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Eco-innovations as a booster of energy efficiency and productivity:

Evidence from Austrian manufacturing firms

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Abstract

This paper examines whether R&D-driven eco-innovations improve the energy efficiency and productivity of Austrian manufacturing firms. Using firm-level microdata from the Austrian Micro Data Center, we link innovation surveys, environmental technology patents, use-of-goods statistics, and structural business statistics. We develop a theoretical framework in which eco-innovation raises energy efficiency, which in turn lowers unit costs and increases productivity. Empirically, we extend the innovation-process model of Crépon et al. (1998), as augmented by Griffith et al. (2006), to estimate the effects of eco-innovation on energy intensity, labour productivity, and total factor productivity. We find that predicted R&D investment raises the probability of eco-innovation, and that eco-innovating firms exhibit significantly lower energy intensity and higher sales and gross value added per employee, whereas total factor productivity only increases with a lag.

Keywords: eco-innovation; green technology; energy efficiency; productivity; Austrian manufacturing; firm-level data; CDM model

JEL classification: D22; J23; O30; O31; Q40

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1 Introduction

Climate change has become a major concern in both academia and the policy arena. The increase in greenhouse gas (GHG) emissions since the First Industrial Revolution has raised global temperatures and intensified the need for technological change to reduce the environmental footprint of production. Global carbon dioxide emissions have risen dramatically since the onset of industrialisation, particularly following the Second Industrial Revolution and the globalisation of manufacturing. At the same time, the emergence of green technologies offers the possibility for economies to reduce emissions without forgoing economic growth (Hegerl et al., 2007; Stocker, 2014; Ritchie et al., 2020). The policy response to climate change increasingly emphasises the development and adoption of green technologies. International climate agreements, including the Kyoto Protocol and the Paris Agreement, place climate neutrality and mitigation at the centre of policy discussions. In practice, firms are expected to adjust production processes, use cleaner inputs, adopt renewable-energy technologies, and introduce climate-neutral products. Energy efficiency is particularly important because it can lower emissions and production costs simultaneously (Worrell et al., 2009; Lenaerts et al., 2021).

This paper analyses how eco-innovations and green patenting affect energy efficiency and productivity in Austrian firms with a focus on the firm-level mechanisms behind such adjustments. Austrian manufacturing firms provide a useful empirical setting because the country combines an advanced manufacturing base, ambitious energy-transition objectives, and high-quality administrative microdata. Austria's policy target of producing all electricity from renewable sources by 2030 makes the relationship between eco-innovation, energy efficiency, and productivity especially relevant (International Energy Agency, 2020). Manufacturing firms also remain central to the climate challenge, as they consume large amounts of energy and account for a considerable part of the environmental footprint of production (Erhart and Erhart, 2023).

This paper contributes to the literature by developing and empirically applying a unified firm-level framework that combines four strands of research which have usually been studied separately. First, it builds on the eco-innovation and energy-efficiency literature, which shows that environmental innovations can reduce energy use and improve environmental performance, although the literature often provides limited microeconomic structure for the channels through which such effects arise (Wurlod and Noailly, 2018; Zhang et al., 2017; Murshed et al., 2021; Sun et al., 2019). Second, it relates to the literature on eco-innovation and firm performance, where environmental innovation may improve productivity, efficiency, and competitiveness, but where the estimated effects are often heterogeneous across firms, innovation types, and regulatory contexts (Rennings and Rammer, 2011; Hojnik et al., 2017; Antonioli et al., 2018). Third, it builds on the induced-innovation and directed-technical-change traditions, according to which firms direct innovative effort towards costly, scarce, or policy-relevant inputs and constraints (Popp, 2002; Acemoglu et al., 2012; Aghion et al., 2016). Fourth, the empirical structure follows the innovation-process approach of Crépon et al. (1998) (Crépon, Duguet, and Mairesse, CDM) and Griffith et al. (2006), in which R&D investment, innovation output, and firm performance are linked through a system of equations.

The main contribution is to combine these elements in a resource-biased eco-innovation

framework that embeds the CDM innovation sequence in a production-cost structure in which ecological innovation raises energy efficiency. Eco-innovation can immediately reduce energy intensity and boost labour productivity by lowering the effective price of energy services and reducing unit costs. However, we find that total factor productivity (TFP) gains only arise with a delay because they require learning-by-using, organisational adjustment, and complementary capital investment. This distinction helps explain why eco-innovation may be associated with lower energy intensity and higher sales or gross value added (GVA) per employee even when contemporaneous TFP effects are weaker. The framework therefore provides a theoretical bridge between the Porter-hypothesis view of efficiency-enhancing environmental innovation (Porter and van der Linde, 1995; Cohen and Tubb, 2018), the induced-innovation and directed-technical-change perspectives (Popp, 2002; Acemoglu et al., 2012), and the empirical CDM approach linking investment in research, innovation output, and productivity (Crépon et al., 1998; Griffith et al., 2006).

The underlying theoretical framework based on a CES production function interprets eco-innovations as a resource-biased process innovation if it increases energy efficiency. This raises the effective productivity of energy, lowers unit costs, and reduces energy intensity. Because manufacturing technologies often combine energy with machinery, materials, and labour in relatively fixed proportions (at least in the short run), this framework predicts that energy-saving innovation can reduce both energy use relative to output and the share of energy in total costs. At the same time, lower unit costs and process upgrading increase sales and GVA per employee. Empirically, we find that broader Hicks-neutral productivity gains materialise with a lag, as these require organisational adjustment, learning-by-using, and complementary investment.

The empirical results are consistent with this mechanism. The innovation-input equations show that predicted R&D expenditure is positively related to ecological innovation, especially when firms possess complementary capabilities (e.g. human capital, external knowledge, and capital investment). The final-stage estimates indicate that ecological innovation is associated with lower energy intensity as well as higher sales and GVA per employee. The absence of a strong contemporaneous TFP effect, together with evidence of a lagged TFP response, indicates a distinction between immediate resource-saving efficiency gains and delayed TFP gains.

The paper is structured as follows. Section 2 reviews the literature on eco-innovation, energy efficiency, productivity, and the determinants of environmental innovation. Section 3 develops the theoretical framework showing the main mechanisms through which resource-biased eco-innovation may affect firms' energy intensity, energy-cost shares, and labour productivity. Section 4 presents the econometric strategy, building on the CDM innovation-process framework, and discusses the data sources and the variables used in the estimation. Section 5 discusses the empirical results from the R&D selection and intensity equations, the link between R&D and eco-innovation output, and the estimated effects of eco-innovation on energy efficiency and productivity. Section 6 concludes by summarising the main findings and discussing their implications for green innovation policy, energy-efficiency support, and firm competitiveness.

2 Literature review

2.1 Eco-innovation, energy efficiency, and sustainable growth

Innovation is usually treated as an important source of productivity growth, but not all innovations reduce environmental pressure. Innovations that intensify carbon use can worsen environmental outcomes, whereas eco-innovations (i.e. innovations in products, processes, organisational practices, or business models that reduce environmental harm) can contribute to sustainable growth (Ferreira et al., 2020; Voegtlin and Scherer, 2017). The United Nations' Sustainable Development Goals and the European Green Deal both stress the role of innovation in the transition towards climate neutrality.

Energy efficiency is commonly defined as the amount of energy input needed to produce a given quantity of goods and services. A reduction in energy use per unit of output therefore represents an efficiency gain (Patterson, 1996). In growth and trade models, improvements in energy efficiency can boost competitiveness because lower energy requirements reduce production costs and the relative price of final goods (Madlener and Alcott, 2009; Koesler et al., 2016). The environmental economics literature has also emphasised that policy-induced innovation is central to the long-run cost of climate mitigation (Popp, 2019). In the renewable-energy domain, for example, Johnstone et al. (2010) show that public policy instruments are important drivers of patenting in renewable-energy technologies, while Calel and Dechezleprêtre (2016) find that the EU Emissions Trading System increased low-carbon patenting among regulated firms.

Empirical evidence on the impact of green innovation on energy use is still relatively scarce and not fully conclusive. At the sector level, Wurlod and Noailly (2018) find that green patenting is associated with lower energy intensity in Organisation for Economic Co-operation and Development (OECD) countries. Noailly and Smeets (2015) use firm-level patent data to analyse the direction of technical change in electricity generation and show that firm heterogeneity is important for the redirection of innovation from fossil-fuel to renewable-energy technologies. Other studies show that environmental innovation can reduce environmental footprints in China, South Asia, and broader samples of developed and developing economies (Zhang et al., 2017; Murshed et al., 2021; Sun et al., 2019). However, these studies rarely identify the firm-level mechanisms through which eco-innovation affects energy efficiency.

A key insight from recent empirical work is that eco-innovation is not homogeneous. Resource-saving innovations that reduce energy or material use can have different economic effects from end-of-pipe or externality-reducing technologies. This distinction is central to our paper because the theoretical framework below interprets eco-innovation as a resource-biased process innovation: it increases the efficiency with which measured energy inputs are transformed into productive energy services. The immediate empirical implication is therefore stronger for energy intensity and energy-cost shares than for broad contemporaneous TFP.

2.2 Firm performance and productivity effects

Research on the economic effects of eco-innovation has examined a range of outcomes, including employment, sales, productivity, profitability, and firm efficiency. The evidence is heterogeneous. Rennings and Rammer (2011) show that not all eco-innovations improve firm performance, and that the effect depends on the specific type of eco-innovation and on whether it is regulation-driven. Hojnik et al. (2017) find positive links between eco-innovation and firm efficiency for Slovenian firms, while Antonioli et al. (2018) report productivity benefits from the joint adoption of information and communication technologies and environmental innovations.

Several studies are particularly relevant for the mechanism developed in this paper because they distinguish resource-efficiency improvements from other environmental innovations. Rexhäuser and Rammer (2014) show that environmental innovations that improve material or energy efficiency have positive profitability effects, whereas environmental innovations that do not improve resource efficiency do not generate positive profitability returns. Similarly, Ghisetti and Rennings (2014) find that energy- and material-saving environmental innovations are associated with positive competitiveness effects, while externality-reducing innovations may reduce profitability. More recently, Cheng et al. (2025) distinguish between pollution-prevention and pollution-control patents and show that pollution-prevention innovations are more likely to improve both future environmental and financial performance through sales growth and cost efficiency. These findings support the idea that the economic return to eco-innovation depends on whether the innovation directly reduces input requirements and unit costs.

