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# The effects of environmental innovations on labor productivity: how does it pay to be green

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# The effects of environmental innovations on labor productivity: how does it pay to be green

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**ABSTRACT**

Due to growing environmental concerns, environmental innovations (EIs) have gained prominence in firms' strategies. This study delves into the productivity effects of regulation-driven environmental innovations using data from four Finnish Community Innovation Survey (CIS) waves. Instrumental variable estimation controls for the endogeneity of voluntary and regulation-driven EIs in a novel way. Our results support the prior findings on the strong Porter hypothesis that environmental regulation improves performance. However, the results also hint at a delay before environmental innovations translate into higher productivity. We also find that regulation-driven EIs improve performance in services. Small firms do not benefit relatively less, although they are inclined to do fewer voluntary EIs. Environmental regulation may favor firms in the Nordic context due to firms being close to the industry frontier.

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## 1. Introduction

Environmental innovations (EIs) have become important to firms' strategies due to environmental concerns. These innovations can help improve sustainability and lead to economic gains for companies. However, private investment in environmental innovations will likely remain suboptimal without government interventions through subsidies and regulations (Horbach, Rammer, and Rennings 2012; Rennings 2000). The Porter hypothesis suggests that well-designed environmental regulation can lead to both environmental and economic benefits (Porter and Van der Linde 1995), but empirical evidence is context-specific (Ambec et al. 2013; Barbieri et al. 2016; Dechezleprêtre and Sato 2017; Horváthová 2010). Supportive evidence has also been found regarding the European Union emissions trading scheme that can mitigate carbon emissions and support economic performance (Dechezleprêtre, Nachtigall, and Venmans 2018; Koch and Themann 2022).

This paper aims to analyze Porter's hypothesis about whether the productivity effects of EIs differ depending on whether the EI is voluntary or motivated by regulation. We combine four waves of the Finnish Community Innovation Survey (CIS) – 2004, 2006, 2008, and 2014 – with balance sheet and employe data. Innovations reported in survey data also cover the two previous years; thus, those years are also part of the sample.

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Prior studies by Rennings and Rammer (2011), Ghisetti and Rennings (2014), and Rexhäuser and Rammer (2014) rely on cross-sectional data to compare the effects of regulation-motivated and voluntary EIs on firm profitability. The literature suggests significant heterogeneity among firms regarding the type of innovation with which they can respond to regulation. Firms may adopt existing environmental technologies or develop innovations to meet regulation requirements related to, e.g. lower vehicle emissions (Rennings and Rammer 2011). Some firms may avoid regulation by offshoring or by ignoring regulations (Drake and Just 2016). The main contribution of the present analysis is to cover a longer period of regulatory regimes and analyze the dynamics over time. Only a few prior studies using firm-level innovation panel data combined with regulation information exist. Related prior studies, e.g. Marin (2014), Marin and Lotti (2017), and Van Leeuwen and Mohnen (2017), have studied the productivity effects of EIs or environmental patents. While they have compared the productivity effects of different kinds of EIs and patents, they have yet to analyze the effects of regulation-induced EIs.

Instrumental variable regression with two-step least squares (2SLS) uses information on environmental innovations over several CIS panels. Lanoie, Patry, and Lajeunesse (2008) find that the positive performance effects of regulation-induced EIs are more likely to be observed after a time lag. However, their measure for regulation was different from the Porter hypothesis as it relates merely to pollution expenses as the ratio of investment in pollution-control equipment to the total cost in the industry. In contrast, the CIS survey identifies companies that engage in EIs due to environmental regulation. We also use the Wooldridge (2009) method to measure performance by intangibles-adjusted multi-factor productivity (MFP). Thus, our results are robust to productivity shocks or variations of returns to intangible capital (IC) over time. The traditional total factor productivity, TFP, would also account only for tangible capital deepening.

EIs include both resource-saving and pollution-reducing innovations. In the CIS survey data, the regulation motive for innovations is surveyed for the EIs as a whole and not separately for resource-saving and pollution-reducing EIs. Our research shows that regulation-driven EIs have improved MFP, and the results are robust and extend to all types of firms and EIs.

We also consider occupational intangible capital, which relies on the ISCO 2008 standard classification (Piekkola 2011, 2018). The measurement of an intangible asset relies on the Horizon 2020 GLOBALINTO project and the 7th Framework Program INNODRIVE project, which focused on the estimation of own account production of intangibles, including the costs of labor, intermediates, and capital needed to produce these assets (Piekkola et al. 2024). We rely on occupation and wage income data combined with intermediate and tangible capital used in intangible capital creation. ICT is also considered a vital part of intangibles. Piekkola (2024) is among the many recent papers finding that R&D, organizational capital, and digitalization are essential to innovations that improve productivity growth.

The paper is structured as follows. Section 2 provides an overview of the theoretical and empirical literature on environmental innovations. Section 3 presents our data. Section 4 shows descriptive statistics and discusses the econometric model. Section 5 presents and discusses the estimation results. Finally, Section 6 offers conclusions.

## 2. Literature review

### *2.1. Theoretical literature*

The weak version of the Porter hypothesis states that environmental regulation increases technical (product or process) innovation (Ambec et al. 2013). For example, Calel and Dechezleprêtre (2016) find that some environmental regulations tend to increase regulated firms' overall rate of patenting, redirecting innovation toward clean and away from polluting technologies. Our main focus is on the strong version of the Porter hypothesis that states that environmental regulation also improves economic performance. Lanoie, Patry, and Lajeunesse (2008) argue that the Porter hypothesis is dynamic, i.e. positive benefits accrue after the initial high costs of familiarizing with new technology. Studies following Porter and Van der Linde (1995) have provided theoretical arguments for why profit-maximizing firms need regulation to achieve these environmental innovations and economic gains. The studies argue that rent-seeking managers may be present-biased or underestimate the economic benefits of environmental activities (Ambec et al. 2013; Ambec and Barla 2006). Various market failures may also lead to the same outcome. Therefore, government regulation can help managers and firms overcome these problems.

EI is defined as the production, assimilation, or exploitation of a new or modified process, product, service, management practice, or business method that is novel to the organization and creates environmental benefits throughout its life cycle compared to relevant alternatives (Kemp and Pearson 2007). EIs also create double externalities (Barbieri et al. 2016). First, EIs can reduce the negative environmental externalities of production. Second, like all innovations, EIs can produce positive knowledge spillovers that benefit other firms, individuals, and countries besides the innovator.

EIs include resource-saving innovations likely to alter the internal production processes and pollution-reducing innovations, also called end-of-pipe type innovations. However, Demirel and Kesidou (2011) find that both end-of-pipe and clean production technologies are motivated by equipment upgrades and thus improve efficiency. Ghisetti and Rennings (2014) find that the economic gains are higher from EIs that reduce energy or material use. Horbach, Rammer, and Rennings (2012) find that various pollution-reducing innovations, such as $CO_2$ emission-reducing and recycling-improving innovations, are typically motivated by regulation. Furthermore, Horbach and Rennings (2013) show that material- and energy-saving EIs are also positively associated with employment growth, while air and water pollution-reducing innovations are negatively associated with employment growth. One conclusion about these ambiguities, depending on the type of EI, is that it is important to analyze the two types of EIs separately.

### 2.2. Empirical literature

The weak version of the Porter hypothesis about technical innovations has mostly been supported by empirical studies (see the surveys by Horváthová (2010), Ambec et al. (2013), and Dechezleprêtre et al. (2019)). Regarding the strong version of Porter's hypothesis, Dechezleprêtre et al. (2019) review the literature on environmental regulations and competitiveness and conclude that they are correlated and that environmental policies generally do not negatively affect economic activity. However, causal evidence regarding the strong version of the hypothesis remains scarce. The survey also concluded that pollution-reducing investments do not seem to hurt firms' productivity but also noted that evidence mostly covers the power generation or the manufacturing sector.

Jaffe, Newell, and Stavins (2003) focus on whether environmental regulations impact firms' competitiveness. In their study, a competitive company can succeed in the market, grow, and be profitable. Based on the authors' findings, there were no links between the tightening of regulations and declining competitiveness. The results are still inconclusive as voluntary investments due to a change in customer demand were not included, causing missing variable bias (Brännlund and Lundgren 2009). Hottenrott and Rexhäuser (2015) find that regulation and subsidies do not affect innovations or related fixed assets in the cross-section data. Instead, Popp and Newell (2012) show evidence of competition between alternative energy and other patents. However, the alternative energy patents receive more citations, which implies a higher value for these patents. Yang, Tseng, and Chen (2012) and Franco and Marin (2017) find that environmental regulation positively affects productivity. More nuanced positive results regarding the strong version of the hypothesis have also been reported (Albrizio, Kozluk, and Zipperer 2017; Ambec et al. 2013).

