GLOBALINTO

## Deliverable D5.12

# Broad intangibles and environmental policy as drivers of environmental innovations and economic performance

**Due date of deliverable: 2020/10/30**

**Actual submission date: 2020/11/11**

**Revised submission date: 2022/10/03**

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|---|---|
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| Work package /title: | WP5.12 Broad intangibles and environmental policy as drivers of environmental innovations and economic performance |
| Document status: | draft / final |
| Confidentiality: | confidential / restricted / public |

# Table of Contents

# Executive Summary

Because of growing environmental concerns, environmental innovations (EIs) have become increasingly salient in the environmental policy and innovation strategies of firms. Exogeneity of reported innovations is improved by using predicted values of innovations as instruments. The aim of this paper is to analyze whether and how the productivity effects of EIs differ 1) depending on whether the EI is regulation motivated or voluntary, 2) depending on the environmental benefits achieved, 3) in comparison to product innovations and when their endogeneity is controlled. As an addition to the prior literature analyzing regulation, environmental innovativeness and firm performance, we control for organizational efficiency and the endogeneity of all innovations by utilizing instrumental variables, panel data and a tripartite model of innovation decisions. We thus analyze product innovations together with pollution-reducing and resource-saving EIs and with the EIs separately when EI decisions are induced by environmental regulation. This paper shows the productivity effects of innovations vary across different types of environmental innovations. The strong version of the Porter hypothesis gains support in Nordic countries such as here Finland. We find that environmental regulation-induced EIs enhance firm performance.

The strategy of introducing new environmental regulations will increase innovativity, which in turn leads to improved firm performance that can apparently cover all of the costs from regulation. Nordic including Finnish firms have benefitted from a first-mover advantage by becoming “green” in many industries, a reason for good performance suggested initially by Lieberman and Montgomery (1988). This is evidently driven by regulation that has become more stringent especially in last observation year 2014 so that the shares of environmental innovations driven by regulation have increased over time.

It is clear that EIs require cooperation with consultants, while they are unrelated to organizational change or even negatively to organizational investment. The organizational structure within firms is less important than the ability to be connected with experts and consultants who can enable firms to fulfill the targets set by environmental regulations.

# 1. Introduction

Because of growing environmental concerns, environmental innovations have become increasingly salient in the innovation strategies of firms and in economic research. Environmental innovations (EIs) and technological progress can contribute to improved environmental sustainability through, e.g., more efficient use of natural resources, lower emissions and improved recycling. These improvements are also likely to lead to private economic gains for innovating firms. However, positive environmental and knowledge externalities, so-called double externality, mean that private innovation incentives are below the socially optimal level (Rennings, 2000). Thus, private investments in EIs are likely to remain suboptimal without policy intervention. Accordingly, governments have often intervened with subsidies and regulations, which are widely understood to be important motivations for EIs, along with market and technological factors (Horbach et al., 2012). According to the classical view, however, environmental regulation will lead to inferior performance for regulated firms. Accordingly, regulation-induced environmental innovations should lead to inferior firm performance in comparison to other innovations (Ambec and Barla, 2006). In contrast, according to the Porter hypothesis, well-designed environmental regulation improves firm performance and leads to both environmental and economic gains (Porter and Van der Linde, 1995a). Such regulation will cover specifications of maximum permitted emissions, environmental taxes or detailed requirements for products, production processes or technologies. However, the research findings remain mixed, and are often context specific despite the generally wide empirical literature on the Porter hypothesis (Horváthová, 2010, Barbieri et al., 2016, Ambec et al., 2013). The categorization of policy instruments as incentive-based or regulation (command-and-control) has been also argued to be misleading or they have found to have similar effects (Bohm and Russell, 1985, Bye and Klemetsen, 2018).