The firm-level productivity effects may also depend on complementary organisational and technological capabilities. Hottenrott et al. (2016) show that green technology adoption alone may not automatically raise productivity, but that productivity outcomes improve when green technology adoption is combined with organisational change. This is consistent with the view that firms need learning-by-doing, internal reorganisation, and complementary investment before environmental technologies can translate into broader productivity gains. Evidence from the DACH region (i.e. Germany, Austria, and Switzerland) is also relevant for our Austrian manufacturing setting. Peneder et al. (2022) analyse firms in the DACH region and find that green energy technologies are associated with improvements in energy efficiency and reductions in CO_2 emissions, while the average effect on competitiveness is more neutral. These findings suggest that green technologies may first appear as energy-efficiency improvements rather than as immediate gains in profitability or TFP.

This literature motivates the distinction made in our theoretical framework between immediate energy-services efficiency and delayed Hicks-neutral productivity. Eco-innovation can raise sales or GVA per employee if it lowers unit costs, improves process organisation, or creates demand-side advantages. At the same time, contemporaneous TFP effects may be weaker if implementation requires downtime, retraining, complementary investment, or organisational adjustment. This interpretation is consistent with the broader innovation-productivity literature, where the productivity effects of innovation are often conditional on firm capabilities and may materialise with a lag (Bloom and Van Reenen, 2002; Mohnen and Hall, 2013; Crespi and Zuniga, 2012).

2.3 Determinants of eco-innovation

A related strand of the literature studies the determinants of energy-efficiency and environmental innovation. Costa-Campi et al. (2015) analyse innovative Spanish firms, Rexhäuser and Löschel (2015) compare energy-efficiency and renewable-energy inventions among German firms, and Costantini et al. (2017) study the role of policy mixes in fostering energy-efficient technologies. Access to green loans, public subsidies, and credit policies can support clean-production innovation, although the effectiveness of such instruments depends on firm capabilities and policy design (Li et al., 2018; Song et al., 2021; Chen et al., 2022).

The determinants of eco-innovation differ across innovation types. Horbach et al. (2012) show that regulation, cost savings, and customer requirements affect different types of eco-innovation in different ways. In particular, cost savings are especially important for innovations that reduce material and energy use, while current and expected regulation matters more for emissions, hazardous substances, and recyclability. This directly supports the resource-biased mechanism in our model: firms with higher energy shares should have stronger incentives to introduce energy-saving eco-innovations. Triguero et al. (2013) provide evidence on small and medium-sized enterprises (SMEs) in Europe, showing that supply-side factors, market demand, and collaboration with research institutions influence different eco-innovation types differently, with cost savings being particularly relevant for process eco-innovation. De Marchi (2012) further shows that environmental innovators rely more strongly on R&D cooperation with external partners, including suppliers, knowledge-intensive business services, and universities.

Environmental regulation is another important driver, but its economic consequences are nuanced. Lanoie et al. (2011) test different variants of the Porter hypothesis and link environmental policy, R&D, environmental performance, and business performance. Dechezleprêtre and Sato (2017) review evidence showing that environmental regulation can induce clean innovation, while short-run competitiveness effects are usually small but may be more relevant in pollution- and energy-intensive sectors. Albrizio et al. (2017) provide cross-country firm- and industry-level evidence that environmental policy stringency can raise productivity growth for technologically advanced firms but may slow productivity growth among less productive firms. These findings imply that the effect of environmental policy and eco-innovation should be heterogeneous across firms, depending on absorptive capacity, productivity, energy intensity, and the ability to adapt production processes.

The empirical approach used in this paper is related to the innovation-process literature initiated by Crépon et al. (1998). The CDM model links innovation investment, innovation output, and firm performance in a system of equations. Griffith et al. (2006) extend this framework for cross-country firm-level analyses, and subsequent studies apply similar innovation-productivity systems to different country and firm samples (Crespi and Zuniga, 2012; Mohnen and Hall, 2013). This paper adapts the framework in three ways: first, the innovation-output equation focuses on eco-innovation rather than innovation in general; second, the model includes controls for climate-change relevance and digital technologies where available; and, third, the performance equation considers energy efficiency, labour productivity, and TFP.

2.4 Patents, green patents, and the measurement of environmental innovation

A final strand of literature concerns the use of patents as indicators of innovation. Patent data are attractive because they provide internationally comparable, technology-specific, and time-varying information on inventions. They are especially useful for environmental innovation because classifications (e.g. the OECD environment-related technology taxonomy) allow researchers to identify green inventions in patent data (Haščič and Migotto, 2015). We therefore use green patents in this paper as an objective but narrower complement to the eco-innovation indicators derived from the Community Innovation Survey (CIS).

However, the broader patent literature warns that patenting should not be interpreted mechanically as productivity-enhancing innovation. Boldrin and Levine (2013) argue that there is little evidence of a systematic positive relationship between patenting and productivity at the aggregate or sectoral level. Danguy et al. (2014) show that the global increase in patenting reflects not only research productivity but also appropriability and filing strategies. At the firm level, Balasubramanian and Sivadasan (2011) find that patenting is associated with firm size, scope, skill intensity, and capital intensity, while the evidence for TFP is weaker. Bloom and Van Reenen (2002) find that patents can affect market value quickly but productivity more slowly, which is consistent with delayed realisation of productive gains. Exadaktylos et al. (2024) provide recent global information and communication technology (ICT) evidence showing that the positive correlation between patents and firm outcomes weakens after controlling for reverse causality and endogeneity; their causal estimates point mainly to gains in market share and firm size for smaller firms rather than to direct effects on profitability or productivity.

Recent firm-level evidence by Exadaktylos et al. (2024) is particularly relevant for interpreting patent-based measures in the present paper. Using matched financial accounts and patent grants for 179,660 firms in the global ICT industry across 39 countries, they show that patenting is strongly concentrated among a small number of large firms, and that simple correlations between patenting, market shares, productivity, firm size, and capital intensity can be misleading. After controlling for reverse causality and endogeneity through a difference-in-differences and instrumental-variable (IV) strategy, they find that patent grants mainly increase market shares and firm size for smaller firms, while effects for larger firms largely fade away. Importantly, they do not find a direct causal effect of patent grants on profitability or productivity. This evidence reinforces our decision to treat green patents as an objective but narrow proxy for technological eco-innovation and to interpret patent-based correlations with productivity cautiously. In the context of the present paper, green patenting is therefore best understood as complementary evidence on environmental technological activity rather than as a sufficient indicator of realised productivity gains.

Recent measurement work makes a similar point for green innovation. Block et al. (2025) compare green patents, green trademarks, and survey measures, showing that many green innovative firms are missed when researchers rely solely on intellectual-property-based measures. Leippold and Yu (2026) develop a text-based firm-level measure of green innovation that captures both invention and adoption, emphasising that patents alone may miss non-patentable inventions and the adoption of green technologies by firms that are not themselves inventors. These studies

support the empirical strategy of the present paper: survey-based eco-innovation indicators capture a broader set of environmental changes, while green patents provide a more objective but narrower measure of technological eco-innovation.

The theoretical argument below combines this CDM logic with a production-cost model of resource-biased technical change. It is related to the Porter-hypothesis literature, which argues that environmental innovation can improve competitiveness when it uncovers efficiency gains or relaxes organisational inefficiencies (Porter and van der Linde, 1995; Cohen and Tubb, 2018). It is also consistent with the induced-innovation and directed-technical-change view, according to which firms allocate innovative effort towards the inputs and constraints with the highest expected return (Popp, 2002; Acemoglu et al., 2012; Aghion et al., 2016). The novelty of our framework is to place the CDM sequence inside a firm-level energy-services technology, thereby deriving the expected signs of the empirical coefficients for R&D participation, eco-innovation, energy intensity, labour productivity, and delayed TFP within a single model.

3 Theoretical framework: resource-biased eco-innovation

This section discusses a resource-biased eco-innovation framework that is designed to rationalise the empirical CDM specification and the main patterns observed in the estimates. The central idea is that ecological innovation differs from generic innovation because it is directed at a specific production constraint (e.g. the use of energy and environmentally harmful inputs). A firm can decide to invest in R&D that may lead to successful innovation output (i.e. eco-innovations that boost energy efficiency), a decrease in unit costs, and an increase in labour productivity. This is the immediate energy-saving channel. Second, once the new process has been integrated into production, workers have learned to use it, complementary capital has been installed, and organisational routines have been adjusted, the innovation can also raise TFP. This is the delayed frontier-shifting channel that is weaker contemporaneously but may appear in lagged TFP measures. This distinction is important for interpreting the empirical results: whereas eco-innovations raise sales or GVA per employee and reduce energy intensity, the effect on contemporaneous TFP remains statistically weak but increases with a lag.

3.1 Innovation decision, R&D intensity, and eco-innovation output

The first two stages of the CDM framework applied below can be motivated as follows. Suppose that a firm chooses R&D expenditure $R \geq 0$ before observing whether the eco-innovation is successfully implemented.[1] Let the probability of producing an implementable eco-innovation be given by the cumulative distribution function of the exponential distribution

$$\Pr(I = 1) = 1 - \exp\left[-\chi R\right], \qquad \text{with } \chi > 0 \text{ and } R \geq 0, \tag{1}$$

where χ captures the productivity of R&D that might depend positively on absorptive capacity (e.g. skilled workers, cooperation with other firms or research institutes, and the use of external

[1] For the sake of simplicity, we skip firm, industry, and time indices when appropriate.

knowledge and spillovers). The expected present value future profits of a successful eco-innovation at time t is denoted by ΔV_t.[2] This first depends on the direct cost-saving value, which is larger for firms with higher energy shares (as shown below).[3] We assume that the firm chooses R&D to maximise the expected net innovation value:

$$\max_{R \geq 0} \; [1 - \exp(-\chi R)] \, \Delta V - p^R R - F^R, \tag{2}$$

where p^R denotes the marginal cost of R&D and F^R is a fixed cost of maintaining an R&D programme. If the firm invests in R&D, the first-order condition is

$$\chi \exp(-\chi R) \Delta V = p^R, \tag{3}$$

which implies an optimal level of R&D given by

$$R^* = \frac{1}{\chi} \ln \left(\frac{\chi \Delta V}{p^R} \right) \qquad \text{if } \chi \Delta V > p^R. \tag{4}$$

However, R&D participation only occurs when the expected surplus is positive after paying the fixed cost.

This reasoning motivates the first two stages of the CDM applied below (i.e. the R&D selection and intensity equations). The third stage of the CDM then indicates whether this R&D spending actually increases the probability that eco-innovations will lead to more energy efficiency.

