innovation

The firm's ability to link internal knowledge to that generated outside the organisation is considered one of the conditions for realising innovation activity (Albort-Morant et al., 2018; Vinding, 2006), and a premise of the notion of absorptive capacity (Cohen and Levinthal, 1990). It is argued that the impact of absorptive capacity on innovation performance is higher in contexts characterised by high market uncertainties and technological turbulence (Lichtenthaler, 2009). The market and technological uncertainties that characterise many EE technologies (Venmans, 2014) suggest that complementarities between internal knowledge and external cooperation are essential for EE innovations. Several contributions to the general innovation literature support this complementarity argument (Cassiman and Veugelers, 2006; Forés and Camisón, 2016; Subramaniam and Youndt, 2005). Prior research in EE innovation supports the criticality of prior knowledge (section 2.2.1.) and external knowledge cooperation (section 2.2.4). However, besides a few studies indicating an interrelation effect between these variables (Cagno and Trianni, 2013; Chai and Yeo, 2012), empirical evidence of this phenomenon is scarce in the EE literature. Nevertheless, building on insights from the innovation literature, we here hypothesise:

H4. The interaction-effect of knowledge sources is positively related to firms' EE innovation.

2.2.5. Control variables: motivational factors and firm size

Research on the drivers of EE innovation in manufacturing firms indicates the relevance of various motivational factors, firm size, and sector characteristics (May et al., 2017; Solnørdal and Foss, 2018). Empirical studies show that firms are sensitive to increased energy prices, which might affect their competitiveness (Conrad, 2000; Thollander et al., 2013; Venmans, 2014). Hence, the reduction of energy use and related energy costs are strong motives for increased EE (e.g.: Anderson et al., 2004; Brunke et al., 2014; Cagno et al., 2015b; Thollander et al., 2013). The literature also implies that industrial EE is strongly motivated by environmental objectives (Costa-Campi et al., 2015). Relatedly, proactive energy-efficient firms are recognised by long-term environmental strategies (Brunke et al., 2014), managers' awareness of environmental issues (Kostka et al., 2013; Zilahy, 2004), and their involvement in EE projects (Apeaning and Thollander, 2013). Finally, the EE literature has identified a positive relationship between firm size and EE (Costa-Campi et al., 2015; Kounetas et al., 2011; Trianni et al., 2016b). The significance of size may be attributable to larger firms' exposure to higher energy costs (Ru and Si, 2015) and better access to the resources necessary to engage in EE projects, such as competences, organisational slack, networks and capital (DeCanio, 1998; Kounetas et al., 2011; Trianni and Cagno, 2012; Trianni et al., 2013a). Hence, this study controls for cost-savings objective, public subsidies, environmental objectives, and firm size.

Research on the determinants of EE innovation also points to the impact of sectorial differences (Palm and Thollander, 2010). Sector characteristics are in this paper accounted for using industry-specific dummies in Model 1a. Moreover, since it is assumed that energy-intensive firms are more willing and able to pursue EE innovation than non-energy intensive firms (Boyd and Curtis, 2014; Cagno et al., 2017; Costa-Campi et al., 2015; Trianni et al., 2016a), the model is analysed separately for energy-intensive and non-energy-intensive sectors, as respectively presented in Models 1b and 1c. The classification follows the Norwegian Water Resources and Energy Directorate report (NVE, 2013), which shows that, over several years, sectors 17, 20, 23, and 24 have consistently been considerably more energy intensive than other sectors. Energy intensity is calculated as energy consumption in kWh divided by net sales of production.

Fig. 1 illustrates the proposed models for analysing the relations between absorptive capacity and EE innovation in manufacturing firms. Model 1 analyses the direct relationship between the explanatory variables and EE innovation, while Model 2 includes the interaction effect of different knowledge sources.

3. Methodology

The data used in this analysis were collated from the Norwegian CIS and the Business Enterprise R&D surveys for the period 2010–2014. All data were collected by Statistics Norway (SSB), and every Norwegian firm with more than 50 employees, as well as a representative sample of firms with less than 50 employees, participated in the surveys. As the Norwegian Statistics Act stipulate firms' obligation to provide information in SSB surveys, the response rate was high (> 95%), thus eliminating concerns of non-response bias. The panel dataset consists of manufacturing firms (sectors 10–32[1]).

The dataset comprises of 6,021 observations from 2,933 firms, and consists of both innovative and non-innovative firms. In the analysis, we only consider innovative firms. To control for possible selection bias occurring from the exclusion of non-innovative firms, we apply a two-stage logit model (De Marchi, 2012; Vega-Jurado et al., 2009). In the first stage, the probability of a firm becoming an innovator (*PrINNOVATION*) is estimated by regressing the variable *INNOVATION*, a dichotomous variable indicating if the firm introduced any product or process innovation in the period of 2010–2014, on several variables measuring exogenous obstacles to innovation for both innovative and non-innovative firms. The variables measuring obstacles to innovation are lack of external financial sources (*HFOUT*), if it was hard to find cooperation partners for innovation (*HPAR*), and if there was lack of demand for innovation (*HMAR*). In addition, number of employees (*SIZE)*, and industrial sector dummies are included as explanatory variables. The results from the first-stage logit regression are presented in table A1, Appendix A. After the non-innovative firms are removed from the dataset, the dataset comprises 5,336 observations from 2,340 firms. Our sample comprises of 226 observations from 128 firms reporting EE innovation in one or more years in the study period.

The sectoral distribution of innovative firms is presented in Table 1. The four most prominent innovative sectors are sector 10–12 (20%); sectors 30–32 (13%); sector 28 (11%); and sector 25 (8%). However, those most prominent in pursuing EE innovation are sectors 27 (13%), sector 28 (13%), sector 24 (13%), and sector 19–21 (13%). This suggests that high innovative behaviour in a sector does not necessarily signify high engagement in EE innovation.

The dependent variable in our analysis is EE innovation, represented by IE_{it}. It is generated based on the questionnaire item about R&D investments in 'other environmental energy: energy saving, energy efficiency, energy systems, environmentally friendly transport, etc'. IE_{it} is a dichotomous variable that equals 1 if firm i reports such investments at time t, and 0 otherwise. R&D investment is commonly used as a measure for innovation (Jaffe and Palmer, 1997). By considering investments in EE R&D, we can identify the characteristics of firms that have actually invested in EE, thereby avoiding the partial observability cases discussed by (Poirier, 1980). Our explanatory variables are designed according to the hypotheses and control variables detailed in section 2.2; full definitions are presented in Table A2, Appendix A.

Table 2 reports descriptive statistics for the explanatory variables. It shows that when comparing firms pursuing EE innovation with other innovative firms, there are significant differences at the 5% level for all explanatory variables except *RDPROD*. This implies that, on average, there is a significant difference in the characteristics of firms that pursue in EE innovation compared to other innovative firms.

Since the dependent variable is dichotomous, a logit regression model was used to estimate Equation (1) in Stata version 15:

$$\begin{aligned} p(IE_{it}) = \Lambda(&\beta_1 + \beta_2 HDSHRE_{it} + \beta_3 DRSHRE_{it} + \beta_4 COOPCUS \\ &+ \beta_5 COOPSUP_{it} + \beta_6 COOPCOMP_{it} + \beta_7 COOPCONST_{it} \\ &+ \beta_8 COOPUNIS_{it} + \beta_9 ENVPUR_{it} + \beta_{10} MATPUR_{it} + \beta_{11} LSIZE_{it} \\ &+ \beta_{12} RDPROD_{it} + \beta_{13} SHRRD_{it} + \beta_{14} PUBLFUN_{it} + \alpha_i + \mu_{it}) \end{aligned} \tag{1}$$

$\beta_1 - \beta_{14}$ are the estimated parameters, α_i is an unobserved time invariant individual effect, and μ_{it} is a zero-mean residual. In the study period, most firms in our sample do not report EE innovation while some report EE innovation at every year in our study period. Thus, using a fixed-effects model would result in the loss of 2,244 firms (4,922 observations), which is around 95% of the firms in our sample. We therefore employ a random-effects model in this study. Not all firms are represented in every year of our study period, making our panel unbalanced. The logit model was used because the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) indicated that it was more suitable than the probit model, and, when testing, the probit model produced similar results to those presented in the paper. To control for heteroscedasticity, the model is run with cluster-robust standard errors. We include *PrINNOVATION* from the first-stage logit regression as an explanatory variable to control for possible selection bias by including the effects of firms that did not innovate (De Marchi, 2012).

The analysis of Norwegian CIS and BERD data is useful to gain insights based on a large number of observations, however it has also some limitations. The first concerns how the dataset was sourced. Since the Norwegian CIS and BERD surveys collect self-reported data from firms, the reported investments of EE and R&D depend on the respondents' understanding of the questions and their methods for estimating the requested data. Although both EE investments and R&D are commonly used measures for innovation, with the advantage of being objective and traceable, they pose the risk of measuring biases since neither R&D nor investments are guaranteed to produce innovations. Moreover, the dataset does not permit the fine-grained analysis of the various forms of R&D expenditures. In addition, the dependent variable used is a proxy that not allows distinguishing between firms that introduced just few EE innovations from other whose entire innovative effort is devoted toward EE innovations. Given these limitations, the findings should be understood as indications of the relationship between absorptive capacity and EE innovation in manufacturing firms.