The aim of this paper is to analyze with controlling for endogeneity of dichotomous values of reported innovations whether and how the productivity effects of EIs differ 1) depending on whether the EI is regulation motivated or voluntary, 2) depending on the environmental benefits achieved and 3) and in comparison to product innovations. There exists only a few prior studies using firm-level innovation panel data. These prior studies, e.g., Marin (2014) and Marin and Lotti (2017), have compared the productivity effects of environmental patents to the effects of patents in general. Their studies find possible crowding out of other patents. Although they do not directly analyze regulation, they suggest that the low or nonexistent productivity effects of environmental patents that they find are due to regulation. Other studies not using panel data, such as Rennings and Rammer (2011), Ghisetti and Rennings (2014), and Rexhäuser and Rammer (2014), have compared the effects of regulation motivated and voluntary EIs on firm profitability, as well as the effects of resource-saving and pollution-reducing EIs. However, these studies rely on cross-sectional data and do not address the endogeneity of firm innovation decisions. Endogeneity is an important issue because there is likely to be significant heterogeneity among firms in terms of whether and with what type of innovation they can respond to regulation. Some firms may adopt existing environmental technologies or develop new innovations to meet regulation requirements related to, e.g., lower vehicle emissions (Rennings and Rammer, 2011), while some firms may choose to avoid regulation by offshoring or ignoring regulations altogether (Drake and Just, 2016). These responses depend on the regulatory regime but also on firms' strategies, capabilities and resources, which makes engaging in EI and regulation-induced EI an endogenous decision for firms. We attempt to compare the productivity effects of different categories of EIs while addressing the endogeneity of innovation activities in our empirical analysis.

We use an instrumental variable approach to estimate the productivity effect of endogenous innovation variables. We apply and extend the CDM model of Crépon et al. (1998) to do so. We utilize four waves of the Finnish Community Innovation Survey (CIS) and combine them with balance sheet data and R&D survey information for 2003-2008 and 2013-2014[1]. Panel data, together with an instrumental variables approach allows for a more reliable causal interpretation of our results.

Our empirical method using Finnish data utilizes a tripartite model including also innovations other than EIs and is close to the method of Van Leeuwen and Mohnen (2017) using Dutch data that also holds innovation variables as endogenous and controls for the complementarity between resource-saving and pollution-reducing EIs. We find that product innovations alone without EIs do not improve productivity and among EIs its is especially the regulation-driven EIs that improve productivity. The Porter hypothesis of double benefits from environmental regulation holds in the sense that firms engaging in regulation-driven EI are also more productive than other firms.

The paper is structured as follows. Section 2 provides an overview of the theoretical framework for environmental innovations. Section 3 discusses the prior empirical literature. In Section 4, our data and descriptive statistics are presented. Section 5 discusses the econometric model. Section 6 presents and discusses the estimation results. Finally, Section 7 concludes.

# 2 Theoretical framework for environmental innovations

Environmental innovation (EI) can be 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 that creates environmental benefits throughout its life cycle compared to relevant alternatives (Kemp and Pearson, 2007). Positive environmental effects may emerge through reduced use of energy or resources; reductions in air, water, noise or soil pollution; or reductions in environmental risks or waste generation. This definition indicates that not all EIs leading to reduced environmental externalities have been predominantly motivated by environmental objectives. Some studies use the terms EI and eco-innovation interchangeably. However, eco-innovation was originally considered a subclass of EI; i.e., eco-innovations entail both environmental and economic benefits (Huppes et al., 2008). In the present study, we discuss EIs because we have no prior reason to believe that all EIs should also bring about economic gains.

[1] Unfortunately, the CIS does not include questions on the environmental benefits of innovations in each year.

EIs are characterized by a double externality (Barbieri et al., 2016). First, EIs have the potential to reduce the negative environmental externalities of production. Second, like all innovations, EIs can produce positive knowledge spillovers that benefit other firms, individuals and countries, in addition to the innovator. These externalities indicate that firms' private incentives for engaging in EI are lower than the social benefits; thus, governments often wish to interfere by using policy instruments to promote EI. The double externality as well as policy interventions imply that the drivers and impacts of EIs can differ substantially from those of other innovations. Drivers of EIs are typically divided into different categories: market pull factors (such as customer demand), policy factors (such as regulation and subsidies) and technology- and firm-specific push factors (such as R&D and environmental management systems) (Horbach, 2008, Ghisetti and Pontoni, 2015).