3.2 Eco-innovation and firm performance

3.2.1 Production function and unit costs

To motivate the effects of eco-innovations on firm performance, assume that the firm faces a CES production function given by

$$Y = A \left[\omega X^{\frac{\sigma-1}{\sigma}} + (1-\omega) B^{\frac{\sigma-1}{\sigma}} E^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma \neq 1, \tag{5}$$

[2] This can be interpreted as the expected present value of additional profits generated by a successful implementation of the innovation:

$$\Delta V_t = \mathbb{E}_t \left[\sum_{h=0}^{\infty} \beta^h \Delta \pi_{t+h} \,\middle|\, \text{successful implementation} \right], \qquad 0 < \beta < 1.$$

Here, $h = 0, 1, 2, \ldots$ indexes the number of periods after the evaluation date t, so $t+h$ denotes the period in which a profit flow occurs. The parameter β is the one-period discount factor, and β^h converts a profit flow received in period $t+h$ into its value at date t. The operator $\mathbb{E}_t[\cdot \mid \text{successful implementation}]$ denotes the expected value of future profit flows, using information available at date t and conditional on the innovation being successfully implemented.

[3] Further, in the empirical specification, we assume that it depends on the overall market demand for greener products and the possibility that wider or more demanding markets reward environmental quality, policy-induced demand (including domestic and foreign public procurement), and implementation costs, which are controlled for in the econometric specification.

where Y denotes output, A is TFP (or a Hicksian technology shifter), X is a composite input bundle $X = K^{\alpha}L^{1-\alpha}$ with $0 < \alpha < 1$, E denotes energy inputs, B is our indicator of energy efficiency, and $0 < \omega < 1$ denotes a cost share parameter. σ is the elasticity of substitution, for which we assume $\sigma < 1$, assuming that the composite input bundle of capital and labour is not easily substitutable with energy. Standard cost minimisation yields the unit cost function given by

$$c = A^{-1}\left[\omega^{\sigma}(p^X)^{1-\sigma} + (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}\right]^{1/(1-\sigma)}, \tag{6}$$

where p^X and p^E are the input prices. The respective cost shares are then given by

$$s^X = \frac{\omega^{\sigma}(p^X)^{1-\sigma}}{[\omega^{\sigma}(p^X)^{1-\sigma} + (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}]} \qquad \text{and} \qquad s^E = \frac{(1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}}{[\omega^{\sigma}(p^X)^{1-\sigma} + (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}]}$$

with $s^X + s^E = 1$.

3.2.2 The effect of eco-innovation on unit costs

The first derivative of unit costs with respect to energy efficiency is

$$\frac{\partial c}{\partial B} = -\frac{1}{B}c[.]^{-1}(1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma} = -\frac{1}{B}cs^E.$$

The unit costs fall with an increase in B, and the effect is larger the larger their share s^E in the overall costs is. The partial elasticity of a change in B is equal to the negative cost share

$$\frac{\partial c}{\partial B}\frac{B}{c} = \frac{\partial \ln c}{\partial \ln B} = -s^E.$$

In other words, a 1% increase in B would reduce unit costs by s^E%.

3.2.3 Link to innovation output

One can also establish a direct link to the eco-innovations by assuming that energy efficiency depends on innovation output $\mathcal{I}$ (as we find empirically). For example, assuming a linear functional relation $B = \mathcal{I}_0 + \lambda\mathcal{I}$ and $\frac{\partial B}{\partial \mathcal{I}} = \lambda$ shows that

$$\frac{\partial c}{\partial B}\frac{\partial B}{\partial \mathcal{I}} = -\frac{1}{B}cs^E\lambda \Rightarrow \frac{\partial c}{\partial B}\frac{B}{c}\frac{\partial B}{\partial \mathcal{I}} = -s^E\lambda.$$

The change in energy efficiency depends on the extent to which (general) innovations are relevant for changes in energy efficiency.

3.2.4 The effect on the energy share and energy intensity

To show the effects of an improvement in energy efficiency on the energy share in total costs, one can calculate the first derivative of the energy cost share with respect to B, which is

$$\frac{\partial s^E}{\partial B} = (\sigma-1)B^{-1}s^E s^X = (\sigma-1)B^{-1}s^E(1-s^E)$$

with a partial elasticity given by

$$\frac{\partial s^E}{\partial B}\frac{B}{s^E} = (\sigma - 1)(1 - s^E).$$

The energy cost share declines if (as assumed) $\sigma < 1$ (i.e. energy services and the non-energy composite input are gross complements).[4]

The respective changes in energy intensity can be derived as well. According to Shephard's lemma, demand for energy is given by

$$E = \frac{\partial c}{\partial p^E} = Y(1-\omega)B^{\sigma-1}(p^X)^{-\sigma}[.]^{\sigma/(1-\sigma)},$$

resulting in an energy input coefficient given by

$$a_E = \frac{E}{Y} = (1-\omega)B^{\sigma-1}(p^X)^{-\sigma}\left[\omega^\sigma(p^X)^{1-\sigma} + (1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}\right]^{\sigma/(1-\sigma)}.$$

Taking the first derivative of this coefficient with respect to energy efficiency results in

$$\frac{\partial a_E}{\partial B} = (\sigma - 1)B^{-1}a_E - \sigma a_E B^{-1}s^E$$

with the partial elasticity given by

$$\frac{\partial a_E}{\partial B}\frac{B}{a_E} = (\sigma - 1) - \sigma\theta^E < 0 \Rightarrow \sigma < \frac{1}{1 - s^E}.$$

This derivative is negative whenever $\sigma < 1/(1 - s^E)$, which includes when the composite input and energy are gross complements (i.e. $\sigma \leq 1$).

3.2.5 Effect on the composite input and labour productivity

In an analogous way, one can show that

$$\frac{\partial a_X}{\partial B}\frac{B}{a_X} = -\sigma S^E < 0.$$

Thus, the input intensity of the composite factor (a_X) is decreasing, implying that productivity $1/a_X$ is increasing. As we assume that the composite input is a Cobb-Douglas form $X = K^\alpha L^{1-\alpha}$, it holds that $a_L = \frac{L}{Y} = (1-\alpha)\frac{p^X a_X}{w}$. For a constant parameter α and input prices, eco-innovation therefore increases labour productivity.

[4] With the same reasoning as above, one can link this result to innovation output. For example, for the linear specification discussed above, the elasticity would become

$$\frac{\partial s^E}{\partial B}\frac{B}{s^E}\frac{\partial B}{\partial \mathcal{I}} = (\sigma - 1)(1 - s^E)\lambda.$$

3.2.6 Other performance measures

These results are maintained for the empirically observed variables. Under the small-firm assumption (i.e. that firms take factor and output prices as given), these results carry over to sales per employee or GVA per employee (when assuming constant prices of intermediarie inputs and separability of the production function), which are increasing with increasing energy efficiency. Analogously, results hold for energy expenditure relative to gross output (or sales) or the energy share in total costs, which are falling with increasing energy efficiency.

Finally, the model distinguishes energy efficiency B from Hicks-neutral productivity A. There should therefore not be a contemporaneous impact of eco-innovation on TFP. At the same time, measured TFP may respond weakly in the implementation period because energy-saving improvements are partly captured by energy-intensity outcomes and because transition costs offset some of the broader efficiency gains. This is in line with earlier papers in the literature, such as Boldrin and Levine (2013). However, over time, it may be that A adjusts slowly as firms gain experience with the new technology (learning-by-doing), adjust the organisation of their processes, and make complementary investments.

3.3 Testable propositions

This framework yields five propositions that guide the empirical interpretation. First, R&D participation and R&D intensity increase with the expected value of eco-innovation, absorptive capacity, cooperation, external knowledge, investment, and market scope, and they decrease with high implementation and legacy-capital costs. Second, conditional on selection into R&D, higher predicted R&D intensity increases the probability of observing eco-innovation. Human capital, external intellectual property rights (IPR), and capital investment should reinforce this relationship. Third, eco-innovation reduces energy intensity when energy services and other inputs are complementary and not easily substitutable. The effect should be stronger among energy-intensive firms. Fourth, eco-innovation increases sales and GVA per employee through lower unit costs, more efficient process organisation, and possible demand expansion. Fifth, contemporaneous TFP effects are theoretically ambiguous because resource-saving and implementation-cost channels work in opposite directions. Lagged TFP effects should be more positive once learning and complementary capital adjustment have occurred.

4 Methodology and data

These propositions motivate the empirical CDM system we test in this section. The first two propositions correspond to the R&D-selection, R&D-intensity, and eco-innovation-output equations. The last three propositions correspond to the final performance equations for the effect of eco-innovations on first energy intensity and then on firm performance, as discussed immediately below.

4.1 Econometric framework

The baseline empirical framework follows the CDM model, which consists of a four-stage simultaneous equation system. The first two equations describe the innovation-input decision, the third equation describes innovation output, and the fourth equation links innovation output to firm performance. The framework discussed in Section 3 gives the economic interpretation of each stage: firms invest in R&D when the expected value of resource-saving innovation exceeds the fixed and marginal cost of innovation; R&D and complementary capabilities increase the probability of ecological innovation; and then ecological innovation affects energy intensity, labour productivity, and TFP.

Let g_{fst} denote a binary indicator equal to one if firm f in sector s and survey period t invests in R&D. Let k_{fst} denote observed R&D intensity, typically measured as R&D expenditure per employee or a transformation of R&D expenditure. Let I_{fst} denote eco-innovation output, measured either by the CIS ecological-innovation indicator or by green patenting. Let y_{fst} be a performance indicator. The four-stage model can then be written as:

$$g^*_{fst} = \beta_1 x_{1,fst} + \gamma_1 z_{st} + \theta_1 T_t + \varepsilon_{1,fst}, \qquad g_{fst} = \mathbf{1}\{g^*_{fst} > 0\}, \tag{7}$$

$$k_{fst} = \beta_2 x_{2,fst} + \delta\, \widehat{\lambda}_{fst} + \gamma_2 z_{st} + \theta_2 T_t + \varepsilon_{2,fst}, \tag{8}$$

$$I_{fst} = \beta_3 x_{3,fst} + \alpha_3 \widehat{k}_{fst} + \gamma_3 z_{st} + \theta_3 T_t + \varepsilon_{3,fst}, \tag{9}$$

$$y_{fst} = \beta^y_4 x_{4,fst} + \alpha^y_4 \widehat{I}_{fst} + \gamma^y_4 z_{st} + \theta^y_4 T_t + \varepsilon^y_{4,fst}, \quad y \in \{EI, LP, TFP\}, \tag{10}$$

where EI stands for energy intensity, LP for labour productivity, and TFP for total factor productivity. In Equation (7), g^*_{fst} is the latent propensity to perform R&D. The vector $x_{1,fst}$ includes firm-level determinants of expected innovation value and R&D productivity (e.g. size, age, public procurement, market orientation, and industry characteristics). z_{st} captures sector-level controls, and T_t denotes survey-period fixed effects. In Equation (8), $\widehat{\lambda}_{fst}$ is the inverse Mills ratio from the selection equation; its inclusion corrects for the fact that R&D intensity is only observed for firms that select into R&D. The vector $x_{2,fst}$ contains determinants of R&D intensity, including cooperation, procurement, market orientation, and firm age.