Rexhäuser and Rammer (2014), using cross-sectional German data, find that profitability improvements are slightly higher when EIs are regulation-induced. However, pollution-reducing innovations were found not to improve profitability. On the other hand, by utilizing German innovation survey data, Rennings and Rammer (2011) find no clear difference in the innovation success or profitability of regulation-motivated EIs compared to other EIs.

Positive results appear clearer with dynamic modeling. Ambec et al. (2013) show that most previous studies have no panel data and thus cannot consider the Porter Hypothesis's dynamic dimensions that regulation affects firm behavior with a time lag. The firm-level panel also enables a larger sample size and controls factors such as firm size, intangibles, and regions. Kunapatarawong and Martínez-Ros (2016) study EIs and employment using Spanish panel data. They find that voluntary EIs improve employment growth, but regulation-motivated EIs do not. However, as Lanoie, Patry, and Lajeunesse (2008) argue, initial negative effects are possible, and positive performance effects are more likely to be observed after a time lag.

Our paper uses panel data and, thus, better controls for endogeneity in environmental innovations. Our analysis covers a longer period, from 2003 to 2014, than single cross-country surveys, with 65% of the firms involved in more than one survey. Most of the prior evidence covers the power generation or the manufacturing sector, while here, about 40% of firms are in market services, which provides novel results. As discussed, using the dynamic structure of panel data allows the study of dynamic aspects of the strong Porter hypothesis. An important distinction to earlier approaches is to measure performance by marginal factor productivity net of the changes in returns on IC over time. The IC is evaluated from ICT; R&D, management and marketing work (Piekkola 2024). Organizational capital evaluated from management and marketing capital (OC) also improves sustainable competitive advantage (Carlin, Chowdhry, and Garmaise 2012; Eisfeldt and Papanikolaou 2013; Lev and Radhakrishnan 2005) and creates regional knowledge spillovers (Piekkola 2020).

Moreover, as Dechezleprêtre et al. (2019) note, only a handful of research has analyzed the causal effects of economic regulation on economic performance. None of the studies in Dechezleprêtre et al. (2019) analyze economic performance using instrumenting techniques. We utilize new instruments, such as regional EI as Telle (2006) suggested. The log growth of organizational capital (OC) is also used as an instrument as regulation may require organizational effort that is not tied directly to improving performance. The approach also brings clarity to the ambiguous cross-sectional analysis that only regulation-driven resource-saving EIs improve firm performance when voluntary EIs are controlled (see Rexhäuser and Rammer (2014), Ghisetti and Rennings (2014)).

On the cost side, economic performance is attained through reduced cost of inputs, particularly due to lower energy costs, for which we have no data. We are instead controlling the other potential cause of reduced costs using intangible capital adjusted TFP, which is not evaluated from growth accounting (Bontadini et al. 2024) but rather from econometric estimation of production function (Corrado et al. 2021). Our analysis also covers a considerable period with four waves of CIS survey.

In our approach, dynamism is tested by whether the Porter hypothesis would be stronger in the early adoption in the 2004, 2006, and 2008 waves compared to the most recent one, 2014. In the concluding section, we also discuss the possibility that Nordic countries such as Finland may have benefitted from the first-mover advantage in setting regulation controls earlier than some other regions or are generally from being advanced in technology.

### 2.3. Hypotheses

Our first hypothesis is a verification of the strong Porter hypothesis and verification of the studies reviewed by Dechezleprêtre et al. (2019) survey. Our instrument set can also verify this in resource-saving EIs, where results have been diverse. While the prior evidence regarding the strong version of the hypothesis has been somewhat mixed, Koch and Themann (2022) showed that Northern European firms especially have benefited from the EU ETS. Thus, we hypothesize that among Finnish firms, EIs induced by environmental regulation improve economic performance. However, we also find a contradiction to the literature on the relative disadvantage of small firms in responding to environmental regulation. In line with these arguments and the theoretical discussion in section 2.1, we propose the first hypothesis as follows:

(1) Strong Porter hypothesis: Innovations fostered by environmental regulation generate benefits that more than compensate compliance costs and increase firm productivity

Following the arguments of Lanoie, Patry, and Lajeunesse (2008), the environmental regulations may incur initial costs, and the benefits of regulation-induced innovations may come after a delay. As also discussed in sections 2.1 and 2.2, managers may be present-biased, which could suggest that firms engage voluntarily in EIs with more immediate benefits but are only pushed by regulation to engage in EIs that bring benefits more slowly. Thus, we are also testing the dynamic nature of Porter hypothesis, i.e. how the environmental regulation may become visible in the productivity in later periods. The empirical evidence regarding the dynamic effects remains relatively scarce (Kunapatarawong and Martínez-Ros 2016; Lanoie, Patry, and Lajeunesse 2008; Rassier and Earnhart 2015). Our second hypothesis is:

(2) There is a delay before environmental innovations translate into higher productivity

Our analysis uses the property of the data that a large set of firms also entered the previous EI survey two years ago, so we can also control dynamism with the delay in productivity improvement. An alternative approach would be to explain Tobin's Q and expected future effects on the firm's market value instead of comparing the immediate versus delayed effects on MFP. However, Rassier and Earnhart (2015) show that the actual profitability effect is consistent with the strong Porter hypothesis, while the expected profitability effects evaluated by investors have a negative relationship between clean water discharge limits and profitability. This finding suggests that market expectations only sometimes anticipate how the new measures required to meet the new regulation can improve profitability in the long run.

We further test the hypotheses' robustness by analyzing firms of different sizes separately. We analyze smaller firms with less than 50 employes on average and large firms separately to see whether only large firms eventually experience a productivity push when environmental regulations are introduced. Andries and Stephan (2019) argue that small firms are agile in small-scale problem-solving, such as emission reduction. However, they also argue that small firms have limited resources available for resource-using activities since these require resources to engage in broader environmental practices that yield long-term strategic benefits (Andries and Stephan 2019; Khanna 2001). Larger firms often benefit from lower marginal costs of abatement due to economies of scale, which allows them to allocate more personnel to meet administrative and technical requirements of environmental regulations that are more needed in resource-saving EIs. However, our data shows that resource-saving EIs are more common than pollution-reducing EIs in small firms. One reason is that market services firms are a large part of the data, where environmental innovations are more introduced in response to customer demand rather than being related to end-of-pipe investments. Small firms can have relative strengths in responding to customer demands given their relative strengths that Aragón-Correa et al. (2008) relate to shorter lines of communication, closer interaction within the SMEs, the presence of a founder's vision or entrepreneurial orientation, and the flexibility in managing external relationships. We follow the limited resources view and propose the third hypothesis as follows (which we cannot confirm):

(3) Small firms' relative disadvantage: Environmental regulation-driven innovations improve performance less in small firms than in large firms.

## 3. Data

### *3.1. Variable formation*

We use an unbalanced panel dataset formed by linking several firm-level datasets. The Finnish Community Innovation Survey (CIS) is a key data source, conducted every second year, and covers three-year periods. We use surveys from 2004, 2006, 2008, and 2014. CIS does not include comparable EI questions in 2010 and 2012 or later in 2016 and 2018.

Our empirical approach defines EIs as innovations that reduce material or energy use or lower pollution. Specifically, the 2004 and 2006 innovation surveys ask about the effects of innovation and the importance of these effects. If these effects include either (1) 'reduced materials and energy per unit of output' or (2) 'reduced environmental impacts or improved health and safety,' the firm is recorded as having adopted an EI. Thus, EI is a binary variable. Using these questions, we also categorize EIs as leading to either (1) resource savings or (2) pollution reduction. Dichotomous EIs include all importance categories (high, medium, low). The 2008 and 2014 CIS waves contain more detailed questions on the environmental benefits of innovations. We define the firm as adopting an EI if the firm answers yes to at least one environmental benefit question. We count an innovation as a resource-saving EI if the firm reports the following benefits: reduced material uses per unit of output; reduced energy use or $CO_2$ footprint per unit of output; reduced energy use or $CO_2$ footprint by the end user; recycled waste, water, or materials; or improved recycling of the product post-use. Pollution-reducing EIs include the following benefits: replacement of materials with less polluting or less hazardous substitutes; reduced soil, water, noise, or air pollution; or reduced air, water, soil, or noise pollution by the end user.