Ghisetti and Rennings (2014) review the factors that may cause the economic gains of EIs to exceed the gains from other types of innovations. First, the economic benefits of EIs are often underestimated by managers due to, e.g., information search costs, which leads to suboptimal investment. Second, the corporate social responsibility literature identifies sources of positive economic gains from socially responsible behavior, such as better access to certain markets, product differentiation, sales of pollution control technology and cost reductions in risk management, materials, energy, capital or labor (Ambec and Lanoie, 2008).

The impacts of EIs can also differ depending on the reasons they were adopted, e.g., regulation or economic motivations. Typically, environmental regulation is seen as a cost to firms. Regulation causes firms to divert resources from other, more profitable investments into environmental investments because profit-maximizing firms would have already curbed their environmental impact if it would have improved their productivity. Regulation-induced EIs should thus lead to lower economic benefits than other innovations. In contrast, the well-known Porter hypothesis presented by Porter and Van der Linde (1995b) states that well-designed environmental regulation improves firm performance. According to the weak version of the hypothesis, environmental regulation increases environmental innovation. The strong version of the Porter hypothesis states that the positive effects of regulation also exceed its costs, and firm productivity improves because, e.g., the firm gains an early-mover advantage. To provide a theoretical justification for why profit-maximizing firms would benefit from regulation, subsequent research has argued that firm decisions are made by rent-seeking managers who thus have other objectives in addition to profit maximization (Ambec and Barla, 2006, Ambec et al., 2013). Therefore, government regulation can help managers and firms to overcome these problems. This also provides motivation to integrate organizational capital (OC) in the model as done in this study. Other theoretical arguments in favor of the Porter hypothesis link the hypothesis to other market failures. Government regulation may help to overcome problems of market power and R&D spillovers (Ambec et al., 2013). A substantial empirical literature has tested the Porter hypothesis both in relation to EIs and to firm performance in general. The findings of the prior literature using firm-level data are summarized in Section 3.

In addition to regulation, other characteristics of EIs can also matter for their firm performance effects. A distinction analyzed in this paper and some earlier studies is whether the environmental benefits of innovation relate to material and energy savings or to a reduction in pollution. Material or energy saving EIs change the production process and lead to a reduction in the use of physical resources. Other EIs reduce pollution in other ways. According to Horbach et al. (2012), resource-saving innovations are often motivated by cost savings or market demand, which implies clear economic gains from these innovations. In contrast, Horbach et al. (2012) show that various pollution-reducing innovations are typically motivated by current or expected regulation. $CO_2$-emission reducing and recycling improving innovations are motivated by both economic and regulatory considerations (Horbach et al., 2012).

However, Demirel and Kesidou (2011) find that both end-of-pipe and clean production technologies are motivated by equipment upgrades and aim to improve efficiency. End-of-pipe technologies are in turn also motivated by regulations. Thus, both types of EIs can be linked to changes in the production processes and to economic gains. Bye and Klemetsen (2018) analyze environmental regulation and environmental performance measured by emission intensity in Norway. They find evidence that direct regulations lead to dynamic and persistent effects, in contrast to former beliefs (Jaffe and Stavins, 1995, Perman et al., 2003). Non-tradable quotas can create an incentive for the firm to reach this level at the lowest cost by reorganizing the production process or investing in new technologies.

# 3 Data

We use an unbalanced panel dataset that is formed by linking several firm-level datasets. A key data source is the Finnish Community Innovation Survey (CIS), which is conducted every other year and covers three-year periods. We use surveys from 2004, 2006, 2008 and 2014. Most firms do not appear in the survey every year; however, approximately 55% of the firms are included in more than one survey. During these years, the Finnish CIS contained questions on the environmental benefits of innovations. Unfortunately, similar questions were not included in every survey; thus, our data are limited to these years. 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 in which 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-year period because this year is covered by another survey.