In the innovation-output equation, Equation (9), the coefficient α_3 measures whether predicted R&D intensity increases the probability of observing eco-innovation. The theory predicts $\alpha_3 > 0$, including when R&D is controlled for by human capital, external knowledge, and capital investment. The final-stage equation, Equation (10), estimates the association between predicted eco-innovation and three groups of outcomes: energy intensity (EI), labour productivity (LP), and total factor productivity (TFP). The theoretical predictions are $\alpha^{EI}_4 < 0$ when the dependent variable is energy intensity, $\alpha^{LP}_4 > 0$ for sales or GVA per employee, and an ambiguous contemporaneous but potentially positive lagged α^{TFP}_4.

Because several outcome variables may contain zeros and because heteroskedasticity is likely in firm-level data, robustness checks will use Poisson pseudo-maximum likelihood (PPML) estimators where appropriate (Santos Silva and Tenreyro, 2006; Yotov et al., 2016; Correia et al., 2019a,b). Additional robustness checks will examine alternative definitions of energy intensity

and eco-innovation, alternative samples, alternative treatment of non-innovating firms, lagged TFP specifications, and sensitivity to industry controls.

4.2 Data sources

The analysis uses microdata accessed through the Austrian Micro Data Center (AMDC) provided by the Austrian Statistical Office. Several firm- and individual-level datasets are linked through firm identifiers. The main datasets are summarised in Table 1.

Table 1: Main data sources

Dataset	Role in the analysis
Community Innovation Survey (CIS 2014)	Source for innovation inputs, innovation outputs, environmental innovation indicators, R&D expenditure, cooperation, barriers to innovation, and policy incentives. Surveyed firms are active in the following NACE sectors: B, C, D, E, G, H, J, K, M.
Use of goods statistics (GES)	Source for energy-use and energy-cost indicators used to construct measures of energy efficiency. The database relies on voluntary reporting from firms active in NACE industries B to F.
Performance and structural statistics (LSE-RE)	Source for output, employment, capital, industry controls, and productivity measures, including labour productivity and TFP.
Additional firm-level datasets, where available	Used for robustness checks and additional controls, including digital technologies, group status, and firm characteristics.
Patents	Obtained from Orbis Intellectual Property, imported to AMDC, and matched with firms' registry IDs.

The most important dataset is the CIS, which motivates a cross-sectional modelling strategy. CIS 2014 covers innovative activities during the 2012-2014 period. This survey contains questions on environmental innovations, including reductions in material or water use; reductions in energy consumption; reductions in soil, water, or air pollution; substitution towards environmentally friendly materials; replacement of fossil fuels with renewable energy sources; and recycling of waste, water, or other materials.

4.3 Variables

The empirical variables are chosen to correspond as closely as possible to the theoretical outline in Section 3. The main innovation-output variable is ecological innovation, denoted by I_{fst} and measured as an indicator equal to one when firm f in sector s and survey period t reports an innovation with an environmental benefit. This indicator is further differentiated into energy- and non-energy-related eco-innovation concerning both production processes and consumption patterns at the firm level. In other words, energy-related innovation covers reductions in energy use or carbon footprints and the replacement of fossil energy sources in production alongside lower energy use during consumption. Non-energy-related innovation includes material and water savings and pollution reduction and recycling in production as well as reduced pollution,

improved recycling, and longer product lifespans on the consumption side. As an alternative innovation indicator, information on green patenting from Orbis Intellectual Property (IP) is used as a more objective but narrower proxy for technological eco-innovation. Green technologies are identified following the classification by the OECD, which identifies environment-related technologies (Haščič and Migotto, 2015) in the Cooperative Patent Classification (CPC). These are technology classes that mitigate climate change, such as those related to energy generation, transportation, or buildings as well as to environmental management, water management, or the storage and disposal of GHGs.

Innovation-input variables include an R&D participation dummy (g_{fst}), R&D expenditure or R&D intensity (k_{fst}), cooperation in innovation, cooperation with research institutes, acquisition of external IPR, and human capital (measured by the share of highly educated workers), which is taken as a proxy for determining R&D success. Firm size, investment per employee, market orientation, domestic public procurement, and foreign public procurement proxy the expected value of innovation. Firm age and sector indicators capture differences in legacy capital, implementation costs, technological opportunity, and energy dependence. Control variables include firm size class, firm age, industry dummies (at the NACE 1-digit level), capital-to-labour intensity, investment per employee, public procurement, cooperation in innovation, and market orientation as well as industry classes (NACE Rev. 2.1 1-digit).

The key performance outcomes are grouped into three families. First, energy intensity is measured by either the cost of energy relative to gross output or by the share of energy in total costs. These variables are inverse indicators of energy efficiency: a negative coefficient in an energy-intensity regression means that eco-innovation improves energy efficiency. Second, labour productivity is measured as sales per employee and GVA per employee. Third, TFP is estimated following Ackerberg et al. (2015) and is interpreted as the empirical counterpart of Hicks-neutral productivity parameter A in the theoretical framework.

Table 2 presents weighted descriptive statistics for a sample of 3,121 firms from the CIS, representing a population of 17,618 firms through the applied weighting scheme. The dataset, which covers the 2012-2014 survey period, includes information on firms' innovation activities, demographic and financial characteristics, and energy-related variables. Regarding firm demographics, the average firm age is 27 years, with a greater standard deviation, suggesting a right-skewed distribution. Regarding economic activity, most of the firms are in Manufacturing (38%), followed by Wholesale and Retail (21%), Transportation (15%), and Professional, Scientific and Technical Activities (9%). Firm size and performance are measured using variables such as the number of employees (in full-time equivalent units), investment, and turnover (sales). On average, firms have 62.5 employees, 30% of whom are highly educated (i.e. they hold at least a university degree or equivalent). Most firms operate at the local or regional level within Austria (43%), followed by the national market (37%), the EU market (17%), and extra-EU markets (3%).

Moving to innovation indicators, roughly 21% of firms report engaging in ecological innovation.[5] R&D activities are pursued by 22% of the firms. R&D expenditure averages EUR 340,291 per

[5]The breakdown by economic activity of innovative firms follows the same sectoral distribution as the overall sample.

employee but exhibits substantial dispersion, with a standard deviation of over EUR 5 million, indicating a strongly right-skewed distribution in which most firms report low or zero expenditure and a few account for most R&D activity. Cooperation in R&D activities is observed in 23% of the firms. Concerning public procurement, 33% of the firms supply goods or services to domestic public bodies, compared to only 7% supplying foreign public entities, making domestic procurement considerably more prevalent.

Productivity is measured using two sets of indicators. The first includes conventional measures, such as turnover per employee, GVA per employee, and TFP, estimated following Ackerberg et al. (2015). In the first specification, TFP is estimated using value added as output and the number of employees as the labour input. In the second specification, sales revenue serves as output and employee costs as the labour input. Both specifications use fixed capital as the state variable and investment as the proxy variable. The second set focuses on energy-related measures, which are only available for the subsample covered by the AMDC-GES database. The energy-cost variable is highly skewed (mean: 1,413.751; standard deviation: 11,916.293), indicating that most firms report values well below the mean. Based on this variable, two additional measures of energy intensity are constructed: energy bill per gross output (GO), defined as the logarithm of the ratio of energy cost to gross output, and the share of energy bill in total costs.

Table 2: Descriptive statistics

Variable name	Total weighted	Total	Missing	Mean	St. dev.
Dummy internal R&D	17,618	3,121	0	0.224	0.459
R&D exp. per empl.	17,618	3,121	0	340,291	5,021.739
R&D exp. per empl. (log)	17,618	3,121	2,309	1.412	2.017
R&D exp. per empl. (IHS)	17,618	3,121	16	0.462	1.256
Dummy ecological innov.	17,618	3,121	0	0.209	0.448
Sub-categories Ecol.-Innovation (dummies):					
- Energy production	17,618	3,121	0	0.133	0.374
- Other than ener. production	17,618	3,121	0	0.174	0.418
- Energy consumption	17,618	3,121	0	0.115	0.352
- Other than ener. cons.	17,618	3,121	0	0.138	0.38
Dummy green patent (appl. year)	17,618	3,121	0	0.12	0.118
Dummy green patent (prior. year)	17,618	3,121	0	0.9	0.102
Age	17,618	3,121	146	27.342	29.332
Dummy cooperation R&D	17,618	3,121	0	0.227	0.462
Dummy foreign public procurement	17,618	3,121	0	0.067	0.276
Dummy domestic public procurement	17,618	3,121	0	0.327	0.517
Dummy external (IPR)	17,618	3,121	0	0.48	0.236
Number of employees	17,618	3,121	13	62.548	327.297
Share high education	17,618	3,121	134	0.299	0.27
Investment per employee (log)	17,618	3,121	13	1.303	1.474
Sales per employee (log)	17,618	3,121	13	5.232	1.044
GVA per employee (log)	17,618	3,121	28	4.179	0.727
Energy bill	17,618	3,121	2,438	1,413.751	11,916.293
Energy bill / GO (log)	17,618	3,121	2,438	-4.529	1.466
Energy bill (share)	17,618	3,121	2,438	0.02	0.073
TFP (Li)	17,618	3,121	1,799	2.951	1.587
TFP (Ci)	17,618	3,121	1,799	4.062	1.026

Notes: To comply with AMDC's confidentiality requirements, only sample means and standard deviations are reported. Total factor productivity (TFP) measures are computed following Ackerberg et al. (2015), using labour quantity (Li) and labour costs (Ci) as free input variable, respectively. All continuous variables are averaged over the 2012-2014 period. Employment variables are calculated with respect to full-time equivalent units.

5 Econometric results

5.1 R&D decision and investment intensity

The first two stages of the CDM model deal with the Selection Equation (7) and Intensity Equation (8), where the former captures the decision to engage in any internal R&D activity and the latter reports the corresponding R&D expenditure. Table 3 reports the results of the corresponding estimation via a Heckman selection model. Specifically, column (1) presents the firm selection equation (i.e. the probability of being R&D-active), while columns (2)–(3) report the outcome equation for R&D intensity per employee, conditional on selection.

Regarding the selection equation, foreign public procurement shows a strong and positive effect on the likelihood of engaging in R&D activities, whereas domestic procurement is not statistically significant. Firm size emerges as a key determinant: compared to the omitted reference category (<50 employees), all larger size classes exhibit positive and increasing coefficients, indicating that larger firms are systematically more likely to be R&D-active. Firm age also plays a role, with younger firms being more likely to engage in R&D than older ones, consistent with the idea that younger firms may face lower legacy-capital and organisational-adjustment costs (Baumann and Kritikos, 2016; Cohen and Levinthal, 1990). Cooperation variables (i.e. within the same corporate groups or with external firms and research institutes) are excluded from the selection equation, as they are only relevant for the outcome equation.