We use CIS data to determine whether the innovations are motivated by regulation, as in Ghisetti and Rennings (2014). The 2004 and 2006 CIS waves contain questions on whether the effects of innovation included 'met regulatory requirements.' We consider an innovation to be regulation-motivated if regulatory requirements are of high or medium importance. The 2008 CIS asks whether firms introduced an environmental innovation in response to (1) existing environmental regulations or taxes on pollution or

(2) expected regulations or taxes in the future. The 2014 surveys also distinguish between pollution regulations and taxes. Thus, in 2014, innovation was recorded as being driven by regulation if the firm answered yes to either of these questions.

Our financial data come from Statistics Finland's firm-level financial accounts data. We use value-added, employment, intermediate inputs, and intangible and tangible investment data to evaluate intangibles-adjusted marginal factor productivity (MFP), which thus also considers the variation in IC deepening. R&D and OC and information and communication technology capital (ICT) measurement using the proportionated method from the EU FP7 framework project INNODRIVE, followed in Piekkola (2016). Industry-level OC from supply and use tables in Corrado et al. (2021) differs from our internal assessment not only by relying solely on industry-level data but also by including an evaluation of external consulting expenses as part of OC, while considering marketing work as part of branding. Here, the intangible labor cost related to the intangible capital occupations also depends on the share of worktime assumed to be spent on intangible work. Overhead should cover other factor inputs, such as the intermediate and tangible inputs used to construct intangible investments. Overhead shares are evaluated by value-added in knowledge-intensive services that produce R&D, OC, or ICT (See Appendix A). Appendix A Table A1 shows the R&D, OC, and ICT occupations that create IC with certain time use, and factor multipliers measure intermediate and tangible capital proportions. These are also originally evaluated from supply and use tables at the EU level for IC-producing industries. The proportionate measures follow the EU Horizon 2020 project GLOBALINTO (Piekkola et al. 2024). R&D investment data from R&D surveys are not used since they are correlated by 0.78 with occupational R&D. The occupational OC likewise measures internal OC, excluding external consulting help.

Knowledge spillovers measure intangible work-biased technological change (IBTC) (Piekkola 2020; Piekkola et al. 2022), which is analogous to skill-biased change. The measure here concerns organizational (management and marketing) work rather than educational level, as in the skill-biased technical change. For any single firm, the quality of OC work relative to non-intangible work unrelated to OC, R&D, or ICT work (non-IC work) is first proxied by the value of the wages of OC workers relative to the average wage of non-IC workers. A production function estimation over 160 NACE 3-digit industries evaluates the relative quality of OC workers relative to other workers, taking the relative wages as the first proxies. The approximation for OC-work driven IBTC (OC-IBTC) is the total share of OC workers from other than IC workers (non-IC workers) and the relative quality of OC workers relative to the non-IC workers in the firm. Productivity improves if the share of OC workers increases and depends on the degree to which their quality is better than for non-IC workers. The adjustment goes toward the average quality/productivity differential being less than the wage differential between OC and non-IC workers. OC-IBTC is highly heterogeneous in MFP effects, with a higher value when the firm is closer to the frontier (Piekkola 2024).

Ugur, Churchill, and Luong (2020) find that R&D spillovers are generally weak within the same industry. We utilize a regional dimension and apply regional industry OC-IBTC spillover since access to high-quality organizational capital workers has an important local dimension. The regional OC-IBTC spillover is the annual effect in about 160 industries using each firm's labor shares as weights in each industry and excluding the firm's contribution to knowledge spillovers. The labor share weights proxy the frequency of knowledge flows to other firms, which depends on the number of job switches. OC-IBTC spillover is important to control as it indicates good management practices, which Bloom et al. (2010) have found to be associated with lower energy intensity and higher MFP.

### *3.2. Descriptive statistics*

All of the questions on the survey relate to three-year periods. If a firm responds that it introduced an innovation, the survey does not require the firm to specify the year it was introduced. Therefore, for the innovation variables, we use the values from 2004, 2006, 2008, and 2014 for 2003, 2005, 2007, and 2013, respectively, following Van Leeuwen and Mohnen (2017). We do not use the values from the first year of the three years because the previous survey covers this year.

Given the assumed coverage of reported EIs for two years, most firms enter the unbalanced panel in even years. The coverage is 40% with two years, 26% with four years, 18% with six years, and 10% with eight years of the firm in the panel, totaling 94% of all firm-year observations of 17,044. Observations are equally distributed over the years, with around 2100 firms per year from 2003 to 2008 and 2013 to 2014. We include all industries with EIs in our analysis and consider firms with at least ten employes on average.

Table A2 in the appendix shows the industry decomposition covering production and market services (excluding the financial sector) and industries divided into eight technology types following OECD guidelines. Table A3 in the appendix shows that the share of firms reporting an EI varies between 41% and 56% over the years, while in large firms, the share is 55% compared with small firms at 37%. In 2004 and 2006, firms with EIs must have product or process innovations. Table A3 in the appendix shows that regulation-driven EIs vary between 17% and 26% over the years. The share of firms reporting EIs due to regulatory push remained at approximately 20% until 2014 and climbed to 26% in 2014. On average, one-third, or 28%, of large firms have regulation-induced EIs, while the share is about one-half, 15%, among small firms. Such skewness towards large firms has also been found in the literature (Andries and Stephan 2019). Resource-saving and pollution-reducing EIs are almost equally common, 36%–38% in 2004 and 2006, while pollution-reducing EIs dominated in 2008 and resource-saving EIs in 2014. However, small firms have relatively more regulation-driven resource-saving rather than pollution-reducing EIs, which we expect to relate to most small firms being in market services. Regulation-driven EIs include

**Table 1.** Descriptive statistics.

| Variable | Mean | Sd | p50 | *N* |
|---|---|---|---|---|
| Product, process innovation | 0.43 | 0.49 | 0 | 9915 |
| EI environmental innovation | 0.47 | 0.50 | 0 | 9915 |
| EI resource-saving | 0.41 | 0.49 | 0 | 9915 |
| EI pollution-reducing | 0.40 | 0.49 | 0 | 9915 |
| EI regulation-driven | 0.22 | 0.41 | 0 | 9915 |
| EI regulation-driven, resource-saving | 0.19 | 0.39 | 0 | 9857 |
| EI regulation-driven, pollution-reducing | 0.18 | 0.38 | 0.0 | 9857 |
| R&D/L | 57.2 | 84.4 | 31.5 | 8991 |
| OC/L | 24.5 | 31.1 | 15.9 | 8261 |
| ICT/L | 13.7 | 33.8 | 3.1 | 4979 |
| Machinery, Equipment investment/L | 314.8 | 349.8 | 259.8 | 9915 |
| Marginal factor productivity | 6.3 | 0.9 | 6.2 | 9915 |
| Value added/L | 105.0 | 108.7 | 86.2 | 9915 |
| Employment L | 202 | 806 | 56 | 9915 |
| Intermediate/L | 300 | 1313 | 135 | 9915 |
| Firm age | 23 | 9 | 26 | 9915 |
| Herfindahl index | 0.16 | 0.19 | 0.09 | 9915 |
| Incorporated | 0.98 | 0.15 | 1.00 | 9915 |
| Group | 0.18 | 0.39 | 0.00 | 9915 |
| Regional OC-IBTC spillover | 0.0047 | 0.0016 | 0.0045 | 9915 |

In thousand 2015€.

those driven by expected future environmental regulation, and pressures to implement sustainable environmental policy have increased over the years, explaining the highest figures for 2014. Given the somewhat different figures for 2014, our robustness check is to restrict to three consecutive survey years: 2004, 2006, 2008, and omit 2014.

Table 1 below presents descriptive statistics for the variables used in the empirical analysis. Monetary values were deflated to 2015 prices using the NACE 2-digit level GDP deflator for value-added, investment price index for physical capital investment, and the R&D and ICT investments price index for R&D, ICT respectively, while OC uses the GDP deflator in OC (Legal and accounting activities M69, Activities of head offices M70, Architectural and engineering activities M71, Advertising and market research M73) depending on their value-added shares.