4. Results and discussion

4.1. Model 1: direct impact of absorptive capacity on EE innovation

Equation (1) is estimated with all the sectors in the sample, presented in Model 1a (Table 3), as well as with subsamples of only energy intensive and non-energy intensive sectors, respectively presented in

[1] The EU NACE rev.2 and UN ISIC standards are basis for the Norwegian Standard Industrial Classification (SIC, 2007).

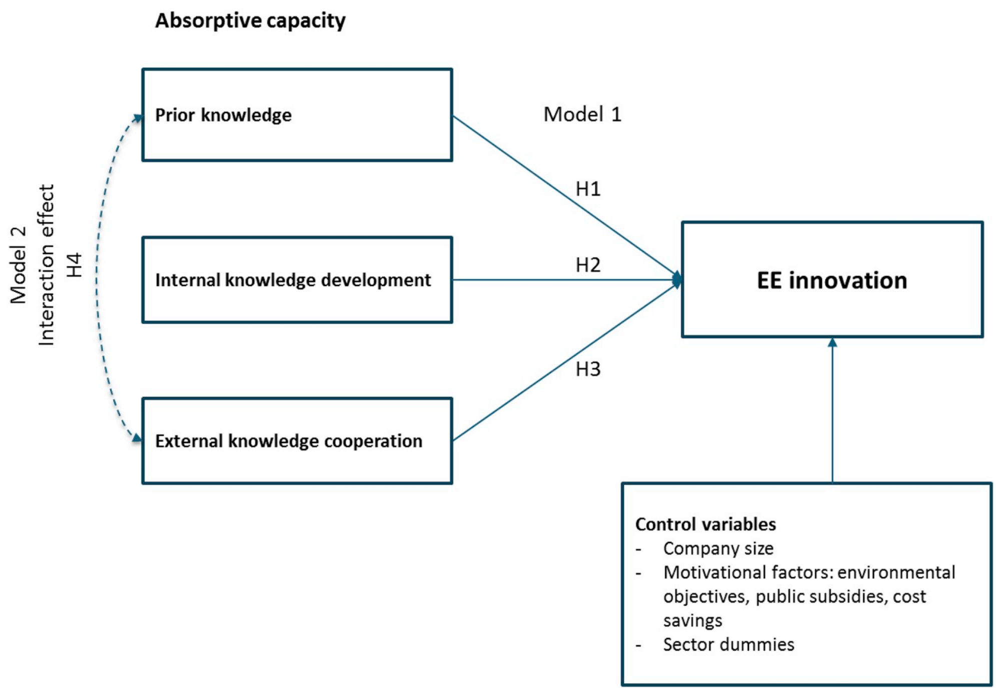

Fig. 1. Analytical framework and hypotheses.

Table 1
Manufacturing sectors and distribution of innovative firms and EE-innovators.

Sector code+ (SN 2007)	Industrial sector	Energy-intensive	Innovative firms		Energy efficiency innovators	
			Obs.	Percent*	Obs.	Percent*
10–12	Food, beverage, and tobacco	No	473 (1,017)	20% (19%)	9 (11)	7% (5%)
13–15	Textile, clothing, and leather	No	118 (279)	5% (5%)	1 (1)	1% (0%)
16	Wood and cork	No	166 (351)	7% (7%)	9 (14)	7% (6%)
17–18	Pulp and paper, printing	Yes	94 (228)	4% (4%)	4 (5)	3% (2%)
19–21	Coal and refined petroleum products, chemicals, and pharmaceuticals	Yes	120 (345)	5% (6%)	13 (31)	13% (14%)
22	Rubber and plastic products	No	112 (224)	5% (4%)	4 (9)	3% (4%)
23	Other non-metallic mineral products	Yes	126 (279)	5% (5%)	12 (21)	9% (9%)
24	Metallurgy	Yes	62 (175)	3% (3%)	16 (33)	13% (15%)
25	Manufacture of fabricated metal products, except machinery and equipment	No	193 (473)	8% (9%)	9 (18)	7% (8%)
26	Manufacture of computer, electronic and optical products	No	131 (360)	6% (7%)	5 (8)	4% (4%)
27	Manufacture of electrical equipment	No	126 (259)	5% (5%)	16 (29)	13% (13%)
28	Machinery and mechanical equipment	No	246 (539)	11% (10%)	17 (28)	13% (12%)
29	Motor vehicles and trailers	No	80 (178)	3% (3%)	8 (12)	6% (6%)
30–32	Production of transport equipment, furniture, and other manufacturing industries	No	293 (629)	13% (12%)	5 (6)	4% (3%)
	SUM		2,340 (5,336)	100%	128 (226)	100%

*Percentages are calculated based on total innovative firms and total EE-innovators, respectively. The obs. column is number of firms, and number of observations in parentheses.
+Some related industries have been merged due to the small number of firms. There are no firms in industry 12 (Manufacture of tobacco products).

Models 1b and 1c (Table 4). The estimated parameters, odds ratios, and marginal effects are reported in Table 3. The variance inflation factor (VIF) is below 2.5 for each variable, and the mean VIF is 1.65, confirming that there are no issues with multi-collinearity.

H1 predicts that prior knowledge is positively related to firms' EE innovation. In Model 1a, the coefficients estimated for *HDSHRE* and *DRSHRE* are significant and positive. The average marginal effect shows that a 100% increase in staff members with a master's or PhD degree in the R&D department would, on average, increase the probability of EE innovation by 4.9% or 2.6%, respectively. The odds ratios are 12.48 for *HDSHRE* and 3.78 for *DRSHRE*, indicating that an R&D department with twice as many R&D staff members with a master's degree (PhD degree) is 12.48 (3.78) times more likely to pursue EE innovation. This result supports prior studies advocating the positive effect of education and staff training on EE innovation (Cagno and Trianni, 2013; Sardianou, 2008), and suggests a positive relationship between education and EE innovation. Even though our analysis denote a statistical relationship between education and EE innovation, one must exercise caution when interpreting the causal effect of education on EE innovation. In fact, Haltiwanger et al. (1999) found that while workers' educational level was significantly related to firms' productivity, the changes in productivity could not be explained by changes in workers' education level. Thus, our result might reflect that EE innovative and high-productivity firms have more skilled workers (Sardianou, 2008), or that higher educated employees influence their firms' strategies and EE innovative behaviour (Tonn and Martin, 2000), or a combination of the two.

H2 posits that internal knowledge development is positively related

Table 2
Descriptive statistics.

Explanatory variables		Innovative firms (excl. EE)		EE-innovators	
Variable	Variable description	Mean	SD	Mean	SD
HDSHRE	Level of individual competence in R&D department	0.13	0.27	0.32	0.31
DRSHRE	Level of individual research competence in R&D department	010	0.24	0.21	0.29
RDPROD	R&D investment per employee	56.38	225.77	81.71	127.05
SHRRD	R&D capacity	0.06	0.15	0.10	0.15
COOPCUST	Cooperation with customers	0.17	0.37	0.41	0.49
COOPSUP	Cooperation with suppliers	0.18	0.39	0.43	0.50
COOPCOMP	Cooperation with competitors	0.06	0.24	0.19	0.40
COOPCONS	Cooperation with consultants	0.12	0.32	0.26	0.44
COOPUNIS	Cooperation with universities	0.17	0.38	0.50	0.50
ENVPUR	Environmental motivation	0.39	0.49	0.71	0.46
MATPUR	Economic motivation	0.45	0.50	0.73	0.44
PUBLFUN	Public funding	0.22	0.41	0.54	0.50
LSIZE	Company size	3.79	1.23	4.75	1.22
PrINNOVATION	Probability of being an innovator	0.76	0.16	0.87	0.12
HDDR	Firms with R&D staff with master's or PhD degree	0.34	0.47	0.83	0.37

Table 3
Estimated parameters, odds ratios, and average marginal effects of logit regression. Dependent variable: EE innovation.

Hypothesis	Variables	(1a) Total		
		Coef.	Odds ratios	AME
H1:	HGSHRE	2.524*** (0.000)	12.477 *** (0.000)	0.049*** (0.000)
	DRSHRE	1.329*** (0.009)	3.776*** (0.009)	0.026 *** (0.008)
H2:	RDPROD	−0.000 (0.712)	1.000 (0.712)	−0.000 (0.713)
	RDSHRE	2.525** (0.012)	12.490** (0.012)	0.049** (0.013)
H3:	COOPCUST	−0.336 (0.408)	0.714 (0.408)	−0.007 (0.407)
	COOPSUP	0.305 (0.373)	1.356 (0.373)	0.006 (0.374)
	COOPCOMP	0.712* (0.051)	2.038* (0.051)	0.014* (0.051)
	COOPCONS	−0.421 (0.254)	0.657 (0.254)	−0.001 (0.254)
	COOPUNIS	0.990*** (0.010)	2.692*** (0.010)	0.019*** (0.010)
Controls:	LSIZE	0.790*** (0.000)	2.204*** (0.000)	0.015*** (0.000)
	ENVPUR	0.841*** (0.007)	2.320** (0.007)	0.016** (0.007)
	MATPUR	0.334 (0.325)	1.397 (0.325)	0.007 (0.325)
	PUBLFUN	0.628* (0.052)	1.874* (0.052)	0.012** (0.053)
	PrInnovation	1.745 (0.272)	5.727 (0.272)	0.034 (0.274)
	Constant	−14.871*** (0.000)	0.000*** (0.000)	
Sector dummies	IND13-15	−0.053 (0.971)	0.949 (0.971)	−0.001 (0.971)
	IND16	2.911*** (0.000)	18.379*** (0.000)	0.056*** (0.000)
	IND17-18	1.305 (0.162)	3.686 (0.162)	0.025 (0.164)
	IND19-21	1.679** (0.047)	5.361** (0.047)	0.033** (0.047)
	IND22	1.998** (0.031)	7.376** (0.031)	0.039** (0.031)
	IND23	3.114*** (0.000)	22.530*** (0.000)	0.061*** (0.000)
	IND24	4.283*** (0.000)	72.587*** (0.000)	0.084*** (0.000)
	IND25	2.423*** (0.004)	11.279*** (0.004)	0.047*** (0.004)
	IND26	−0.132 (0.896)	0.876 (0.896)	−0.003 (0.896)
	IND27	3.807*** (0.000)	45.028*** (0.000)	0.074*** (0.000)
	IND28	2.116*** (0.006)	8.299*** (0.006)	0.041*** (0.006)
	IND29	3.180*** (0.000)	24.050*** (0.000)	0.062*** (0.000)
	IND30-32	−0.139 (0.880)	0.871 (0.880)	−0.003 (0.880)
Observations (groups)		5,336 (2,340)	5,336 (2,340)	5,336 (2,340)

*, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively. AME denotes average marginal effects. P-values in parentheses. Regression is run with cluster robust standard errors. The sector variable IND-10-12 are in the basis.

to firms' EE innovation. The result is not significant for *RDPROD* but significant for *SHRRD*. This indicates that the share of human resources allocated to R&D positively affects EE innovation, while the effect of financial resources allocated to R&D is not identified. The average marginal effects suggest that an increase of 100% in R&D employees would, on average, increase the probability of pursuing EE innovation by 4.9%. Finding that *RDPROD* is not significant contradicts our hypothesis but reflects the inconsistent results in the literature regarding this variable's impact on EE innovation. RDPROD is measured here as the sum of investments in R&D, including wages, infrastructure, and other costs, whereas other studies have considered the various investments as separate variables (Horbach et al., 2012; Martínez, 2010), assessed the continuity of R&D activities (De Marchi, 2012), or analysed the participation of the R&D department in the innovation process (Rennings et al., 2006). This heterogeneity in measuring R&D might explain why little consensus has been reached on the influence of internal R&D on EE innovation.

Hypothesis H3 predicts that external knowledge cooperation is

Table 4
Estimated parameters, odds ratios, and average marginal effects for energy-intensive and non-energy-intensive sectors.

Variables	(1b) Energy-intensive			(1c) Non-Energy-intensive		
	Coef.	Odds ratios	AME	Coef.	Odds ratios	AME
HGSHRE	2.881*** (0.005)	17.826*** (0.005)	0.094 *** (0.001)	2.550*** (0.000)	12.812*** (0.000)	0.0389*** (0.000)
DRSHRE	1.826* (0.089)	6.211** (0.089)	0.058 *** (0.048)	1.200** (0.045)	3.320** (0.045)	0.018** (0.049)
RDPROD	−0.001 (0.563)	0.999 (0.563)	−0.000 (0.635)	0.000 (0.890)	1.000 (0.890)	0.000 (0.890)
RDSHRE	6.698*** (0.001)	811.012*** (0.001)	0.226*** (0.009)	1.322 (0.336)	3.751 (0.336)	0.020 (0.337)
COOPCUST	−0.468 (0.426)	0.626 (0.426)	−0.015 (0.415)	−0.139 (0.780)	0.871 (0.780)	−0.002 (0.780)
COOPSUP	0.421 (0.481)	1.523 (0.481)	0.014 (0.487)	0.009 (0.986)	1.009 (0.986)	0.000 (0.986)
COOPCOMP	0.340 (0.542)	1.405 (0.542)	0.010 (0.606)	0.885* (0.070)	2.424* (0.070)	0.013* (0.070)
COOPCONS	−0.342 (0.591)	0.711 (0.591)	−0.011 (0.573)	−0.344 (0.468)	0.709 (0.468)	−0.005 (0.466)
COOPUNIS	1.151* (0.093)	3.162** (0.093)	0.038** (0.076)	0.969** (0.048)	2.634** (0.048)	0.015* (0.046)
LSIZE	1.734*** (0.000)	5.663*** (0.000)	0.056*** (0.000)	0.462** (0.026)	1.587** (0.026)	0.007** (0.027)
ENVPUR	0.753 (0.314)	2.124 (0.314)	0.025 (0.294)	0.842** (0.032)	2.321** (0.032)	0.013** (0.034)
MATPUR	0.221 (0.784)	1.248 (0.784)	0.007 (0.778)	0.282 (0.468)	1.326 (0.468)	0.004 (0.467)
PUBLFUN	−0.982 (0.109)	0.375 (0.109)	−0.033* (0.093)	1.344*** (0.001)	3.836*** (0.001)	0.020*** (0.001)
Constant	−11.978*** (0.000)	0.000*** (0.000)		−14.656*** (0.000)	0.000*** (0.000)	
IND13-15	Omitted	Omitted	Omitted	−0.433 (0.788)	0.649 (0.788)	−0.007 (0.788)
IND16	Omitted	Omitted	Omitted	2.854*** (0.001)	17.362*** (0.001)	0.043*** (0.001)
IND17-18	−3.243*** (0.004)	0.039*** (0.004)	−0.105*** (0.004)	Omitted	Omitted	Omitted
IND19-21	−2.06** (0.022)	0.127** (0.022)	−0.071** (0.022)	Omitted	Omitted	Omitted
IND22	Omitted	Omitted	Omitted	1.642 (0.108)	5.164 (0.108)	0.025 (0.110)
IND23	−0.972 (0.182)	0.378 (0.182)	−0.033 (0.245)	Omitted	Omitted	Omitted
IND25	Omitted	Omitted	Omitted	2.361*** (0.007)	10.604*** (0.007)	0.036*** (0.007)
IND26	Omitted	Omitted	Omitted	−0.599 (0.584)	0.549 (0.584)	−0.009 (0.582)
IND27	Omitted	Omitted	Omitted	3.515*** (0.000)	33.613*** (0.000)	0.054*** (0.000)
IND28	Omitted	Omitted	Omitted	1.909** (0.014)	6.745** (0.014)	0.029** (0.015)
IND29	Omitted	Omitted	Omitted	2.932*** (0.004)	18.769*** (0.004)	0.045*** (0.004)
IND30-32	Omitted	Omitted	Omitted	−0.077 (0.934)	0.925 (0.934)	−0.001 (0.934)
Observations (groups)	1,027 (402)	1,027 (402)	1,027 (402)	4,309 (1,940)	4,309 (1,940)	4,309 (1,940)

*, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively. AME denotes average marginal effects. P-values in parentheses. Regression is run with cluster robust standard errors. The sector variable IND 24 are in the basis for model 1b, and IND-10-12 are in the basis for model 1b.

positively related to EE innovation. Both *COOPUNIS* and *COOPCOMP* are found to be significant and positive. The average marginal effects for *COOPUNIS* show that cooperation with universities and private and public research institutions (henceforth universities) increases the probability of pursuing EE innovation by 1.9%, and the odds ratio of 2.69 indicates that the odds for pursuing EE innovation are more than two and a half times higher for firms that cooperate with universities. The positive effect of cooperation with knowledge institutions is supported by prior research (Miah et al., 2015; Tonn and Martin, 2000). The finding might also reflect that environmental innovations are knowledge-demanding (De Marchi and Grandinetti, 2013; Horbach et al., 2013), and that external cooperation can compensate for internal resource scarcity (Trianni et al., 2013b), and reduces transaction costs and risk (Kounetas and Tsekouras, 2008; Venmans, 2014). The analysis also suggest that cooperation with competitors increases the probability of pursuing EE innovation by 1.4%, with an odds ratio of 2.04 indicating that the odds of pursuing EE innovation are twice as big for firms cooperating with competitors. However, Lööf and Heshmati (2002) and Belderbos et al. (2006) found that cooperation with competitors and research institutions has a generally positive effect on innovations, and our study propose this for EE innovation.

The analysis finds no significant effects for *COOPCUST*, *COOPSUP,* or *COOPCONS*. The limited importance of customers for EE innovation is also identified in previous studies (Ozoliņa and Roša, 2013). However, the identified lack of significance for cooperation with suppliers and consultants is more intriguing. This finding contradicts prior research on the topic, which identifies the relevance of consulting energy service consultancy organisations (Chai and Yeo, 2012; Sandberg and Söderström, 2003) and cooperation with technology suppliers and installers, and other experts (e.g. Rennings and Rammer, 2009; Trianni et al., 2016a).

The control variables assess motivational factors affecting the decision to pursue EE innovation. The estimated coefficients for *LSIZE, PUBLFUN* and, *ENVPUR* are all positive and statistically significant. Larger firms appear more likely to pursue EE innovation, with a 1% increase in the number of employees associated with a 0.015% rise in the probability of pursuing EE innovation. Further, receiving public investment subsidies increases the probability of pursuing EE innovation by 1.2%. The findings also show that firms pursuing EE innovation are more motivated by environmental objectives than other innovative manufacturing firms, and if the environmental purpose is of high or medium importance, then the probability of pursuing EE innovation rises by 1.6%. However, the estimated coefficient for *MATPUR* is not significant, implying that the motive for cost savings is equally important for both innovative manufacturing firms and firms pursuing EE innovation. The sector dummies, *IND12-IND30*, reveal sectorial differences in pursuing EE innovation.