Columns (2) and (3) present the R&D intensity equation. Employment size is used as an exclusion restriction and is therefore only included in the selection equation to ensure identification of the inverse Mills ratio (IMR). In fact, a diagnostic check concerning identification is provided by column (3), since when employment size is added directly to the outcome equation, the IMR coefficient becomes insignificant. This suggests that including employment size in both equations removes the independent variation needed to identify the IMR. In column (2), the IMR coefficient is positive and statistically significant, indicating positive selection. This implies that unobserved firm characteristics which increase the probability of being R&D-active are positively correlated with R&D intensity, leading to upward-biased estimates if the selection mechanism is ignored. Furthermore, the estimated correlation coefficient between the error terms of the selection and outcome equations ($\rho = 0.375$, column (2)) confirms the presence of correlation among the unobservable characteristics in the model and supports the choice to rely on the Heckman correction rather than running a simple ordinary least squares (OLS) model on the selected sample.

Turning to the determinants of R&D intensity, cooperation is positive and significant across all categories, with the largest effect being observed for cooperation with research institutes. Foreign procurement funding remains strongly positive, while domestic procurement is negative and significant, suggesting an asymmetry whereby domestic procurement may be associated with smaller-scale R&D projects. Age and market orientation confirm the results in the selection equation.[6]

[6]Different measures of R&D intensity are used as robustness checks. See Table A1 in the following section on robustness and heterogeneity.

Overall, the results indicate that larger and younger firms are more likely to engage in R&D on the extensive margin, while cooperation (particularly with research institutes), foreign public procurement, and international market orientation are key drivers of R&D intensity on the intensive margin. This pattern is also consistent with the broader innovation-productivity literature, which emphasises absorptive capacity, market scope, and cooperation as determinants of successful innovation (Crépon et al., 1998; Griffith et al., 2006; Cohen and Levinthal, 1990; Halpern and Muraközy, 2012).

Table 3: Heckman selection model on R&D expenditure

	Dependent variables:		
	Internal R&D	R&D exp. per empl.	
	Probit	OLS	OLS
	(1)	(2)	(3)
Domestic public procurement (Ref.: No)	0.099	-0.486***	-0.517***
	(0.076)	(0.170)	(0.178)
Foreign public procurement (Ref.: No)	0.345***	1.042***	0.961***
	(0.188)	(0.200)	(0.172)
Size employment (Ref.: <50 empl.)			
- 50-249	0.496***		-0.311
	(0.066)		(0.319)
- 250-999	1.149***		-0.288
	(0.090)		(0.588)
- 1,000+	1.316***		-0.371
	(0.198)		(0.686)
Age (Reference: <16)			
- 16-40	-0.147**	-0.602***	-0.540***
	(0.071)	(0.143)	(0.166)
- 41-99	-0.336***	-1.172***	-1.036***
	(0.103)	(0.200)	(0.272)
- 100 and over	-0.910***	-1.338***	-1.029*
	(0.147)	(0.353)	(0.610)
Cooperation (Reference: None)			
- Within corporate group		0.611***	0.614***
		(0.215)	(0.217)
- External firm		0.311**	0.309*
		(0.158)	(0.158)
- Research institute		0.930***	0.920***
		(0.176)	(0.177)
Main market (Reference: Local)			
- National	0.443***	0.452**	0.290
	(0.080)	(0.221)	(0.364)
- Europe	0.977***	1.100***	0.767
	(0.091)	(0.284)	(0.620)
- Other extra-EU countries	1.224***	1.704***	1.311*
	(0.163)	(0.329)	(0.738)
Inverse Mills ratio (IMR)		0.683***	0.179
		(0.244)	(0.878)
Constant	-1.310***	-0.804*	0.097
	(0.098)	(0.442)	(1.507)
Observations	3,121	812	812
Industry dummies	Yes	Yes	Yes
Rho (St. Error)	-	0.375 (0.017)	-
R2	0.231	0.29	-
LogLik	-	-865.473	-863.263
Log likelihood	-1,322.358	-1,560.108	-1,559.070
Akaike inf. crit.	2,684.716	3,160.216	3,164.140

Notes: Standard errors are reported in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Industry dummies are defined at NACE 1-digit level.

5.2 R&D investment and innovation output

The third stage of the CDM model links R&D efforts to innovation output by using the predicted values from Equation (8) to estimate the probability of introducing innovations with positive environmental effects (i.e. ecological innovation). Table 4 reports the probit estimates for different measures of ecological innovation. Across all specifications, the predicted value from

the previous stage is positive and statistically significant, suggesting that firms with higher predicted R&D expenditure are more likely to introduce innovations with positive environmental effects. This is consistent with the expected impact of R&D investment on innovation output in the CDM framework (Crépon et al., 1998). Moreover, the other innovation inputs included in the model (i.e. human capital and reliance on external knowledge) also exhibit the expected positive and significant coefficients. Human capital is measured by the share of highly educated employees, while external knowledge is proxied by a dummy variable capturing the acquisition of external IPR. Capital investment per employee is also positively related to ecological innovation in all columns, indicating that firms with greater capital intensity are more likely to engage in ecological innovation. The main-market orientation variables display a generally positive pattern as well, suggesting that firms serving more international markets have a higher probability of innovating in positive ecological terms. Age variables remain largely insignificant, which implies that ecological innovation is driven more by current firm capabilities than by firm age per se.

Table 4: Regression model on ecological innovation, different measures

	Dependent variables:						
		Dummy ecological innov.				Dummy green patent	
	Total	Energy prod.	Other prod.	Energy consum.	Other consum.	Appl. year	Priority year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prediction R&D exp. per empl.	0.110***	0.122***	0.115***	0.120***	0.099**	0.129**	0.177***
(i.e. $\hat{Step2}$)	(0.041)	(0.044)	(0.042)	(0.043)	(0.044)	(0.066)	(0.064)
Dummy external IPR (Ref.: No)	0.688***	0.627***	0.459***	0.527***	0.717***	0.319	0.263
	(0.127)	(0.126)	(0.126)	(0.129)	(0.123)	(0.205)	(0.231)
Domestic public procurement (Ref.: No)	0.123*	0.202**	0.149**	0.225***	0.094	-0.284	-0.311
	(0.072)	(0.079)	(0.074)	(0.082)	(0.079)	(0.181)	(0.197)
Foreign public procurement (Ref.: No)	0.367***	0.087	0.411***	0.074	0.315**	0.042	0.1
	(0.13)	(0.137)	(0.128)	(0.140)	(0.136)	(0.209)	(0.237)
Investment per empl. (log)	0.092***	0.084***	0.114***	0.060**	0.050*	0.153***	0.166***
	(0.025)	(0.028)	(0.027)	(0.029)	(0.027)	(0.050)	(0.056)
Main market (Reference: Local)							
- National	0.318***	0.347***	0.273***	0.304***	0.165*	-0.084	-0.076
	(0.077)	(0.088)	(0.080)	(0.092)	(0.086)	(0.254)	(0.315)
- Europe	0.490***	0.576***	0.427***	0.554***	0.403***	0.448*	0.183
	(0.092)	(0.102)	(0.095)	(0.104)	(0.101)	(0.251)	(0.299)
- Other extra-EU countries	0.877***	1.001***	0.752***	0.893***	0.846***	0.061	-0.109
	(0.156)	(0.163)	(0.152)	(0.161)	(0.156)	(0.272)	(0.324)
Highly educated employees (share)	1.026***	1.025***	0.810***	1.086***	0.872***	2.010***	2.263***
	(0.187)	(0.189)	(0.196)	(0.188)	(0.199)	(0.366)	(0.450)
Age (Reference: <16)							
- 16-40	-0.012	-0.032	0.027	-0.002	0.017	0.015	-0.04
	(0.071)	(0.076)	(0.074)	(0.078)	(0.078)	(0.157)	(0.171)
- 41-99	-0.063	-0.006	-0.014	0.0003	-0.008	0.24	0.215
	(0.090)	(0.097)	(0.094)	(0.102)	(0.10)	(0.213)	(0.261)
- 100 and over	0.194	0.117	0.313**	-0.009	-0.073	0.266	0.383
	(0.149)	(0.163)	(0.156)	(0.176)	(0.173)	(0.338)	(0.356)
Constant	-1.529***	-1.853***	-1.608***	-1.929***	-1.782***	-3.674***	-3.937***
	(0.100)	(0.117)	(0.102)	(0.120)	(0.109)	(0.310)	(0.492)
Observations	2,987	2,987	2,987	2,987	2,987	2,987	2,987
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.153	0.147	0.147	0.144	0.152	0.311	0.349
Log likelihood	-1,320.66	-1,011.65	-1,181.39	-932.562	-1,030.54	-109.059	-83.594
Akaike inf. crit.	2,683.32	2,065.30	2,404.78	1,907.12	2,103.07	260.119	209.188

Notes: Standard errors are reported in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Industry dummies are defined at NACE 1-digit level.

Interestingly, when ecological innovation is broken down into production- and consumption-side inventions – as in columns (2)–(3) and columns (4)–(5), respectively – energy-related inventions show stronger effects than other ecological innovations. In particular, the production-side measures are defined as reductions in carbon footprint and/or reliance on fossil energy, while the consumption-side measures are defined in terms of reductions in firms' energy consumption,

as described in Section 4.3. As a robustness check, the dependent variable is also replaced by an indicator of whether the firm applied for a patent in green technologies during the 2012-2014 survey period, using both the application date in column (6) and the priority date in column (7) as temporal references. The results are broadly consistent with the baseline specifications.

5.3 Effects on productivity and energy efficiency

Table 5 presents the final stage of the CDM model, where the predicted probability of eco-innovation is used to estimate its effect on several productivity and energy-efficiency outcomes. The columns cover three families of dependent variables: labour productivity (cols. (1) and (2) as well as (5) and (6)), energy intensity (cols. (3) and (4)), and TFP (cols. (7) and (8)), with columns (5) and (6) restricted to the energy subsample (N=683) to ensure direct comparability with the energy-intensity results.

Ecological innovation significantly reduces both energy use relative to gross output and the share of energy costs in total costs, providing clear evidence that ecological innovation is introduced to use energy more efficiently, in line with the theoretical framework discussed above. Specifically, this implies that in the relevant Austrian manufacturing activities, energy and other production inputs behave as complements or are not easily substituted in the short run.[7]

Concerning firm performance, eco-innovation has a strong and significant positive effect on both sales and GVA per employee in the full sample (cols. (1) and (2)), pointing to a clear productivity premium among ecological innovators. In the energy subsample (cols. (5) and (6)), the effects are smaller in magnitude but remain statistically significant, confirming that this premium is not an artefact of sample composition.