R&D intensity is approximately €57 thousand per employe, OC intensity €25 thousand per employe, and ICT intensity €14 thousand per employe in firms with them. These values apply to firms with positive values, and most have R&D and OC. Roughly one-third of firms have ICT. Log values in estimation include an additional value of €0.05, so the sample covers firms with no R&D, OC, or ICT (but the firm must have some IC in at least one year). Median employment is 56 employes, given that firms with fewer than ten employes have dropped. The median age of a firm is 26 years, and the Herfindahl index is 0.16. Most firms (98%) in the instrumental regression sample are incorporated. Regional OC-IBTC spillover has skewed distribution, with over half of regions having close to zero value, while the mean value is 0.18. Regions have access to very different quality of management or marketing workers, and we also control the region's rural area. Such controls are important in the analysis since we are using spatial instruments.

## 4. Estimation methods

A firm invests in environmental and other innovation activities in order to improve its productivity. These investment decisions depend on the current productivity and the firm's decisions regarding other production inputs. Thus, the innovations are endogenous to firm productivity. In the context of the Porter hypothesis, e.g. Marin (2014) and Van Leeuwen and Mohnen (2017) applied the CDM model and first explained EIs by intangibles and other factors. Due to the endogeneity of innovation, there needs to be an instrument variable(s) that explains EIs but does not correlate with the error term. Horbach (2008) suggests institutional structure instruments such as environmental policy or regulation, information flow organization, and innovation networks. Telle (2006) suggests that EI measures aggregated to industrial, regional, or national levels are unlikely to correlate to the quality of management of a specific plant (and hence to the model's error term) but should be correlated with environmental innovations. Our estimation starts with the estimation of intangibles-adjusted marginal factor productivity (MPF). We apply a Cobb-Douglas production function and Wooldridge (2009) method and control for productivity shocks to derive MFP, which is not sensitive to variation in gross returns to intangible investment over time (Corrado et al. 2021). We include tangible capital, R&D, and OC as state variables, where tangible capital is the capitalized value of machinery and equipment investment. The flexible variables are non-IC employes and ICT. ICT workers include not only those creating new software or building new databases (see Table A1 in the appendix). Intermediate inputs are a proxy for productivity shock (Levinsohn and Petrin 2003). The log of value added is explained by flexible variables (employment of non-IC workers, ICT) and state variables

$$\ln y_{it} = \delta_0 + \delta_k \ln K_{it} + \sum\nolimits_{IC} \ln R_{ICit} + \ln R_{ICTit} + \delta_l \ln l_{it} + u_{it} \tag{1}$$

where IC = R&D, OC, and estimations are done separately in eight main one-digit industries.[1] MFP as residual $u_{it}$ of (1) is the productivity measure to evaluate in instrumental variable estimation 2SLS the productivity effects of environmental innovations:

$$MFP_{it} = \beta_0 + \sum\nolimits_{z} \beta_z EI_{zit} + C'_{it}\beta + u_{2it} \tag{2}$$

where EIz is the endogenous EI variable that can vary by type z or whether EI is regulation-induced, and C is the scalar of control variables. The variety of firms' characteristics across regions is controlled by measuring MPF after intangible capital deepening. Control variables include firm age, the firm being a part of a group, industry concentration (Herfindahl index), incorporated, and three firm size dummies with firms with average employment between 50 and 249 as the reference. Control dummies include rural Nuts-IV areas and six rural provinces (provinces total 24). The remaining areas have better diffusion of knowledge that requires geographical proximity (Audretsch and Feldman 1996). Higher population density enables face-to-face interaction among employes from different firms and sectors. Otherwise, knowledge spillovers can be high and costly (Roper and Hewitt-Dundas 2015).

A firm invests in environmental and other innovation activities to improve its productivity. These investment decisions depend on the current productivity and the firm's decisions regarding other production inputs. Thus, the innovations are endogenous to firm productivity. In the context of the Porter hypothesis, e.g. Marin (2014) and Van Leeuwen and Mohnen (2017) applied the CDM model and first explained EIs by intangibles and other factors. Due to the endogeneity of innovation, there needs to be an instrument variable or variables that explains EIs but does not correlate with the error term. Horbach (2008) suggests institutional structure instruments such as environmental policy or regulation, information flow organization, and innovation networks. Telle (2006) suggests that EI measures aggregated to industrial, regional, or national levels are unlikely to correlate to the quality of management of a specific plant (and hence to the model's error term) but should be correlated with environmental innovations. We follow this suggestion.

EIs are instrumented by their average annual regional prevalence at Nuts-IV regions (67 regions) as these are natural working areas for employes and, hence, for economic activity. The instruments are the regional average share of firms (i) with regulation-induced EIs regions by eight technology types, (ii) with all EIs the regional average share, and (iii) the log growth of OC. The firm's own contribution to the average value is excluded. A similar instrument is used, e.g. by Chen and Ma (2021). They note that the investment decisions of firms can be affected by the activities of other firms in the same industry or region. Spatial instruments are exogenous as firms sell their products in other regions or export. Regulation-driven EIs also include the technology type dimension since regulation of the firms in high-tech or low-tech production or whether in knowledge-intensive or other services implement the regulation in different ways such as depending on external consulting needed. We categorize spatial regulation-driven EI instruments into eight technology-type categories in Table A2 in the appendix (OC-type services such as Nace M69 and M70 are excluded since firms in this industry do not report EIs in the survey).

Piekkola (2024) and Protogerou et al. (2024) establish that OC increases the probability of all kinds of innovation output. Thus, we also use the log growth of OC as an instrument. The regional quality of highly skilled OC workers (regional OC-IBTC spillover) is uncorrelated with this. Growth in OC is not directly related to the know-how about product and process technologies and the specifications of what is produced (Lipsey and Carlaw 2004). Growth in OC relates to idiosyncratic effects as OC is heterogeneous and depends on how the organizational form has evolved (Dosi, Nelson, and Winter 2000). Growth in OC also appears negatively correlated with regulation-induced EIs that may require consulting help, and hence external OC.

Our preferred model uses all three instruments, and thus, endogenous variables are overidentified. This preferred method is applied when the Hansen overidentification test support three instruments, and we also report the J test about the exogeneity of the instruments (E(Zu) = 0) and whether the model is weakly identified with the two endogenous variables using overidentification J test in weakiv command (Finlay, Magnusson, and Schaffer 2013). Wooldridge autocorrelation test shows that models have significant autocorrelation. We thus apply the generalized least-squares (2SLS) version where errors are serially correlated. We report two-step weak-instrument-robust confidence sets (LC 2sls) using grid search at a 95% level using the twostepweakiv command (Sun 2019) that accounts for heteroskedasticity and autocorrelation.

Instruments are tested following Finlay, Magnusson, and Schaffer (2013) using the Anderson–Rubin (AR) test, which is a joint test of the structural parameter (beta1 = 0 and beta2 = 0, where betas are the coefficients on the endogenous regressors EI and regulation-induced EI). and the J overidentification tests exogeneity of the instruments E(Zu) = 0, where Z are the instruments, and u is the disturbance in the structural equation.

First-stage estimates in 2SLS in Table A4 in the appendix show that regulation-induced EI is positively related to the average regional prevalence of regulation-induced EIs, while all EIs are not. Nuts-IV level regions can have their industrial clusters differently affected by environmental regulations that can differ depending on the technology type of the firm. Thus, regulation-induced EIs are expected to be more strongly influenced by regional regulation-induced innovations and not necessarily by voluntary EIs. Later in the robustness check, we also show the downward bias of results in OLS and the significance of firms' past regulation-driven EIs on performance. We also analyze robustness checks on whether the effect of environmental policy is becoming more stringent over the period considered, especially in 2013–2014, compared to the previous survey years 2007–2008 (Table A2).

## 5. Results

Table 2 shows the estimation of MFP. Productivity shocks are controlled through interactions with material input and interrelations between tangible and intangible assets, including squared terms.

Returns to scale are below one but would be over 1 with simple OLS estimation. More importantly, the control for productivity shocks and variation of returns concerning intangibles equalizes the returns to intangibles across industries to a high degree. There are still important differences across industries. ICT is positively related to MFP only in ICT and other services. ICT may negatively affect MFP in other industries since knowledge spreads quickly and limits the returns to intangibles. OC is important in all industries, and the returns are even higher in manufacturing and energy, while the opposite would be the case with simple OLS. R&D continues to have the highest returns in manufacturing, energy, construction, wholesale, trade, and business services.