The results from Models 1b and 1c is presented in Table 4 and suggest differences between the energy-intensive and non-energy-intensive sectors. For instance, cooperation with competitors only positively influences EE innovation in non-energy-intensive firms, while the share of employees in the R&D department is only significant for energy-intensive firms. Considering the motivational factors, non-energy-intensive firms are motivated by both environmental objectives and public funding, whereas public funding negatively affects EE innovation in energy-intensive firms.

Several studies have investigated the sectorial impact on firms pursuing EE innovation, and the findings are inconclusive (Solnørdal and Foss, 2018). This paper adds to the studies that identifies sectorial differences, but several other studies find no or little evidence of sectorial impact. Therefore, further empirical work is required to identify potential causes for how and when the structural effect of industrial sector affects EE innovation.

4.2. Model 2: interaction effect of knowledge sources of EE innovation

Hypothesis H4 posits an interaction effect between prior knowledge and knowledge cooperation that is positively related to EE innovation. Thus, Equation (2) examines the interaction effect between the variables education level *(HDDR)* and cooperation (*COOPCOMP and COOPUNIS*), which was found to be significant in Model 1a. The following equation is estimated:

$$p(IE_{it}) = \Lambda(\delta_1 + \delta_2 COOPCUS + \delta_3 COOPSUP_{it} + \delta_4 COOPCONS_{it} + \delta_5 ENVPUR + \delta_6 ENVPUR_{it} + \delta_7 MATPUR_{it} + \delta_8 LSIZE_{it} + \delta_9 RD_{it} + \delta_{10} SHRRD_{it} + \delta_{11} PUBLFUN_{it} + \delta_{12}(HDDR_{it} \times COOPCOMP_{it}) + \delta_{13}(HDDR_{it} \times COOPUNIST_{it}) + \alpha_i + \mu_{it}) \quad (2)$$

Some studies warn against estimating interaction effects in non-linear models (Ai and Norton, 2003; Allison, 1999). However, as Kuha and Mills (2018) note, the need for caution depends on whether the model of interest is the continuous latent variable of Y^* or the underlying observed binary response of Y. In the latter case, the group comparison problem disappears. In this study, the model of interest is whether innovative manufacturing firms are pursuing EE innovation. Since this is the binary response of Y, we believe that group comparison is appropriate in this context.

Table 5 depicts the coefficients and odds ratios for the estimated parameters of Model 2. The results show a significant and positive interaction effect between higher education and cooperation with both competitors and universities.

Following the procedure proposed by Buis (2010), we estimate the multiplicative and marginal effects of the interaction between *HDDR* and cooperation with competitors, as well as the interaction between *HDDR* and cooperation with universities; these results are presented in Table 6.

For firms whose R&D department employees do not have a higher education degree, cooperation with competitors or universities is not associated with more EE innovation. However, for firms whose R&D staff have a higher education degree, cooperation with competitors and universities increases the probability of pursuing EE innovation by 4.0% and 2.9%, respectively. These findings indicate that EE innovation are likely to be highest where staff have a higher education degree *and* the firm cooperates with competitors or universities.

This result reinforces a study by Subramaniam and Youndt (2005)

Table 5
Estimated parameters and odds ratios of Equation (2).

Variables	Coef.	Odds ratio	P-value
RDPROD	0.000	0.999	0.884
RDSHRE	0.501	7.949	0.648
COOPCUST	−0.385	0.731	0.278
COOPSUP	0.200	1.060	0.584
COOPCONS	−0.531	0.782	0.130
LSIZE	0.698***	2.092	0.000
ENVPUR	0.811**	2.207	0.013
MATPUR	0.185	1.186	0.573
PUBLFUN	0.251	1.109	0.398
HDDR	3.647***	32.492	0.000
COOPCOMP	−0.248	0.461	0.844
COOPUNIS	2.931***	21.284	0.001
HDDR x COOPCOMP	1.010	4.462	0.432
HDDR x COOPUNIS	−2.038**	0.123	0.024
BASELINE	−12.517***	0.000	0.000

*, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively. Regression is run with cluster robust standard errors.

Table 6
Multiplicative and marginal effects of interaction between *HDDR* and external cooperation.

(***HDDR*** × ***COOPCOMP***)	Multiplicative effects	Marginal effects
HDDR = 0, COOPCOMP = 0	0.000 (0.106)	
HDDR = 0, COOPCOMP = 1	0.001 (0.358)	0.001 (0.448)
HDDR = 1, COOPCOMP = 0	0.014*** (0.003)	
HDDR = 1, COOPCOMP = 1	0.054** (0.015)	0.040 (0.043)
HDDR = 0, COOPUNIS = 0	0.000 (0.119)	
HDDR = 0, COOPUNIS = 1	0.002 (0.171)	0.002 (0.182)
HDDR = 1, COOPUNIS = 0	0.007*** (0.008)	
HDDR = 1, COOPUNIS = 1	0.036** (0.003)	0.029*** (0.008)

*, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively. P-values in parentheses.

also identifying the positive interaction effect between organisations' human capital and cooperative abilities on innovative performance. This finding coheres with the theory of absorptive capacity, advocating the importance of prior knowledge for taking in new external knowledge and exploiting it for EE innovation.

5. Conclusion and policy implications

Increasing EE innovation in the manufacturing sector is essential to tackle the challenges of global warming. By applying absorptive capacity as a theoretical framework, this study has examined the relationship between knowledge characteristics and EE innovation in Norwegian manufacturing firms. The paper is motivated by the increasing importance of understanding the determinants of EE innovation in order to inform efficient energy policies. Following the theory of absorptive capacity, we adopted an analytical framework for selecting and separating the explanatory variables: prior knowledge, knowledge development, and external knowledge cooperation. The related hypotheses (H1-H4) were tested using logit random-effects models on a sample of innovative firms from the Norwegian manufacturing sector for 2010–2014. A two-stage logit model was applied to control for possible selection bias occurring from the exclusion of non-innovative firms. The direct effect of the explanatory variables is analysed in Model 1a-c (Tables 3 and 4), while their interaction effect is analysed in Model 2 (Tables 5 and 6). We also controlled for motivational factors, firm size, and sectors.

Hypotheses H1–H3 (Model 1a) are either fully or partly supported by our empirical analysis, indicating that prior knowledge, knowledge development, and external knowledge cooperation are positively related to EE innovation. The analysis also suggests that universities and competitors are particularly relevant for EE cooperation. Hypothesis H4 is also supported, suggesting that the interaction of higher education and external cooperation are leading firms to pursue EE innovation more extensively, compared to a situation characterised by either higher educated employees or external cooperation. Accordingly, the paper suggests that higher educated employees contribute to increase the firm's ability to effectively assimilate and exploit outside knowledge, and coheres with Cohen and Leventhal's (1990) assertion that individual and organisational absorptive capacities are cumulative. The suggested relevance of prior knowledge might contribute to explain why some firms (Camisón and Forés, 2011; Escribano et al., 2009) experience different levels of difficulties in exploiting external information about EE solutions (Anderson and Newell, 2004; Thollander et al., 2007; Tonn and Martin, 2000), and do not derive equal innovation performance (Camisón and Forés, 2011; Escribano et al., 2009). In this vein, the study's empirical results support the paper's initial argument that absorptive capacity is an antecedent for EE innovation in manufacturing firms.

These findings propose several interesting implications for policy, which are discussed in the following. The analysis suggest that universities play a prominent role for industrial EE innovation, as providers of both higher education and as cooperation partners. The indicated relationship between higher education and EE innovation implies that higher education programmes have a positive impact on firms' EE innovativeness. However, since the model only depict the statistical relationships, there are several plausible explanations for this finding. One can be that the innovative and high-productivity firms that consistently adopt the latest technology exhibit the most innovative workforce practices and have more skilled workers (Sardianou, 2008). Another explanation can be that employees with higher education influence the strategies and innovative behaviour of their firms (Tonn and Martin, 2000). Nonetheless, in both cases, firms targeting EE innovation seem to need a higher educated workforce. In this regard, it can be advisable that policymakers make available higher education and education welfare systems, stimulating the population to enter higher education.

In addition, universities also appear as important cooperation partners enhancing industrial EE innovation, since firms pursuing EE innovation seem to cooperate significantly more with universities than other innovative firms. There are indeed many benefits that can motivate firms to cooperate with universities for innovation (Ankrah and Al-Tabbaa, 2015; Tether, 2002). In particular, universities are important providers of technological know-how and expertise about EE solutions (Miah et al., 2015; Tonn and Martin, 2000). Prior research has also identified that differing institutional environments in academia and industry can create barriers for university-industry cooperation (Bruneel et al., 2010). Nonetheless, prior collaboration experience and breadth of interactions facilitates the transfer of knowledge between innovation partners, and can help to overcome this barrier (Bruneel et al., 2010; Inkpen and Tsang, 2005; Steinmo and Rasmussen, 2018). Thus, in order to stimulate industrial EE innovation, it can be advisable to design policy programmes facilitating learning networks and encourage the development of university-industry cooperation platforms where industry and universities can meet at regularly basis.