The TFP results stand in contrast to the labour-productivity findings, as the coefficient on ecological innovation is not statistically significant in either specification (cols. (7) and (8)). However, as shown in Table A4, a positive and significant effect emerges with a one-year lag at time $t + 1$. This timing is consistent with the above arguments that eco-innovation seems to first operate through energy-services efficiency and cost savings, while broader Hicks-neutral productivity gains only materialise after learning and complementary organisational adjustment.

Control variables display the expected signs across all specifications. Capital investment per employee is positively and significantly associated with outcomes in all models except TFP. The capital-to-labour ratio is less consistently significant but always of the expected sign. Firm age is positively associated with labour productivity in the full sample (cols. (1) and (2)), which is consistent with the accumulation of capital and market position over time, but this advantage reverses in the energy subsample (cols. (5) and (6)), indicating that older firms in energy-intensive sectors tend to be less energy efficient. Similarly, larger firms display higher productivity in the full sample but significantly lower sales per employee in the energy subsample, which may again reflect compositional differences among energy-reporting firms.

[7] It should be noted that the sample drops to 683 observations, reflecting the limited availability of firm-level data on energy consumption.

Table 5: Regression model on firm productivity, different measures

	Dependent variables:							
	Sales per empl. (log)	GVA per empl. (log)	Energy bill / GO (log)	Energy bill (share)	Sales per empl. sample (3)-(4)	GVA per empl. sample (3)-(4)	TFP (Li)	TFP (Ci)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prediction prob.	1.314***	0.800***	-2.029***	-0.036***	0.564***	0.510***	-0.232	0.066
ecological innov. (i.e. $\hat{Step3}$)	(0.123)	(0.098)	(0.299)	(0.008)	(0.138)	(0.114)	(0.366)	(0.191)
Investment per empl. (log)	0.139***	0.166***	0.261***	0.005***	0.099***	0.125***	-0.287***	-0.179***
	(0.016)	(0.012)	(0.060)	(0.002)	(0.034)	(0.026)	(0.064)	(0.025)
Capital-to-labour ratio	0.048***	0.026**	-0.095	-0.002*	0.04	0.016	-0.053	0.097**
	(0.014)	(0.012)	(0.066)	(0.001)	(0.030)	(0.021)	(0.116)	(0.041)
Age (Reference: <16)								
- 16-40	0.156***	0.090***	0.158	-0.001	-0.159**	-0.168***	0.067	0.062
	(0.04)	(0.027)	(0.123)	(0.003)	(0.064)	(0.052)	(0.096)	(0.061)
- 41-99	0.072	0.071*	0.182	0.004	-0.149**	-0.187***	-0.08	0.101
	(0.051)	(0.037)	(0.132)	(0.004)	(0.066)	(0.059)	(0.133)	(0.075)
- 100 and over	0.275***	0.207***	0.325*	0.002	-0.244*	-0.139	-0.547	0.207
	(0.067)	(0.050)	(0.196)	(0.005)	(0.131)	(0.130)	(0.566)	(0.129)
Size employment (Ref.: <50 empl.)								
- 50-249	0.129***	0.033	0.331	-0.004	-0.708***	-0.225**	-0.048	0.428***
	(0.033)	(0.024)	(0.203)	(0.005)	(0.098)	(0.089)	(0.125)	(0.061)
- 250-999	0.218***	0.058*	0.346*	-0.005	-0.661***	-0.172*	0.024	0.593***
	(0.042)	(0.030)	(0.206)	(0.005)	(0.101)	(0.090)	(0.134)	(0.076)
- 1,000+	0.278***	0.095	-0.079	-0.036	-0.425***	0.008	-0.016	0.966***
	(0.102)	(0.064)	(0.301)	(0.022)	(0.143)	(0.112)	(0.285)	(0.254)
Constant	4.439***	3.530***	-4.578***	0.021***	6.132***	4.247***	3.182***	3.947***
	(0.046)	(0.032)	(0.250)	(0.006)	(0.135)	(0.103)	(0.127)	(0.061)
Observations	3,092	3,092	683	683	683	683	1,322	1,322
Nace 1-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.201	0.234	0.18	0.422	0.254	0.232	0.092	0.125
LogLik	-1046.15	-501.067	-208.51	-0.367	-114.799	-75.211	-1085.229	-436.475
Log likelihood	-4,044.26	-2,908.22	-1,066.56	1,099.31	-646.467	-501.633	-2,397.06	-1,795.01
Akaike inf. crit.	8,124.51	5,852.44	2,165.11	-2,166.62	1,324.93	1,035.27	4,824.11	3,620.01

Notes: Standard errors are reported in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Industry dummies are defined at NACE 1-digit level. Abbreviations: GVA = gross value added; GO = gross output; TFP = total factor productivity.

6 Concluding remarks

This paper provides firm-level evidence on whether R&D-driven eco-innovation improves energy efficiency and productivity in Austrian manufacturing. To do so, the paper first investigates the channels through which firms decide to invest in R&D and introduce eco-innovation. Second, it connects environmental innovation to concrete firm performance outcomes. The econometric model is guided by a theoretical framework that shows how ecological innovation may reduce energy intensity and raise productivity.

Taken together, the theoretical and empirical results provide a coherent and nuanced picture. Ecological innovation is associated with higher labour productivity and improved energy efficiency, consistent with a 'win-win' interpretation in which environmental and economic performance can be complementary rather than substitutional. In the model, this complementarity arises because eco-innovation raises the efficiency with which measured energy is transformed into productive energy services. This, in turn, lowers unit costs and energy intensity, especially when energy and other inputs are complementary in the short run. The empirical evidence that eco-innovation reduces energy intensity and raises sales and GVA per employee fits this mechanism.

The weaker contemporaneous TFP results should not be interpreted as evidence that eco-innovation lacks technological relevance. The theoretical framework distinguishes immediate resource-saving gains from delayed frontier-shifting gains. Eco-innovation can first appear as lower energy costs and higher labour productivity, while broader TFP effects require learning, complementary capital investment, and organisational adjustments. Evidence of a positive lagged TFP effect is therefore consistent with the view that ecological innovation is transformative but gradual.

From a policy perspective, the framework suggests that green innovation policy should not focus solely on the invention of new environmental technologies. Instead, it should also support the complementary capabilities that turn R&D into implemented eco-innovation: skilled labour, cooperation with research institutes, external knowledge acquisition, capital investment, and access to demanding markets. The stronger role of foreign public procurement in the R&D equations suggests that sophisticated demand can be an important driver of environmental innovation. For energy-intensive firms, targeted support may be particularly effective because the private and social returns to energy-saving innovation are likely to be larger.

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Appendix

A TFP estimation

The empirical analysis reports two productivity indices, denoted Li and Ci, constructed using the Ackerberg–Caves–Frazer approach (Ackerberg et al., 2015). The TFP Li specification uses value added as the dependent variable, employment as the freely variable labour input, fixed capital as the state variable, and investment as the proxy variable. The TFP Ci specification instead uses sales revenue as the dependent variable and labour costs as the freely variable input, retaining fixed capital as the state variable and investment as the proxy. Thus, these specifications differ in both their output measure and their labour-input measure.

The proxy approach addresses the dependence between firms' input choices and productivity observed by the firm but unobserved by the researcher. Under the maintained timing and invertibility assumptions, investment provides information about this unobserved productivity conditional on the state variables. The production-function coefficients are estimated using the control-function procedure and its associated moment conditions. Investment consequently serves an identification role.

B Robustness and heterogeneity

In addition to the heterogeneity and robustness analyses presented above, we conduct further sensitivity checks at different stages of the CDM model. For the Intensity Equation (8), alternative measures of R&D expenditure are used in Table A1. In the productivity analysis, the ecological innovation indicator is replaced by the probability of green patenting by application and priority year, as shown in Tables A2 and A3, respectively. The lagged effects on TFP are estimated in Table A4.

Finally, we replicate the full analysis using the CIS 2020 wave. The results are broadly consistent with those for 2014, except that the relationship between R&D investment and innovation output (Equations (1) and (9)) is no longer statistically significant. This difference may reflect disruptions associated with the COVID-19 crisis. These results for the 2020 wave are available upon request.

Table A1: Regression model on R&D expenditure, alternative measures

	Dependent variables:		
		R&D exp. per empl.	
	Log transf. (normal)	no transf. (Poisson)	IHS transf. (normal)
	(1)	(2)	(3)
Foreign public procurement (Ref.: No)	1.042***	0.921***	0.808***
	(0.188)	(0.200)	(0.172)
Domestic public procurement (Ref.: No)	-0.486***	-0.726***	-0.338**
	(0.170)	(0.206)	(0.142)
Age (Reference: <16)			
- 16-40	-0.602***	-0.639***	-0.371***
	(0.143)	(0.212)	(0.126)
- 41-99	-1.172***	-0.973***	-0.564***
	(0.200)	(0.274)	(0.148)
- 100 and over	-1.338***	-1.708***	-0.984***
	(0.353)	(0.348)	(0.279)
Cooperation (Reference: None)			
- Within corporate group	0.611***	0.661	0.532***
	(0.215)	(0.426)	(0.201)
- External firm	0.311**	0.057	0.330**
	(0.158)	(0.279)	(0.133)
- Research institute	0.930***	0.670**	0.857***
	(0.176)	(0.262)	(0.160)
Main market (Reference: Local)			
- National	0.452**	0.193	0.321*
	(0.221)	(0.392)	(0.187)
- Europe	1.100***	0.667*	1.154***
	(0.284)	(0.342)	(0.238)
- Other extra-EU countries	1.704***	1.282***	1.728***
	(0.329)	(0.441)	(0.285)
Inverse Mills ratio	0.683***	0.910**	0.642***
(IMR)	(0.244)	(0.398)	(0.194)
Constant	-0.804*	-0.093	-0.067
	(0.442)	(0.663)	(0.361)
Observations	812	887	887
Industry dummies	Yes	Yes	Yes
R^2	0.29	0.153	0.281
Log likelihood	-1,560.108		-1,609.679
Akaike inf. crit.	3,160.216		3,259.358

Notes: Standard errors are reported in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Industry dummies are defined at NACE 1-digit level.