Table 3 shows the MFP effects of EIs and regulation-motivated EIs using 2SLS. Variance inflation factor (VIF) using OLS showed that none of the explaining variables has VIF values greater than 2.5

**Table 2.** Production function estimation of value added in seven industries.

| | Food – Petroleum C10-C19[a] | Chemical-Motor vehicles C20-C29[b] | Energy, Construction C30-C33, D, E[c] | Wholesale-Storage G45-G49[d] | Water transport-Accommodation H50-H53[e] | ICT J60-J63[f] | Business services M70-M79[g] |
|---|---|---|---|---|---|---|---|
| Log of non-intangible employes | 0.586* | 0.542* | 0.578* | 0.601* | 0.534* | 0.620* | 0.503* |
| | (0.007) | (0.005) | (0.008) | (0.002) | (0.004) | (0.005) | (0.003) |
| Log of ICT | −0.006 | −0.009* | −0.031* | 0.001 | −0.023* | 0.015* | 0.007* |
| | (0.003) | (0.002) | (0.004) | (0.002) | (0.003) | (0.002) | (0.002) |
| Log of Tangible | 0.102* | 0.082* | 0.064* | 0.108* | 0.045* | 0.051* | 0.019* |
| | (0.007) | (0.006) | (0.008) | (0.003) | (0.005) | (0.004) | (0.003) |
| Log of OC | 0.036* | 0.014* | 0.039* | 0.028* | 0.021* | 0.024* | 0.029* |
| | (0.004) | (0.003) | (0.006) | (0.002) | (0.004) | (0.003) | (0.003) |
| Log of R&D | 0.048* | 0.036* | 0.042* | 0.030* | 0.013* | 0.014* | 0.056* |
| | (0.003) | (0.003) | (0.004) | (0.002) | (0.003) | (0.003) | (0.002) |
| Returns to scale | 0.772 | 0.674 | 0.693 | 0.768 | 0.593 | 0.724 | 0.614 |
| Observations | 59678 | 81958 | 44298 | 488738 | 117320 | 127209 | 191864 |

[a]Manufacturing Food, Textiles, Wood, Pulp, Paper, Printing, Petroleum.
[b]Manufacturing Chemical, Pharmaceutical products, Metal Electronic, Electrical equipment, Machinery and Equipment.
[c]Manufacturing Land transport, Furniture, Other, Repair and Installation, Electricity, Gas, Water, Construction etc.
[d]Wholesale, Retail, Land Transport, Storage.
[e]Transport water, Air, Warehouse, Accommodation.
[f]ICT, Telecommunication.
[g]Business services.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

**Table 3.** 2SLS estimation of impacts of EIs and regulation-driven EIs.

| | MFP | | |
|---|---|---|---|
| | EI all | EI resource-saving | EI pollution-reducing |
| Regulation-induced | 0.555** | 1.846* | 0.653** |
| | (0.241) | (1.107) | (0.300) |
| Confidence interval – AR | [.162, .947] | [ .115, 1.47] | [.162,1.38] |
| All | 0.068 | −1.584 | 0.124 |
| | (0.161) | (1.187) | (0.120) |
| Confidence interval – AR | [−.193, .330] | [−1.34, .216] | [−.071,.320] |
| Firm age | 0.003*** | 0.004** | 0.003*** |
| | (0.001) | (0.002) | (0.001) |
| Herfindahl index | 0.306*** | 0.446*** | 0.287*** |
| | (0.057) | (0.105) | (0.061) |
| Incorporated | 0.001 | 0.112 | −0.002 |
| | (0.055) | (0.101) | (0.055) |
| Part of group | 0.063*** | 0.103** | 0.063*** |
| | (0.018) | (0.040) | (0.018) |
| Regional OC-IBTC spillover | 8.683* | −6.714 | 17.521*** |
| | (5.127) | (13.402) | (5.260) |
| Size < 50 | −0.667*** | −0.776*** | −0.661*** |
| | (0.024) | (0.073) | (0.022) |
| Size 250–499 | 0.523*** | 0.606*** | 0.505*** |
| | (0.036) | (0.068) | (0.041) |
| Size 500- | 0.916*** | 0.992*** | 0.873*** |
| | (0.056) | (0.088) | (0.072) |
| Constant | 6.154*** | 6.505*** | 6.085*** |
| | (0.080) | (0.246) | (0.083) |
| Observations | 9915 | 9915 | 9915 |
| AR $p$-value | 0.0067 | 0.0572 | 0.0047 |
| Wald $p$-value | 0.0149 | 0.1570 | 0.0117 |
| J $p$-value | 0.0618 | 0.5094 | 0.0744 |
| Hansen overidentification test $p$-value | 0.0733 | 0.6900 | 0.0903 |
| First-stage F statistics | 462 | 226 | 436 |

Notes: Heteroskedasticity and autocorrelation robust standard errors. Includes year, rural region-province dummies. Instruments include regional average regulation-driven prevalence of respective EIs by technology types, and regional average prevalence of respective all EIs and growth in OC.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

and thus does not merit further investigation. We estimate a model with all and regulation-driven EIs and repeat this for resource-saving EIs and pollution-reducing EIs. The coefficient of regulation-driven EIs becomes on top of the effects for all EIs, including voluntary EIs, that affect MFP.

Following first-stage estimates in Table A4 in Appendix A, regulation-driven EIs in all EIs and within resource-saving or pollution-reducing EIs categories are positively related to the respective regional prevalence of regulation-induced EIs by technology types. regional all EIs. Regulation-driven EIs by technology type appear hence to have a different regional allocation by technology types than voluntary EIs.

However, all EIs relate positively to the regional prevalence of all EIs and the regulation-induced EIs by technology types. This result also holds within pollution-reducing EIs but outside resource-saving EIs. The log growth of OC is a more important instrument for resource-saving EIs than regional all EIs, although it remains insignificant. The log growth of OC tends to have a negative relation to regulation-driven EIs. This negative effect is a differentiating factor of regulation-driven from voluntary EIs and especially within resource-saving EIs. This third instrument is needed especially when considering resource-saving EIs. We have also reported in Table A4 among the exogenous variables regional OC spillover. It is an important control variable indicating organizational agility to regulation- driven and resource-saving EIs in the region.

Table 3 shows the second-state results in explaining MFP. F statistics show that instruments have strong effects on the endogenous variables. The J-test shows that the instruments are unrelated to the model's residual. The instruments then identify the two endogenous variables, as shown by all the test statistics. The Pagan-Hall IV heteroskedasticity test *p*-value shows that we cannot reject the null hypothesis of homoskedasticity, and we report heteroskedasticity robust estimates. The Wooldridge autocorrelation test showed significant autocorrelation, so standard errors also consider these.

The main outcome of Models 1–3 in Table 3 and later is that environmental innovations motivated by regulation are important drivers of productivity. Approximately half of EIs were driven by regulation (Table A2). Regulation-driven EIs have a point estimate of around 0.56; the 95% confidence interval in grid search (Confidence interval – AR) varies between 0.07 and 0.94, which implies that the confidence interval is close to that implied by point estimate and standard error. The resource-saving and pollution-reducing types of EIs in columns 2 and 3 have similar relations. All EIs have a lower and insignificant sign except for the insignificant negative effect of resource-saving EIs. The total effect is the sum of EI-regulation driven and overall effect, around 0.6–0.8, except lower 0.30 for resource-saving EIs (the sum of regulation-induced and overall).

Comparing the results to the prior literature, we can note that the findings for regulation-driven EIs have been positive. The hypothesis 1 is valid that environmental regulations improves productivity. Dechezleprêtre et al. (2019) review concludes that environmental policies generally do not negatively affect economic activity. Van Leeuwen and Mohnen (2017) find that introducing cleaner production process innovations that save energy costs leads to higher productivity. However, the findings are different from cross-sectional data findings, where regulation improves productivity only for resource-saving EIs (see Rexhäuser and Rammer (2014), Ghisetti and Rennings (2014)). Finally, controlling variables have about the same coefficient irrespective of the model. Firm age and the industry concentration (the Herfindahl index) increase MFP. Highly qualified industry OC in the region also improves MFP. The analysis also implies that EIs are more common in large firms.

We also report an alternative model with two regional instruments and dropping log growth of OC (Table 4).