Furthermore, the study suggests there is an interaction between higher educated workforce and collaboration with universities that accelerate firms' pursuit of EE innovation. The literature emphasise the importance of prior experience for overcoming barriers for university-industry collaboration (Bruneel et al., 2010). However, EE innovations can represent a technological frontier on which firms are more inexperienced, and thus face the challenge of lacking prior cooperation experiences with relevant partners and experts. In such cases, employees' affiliation with universities from higher education can serve as relevant prior experiences (Steinmo and Rasmussen, 2018), creating necessary trust between the partners (Inkpen and Tsang, 2005). Moreover, the results of the analysis may reflect that higher education leads to greater EE innovation not only by improving the technical, cognitive and relational skills of employees, but also by developing a common knowledge platform (Smith et al., 2005), that permits university and industry to share more efficiently knowledge not previously common between them. In this way can higher education contribute to accelerate the effect of university-industry cooperation and increase the EE innovation output. Consequently, it can be recommendable that policies take in how firms with varying degrees of experience in cooperation with universities rely on different mechanisms to achieve successful cooperation with universities. This also imply that research cooperation should not only be evaluated in terms of their direct effect to EE innovation, but also by the development of the firms' absorptive capacity, which may form the basis for future collaborations.

The results also imply that cooperation with competitors contributes to increasing EE innovation in manufacturing firms. Cooperation with competitors is found to be suitable when they face common problems, considered as being outside the realms of competition such as e.g. the regulatory environments. It might also be motivated by firms' need for standard setting and encouragement of the market, which can be reluctant to take up a new technology when there is only one provider (Tether, 2002), and when prevailing system act as a barrier to the creation and diffusion of a new EE system. Nevertheless, Ritala and Hurmelinna-Laukkanen (2013) find that firms' engagement in cooperation with competitors depends on the firms' absorptive capacity and ability to protect its core knowledge and innovations against imitation. Given that several firms report that EE innovations is not a part of their core competence (Harris et al., 2000; Rudberg et al., 2013; Sardianou, 2008; Sathitbun-anan et al., 2015), it might thus seem like EE innovations is particularly appropriate for cooperation with competitors. This imply that firms might improve their EE innovativeness by both increasing their absorptive capacity and disregard the traditional skepticism about cooperating with competitors. To achieve this visionary coordination of policies, regulation and firm strategies are needed.

This study also controlled for firm size, industry sector, and three motivational factors: environmental objectives, public funding, and cost savings. We find that firm size generally has a positive effect on firms' willingness to pursue EE innovation, despite some sectorial variation. Furthermore, EE-innovative firms seem to be more motivated by environmental objectives than other innovative firms. The analysis also indicates that firms funded by public institutions are more willing to pursue EE innovation. However, the cost-savings motive is not found to have a significant effect, which might signal that cost-savings is equally important for all innovative firms. These findings suggests the relevance of policy programmes providing access to capital and raising environmental awareness.

The literature is inconsistent regarding the sectorial impact on industrial firms' pursue of EE innovations (Solnørdal and Foss, 2018), signalling the need for more research on the topic before conclusions can be drawn. In this study, some sectorial differences between energy-intensive and non-energy-intensive sectors (Models 1b and 1c) are observed. The results indicate that higher education, firm size, and cooperation with universities are the common factors linked to EE innovation in both sectors. Energy-intensive firms with a higher share of human resources allocated to R&D pursue EE innovation compared to other innovative firms in the same sector. On the other hand, the analysis signals that non-energy intensive firms pursuing EE innovation are encouraged by environmental motives, public funding and cooperation with competitors. This may be related to sectorial differences with respect to development: some sectors characteristically undertake in-house process development, while others depend more extensively on external knowledge (Wesseling and Edquist, 2018). These findings add to the ongoing discussion in the EE literature on sectorial differences (Boyd and Curtis, 2014; Cagno et al., 2017; Costa-Campi et al., 2015; Trianni et al., 2016a), and suggest a need for customised energy programmes at both sectorial and firm level.

The findings of the paper also points to several other interesting avenues for future research.

In fact, the dataset used here only includes Norwegian firms and covers a limited time period (2010–2014), with data collected shortly after the global financial crisis (GFC) of 2008 and during the ensuing global recession. During this period, access to external funding was probably more limited compared to circumstances of a steady-state economy. Hence, according to the OECD (2012b), the lack of accessible funding after the crisis negatively affected business innovation and R&D development in every country. Norway was also undoubtedly affected, since investments in innovation declined in 2009 compared to 2006–2008 (Filippetti and Archibugi, 2011). Given that manufacturing firms often have limited capital available for efficiency projects (Anderson and Newell, 2004), one might risk that some firms in our dataset would have pursued EE innovation in other circumstances but were restricted by reduced access to financial resources. However, the impact of the GFC and the recession was relatively shallow in Norway compared to other OECD countries (OECD, 2010), and the Norwegian economy had essentially recovered in the first half of 2011 (OECD, 2012a). Thus, there is a risk that national economic factors might bias the paper's results. Additional research is accordingly needed to verify whether the study's findings hold for firms in different economic systems, and facing other exogenous macroeconomic conditions compared to the firms studied here.

Further, the results of this paper indicate a positive relationship between firms absorptive capacity and pursue of EE innovations. However, to expand our understanding of how firms' characteristics affect their propensity for EE innovations, and the interaction effect between these variables future research may include the impact of contingent factors such as organisational structure and strategy design, and environmental factors such as location in a network, energy policies, and macroeconomic elements.

Using survey data from the Norwegian CIS and BERD questionnaires is useful to gain insights based on a large number of observations, but it also comes with some caveats. The data set is based on self-reported variables, and it does not allow to distinguish between firms according to level of involvement in EE innovation or form of R&D expenditure, as discussed in Section 3. Given these limitations, the results should be interpreted as indications of the relationship between absorptive capacity and EE innovations for manufacturing firms. In order to gain more understanding about the causal relationships underlying the results presented herein, applying qualitative methods in further research is needed. This is particularly important for better understanding the interaction effect between the explanatory variables. Bansal et al. (2018) argue that qualitative research methods are increasingly needed to unpack the complex challenges our world faces, and this includes climate challenges, to build theory inductively. Thus, a contribution that future research should attempt to provide is to focus on the causal relationships between the variables and to describe the various stakeholders, motives, activities, and resources involved in the EE innovation processes.

Acknowledgements

A previous version of this paper was presented at the 9th International Conference on Applied Energy (ICAE2017), Cardiff (UK), August 21–24, 2017, and published in the proceedings (Solnørdal and Thyholdt, 2017). We thank the conference participants for their helpful comments. We are grateful to Lene Foss, Elin Anita Nilsen, Lars Coenen, Giovanna Bertella, Babak Ghassim, Tahrir Jaber, and three anonymous referees for helpful comments and suggestions. We also thank SSB for providing the dataset.

This research has not received any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix

Table A1
First-stage logit regression

Variables	Coef.	P-value
LSIZE	0.587	0.000
HPAR	0.366	0.000
HFOUT	0.592	0.000
HMAR	−0.402	0.000
Sector dummies	Included	
Constant	−1.524	0.000

Regression is run with cluster robust standard errors.

Table A2
Description of variables (the panel data indicate the activity firm *i* at time *t*).

Variable	Description	Measure
IE_{it}	Energy efficiency innovation	Dichotomous variable: 1 if the firm has invested in R&D in 'other environmental energy: energy saving, energy efficiency, energy systems, environmentally friendly transport, etc.'; 0 if not
$Innovation_{it}$	Innovative firm	Dichotomous variable: 1 if the firm introduced a product or process innovation during 2010–2014; 0 if not.
$HDSHRE_{it}$	Higher education at master's level in R&D department	Share of staff in R&D department with higher education degree at master's level or equivalent
$DRSHRE_{it}$	Higher education at PhD level in R&D department	Share of staff in R&D department with a PhD degree or equivalent
$RDPROD_{it}$	R&D investment	Sum of investment in R&D (wages, infrastructure investments, and other costs) per employee.
$SHRRD_{it}$	R&D capacity	Share of employees in R&D department
$COOPCUS_{it}$	Cooperation along the value stream	Dichotomous variable: 1 if firm cooperates with customers; 0 if not
$COOPCOMP_{it}$	Cooperation with competitors	Dichotomous variable: 1 if firm cooperates with competitors; 0 if not
$COOPSUP_{it}$	Cooperation with suppliers	Dichotomous variable: 1 if firm cooperates with suppliers; 0 if not
$COOPCONS_{it}$	Cooperation with consultants	Dichotomous variable: 1 if firm cooperates with consultants; 0 if not
$COOPUNIS_{it}$	Cooperation with universities	Dichotomous variable: 1 if firm cooperates with universities, private and public research institutions, and/or commercial laboratories; 0 if not
$ENVPUR_{it}$	Environmental motivation	Dichotomous variable: 1 if reducing environmental impact is considered of medium or high importance; 0 if not
$MATPUR_{it}$	Cost savings	Dichotomous variable: 1 if reducing material and energy costs is considered of medium or high importance; 0 if not
$PUBLFUN_{it}$	Public funding	Dichotomous variable: 1 if firm has received funding from public institutions; 0 if not
$LSIZE_{it}$	Company size	Natural logarithm of number of employees in the firm
$PrINNOVATION_{it}$	Probability of being an innovator	Probability of being an innovator, estimated in the first-stage logit regression.
$HDDR_{it}$	Educational level in R&D department	Dichotomous variable: 1 if firm has employees in the R&D department with a master's and/or PhD degree; 0 if not
$HFOUT_{it}$	Financing obstacle for innovation	The importance of lack of external financial sources as obstacle for innovation. Factor variable: 3 if it was very important, 0 if it was not relevant
$HPAR_{it}$	Cooperation obstacle for innovation	The importance of lack of cooperation partners as obstacle for innovation. Factor variable: 3 if it was very important, 0 if it was not relevant
$HMAR_{it}$	Demand obstacle for innovation	The importance of lack of demand for innovations in the market as obstacle for innovation. Factor variable: 3 if it was very important, 0 if it was not relevant.