Table A2: Regression model on firm productivity, different measures. Innovation output measured as probability of green patenting (application year)

	Dependent variables:							
	Sales per empl. (log)	GVA per empl. (log)	Energy bill / GO (log)	Energy bill (share)	Sales per empl. sample (3)-(4)	GVA per empl. sample (3)-(4)	TFP (Li)	TFP (Ci)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prediction prob.	3.528***	2.436***	-6.081***	-0.093***	1.443***	1.587***	0.092	0.699
Green patent – application year (i.e. $\hat{Step3}$)	(0.516)	(0.327)	(0.899)	(0.019)	(0.460)	(0.358)	(1.192)	(0.617)
Investment per empl. (log)	0.152***	0.173***	0.278***	0.005***	0.095***	0.121***	-0.296***	-0.181***
	(0.016)	(0.012)	(0.060)	(0.002)	(0.034)	(0.026)	(0.067)	(0.025)
Capital-to-labour ratio	0.050***	0.027**	-0.099	-0.002*	0.042	0.017	-0.06	0.095**
	(0.014)	(0.012)	(0.067)	(0.001)	(0.031)	(0.022)	(0.117)	(0.040)
Age (Reference: <16)								
- 16-40	0.156***	0.090***	0.16	-0.001	-0.159**	-0.169***	0.072	0.062
	(0.041)	(0.027)	(0.125)	(0.003)	(0.064)	(0.051)	(0.096)	(0.061)
- 41-99	0.027	0.045	0.310**	0.007	-0.184***	-0.219***	-0.066	0.1
	(0.052)	(0.038)	(0.135)	(0.004)	(0.067)	(0.058)	(0.134)	(0.075)
- 100 and over	0.242***	0.188***	0.248	0.001	-0.222*	-0.12	-0.554	0.211*
	(0.065)	(0.048)	(0.187)	(0.004)	(0.130)	(0.131)	(0.567)	(0.128)
Size employment (Ref.: <50 empl.)								
- 50-249	0.173***	0.059**	0.202	-0.006	-0.677***	-0.190**	-0.067	0.427***
	(0.033)	(0.024)	(0.208)	(0.005)	(0.099)	(0.089)	(0.120)	(0.059)
- 250-999	0.301***	0.104***	0.16	-0.008	-0.611***	-0.124	-0.013	0.587***
	(0.041)	(0.029)	(0.207)	(0.006)	(0.101)	(0.090)	(0.113)	(0.072)
- 1,000+	0.372***	0.142**	-0.195	-0.038*	-0.386***	0.036	-0.084	0.934***
	(0.108)	(0.065)	(0.293)	(0.023)	(0.147)	(0.111)	(0.274)	(0.245)
Constant	4.640***	3.653***	-4.996***	0.013***	6.248***	4.351***	3.156***	3.961***
	(0.045)	(0.030)	(0.267)	(0.005)	(0.142)	(0.099)	(0.106)	(0.062)
Observations	3,092	3,092	683	683	683	683	1,322	1,322
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.18	0.22	0.182	0.419	0.249	0.235	0.092	0.126
Log likelihood	-4,085.877	-2,935.593	-1,065.348	1,098.001	-648.695	-500.279	-2,397.444	-1,794.297
Akaike inf. crit.	8,207.754	5,907.185	2,162.696	-2,164.003	1,329.391	1,032.558	4,824.888	3,618.595

Notes: Standard errors are reported in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Industry dummies are defined at NACE 1-digit level. Abbreviations: GVA = gross value added; GO = gross output; TFP = total factor productivity.

Table A3: Regression model on firm productivity, different measures. Innovation output measured as probability of green patenting (priority year)

	Dependent variables:							
	Sales per empl. (log)	GVA per empl. (log)	Energy bill / GO (log)	Energy bill (share)	Sales per empl. sample (3)-(4)	GVA per empl. sample (3)-(4)	TFP (Li)	TFP (Ci)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prediction prob.	3.033***	2.348***	-7.069***	-0.091***	1.617***	1.814***	-0.244	0.573
Green patent – priority year (i.e. $\widehat{Step3}$)	(0.541)	(0.400)	(1.103)	(0.019)	(0.510)	(0.401)	(1.405)	(0.77)
Investment per empl. (log)	0.155***	0.175***	0.274***	0.005***	0.097***	0.122***	-0.293***	-0.180***
	(0.016)	(0.012)	(0.060)	(0.002)	(0.034)	(0.026)	(0.066)	(0.025)
Capital-to-labour ratio	0.050***	0.027**	-0.097	-0.003*	0.042	0.016	-0.058	0.096**
	(0.014)	(0.012)	(0.065)	(0.001)	(0.031)	(0.021)	(0.117)	(0.040)
Age (Reference: <16)								
- 16-40	0.157***	0.091***	0.148	-0.001	-0.156**	-0.165***	0.07	0.063
	(0.041)	(0.027)	(0.124)	(0.003)	(0.064)	(0.051)	(0.097)	(0.061)
- 41-99	0.025	0.044	0.305**	0.007	-0.182***	-0.218***	-0.068	0.099
	(0.052)	(0.038)	(0.135)	(0.004)	(0.067)	(0.058)	(0.134)	(0.075)
- 100 and over	0.234***	0.182***	0.325*	0.002	-0.239*	-0.139	-0.554	0.207
	(0.065)	(0.048)	(0.191)	(0.004)	(0.132)	(0.133)	(0.568)	(0.128)
Size employment (Ref.: <50 empl.)								
- 50-249	0.181***	0.064***	0.194	-0.005	-0.676***	-0.189**	-0.066	0.431***
	(0.033)	(0.024)	(0.209)	(0.005)	(0.099)	(0.089)	(0.119)	(0.059)
- 250-999	0.326***	0.119***	0.139	-0.008	-0.607***	-0.118	-0.008	0.595***
	(0.040)	(0.029)	(0.208)	(0.006)	(0.102)	(0.090)	(0.110)	(0.072)
- 1,000+	0.409***	0.161**	-0.198	-0.038*	-0.384***	0.038	-0.063	0.950***
	(0.105)	(0.064)	(0.296)	(0.023)	(0.147)	(0.111)	(0.275)	(0.246)
Constant	4.639***	3.652***	-4.993***	0.013***	6.247***	4.350***	3.153***	3.959***
	(0.045)	(0.030)	(0.267)	(0.005)	(0.142)	(0.099)	(0.105)	(0.062)
Observations	3,092	3,092	683	683	683	681	1,322	1,322
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.175	0.217	0.184	0.417	0.249	0.235	0.092	0.126
Log likelihood	-4,095.24	-2,941.80	-1,064.73	1,096.75	-649.072	-500.494	-2,397.42	-1,794.65
Akaike inf. crit.	8,226.47	5,919.60	2,161.46	-2,161.51	1,330.14	1,032.99	4,824.84	3,619.30

Notes: Standard errors are reported in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Industry dummies are defined at NACE 1-digit level. Abbreviations: GVA = gross value added; GO = gross output; TFP = total factor productivity.

Table A4: Regression model on TFP effects at $t+1$, using different measures of innovation output

Dependent variables (at $t+1$):	TFP Li	TFP Ci	TFP Li	TFP Ci	TFP Li	TFP Ci
	(1)	(2)	(3)	(4)	(5)	(6)
Prob. eco-innov.	1.277**	0.613**				
	(0.622)	(0.286)				
Prob. green patent.			5.804***	0.257		
(appl. year)			(1.945)	(0.637)		
Prob. green patent.					7.502***	-0.147
(priority year)					(2.349)	(0.729)
Investment per empl. (log)	-0.512***	0.001	-0.506***	0.021	-0.512***	0.024
	(0.147)	(0.038)	(0.152)	(0.039)	(0.151)	(0.039)
Capital-to-labour ratio	0.237	0.018	0.237	0.034	0.238	0.036
	(0.156)	(0.063)	(0.151)	(0.063)	(0.150)	(0.064)
Size empl. (Ref. <50 empl.)						
- 50-249	-0.532**	0.692***	-0.476**	0.739***	-0.461**	0.742***
	(0.234)	(0.080)	(0.215)	(0.074)	(0.213)	(0.074)
- 250-999	-2.728***	1.103***	-2.671***	1.189***	-2.644***	1.197***
	(0.512)	(0.113)	(0.487)	(0.102)	(0.487)	(0.100)
- 1,000+	-4.756**	1.050***	-4.820**	1.193***	-4.864**	1.219***
	(2.276)	(0.285)	(2.273)	(0.271)	(2.265)	(0.272)
Age (Ref. <16)						
- 16-40	-0.330*	0.04	-0.340*	0.029	-0.325*	0.028
	(0.191)	(0.072)	(0.189)	(0.073)	(0.190)	(0.073)
- 41-99	-0.007	-0.123	-0.056	-0.157*	-0.051	-0.158*
	(0.223)	(0.087)	(0.219)	(0.090)	(0.218)	(0.090)
- 100 and over	-0.062	-0.415***	-0.005	-0.395**	-0.042	-0.396**
	(0.522)	(0.157)	(0.523)	(0.158)	(0.521)	(0.158)
Constant	3.631***	3.824***	3.830***	3.897***	3.834***	3.894***
	(0.280)	(0.089)	(0.228)	(0.081)	(0.229)	(0.080)
Observations	1,277	1,277	1,277	1,277	1,277	1,277
R^2	0.086	0.172	0.088	0.166	0.09	0.166
Log likelihood	-3,477.461	-1,905.57	-3,475.918	-1,910.629	-3,474.596	-1,910.686
Akaike inf. crit.	6,984.923	3,841.14	6,981.836	3,851.257	6,979.191	3,851.372

Notes: Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Industry dummies are defined at the NACE one-digit level. Abbreviations: TFP Li = total factor productivity estimated using value added as output, the number of employees as the labour input, fixed capital as the state variable, and investment as the proxy variable. TFP Ci = total factor productivity estimated using sales revenue as output, employee costs as the labour input, fixed capital as the state variable, and investment as the proxy variable.

C Technical appendix

C.1 R&D choice, timing, and selection

The R&D problem is a conditional investment decision with a present-value payoff. The firm first chooses $R \geq 0$ and pays its R&D costs; success is then realised and the technology is implemented before the production benefits accrue. The static derivatives refer to the implementation period. A delay between research and implementation shifts and discounts the benefits accordingly.

Let R be research outlay in specified resource units, and let p^R convert each unit into cost, so observed monetary expenditure corresponds to $p^R R$. If R is already measured in euros, set $p^R = 1$ in those units. Conditional on participation, success has a probability of

$$\Pr(I = 1 \mid R) = 1 - \exp(-\chi R), \qquad \chi > 0. \tag{C.1}$$

Here, $\chi > 0$ measures R&D effectiveness, corresponding to the firm-specific R&D productivity parameter χ_{fst} in the main text, with indices suppressed. A higher χ increases the probability of successful innovation for a given positive research outlay R. Conditional on undertaking R&D, the firm chooses its research outlay while taking its own χ and the payoff from successful implementation as given. Thus, χ may differ across firms and periods but is held fixed when solving the individual firm's expenditure choice.