**Table 4.** 2SLS estimation, two instruments with no overidentification.

| | MFP-EI firms | | |
|---|---|---|---|
| | EI all | EI resource-saving | EI pollution-reducing |
| Regulation-induced | 0.500** | 0.735 | 0.636** |
| | (0.210) | (1.521) | (0.264) |
| Confidence interval – AR | [.156, .843] | [−.023, .9844] | [.205, 1.06] |
| All | 0.142 | −0.341 | 0.186 |
| | (0.149) | (1.671) | (0.113) |
| Confidence interval – AR | [−.101, .386] | [−.574, .437] | [.000, .370] |
| Firm age | 0.003*** | 0.004*** | 0.004*** |
| | (0.001) | (0.002) | (0.001) |
| Herfindahl index | 0.251*** | 0.325** | 0.227*** |
| | (0.049) | (0.127) | (0.052) |
| Incorporated | 0.012 | 0.045 | 0.011 |
| | (0.044) | (0.110) | (0.044) |
| Part of group | 0.065*** | 0.074* | 0.066*** |
| | (0.016) | (0.041) | (0.016) |
| Regional OC-IBTC spillover | 6.841 | 4.951 | 14.884*** |
| | (4.355) | (10.814) | (4.329) |
| Size < 50 | −0.671*** | −0.716*** | −0.665*** |
| | (0.020) | (0.096) | (0.018) |
| Size 250–499 | 0.537*** | 0.577*** | 0.516*** |
| | (0.031) | (0.063) | (0.036) |
| Size 500- | 0.916*** | 0.970*** | 0.863*** |
| | (0.047) | (0.068) | (0.061) |
| Constant | 6.105*** | 6.220*** | 6.044*** |
| | (0.065) | (0.283) | (0.065) |
| Observations | 14128 | 14128 | 14128 |
| AR *p*-value | 0.0009 | 0.0342 | 0.0001 |
| Wald *p*-value | 0.0012 | 0.0460 | 0.0003 |
| First-stage F statistics | 586 | 571 | 546 |

See notes in Table 3 with excluding as instrument growth in OC.

The estimates are somewhat higher when growth in OC was included as an instrument, but the results are qualitatively the same. However, regulation-driven resource-saving EIs are no longer a significant factor for MFP. The log growth of OC is in what follows included as the third instrument in all the models if the Hansen test supports this. The results remain qualitatively the same if using two instruments except in resource-saving EIs in market services.

Next, hypothesis 2 is about the stronger effect of regulation-induced EIs with delay. To see the bias downward, we also show OLS results with robust standard errors and include in the model the two-period lagged effects when the firm entered the previous CIS panel two periods ago. The sample was reduced to about 3000 observations (Table 5).

The coefficients of regulation-induced EIs have the same sign when the delayed effect is considered from the previous survey two periods ago. The reduced number of observations makes the magnitude of the effect not directly comparable but suggests a downward bias in the OLS estimate. However, regulation-driven EIs have delayed impacts, with the most positive effects experienced when regulation-motivated EIs were launched two periods ago. Voluntary EIs are instead more effective at the same period, and the relation to productivity stays positive. This finding appears in line with the theoretical arguments in section 2 and hypothesis 2.

In the literature, larger firms are argued to benefit relatively more from regulation-induced EIs. Table 6 analyses regulation-induced and voluntary EIs separately for small firms with an average number of employes in the 10–49 range. Large firms thus also include a large segment of SMEs. We are interested in whether small firms will benefit more or less from regulation-driven EIs. Hypothesis 3 argues that small firms benefit less from regulation due to high compliance costs. We also analyze resource-saving and pollution-reducing EIs separately for small firms since SMEs may prefer pollution-reducing EIs with lower compliance costs (Andries and Stephan 2019).

**Table 5.** OLS estimation of impacts of EIs.

| | EI all | EI resource-saving | EI pollution-reducing |
|---|---|---|---|
| Regulation-driven | 0.047 | 0.046 | 0.019 |
| | (0.031) | (0.033) | (0.032) |
| 2-period lagged | 0.145*** | 0.137*** | 0.130*** |
| | (0.033) | (0.035) | (0.035) |
| All | 0.069*** | 0.058** | 0.086*** |
| | (0.027) | (0.028) | (0.027) |
| 2-period lagged | 0.013 | 0.034 | 0.034 |
| | (0.028) | (0.028) | (0.030) |
| Firm age | 0.007*** | 0.006*** | 0.006*** |
| | (0.001) | (0.001) | (0.001) |
| Herfindahl index | 0.410*** | 0.407*** | 0.403*** |
| | (0.065) | (0.065) | (0.065) |
| Incorporated | −0.129 | −0.129 | −0.141 |
| | (0.121) | (0.118) | (0.117) |
| Part of group | 0.015 | 0.014 | 0.016 |
| | (0.027) | (0.027) | (0.027) |
| Regional OC-IBTC spillover | 20.658** | 19.633** | 19.854** |
| | (8.408) | (8.450) | (8.462) |
| Size < 50 | −0.676*** | −0.681*** | −0.679*** |
| | (0.026) | (0.026) | (0.027) |
| Size 250–499 | 0.521*** | 0.521*** | 0.514*** |
| | (0.033) | (0.033) | (0.033) |
| Size 500- | 0.969*** | 0.967*** | 0.963*** |
| | (0.041) | (0.041) | (0.041) |
| Constant | 6.255*** | 6.282*** | 6.282*** |
| | (0.136) | (0.133) | (0.133) |
| Observations | 2969 | 2981 | 2981 |
| R2 | 0.52 | 0.52 | 0.52 |

Notes: Heteroskedasticity robust standard errors. Includes year, rural region-province dummies.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

**Table 6.** 2SLS estimation of impacts of EIs by firm size.

| | MFP-Small firms | | | MFP-Large firms | | |
|---|---|---|---|---|---|---|
| | EI all | EI resource-saving | EI pollution-reducing | EI all | EI resource-saving | EI pollution-reducing |
| Regulation-driven | 0.347 | 1.803 | 0.276 | 0.857 | 0.202 | 0.613 |
| | (0.364) | (3.221) | (0.495) | (0.587) | (0.490) | (0.432) |
| Confidence interval – AR | [ −.246, 1.237] | entire grid | [..,−2.955] | [−3.45,2.77] | entire grid | [−.091,1.66] |
| All | 0.065 | −1.912 | 0.114 | −0.65 | −0.045 | −0.079 |
| | (0.241) | (3.866) | (0.186) | (0.586) | (0.430) | (0.332) |
| Confidence interval – AR | [−.526, .65619] | entire grid | [ … , .569] | [−3.04, .306] | [ … , 5.19] | [−.890, .4623] |
| Firm age | 0.002* | 0.005 | 0.002** | 0.010*** | 0.010*** | 0.009*** |
| | (0.001) | (0.005) | (0.001) | (0.002) | (0.002) | (0.002) |
| Herfindahl index | 0.082 | 0.189 | 0.081 | 0.984*** | 0.965*** | 0.865*** |
| | (0.095) | (0.179) | (0.097) | (0.119) | (0.106) | (0.111) |
| Incorporated | −0.041 | 0.127 | −0.051 | 0.143 | 0.088 | 0.124 |
| | (0.068) | (0.335) | (0.066) | (0.119) | (0.109) | (0.107) |
| Part of group | 0.105*** | 0.152 | 0.102*** | 0.206*** | 0.189*** | 0.181*** |
| | (0.035) | (0.112) | (0.035) | (0.032) | (0.026) | (0.024) |
| Regional OC-IBTC spillover | 12.846* | 6.748 | 17.862*** | −0.374 | 11.804 | 16.962 |
| | (6.992) | (19.100) | (6.614) | (14.424) | (9.561) | (11.665) |
| Constant | 5.594*** | 5.795*** | 5.574*** | 6.275*** | 6.118*** | 6.013*** |
| | (0.089) | (0.396) | (0.093) | (0.221) | (0.156) | (0.163) |
| Observations | 4826 | 4826 | 4826 | 5061 | 5061 | 5061 |
| AR *p*-value | 0.4109 | 0.4900 | 0.4419 | 0.3308 | 0.8567 | 0.2430 |
| Wald *p*-value | 0.6065 | 0.7970 | 0.6800 | 0.3308 | 0.8567 | 0.2430 |
| J *p*-value | 0.1880 | 0.4260 | 0.1800 | 0.8732 | 0.0972 | 0.3725 |
| Hansen overidentification test *p*-value | 0.1785 | 0.2020 | 0.1717 | 0.8730 | 0.0983 | 0.3930 |
| First-stage F statistics | 7.0700 | 2.8900 | 7.1400 | 35.0000 | 41.9000 | 40.8000 |

Notes: Heteroskedasticity and autocorrelation robust standard errors. Includes year, rural region-province dummies. Instruments include regional average regulation-driven prevalence of respective EIs by technology type, regional average prevalence of respective EIs and growth in OC.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