References

Abadie, L.M., Ortiz, R.A., Galarraga, I., 2012. Determinants of energy efficiency investments in the US. Energy Policy 45, 551–566. https://doi.org/10.1016/j.enpol.2012.03.002.

Abdelaziz, E.A., Saidur, R., Mekhilef, S., 2011. A review on energy saving strategies in industrial sector. Renew. Sustain. Energy Rev. 15, 150–168. https://doi.org/10.1016/j.rser.2010.09.003.

Ai, C., Norton, E.C., 2003. Interaction terms in logit and probit models. Econ. Lett. 80, 123–129. https://doi.org/10.1016/S0165-1765(03)00032-6.

Albort-Morant, G., Henseler, J., Cepeda-Carrión, G., Leal-Rodríguez, A., 2018. Potential and realized absorptive capacity as complementary drivers of green product and process innovation performance. Sustainability 10, 381.

Allison, P.D., 1999. Comparing logit and probit coefficients across groups. Socio. Methods Res. 28, 186–208.

Anderson, N., De Dreu, C.K., Nijstad, B.A., 2004. The routinization of innovation research: a constructively critical review of the state-of-the-science. J. Organ. Behav. 25, 147–173. https://doi.org/10.1002/job.236.

Anderson, S.T., Newell, R.G., 2004. Information programs for technology adoption: the case of energy-efficiency audits. Resour. Energy Econ. 26, 27–50. https://doi.org/10.1016/j.reseneeco.2003.07.001.

Ankrah, S., Al-Tabbaa, O., 2015. Universities–industry collaboration: a systematic review. Scand. J. Manag. 31, 387–408. https://doi.org/10.1016/j.scaman.2015.02.003.

Apeaning, R.W., Thollander, P., 2013. Barriers to and driving forces for industrial energy efficiency improvements in African industries – a case study of Ghana's largest industrial area. J. Clean. Prod. 53, 204–213. https://doi.org/10.1016/j.jclepro.2013.04.003.

Arundel, A., Kemp, R., 2009. Measuring Eco-Innovation. United Nations University Working Paper Series, pp. 1–40.

Backlund, S., Thollander, P., Palm, J., Ottosson, M., 2012. Extending the energy efficiency gap. Energy Policy 51, 392–396. https://doi.org/10.1016/j.enpol.2012.08.042.

Bansal, P., Smith, W.K., Vaara, E., 2018. New ways of seeing through qualitative research. Acad. Manag. J. 61, 1189–1195. https://doi.org/10.5465/amj.2018.4004.

Belderbos, R., Carree, M., Lokshin, B., 2006. Complementarity in R&D cooperation strategies. Rev. Ind. Organ. 28, 401–426. https://doi.org/10.1007/s11151-006-9102-z.

Boyd, G.A., Curtis, E.M., 2014. Evidence of an "Energy-Management Gap" in U.S. manufacturing: spillovers from firm management practices to energy efficiency. J. Environ. Econ. Manag. 68, 463–479. https://doi.org/10.1016/j.jeem.2014.09.004.

Bruneel, J., D'Este, P., Salter, A., 2010. Investigating the factors that diminish the barriers to university–industry collaboration. Res. Pol. 39, 858–868. https://doi.org/10.1016/j.respol.2010.03.006.

Brunke, J.-C., Johansson, M., Thollander, P., 2014. Empirical investigation of barriers and drivers to the adoption of energy conservation measures, energy management practices and energy services in the Swedish iron and steel industry. J. Clean. Prod. 84, 509–525. https://doi.org/10.1016/j.jclepro.2014.04.078.

Buis, M.L., 2010. Stata tip 87: interpretation of interactions in nonlinear models. STATA J. 10 305-208.

Cagno, E., Ramirez-Portilla, A., Trianni, A., 2015a. Linking energy efficiency and innovation practices: empirical evidence from the foundry sector. Energy Policy 83, 240–256. https://doi.org/10.1016/j.enpol.2015.02.023.

Cagno, E., Trianni, A., 2013. Exploring drivers for energy efficiency within small- and medium-sized enterprises: first evidences from Italian manufacturing enterprises. Appl. Energy 104, 276–285. https://doi.org/10.1016/j.apenergy.2012.10.053.

Cagno, E., Trianni, A., Abeelen, C., Worrell, E., Miggiano, F., 2015b. Barriers and drivers for energy efficiency: different perspectives from an exploratory study in The Netherlands. Energy Convers. Manag. 102, 26–38. https://doi.org/10.1016/j.enconman.2015.04.018.

Cagno, E., Trianni, A., Spallina, G., Marchesani, F., 2017. Drivers for energy efficiency and their effect on barriers: empirical evidence from Italian manufacturing enterprises. Energy Efficiency 10, 855–869. https://doi.org/10.1007/s12053-016-9488-x.

Cagno, E., Worrell, E., Trianni, A., Pugliese, G., 2013. A novel approach for barriers to industrial energy efficiency. Renew. Sustain. Energy Rev. 19, 290–308. https://doi.org/10.1016/j.rser.2012.11.007.

Camisón, C., Forés, B., 2011. Knowledge creation and absorptive capacity: the effect of intra-district shared competences. Scand. J. Manag. 27, 66–86. https://doi.org/10.1016/j.scaman.2010.11.006.

Carrillo-Hermosilla, J., del Río, P., Könnölä, T., 2010. Diversity of eco-innovations: reflections from selected case studies. J. Clean. Prod. 18, 1073–1083. https://doi.org/10.1016/j.jclepro.2010.02.014.

Cassiman, B., Veugelers, R., 2006. In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition. Manag. Sci. 52, 68–82. https://doi.org/10.1287/mnsc.1050.0470.

Chai, K.-H., Baudelaire, C., 2015. Understanding the energy efficiency gap in Singapore: a Motivation, Opportunity, and Ability perspective. J. Clean. Prod. 100, 224–234. https://doi.org/10.1016/j.jclepro.2015.03.064.

Chai, K.-H., Yeo, C., 2012. Overcoming energy efficiency barriers through systems approach—a conceptual framework. Energy Policy 46, 460–472. https://doi.org/10.1016/j.enpol.2012.04.012.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35, 128–152. https://doi.org/10.2307/2393553.

Conrad, K., 2000. An econometric model of production with endogenous improvement in energy efficiency, 1970-1995. Appl. Econ. 32, 1153–1160. https://doi.org/10.1080/000368400404290.

Cooremans, C., 2011. Make it strategic! Financial investment logic is not enough. Energy Efficiency 4, 473–492. https://doi.org/10.1007/s12053-011-9125-7.

Costa-Campi, M., García-Quevedo, J., Martínez-Ros, E., 2017. What are the determinants of investment in environmental R&D? Energy Policy 104, 455–465. https://doi.org/10.1016/j.enpol.2017.01.024.

Costa-Campi, M.T., García-Quevedo, J., Segarra, A., 2015. Energy efficiency determinants: an empirical analysis of Spanish innovative firms. Energy Policy 83, 229–239. https://doi.org/10.1016/j.enpol.2015.01.037.

Cui, Q., Li, Y., 2015. An empirical study on energy efficiency improving capacity: the case of fifteen countries. Energy Efficiency 8, 1049–1062. https://doi.org/10.1007/s12053-015-9337-3.

De Marchi, V., 2012. Environmental innovation and R&D cooperation: empirical evidence from Spanish manufacturing firms. Res. Pol. 41, 614–623. https://doi.org/10.1016/j.respol.2011.10.002.

De Marchi, V., Grandinetti, R., 2013. Knowledge strategies for environmental innovations: the case of Italian manufacturing firms. J. Knowl. Manag. 17, 569–582.

DeCanio, S.J., 1998. The efficiency paradox: bureaucratic and organizational barriers to profitable energy-saving investments. Energy Policy 26, 441–454. https://doi.org/10.1016/S0301-4215(97)00152-3.

EIA, 2017. International Energy Outlook 2017. U.S. Energy Information Administration, U.S., pp. 76.

Escribano, A., Fosfuri, A., Tribó, J.A., 2009. Managing external knowledge flows: the moderating role of absorptive capacity. Res. Pol. 38, 96–105. https://doi.org/10.1016/j.respol.2008.10.022.

EU, 2014. 2030 Climate & Energy Framework, COM(2015) 15 Final. EU Commission, Brussels, EU.

Fan, L.W., Pan, S.J., Liu, G.Q., Zhou, P., 2017. Does energy efficiency affect financial performance? Evidence from Chinese energy-intensive firms. J. Clean. Prod. 151, 53–59. https://doi.org/10.1016/j.jclepro.2017.03.044.