Let t denote the period in which the firm evaluates its R&D decision. Define ΔV_t as the expected present value of the additional profits generated by successful implementation of the innovation before deducting research expenditure and the fixed R&D participation cost:

$$\Delta V_t = \mathbb{E}_t \left[\sum_{h=0}^{\infty} \beta^h \Delta\pi_{t+h} \,\middle|\, \text{successful implementation} \right], \qquad 0 < \beta < 1. \tag{C.2}$$

Here, $h = 0, 1, 2, \ldots$ indexes the number of periods after the evaluation date t, so $t + h$ denotes the period in which a profit flow occurs. The parameter β is the one-period discount factor, and β^h converts a profit flow received in period $t + h$ into its value at date t. The operator $\mathbb{E}_t[\cdot \mid \text{successful implementation}]$ denotes the expected value of future profit flows using information available at date t and conditional on the innovation being successfully implemented.

With fixed participation cost $F^R \geq 0$, the research decision is

$$\max_{R \geq 0} \, [1 - \exp(-\chi R)]\Delta V - p^R R - F^R \mathbf{1}\{R > 0\}. \tag{C.3}$$

No participation yields zero. For a positive interior candidate with $\Delta V > 0$, the first-order and second-order conditions are

$$\chi \exp(-\chi R^*)\Delta V = p^R, \qquad -\chi^2 \exp(-\chi R^*)\Delta V < 0. \tag{C.4}$$

Define $q = \chi \Delta V / p^R$. A strictly positive candidate exists only if $q > 1$, and then

$$R^* = \frac{\ln q}{\chi}. \tag{C.5}$$

Substituting into the objective, participation occurs if

$$\Delta V - \frac{p^R}{\chi}(1 + \ln q) - F^R \geq 0, \qquad q > 1, \tag{C.6}$$

with equality allowing indifference. If $\Delta V \leq 0$, or $q \leq 1$, positive research is not optimal. This makes explicit the distinction between the extensive and intensive margins. Holding the other arguments fixed and remaining within the positive-participation region,

$$\frac{\partial R^*}{\partial \Delta V} = \frac{1}{\chi \Delta V} > 0, \qquad \frac{\partial R^*}{\partial p^R} = -\frac{1}{\chi p^R} < 0, \qquad \frac{\partial R^*}{\partial \chi} = \frac{1 - \ln q}{\chi^2} < 0. \tag{C.7}$$

Greater research effectiveness increases the gross participation surplus but can lower conditional expenditure once $q > \exp(1)$. The success probability at the interior optimum is $1 - 1/q$. Capabilities can therefore improve innovation outcomes without necessarily increasing research spending. Their overall empirical association with spending also depends on how they affect innovation value, research costs, and selection.

C.2 Eco-innovation and firm performance

C.2.1 Production function and unit costs

To motivate the effects of eco-innovations on firm performance, assume that the firm faces a CES production function given by

$$Y = A\left[\omega X^{\frac{\sigma-1}{\sigma}} + (1-\omega)B^{\frac{\sigma-1}{\sigma}}E^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma \neq 1, \tag{C.8}$$

where Y denotes output, A is total factor productivity (or a Hicksian technology shifter), X is a composite input bundle $X = K^{\alpha}L^{1-\alpha}$ with $0 < \alpha < 1$, E denotes energy inputs, B is our indicator of energy efficiency, and $0 < \omega < 1$ denotes a cost share parameter. σ is the elasticity of substitution for which we assume $\sigma < 1$, assuming that the composite input bundle of capital and labour is not easily substitutable with energy. Standard cost minimisation yields the unit cost function given by

$$c = A^{-1}\left[\omega^{\sigma}(p^X)^{1-\sigma} + (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}\right]^{1/(1-\sigma)}, \tag{C.9}$$

where p^X and p^E are the input prices. The respective cost shares are then given by

$$s^X = \frac{\omega^{\sigma}(p^X)^{1-\sigma}}{[\omega^{\sigma}(p^X)^{1-\sigma} + (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}]} \qquad \text{and} \qquad s^E = \frac{(1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}}{[\omega^{\sigma}(p^X)^{1-\sigma} + (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}]}$$

with $s^X + s^E = 1$.

C.2.2 The effect of eco-innovation on unit costs

The first derivative of unit costs with respect to energy efficiency is

$$\frac{\partial c}{\partial B} = -\frac{1}{B} c[.]^{-1} (1-\omega)^{\sigma} B^{\sigma-1} (p^E)^{1-\sigma} = -\frac{1}{B} c s^E.$$

The unit costs fall with an increase in B, and the effect is larger the larger their share s^E in the overall costs is. The partial elasticity of a change in B is equal to the negative cost share

$$\frac{\partial c}{\partial B}\frac{B}{c} = \frac{\partial \ln c}{\partial \ln B} = -s^E.$$

In other words, a 1% increase in B would reduce unit costs by s^E%.

C.2.3 Link to innovation output

One can also establish a direct link to the eco-innovations by assuming that energy efficiency depends on innovation output $\mathcal{I}$ (as we find empirically). For example, assuming a linear functional relation $B = \mathcal{I}_0 + \lambda\mathcal{I}$ and $\frac{\partial B}{\partial \mathcal{I}} = \lambda$ shows that

$$\frac{\partial c}{\partial B}\frac{\partial B}{\partial \mathcal{I}} = -\frac{1}{B} c s^E \lambda \Rightarrow \frac{\partial c}{\partial B}\frac{B}{c}\frac{\partial B}{\partial \mathcal{I}} = -s^E \lambda.$$

The change in energy efficiency depends on how much (general) innovations are relevant for changes in energy efficiency.

One might assume other functional forms for this relation, which results in qualitatively similar results.

First, let $B = \mathcal{I}_0 \exp^{\lambda\mathcal{I}}$ and $\frac{\partial B}{\partial \mathcal{I}} = \mathcal{I}_0 \lambda \exp^{\lambda\mathcal{I}} = \lambda B$.

$$\frac{\partial c}{\partial B}\frac{\partial B}{\partial \mathcal{I}} = -\frac{1}{B} c s^E \lambda B = -c\lambda s^E \Rightarrow \frac{\partial c}{\partial B}\frac{B}{c}\frac{\partial B}{\partial \mathcal{I}}\frac{\mathcal{I}}{B} = \frac{\partial \ln c}{\partial \ln B}\frac{\partial \ln B}{\partial \ln \mathcal{I}} = -c\lambda s^E \frac{B}{c}\frac{\mathcal{I}}{B} = -s^E \lambda \mathcal{I}$$

The impact of an increase in innovation output $\mathcal{I}$ on energy efficiency in this case also depends positively on the existing stock of $\mathcal{I}$.

Second, let $B = B_0 \mathcal{I}^{\lambda}$ with $\frac{\partial B}{\partial \mathcal{I}} = B_0 \lambda I^{\lambda-1} = B\lambda\frac{1}{\mathcal{I}}$.

$$\frac{\partial c}{\partial B}\frac{\partial B}{\partial \mathcal{I}} = -\frac{1}{B} c s^E B \lambda \frac{1}{\mathcal{I}} = -c s^E \lambda \frac{1}{\mathcal{I}} \Rightarrow \frac{\partial c}{\partial B}\frac{B}{c}\frac{\partial B}{\partial \mathcal{I}}\frac{\mathcal{I}}{B} = -c s^E \lambda \frac{1}{\mathcal{I}}\frac{B}{c}\frac{\mathcal{I}}{B} = -s^E \lambda$$

C.2.4 The effect on the energy share and energy intensity

To show the effects of an improvement in energy efficiency on the energy share in total costs, one can calculate the first derivative of the energy cost share with respect to B, which is

$$\frac{\partial s^E}{\partial B} = \frac{(\sigma-1)B^{-1}(1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}[.] - (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}(\sigma-1)B^{-1}(1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}}{\left[\omega^{\sigma}(p^X)^{1-\sigma} + (1-\omega)^{\sigma}B^{\sigma-1}(p^E)^{1-\sigma}\right]^2}.$$

Simplifying gives

$$\begin{aligned}\frac{\partial s^E}{\partial B} &= (\sigma-1)B^{-1}(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}\frac{[.]-(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}}{[\omega^\sigma(p^X)^{1-\sigma}+(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}]^2}\\ &= (\sigma-1)B^{-1}s^E\frac{[.]-(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}}{[\omega^\sigma(p^X)^{1-\sigma}+(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}]},\end{aligned}$$

which results in

$$\frac{\partial s^E}{\partial B} = (\sigma-1)B^{-1}s^E s^X = (\sigma-1)B^{-1}s^E(1-s^E).$$

The partial elasticity is given by

$$\frac{\partial s^E}{\partial B}\frac{B}{s^E} = (\sigma-1)(1-s^E).$$

The energy cost share declines if (as assumed) $\sigma < 1$ (i.e. energy services and the non-energy composite input are gross complements).[8]

The respective changes in energy intensity can be derived as well. According to Shephard's lemma, demand for energy is given by

$$E = \frac{\partial c}{\partial p^E} = Y(1-\omega)B^{\sigma-1}(p^X)^{-\sigma}[.]^{\sigma/(1-\sigma)},$$

resulting in an energy input coefficient given by

$$a_E = \frac{E}{Y} = (1-\omega)B^{\sigma-1}(p^X)^{-\sigma}\left[\omega^\sigma(p^X)^{1-\sigma}+(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}\right]^{\sigma/(1-\sigma)}.$$

Taking the first derivative of this coefficient with respect to energy efficiency results in

$$\begin{aligned}\frac{\partial a_E}{\partial B} &= (\sigma-1)B^{-1}(1-\omega)B^{\sigma-1}(p^X)^{-\sigma}[.]^{\sigma/(1-\sigma)}\\ &+ (1-\omega)B^{\sigma-1}(p^X)^{-\sigma}\frac{\sigma}{1-\sigma}[.]^{\sigma/(1-\sigma)}[.]^{-1}(\sigma-1)B^{-1}(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}.\end{aligned}$$

This can be simplified as

$$\frac{\partial a_E}{\partial B} = (\sigma-1)B^{-1}a_E - \sigma a_E[.]^{-1}B^{-1}(1-\omega)^\sigma B^{\sigma-1}(p^E)^{1-\sigma}$$

and results in

$$\frac{\partial a_E}{\partial B} = (\sigma-1)B^{-1}a_E - \sigma a_E B^{-1}s^E,$$

with the partial elasticity given by

$$\frac{\partial a_E}{\partial B}\frac{B}{a_E} = (\sigma-1)-\sigma\theta^E < 0 \Rightarrow \sigma < \frac{1}{1-s^E}.$$

[8] With the same reasoning as above, one can link these results to innovation output. For example, for the linear specification discussed above, the elasticity would become

$$\frac{\partial s^E}{\partial B}\frac{B}{s^E}\frac{\partial B}{\partial \mathcal{I}} = (\sigma-1)(1-s^E)\lambda.$$

This derivative is negative whenever $\sigma < 1/(1 - s^E)$, which includes when the composite input and energy are gross complements (i.e. $\sigma \leq 1$).

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