**Table 7.** 2SLS estimation of impacts of EIs in market services and production.

| | MFP-Market services | | | MFP-Production | | |
|---|---|---|---|---|---|---|
| | EI all | EI resource-saving | EI pollution-reducing | EI all | EI resource-saving | EI pollution-reducing |
| Regulation-induced | 2.115** | 3.189* | 2.910** | 0.635 | 0.455 | 0.803 |
| | (0.831) | (1.861) | (1.461) | (0.548) | (0.546) | (0.999) |
| All | 0.135 | −2.620* | 0.147 | 0.112 | 0.061 | 0.056 |
| | (0.343) | (1.486) | (0.275) | (0.211) | (1.205) | (0.169) |
| Firm age | 0.005*** | 0.005** | 0.006*** | 0.003* | 0.003 | 0.004** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) |
| Herfindahl index | −0.23 | 0.202 | −0.284 | 0.447*** | 0.477*** | 0.452*** |
| | (0.156) | (0.270) | (0.197) | (0.067) | (0.071) | (0.076) |
| Incorporated | 0.008 | 0.083 | −0.002 | 0.03 | 0.041 | 0.05 |
| | (0.088) | (0.163) | (0.099) | (0.073) | (0.090) | (0.080) |
| Part of group | 0.037 | 0.088 | 0.06 | 0.103*** | 0.105** | 0.103*** |
| | (0.040) | (0.088) | (0.053) | (0.025) | (0.044) | (0.026) |
| Regional OC-IBTC spillover | −0.567 | 23.974 | 28.500** | −4.359 | −1.021 | 1.775 |
| | (13.300) | (21.890) | (14.077) | (12.854) | (15.911) | (12.031) |
| Size < 50 | −0.614*** | −0.741*** | −0.623*** | −0.649*** | −0.676*** | −0.649*** |
| | (0.049) | (0.069) | (0.047) | (0.057) | (0.160) | (0.073) |
| Size 250–499 | 0.451*** | 0.692*** | 0.410*** | 0.479*** | 0.516** | 0.466*** |
| | (0.085) | (0.140) | (0.108) | (0.104) | (0.215) | (0.161) |
| Size 500- | 0.561*** | 0.866*** | 0.477** | 0.926*** | 0.979*** | 0.874*** |
| | (0.166) | (0.231) | (0.232) | (0.156) | (0.316) | (0.279) |
| Observations | 5861 | 3930 | 5861 | 5985 | 5985 | 5985 |
| AR *p*-value | 0.0010 | 0.0151 | 0.0008 | 0.6049 | 0.851329 | 0.6026 |
| Wald *p*-value | 0.0358 | 0.1832 | 0.0824 | 0.4397 | 0.678595 | 0.6168 |
| J *p*-value | – | 0.4602 | – | 0.8805 | 0.995202 | 0.3863 |
| Hansen overidentification test *p*-value | – | 0.705 | – | 0.915 | 0.987 | 0.473 |
| First-stage F statistics | 87 | 40 | 61 | 297 | 324 | 276 |

Notes: Heteroskedasticity and autocorrelation robust standard errors. Includes year, rural area-province dummies. Instruments include regional average regulation-driven prevalence of respective EIs by technology type and regional average prevalence of respective EIs, and also the growth in OC for resource-saving EI in market services and manufacturing.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

EI regulation improves productivity among small and large firms. However, the total productivity improvement is about the same, and the results are no longer significant. Our results do not confirm the hypothesis of small firms' relative disadvantage of regulation-driven EIs. Voluntary EIs have, instead, the strongest but insignificant negative productivity effects in resource-saving EIs.

Another dimension is whether regulation-induced EIs differ in productivity effects in production (manufacturing and energy) and market services, which account for about 40% of all firm observations. In market services, Hansen test rejects the use of three instruments except for resource-saving EIs, and hence, the log growth of OC is excluded as an instrument except in resource-saving EIs (Table 7).

Our findings for regulation-induced EIs are stronger for market services. However, the confidence interval (Confidence interval – AR) has expanded significantly and has not been reported.

We analyze whether dropping the last 2014 survey year will lead to changes in our findings. Table A5 in the appendix shows the estimation results. The productivity effects of the regulation-induced EIs are stronger when the years 2013–2014 are dropped. However, the confidence interval increases towards the higher and cannot be reported in a grid search. As discussed, in 2013–2014, about one-fourth of firms were involved in regulation-induced EIs compared with about 20% of the shares before (Table A4) and these observations were important in our findings.

## 6. Conclusions

Regulation-motivated EIs in a dynamic model improve firm performance. At the same time, most of the data available has been cross-sectional and does not compare regulation-induced EI to voluntary EIs. This paper adds to the literature by showing how environmental regulation has a causal effect on improving performance irrespective of the type of EI or firm size. Our instrumenting set can identify regulation-induced EI from other EIs. Regulation-induced EIs improve MFP, which is the case for both resource-saving and pollution-reducing EIs. The dynamic approach also shows a delayed effect of regulation-motivated EIs. One possible caveat of the model is that the occurrence of EIs still has a high correlation with product or process innovations that were in earlier surveys in 2004 and 2006 needed to be reported to have any EI. Our instrumenting helped to identify the performance of EIs alone, but further research is needed to have an extended panel with dynamic effects. Another caveat is that we do not analyze the macro effects, such as the potential impact of the regulation on unregulated firms that face higher prices because they purchase products from regulated firms.

Based on the results, we can offer some practical conclusions. Introducing new environmental regulations and increasing environmental innovativeness leads to improved firm performance that can compensate for all of the costs of regulation. Regulations have also become more stringent, especially in the last observation years, 2013–2014, but productivity effects have increased over time. Companies may also set targets even stricter than the regulations require because they want to set a model for other companies and stakeholders or become known as innovators with a broad innovation base. Nordic firms may have benefited from a first-mover advantage by becoming green in many industries. Lodi and Bertarelli (2023) indeed find that if adopting a clean production technology is too expensive, as in Eastern Europe, regulation-driven EIs can drive firms out of the market. Perhaps for the same reason, even non-innovative firms in Germany may benefit from regulation-induced eco-innovation as they increase exports to Eastern Europe.

## Note

1. Eight industries considered are 1 Manufacturing C10-C19; 2 Manufacturing C20-29; 3 Manufacturing C30-C33, Electricity, Gas, Steam D; 4 Trade D, Land Transport H49; 5 Other transport H50-H53, Accommodation, Food I, Publishing, Motion picture H58_H59; 6 Other Publishing J, Programming, Telecommunication H59-H59; 7 Professional, Scientific and Technical Activities M75-M75, M77-MM79 H50-H53, 8 Administrative, Support Service Activities N, Human Health Q.

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## Appendix 1 Measurement of occupational R&D, OC, and ICT and robustness checks

A list of relevant occupations was prepared for each relevant intangible capital type. Box 2 lists occupations that engage in intangible investment according to our methodology in bold (OC = organizational occupation, R&D = R&D occupation, and ICT = ICT occupation). Table A1 shows the occupations with intangible capital-related work (Piekkola et al. 2024).

GLOBALINTO estimates proportioned shares of factor multipliers from Eurostat national accounts based on production activities in certain knowledge-intensive industries (KIS) to determine how value added is divided into labor costs, capital, and intermediate inputs. Factor multipliers show capital and intermediate inputs for one unit of IC occupation labor costs. We refer to industries engaged in market production of comparable goods to quantify the production function. The knowledge-intensive services (KIS) are:

- Computer and related activities (NACE J59-J63) as a proxy for ICT production;
- Research and development (NACE M72) as a proxy for R&D production;
- Other business activities (NACE M69-71 & M73-M75) as a proxy for OC production.

The multipliers evaluated from these industries evaluate intangible investment in all industries based on intangible work. Factor multipliers are calculated as the average of EU countries. The nominal value of intangible capital investment of type *IC* for firm *i* in year *t* is given by

$$P_{it}^{N}N_{it}^{IC} = A^{IC}M_{it}^{IC},\ \text{for } IC = \{R\&D,\ OC,\ ICT\}, \tag{A.1}$$

where labor costs, $M_{it}^{IC}$, are multiplied by a total multiplier, $A^{IC}$ (0.7 in OC, 1.1 in RD and 0.9 in ICT), to obtain total investment expenditure on intangibles. The total multiplier also demonstrates the innovative share of IC occupations (40% in

OC, 60% in RD, and 45% in ICT) and not only the use of capital and intermediate inputs for one unit of IC occupation labor costs (1.73 in OC, 1.84 in RD and 2.08 in ICT). The parameter, $P_{it}^{N}$, is the price of each of the three types of intangibles. To estimate fixed values, we use the investment deflator for R&D, the innovation property investment deflator (which includes R&D, software, and database) for ICT, and the labor costs weighted average of the producer price deflator over business services (NACE 69–73) for OC.