Filippetti, A., Archibugi, D., 2011. Innovation in times of crisis: national Systems of Innovation, structure, and demand. Res. Pol. 40, 179–192. https://doi.org/10.1016/j.respol.2010.09.001.

Forés, B., Camisón, C., 2016. Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size? J. Bus. Res. 69, 831–848. https://doi.org/10.1016/j.jbusres.2015.07.006.

Gerstlberger, W., Knudsen, M.P., Dachs, B., Schroter, M., 2016. Closing the energy-efficiency technology gap in European firms? Innovation and adoption of energy efficiency technologies. J. Eng. Technol. Manag. 40, 87–100. https://doi.org/10.1016/j.jengtecman.2016.04.004.

Gillingham, K., Newell, R.G., Palmer, K., 2009. Energy efficiency economics and policy. Annual Review of Resource Economics 1, 597–620. https://doi.org/10.1146/annurev.resource.102308.124234.

Gillingham, K., Palmer, K., 2014. Bridging the energy efficiency gap: policy insights from economic theory and empirical evidence. Rev. Environ. Econ. Pol. 8, 18–38. https://doi.org/10.1093/reep/ret021.

Grant, R.M., 1996. Toward a knowledge-based theory of the firm. Strat. Manag. J. 17, 109–122. https://doi.org/10.1002/smj.4250171110.

Haltiwanger, J.C., Lane, J.I., Spletzer, J.R., 1999. Productivity differences across employers: the roles of employer size, age, and human capital. Am. Econ. Rev. 89, 94–98.

Hammar, H., Löfgren, Å., 2010. Explaining adoption of end of pipe solutions and clean technologies—determinants of firms' investments for reducing emissions to air in four sectors in Sweden. Energy Policy 38, 3644–3651. https://doi.org/10.1016/j.enpol.2010.02.041.

Harris, J., Anderson, J., Shafron, W., 2000. Investment in energy efficiency: a survey of Australian firms. Energy Policy 28, 867–876. https://doi.org/10.1016/S0301-4215(00)00075-6.

Horbach, J., 2008. Determinants of environmental innovation—new evidence from German panel data sources. Res. Pol. 37, 163–173. https://doi.org/10.1016/j.respol.2007.08.006.

Horbach, J., Oltra, V., Belin, J., 2013. Determinants and specificities of eco-innovations compared to other innovations—an econometric analysis for the French and German industry based on the community innovation survey. Ind. Innov. 20, 523–543. https://doi.org/10.1080/13662716.2013.833375.

Horbach, J., Rammer, C., Rennings, K., 2012. Determinants of eco-innovations by type of environmental impact — the role of regulatory push/pull, technology push and market pull. Ecol. Econ. 78, 112–122. https://doi.org/10.1016/j.ecolecon.2012.04.005.

Hrovatin, N., Dolšak, N., Zorić, J., 2016. Factors impacting investments in energy efficiency and clean technologies: empirical evidence from Slovenian manufacturing firms. J. Clean. Prod. 127, 475–486. https://doi.org/10.1016/j.jclepro.2016.04.039.

IEA, 2017. Energy Policies of IEA Countries: Norway 2017 Review. International Energy Agency, pp. 165.

IEA, 2018. World Energy Balances: Overview. International Energy Agency, pp. 24.

Inkpen, A.C., Tsang, E.W.K., 2005. Social capital, networks, and knowledge transfer. Acad. Manag. Rev. 30, 146–165. https://doi.org/10.2307/20159100.

Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Rev. Econ. Stat. 79, 610–619.

Jaffe, A.B., Stavins, R.N., 1994. The energy-efficiency gap what does it mean? Energy Policy 22, 804–810. https://doi.org/10.1016/0301-4215(94)90138-4.

Johansson, M.T., 2015. Improved energy efficiency within the Swedish steel industry-the importance of energy management and networking. Energy Efficiency 8, 713–744. https://doi.org/10.1007/s12053-014-9317-z.

Johansson, M.T., Thollander, P., 2018. A review of barriers to and driving forces for improved energy efficiency in Swedish industry– Recommendations for successful in-house energy management. Renew. Sustain. Energy Rev. 82, 618–628. https://doi.org/10.1016/j.rser.2017.09.052.

Kemp, R., Pearson, P., 2007. In: MERIT, U. (Ed.), Final Report of the MEI Project Measuring Eco Innovation, (Maastricht).
Kogut, B., Zander, U., 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organ. Sci. 3, 383–397.
Kostka, G., Moslener, U., Andreas, J., 2013. Barriers to increasing energy efficiency: evidence from small-and medium-sized enterprises in China. J. Clean. Prod. 57, 59–68. https://doi.org/10.1016/j.jclepro.2013.06.025.
Kounetas, K., Skuras, D., Tsekouras, K., 2011. Promoting energy efficiency policies over the information barrier. Inf. Econ. Policy 23, 72–84. https://doi.org/10.1016/j.infoecopol.2010.08.001.
Kounetas, K., Tsekouras, K., 2008. The energy efficiency paradox revisited through a partial observability approach. Energy Econ. 30, 2517–2536. https://doi.org/10.1016/j.eneco.2007.03.002.
Kuha, J., Mills, C., 2018. On group comparisons with logistic regression models. Socio. Methods Res. 1–28. https://doi.org/10.1177/0049124117747306.
Leonard, D., Sensiper, S., 1998. The role of tacit knowledge in group innovation. Calif. Manag. Rev. 40, 112–132. https://doi.org/10.2307/41165946.
Lichtenthaler, U., 2009. Absorptive capacity, environmental turbulence, and the complementarity of organizational learning processes. Acad. Manag. J. 52, 822–846.
Lin, B., Tan, R., 2016. Ecological total-factor energy efficiency of China's energy intensive industries. Ecol. Indicat. 70, 480–497. https://doi.org/10.1016/j.ecolind.2016.06.026.
Lööf, H., Heshmati, A., 2002. Knowledge capital and performance heterogeneity: a firm-level innovation study. Int. J. Prod. Econ. 76, 61–85. https://doi.org/10.1016/S0925-5273(01)00147-5.
Martin, R., Muûls, M., De Preux, L.B., Wagner, U.J., 2012. Anatomy of a paradox: management practices, organizational structure and energy efficiency. J. Environ. Econ. Manag. 63, 208–223. https://doi.org/10.1016/j.jeem.2011.08.003.
Martínez, C.I.P., 2010. Investments and energy efficiency in Colombian manufacturing industries. Energy Environ. 21, 545–562. https://doi.org/10.1260/0958-305X.21.6.545.
Masurel, E., 2007. Why SMEs invest in environmental measures: sustainability evidence from small and medium-sized printing firms. Bus. Strateg. Environ. 16, 190–201. https://doi.org/10.1002/bse.478.
May, G., Stahl, B., Taisch, M., Kiritsis, D., 2017. Energy management in manufacturing: from literature review to a conceptual framework. J. Clean. Prod. 167, 1464–1489. https://doi.org/10.1016/j.jclepro.2016.10.191.
Miah, J.H., Griffiths, A., McNeill, R., Poonaji, I., Martin, R., Morse, S., Yang, A., Sadhukhan, J., 2015. A small-scale transdisciplinary process to maximising the energy efficiency of food factories: insights and recommendations from the development of a novel heat integration framework. Sustainability Science 10, 621–637. https://doi.org/10.1007/s11625-015-0331-7.
MPE, 2016. In: Meld.St 25 (2015-2016) - Power for Change – an Energy Policy towards 2030 (White Paper), Meld. St. 25 (2015–2016) Report to the Storting (White Paper) Ministry of Petroleum and Energy, Government.No, pp. 230.
NVE, 2013. Energiintensiv Industri: En Beskrivelse Og Økonomisk Analyse Av Energiintensiv Industri I Norge. Norges vassdrags- og energidirektorat, pp. 72.
OECD, 2009. Sustainable Manufacturing and Eco-Innovation. OECD, Paris.
OECD, 2010. OECD Economic Surveys: Norway 2010. OECD Publishing, Paris.
OECD, 2012a. OECD Economic Surveys: Norway 2012. OECD Publishing, Paris.
OECD, 2012b. OECD Science, Technology and Industry Outlook 2012. OECD Publishing, Paris.
Ozoliņa, L., Roša, M., 2013. The consumer's role in energy efficiency promotion in Latvian manufacturing industry. Management of Environmental Quality 24, 330–340. https://doi.org/10.1108/14777831311322640.
Palm, J., Thollander, P., 2010. An interdisciplinary perspective on industrial energy efficiency. Appl. Energy 87, 3255–3261. https://doi.org/10.1016/j.apenergy.2010.04.019.
Poirier, D.J., 1980. Partial observability in bivariate probit models. J. Econom. 12, 209–217. https://doi.org/10.1016/0304-4076(80)90007-X.
Porter, M.E., Vanderlinde, C.v.d., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9, 97–118. https://doi.org/10.1257/jep.9.4.97.
Powell, W.W., Koput, K.W., Smith-Doerr, L., 1996. Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. Adm. Sci. Q. 41, 116–145. https://doi.org/10.2307/2393988.
RCN, 2017. Report on Science & Technology Indicators for Norway. The Research Council of Norway, Oslo, NO, pp. 114.
Rennings, K., 2000. Redefining innovation — eco-innovation research and the contribution from ecological economics. Ecol. Econ. 32, 319–332. https://doi.org/10.1016/S0921-8009(99)00112-3.
Rennings, K., Rammer, C., 2009. Increasing Energy and Resource Efficiency through Innovation: an Explorative Analysis Using Innovation Survey Data (2009). ZEW - Centre for European Economic Research Discussion.
Rennings, K., Ziegler, A., Ankele, K., Hoffmann, E., 2006. The influence of different characteristics of the EU environmental management and auditing scheme on technical environmental innovations and economic performance. Ecol. Econ. 57, 45–59. https://doi.org/10.1016/j.ecolecon.2005.03.013.
Ritala, P., Hurmelinna-Laukkanen, P., 2013. Incremental and radical innovation in coopetition—the role of absorptive capacity and appropriability. J. Prod. Innov. Manag. 30, 154–169. https://doi.org/10.1111/j.1540-5885.2012.00956.x.
Ru, L., Si, W., 2015. Total-factor energy efficiency in China's sugar manufacturing industry. China Agricultural Economic Review 7, 360–373. https://doi.org/10.1108/CAER-11-2014-0131.
Rudberg, M., Waldemarsson, M., Lidestam, H., 2013. Strategic perspectives on energy management: a case study in the process industry. Appl. Energy 104, 487–496. https://doi.org/10.1016/j.apenergy.2012.11.027.
Sagar, A.D., van der Zwaan, B., 2006. Technological innovation in the energy sector: R&D, deployment, and learning-by-doing. Energy Policy 34, 2601–2608. https://doi.org/10.1016/j.enpol.2005.04.012.
Sampson, R.C., 2007. R&D alliances and firm performance: the impact of technological diversity and alliance organization on innovation. Acad. Manag. J. 50, 364–386. https://doi.org/10.2307/20159859.
Sandberg, P., Söderström, M., 2003. Industrial energy efficiency: the need for investment decision support from a manager perspective. Energy Policy 31, 1623–1634. https://doi.org/10.1016/S0301-4215(02)00228-8.
Sardianou, E., 2008. Barriers to industrial energy efficiency investments in Greece. J. Clean. Prod. 16, 1416–1423. https://doi.org/10.1016/j.jclepro.2007.08.002.
Sathitbun-anan, S., Fungtammasan, B., Barz, M., Sajjakulnukit, B., Pathumsawad, S., 2015. An analysis of the cost-effectiveness of energy efficiency measures and factors affecting their implementation: a case study of Thai sugar industry. Energy Efficiency 8, 141–153. https://doi.org/10.1007/s12053-014-9281-7.
Smith, K.G., Collins, C.J., Clark, K.D., 2005. Existing knowledge, knowledge creation capability, and the rate of new product introduction in high-technology firms. Acad. Manag. J. 48, 346–357.
Solnørdal, M., Foss, L., 2018. Closing the energy efficiency gap—a systematic review of empirical articles on drivers to energy efficiency in manufacturing firms. Energies 11, 518. https://doi.org/10.3390/en11030518.
Solnørdal, M.T., Thyholdt, S.B., 2017. Drivers for energy efficiency: an empirical analysis of Norwegian manufacturing firms. Energy Procedia 142, 2802–2808. https://doi.org/10.1016/j.egypro.2017.12.425.
Sorrell, S., Mallett, A., Nye, S., 2011. Barriers to Industrial Energy Efficiency: a Literature Review. Working Paper 10/2011 UNIDO. United Nations, Industrial Development Organization.
Stefania, M., Christian, W., 2015. The construct of absorptive capacity in knowledge management and intellectual capital research: content and text analyses. J. Knowl. Manag. 19, 372–400. https://doi.org/10.1108/JKM-08-2014-0342.
Steinmo, M., Rasmussen, E., 2018. The interplay of cognitive and relational social capital dimensions in university-industry collaboration: overcoming the experience barrier. Res. Pol. 47, 1964–1974. https://doi.org/10.1016/j.respol.2018.07.004.
Subramaniam, M., Youndt, M.A., 2005. The influence of intellectual capital on the types of innovative capabilities. Acad. Manag. J. 48, 450–463. https://doi.org/10.5465/amj.2005.17407911.
Svensson, A., Paramonova, S., 2017. An analytical model for identifying and addressing energy efficiency improvement opportunities in industrial production systems – model development and testing experiences from Sweden. J. Clean. Prod. 142 (4), 2407–2422. https://doi.org/10.1016/j.jclepro.2016.11.034.
Tanaka, K., 2011. Review of policies and measures for energy efficiency in industry sector. Energy Policy 39, 6532–6550. https://doi.org/10.1016/j.enpol.2011.07.058.
Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strat. Manag. J. 18, 509–533. https://doi.org/10.2307/3088148.
Tether, B.S., 2002. Who co-operates for innovation, and why: an empirical analysis. Res. Pol. 31, 947–967. https://doi.org/10.1016/S0048-7333(01)00172-X.
Thollander, P., Backlund, S., Trianni, A., Cagno, E., 2013. Beyond barriers – a case study on driving forces for improved energy efficiency in the foundry industries in Finland, France, Germany, Italy, Poland, Spain, and Sweden. Appl. Energy 111, 636–643. https://doi.org/10.1016/j.apenergy.2013.05.036.
Thollander, P., Danestig, M., Rohdin, P., 2007. Energy policies for increased industrial energy efficiency: evaluation of a local energy programme for manufacturing SMEs. Energy Policy 35, 5774–5783. https://doi.org/10.1016/j.enpol.2007.06.013.
Tonn, B., Martin, M., 2000. Industrial energy efficiency decision making. Energy Policy 28, 831–843. https://doi.org/10.1016/S0301-4215(00)00068-9.
Trianni, A., Cagno, E., 2012. Dealing with barriers to energy efficiency and SMEs: some empirical evidences. Energy 37, 494–504. https://doi.org/10.1016/j.energy.2011.11.005.
Trianni, A., Cagno, E., Farné, S., 2016a. Barriers, drivers and decision-making process for industrial energy efficiency: a broad study among manufacturing small and medium-sized enterprises. Appl. Energy 162, 1537–1551. https://doi.org/10.1016/j.apenergy.2015.02.078.
Trianni, A., Cagno, E., Marchesani, F., Spallina, G., 2016b. Classification of drivers for industrial energy efficiency and their effect on the barriers affecting the investment decision-making process. Energy Efficiency 1–17. https://doi.org/10.1007/s12053-016-9455-6.
Trianni, A., Cagno, E., Thollander, P., Backlund, S., 2013a. Barriers to industrial energy efficiency in foundries: a European comparison. J. Clean. Prod. 40, 161–176. https://doi.org/10.1016/j.jclepro.2012.08.040.
Trianni, A., Cagno, E., Worrell, E., 2013b. Innovation and adoption of energy efficient technologies: an exploratory analysis of Italian primary metal manufacturing SMEs. Energy Policy 61, 430–440. https://doi.org/10.1016/j.enpol.2013.06.034.
Tsai, W., 2001. Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business unit innovation and performance. Acad. Manag. J. 44, 996–1004. https://doi.org/10.5465/3069443.
UNFCCC, 2015. Adoption of the Paris Agreement FCCC/CP/2015/L.9/Rev.1. UN. UN.
Vega-Jurado, J., Gutiérrez-Gracia, A., Fernández-de-Lucio, I., 2008. Analyzing the determinants of firm's absorptive capacity: beyond R&D. R&D Management 38, 392–405. https://doi.org/10.1111/j.1467-9310.2008.00525.x.
Vega-Jurado, J., Gutiérrez-Gracia, A., Fernández-de-Lucio, I., 2009. Does external knowledge sourcing matter for innovation? Evidence from the Spanish manufacturing industry. Ind. Corp. Chang. 18, 637–670. https://doi.org/10.1093/icc/dtp023.
Venmans, F., 2014. Triggers and barriers to energy efficiency measures in the ceramic, cement and lime sectors. J. Clean. Prod. 69, 133–142. https://doi.org/10.1016/j.

jclepro.2014.01.076.
Vinding, A.L., 2006. Absorptive capacity and innovative performance: a human capital approach. Econ. Innovat. N. Technol. 15, 507–517. https://doi.org/10.1080/10438590500513057.
Wesseling, J.H., Edquist, C., 2018. Public procurement for innovation to help meet societal challenges: a review and case study. Sci. Publ. Pol. https://doi.org/10.1093/scipol/scy013. scy013-scy013.
Wohlfarth, K., Eichhammer, W., Schlomann, B., Mielicke, U., 2017. Learning networks as an enabler for informed decisions to target energy-efficiency potentials in companies. J. Clean. Prod. 163, 118–127. https://doi.org/10.1016/j.jclepro.2016.11.128.
Worrell, E., Bernstein, L., Roy, J., Price, L., Harnisch, J., 2009. Industrial energy efficiency and climate change mitigation. Energy Efficiency 2, 109–123. https://doi.org/10.1007/s12053-008-9032-8.
Zahra, S.A., George, G., 2002. Absorptive capacity: a review, reconceptualization, and extension. Acad. Manag. Rev. 27, 185–203. https://doi.org/10.2307/4134351.
Zilahy, G., 2004. Organisational factors determining the implementation of cleaner production measures in the corporate sector. J. Clean. Prod. 12, 311–319. https://doi.org/10.1016/S0959-6526(03)00016-7.