The depreciation rate for linear decay in organizational investments $\delta_{OC}$ is set at 20%, according to the survey by Lev et al. (2016) and the paper by Squicciarini and Le Mouel (2012). Recent estimates of R&D depreciation rates are closer to the 15% relied on here than the 20% figure used in Corrado et al. (2014). ICT investments are assigned a 33% depreciation rate.

**Table A1.** Intangible work occupations.

| | |
|---|---|
| Organizational work | • Business services and Administration managers 121<br>• Sales and marketing managers 1221, Advertising and public relations managers 1222<br>• Production managers in agriculture, forestry, and fisheries 131<br>• Manufacturing, mining, construction, and distribution managers 132<br>• Professional services managers 134<br>• Finance professionals 241, Administration professionals 242 |
| R&D work | • Research and development managers 1223<br>• Physical and earth science professionals 211, Engineering professionals 212, Life science professionals 213, Engineering professionals (excluding electrotechnology) 214, Electrical engineering 215<br>• Architects, planners, surveyors, and designers 216<br>• Health professionals: Medical doctors 221, Nursing and midwifery professionals 222, Other health professionals 226<br>• Physical and engineering science technicians 311, Life science technicians and related associate professionals 314, Medical and pharmaceutical technicians 321 |
| ICT work | • Information and communications technology services managers 133<br>• Information and communications technology professionals 25 (software and applications developers and analysts 251 and database and network professionals 252)<br>• Information and communications technology professionals 35 (Information and communications technology operations and user support 351, telecommunications and broadcasting technicians 352) |

**Table A2.** Firm distribution by industry in the sample.

| Industry | | Manufacturing and energy | Firms | % |
|---|---|---|---|---|
| Food and beverages | 10–12 | Low-technology | 489 | 4.93 |
| Textile, leather | 13,14 | Low-technology | 218 | 2.2 |
| Leather and related products | 15 | Low-technology | 78 | 0.79 |
| Wood products and furniture | 16 | Low-technology | 534 | 5.39 |
| Pulp and paper | 17 | Low-technology | 246 | 2.48 |
| Petroleum, chemicals | 20 | High-middle technology | 311 | 3.14 |
| Rubber and plastic | 22 | Low-middle technology | 355 | 3.58 |
| Other non-metallic products | 23 | Low-middle technology | 313 | 3.16 |
| Basic metals | 24 | Low-middle technology | 203 | 2.05 |
| Fabricated metals | 25 | Low-middle technology | 782 | 7.89 |
| Computer, electronic and optical products | 21,26 | High-tech manufacturing | 268 | 2.7 |
| Manufacture of electrical equipment | 27 | High-tech manufacturing | 280 | 2.82 |
| Machinery, equipment and their repair | 28 | High-tech manufacturing | 931 | 9.39 |
| Motor vehicles and other transport equipment | 29 | High-tech manufacturing | 305 | 3.08 |
| Other manufacturing | 32 | Low-middle technology | 380 | 3.83 |
| Electricity, gas, steam and air conditioning | 35 | Low-middle technology | 292 | 2.95 |
| | | Services | | |
| Trade, retail trade | 45–47 | Market services other | 1205 | 12.16 |
| Transport | 49,51,52,58 | Transport communication | 568 | 5.73 |
| Warehouse and support activities 52, postal 53 | 52,53 | Market services other | 441 | 4.45 |
| Publishing activities | 58 | Transport communicaiton | 293 | 2.96 |
| Telecommunications, computing programming | 61,62,63 | ICT services | 709 | 7.15 |
| Architectural and engineering activities, R&D | 71,72 | R&D services | 712 | 7.18 |
| Total | | | 9913 | 100 |

**Table A3.** EI by year in the sample.

| | 2004 | 2006 | 2008 | 2014 | Mean | Mean Small | Mean Large |
|---|---|---|---|---|---|---|---|
| Product innovation | 0.405 | 0.410 | 0.396 | 0.438 | 0.412 | 0.351 | 0.503 |
| Environmental innovation (EI) | 0.406 | 0.431 | 0.556 | 0.411 | 0.451 | 0.367 | 0.554 |
| EI resource-saving | 0.362 | 0.378 | 0.430 | 0.397 | 0.392 | 0.317 | 0.490 |
| EI pollution-reducing | 0.354 | 0.376 | 0.513 | 0.266 | 0.377 | 0.278 | 0.473 |
| EI regulation-driven | 0.188 | 0.174 | 0.197 | 0.256 | 0.204 | 0.151 | 0.277 |
| EI resource saving, regulation-driven | 0.171 | 0.155 | 0.136 | 0.250 | 0.178 | 0.134 | 0.243 |
| EI pollution-reducing, regulation-driven | 0.176 | 0.167 | 0.137 | 0.187 | 0.167 | 0.111 | 0.229 |
| EI regulation driven shares | | | | | | | |
| EI resource-saving | 0.473 | 0.409 | 0.316 | 0.628 | 0.454 | 0.422 | 0.496 |
| EI pollution-reducing | 0.498 | 0.444 | 0.267 | 0.701 | 0.442 | 0.398 | 0.484 |

**Table A4.** First-stage estimations of endogenous variables in 2SLS.

| | EI all | | EI all | | EI resource-saving | |
|---|---|---|---|---|---|---|
| | Regulation-driven | All | Regulation-driven | All | Regulation-driven | All |
| Regional regulation-driven | 0.17*** | 0.10*** | 0.17*** | 0.15*** | 0.14*** | 0.09*** |
| EI by techtypes | (0.025) | (0.029) | (0.026) | (0.030) | (0.026) | (0.031) |
| Regional all EI | −0.01 | 0.35*** | 0.006 | 0.03 | −0.002 | 0.46*** |
| | (0.038) | (0.047) | (0.046) | (0.058) | (0.034) | (0.043) |
| Log growth OC | −0.002 | 0.0049 | −0.003 | 0.0039 | −0.003 | 0.0026 |
| | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) |
| Regional OC-IBTC spillover | 5.0562 | −8.773** | 6.0016* | −4.362 | −4.288 | −16.58*** |
| | (3.064) | (3.615) | (2.999) | (3.606) | (2.953) | (3.556) |

Notes: Includes control variables (reporting only regional OC-IBTC spillover) and dummies.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

**Table A5.** 2SLS estimation of EIs omitting the 2014 Survey.

| | EI all | EI resource-saving | EI pollution-reducing |
|---|---|---|---|
| Regulation-induced | 2.651* | 5.019 | 2.169** |
| | (1.493) | (5.009) | (1.071) |
| Confidence interval – AR | [−1.004, ] | [ −1.2, ] | [−2.015, ] |
| All | −0.689 | −2.576 | −0.874 |
| | (0.567) | (2.986) | (0.545) |
| Confidence interval – AR | [,.236] | [,.898] | [, −.165] |
| Firm age | 0.007*** | 0.011* | 0.008*** |
| | (0.002) | (0.006) | (0.002) |
| Herfindahl index | 0.107 | 0.172 | 0.242* |
| | (0.195) | (0.265) | (0.136) |
| Incorporated | 0.087 | 0.231 | 0.1 |
| | (0.110) | (0.285) | (0.099) |
| Part of group | 0.109** | 0.165 | 0.095*** |
| | (0.044) | (0.123) | (0.034) |
| Size < 50 | 31.442*** | 26.372 | 36.508*** |
| | (10.962) | (16.492) | (10.551) |
| Size 250–499 | −0.620*** | −0.703*** | −0.670*** |
| | (0.069) | (0.107) | (0.048) |
| Size 500- | 0.366** | 0.361 | 0.455*** |
| | (0.148) | (0.246) | (0.100) |
| Regional OC-IBTC spillover | 0.636** | 0.558 | 0.789*** |
| | (0.248) | (0.474) | (0.165) |
| Constant | 5.865*** | 5.978*** | 5.969*** |
| | (0.241) | (0.338) | (0.180) |
| Observations | 7535 | 7535 | 7535 |
| AR $p$-value | 0.0074 | 0.0792 | 0.0097 |
| Wald $p$-value | 0.2065 | 0.5799 | 0.1257 |
| J $p$-value | 0.2095 | 0.7796 | 0.2211 |
| Hansen overidentification test $p$-value | 0.3510 | 0.9040 | 0.3230 |
| First-stage F statistics | 99 | 39 | 138 |

See notes in Table 3.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.