In our empirical approach, EIs are defined as innovations that reduce material or energy use or lower pollution. 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 output” or (2) “Reduced environmental impacts or improved health and safety”, the firm is recorded as having adopted an environmental innovation. Thus, EI is a binary variable. Using these questions, we also categorize EIs as leading to either resource savings (1) or pollution reduction (2). All innovations, regardless of degree of importance (high, medium, low) are counted as EIs. The 2008 and 2014 CIS contain more detailed questions on the environmental benefits of innovations; however, they are yes-no questions. We define the firm as having 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 use 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 after use. The following benefits are counted as pollution-reducing EIs: 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[2,3].

We use CIS data to determine whether the innovations are motivated by regulation, as in Ghisetti and Rennings (2014). The 2004 and 2006 CIS contain questions on whether the effect of innovation is "Met regulatory requirements". We consider an innovation to be regulation motivated if regulatory requirements are given high or medium importance. The 2008 and 2014 CIS instead asks whether the firms introduced an environmental innovation in response to 1) existing environmental regulations or taxes on pollution or 2) regulations or taxes that are expected to be introduced in the future. In 2008 and 2014, innovation is recorded as being driven by regulation if the firm answers yes to either of these questions (2014 survey also separate regulation and taxes on pollution but both are considered together).

As discussed, we also use the CIS questions on whether a firm reported any product innovations. Thus, we also measure product innovations that do not have environmental benefits. The sample of firms, which we were able to link across all the different datasets, contains firms that are on average more innovative than the whole sample of manufacturing and energy sector firms that answered the CIS. Table B.1 in Appendix B shows that in the sample firms the share of firms reporting EI varies between 53% and 66% over the sample period, while the figures are lower for the whole CIS survey. In 2004 and 2006 EIs in the survey questionnaire are related to product or process innovations. In years 2008 and 2014, EIs are not bound only to product or process innovations. Furthermore, in 2004 and 2006, environmental regulation is not separately considered so some firms introduced regulation-motivated innovation, but innovations did not provide environmental benefits. The share of firms reporting EI with regulatory push has remained around 24% until 2008 (even though in 2008 was considered together with taxes on pollution) and climbing up to 36% in 2014 (EI reg). Regulation-motivated resource-saving (EI res regulation) and pollution-reducing EIs (EI pol regulation) are almost equally common, 21-24% except in 2014 with 35%% share of resource-saving EI and 28% share of pollution reducing EI.

A further measure from the CIS data that we utilize covers innovation cooperation with different actors: within the corporate group, with suppliers, with customers, with consultancy firms, with universities and with public or private research institutes. Cooperation between competitors is dropped to reduce multicollinearity.

Our financial data come from Statistics Finland's firm-level financial accounts data. In our empirical analysis, we use data on the value-added, employment, intermediate inputs and tangible investment. We use broad measure of R&D as out primary R&D input since it covers 93% of the final estimation sample, see Table 1. The formal and

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[2] In 2008, we also consider as EIs the innovations that lead to improvement in health and safety, as these effects were in included in the earlier years. For 2014 this question was unavailable. This causes the figures for pollution reducing EIs to be somewhat lower in 2014 compared to the previous years. Moreover, in 2014 we do not consider the environmental benefits related to replacement of fossil energy with renewable energy sources and extension of product life as these were not included in the previous surveys.
[3] Our approach also differs from, e.g., Ghisetti & Renning (2014) who do not analyze EIs that result in environmental benefits in end-user use

broad R&D have a high correlation of 0.78 when both are available. We also report as robustness check results using formal R&D obtained from R&D surveys (a survey with around 4300 firms annually). The EU Horizon 2020 Globalinto 2019-2022 project identifies the structural capital of broad R&D and organizational capital (OC) using occupational data that identifies R&D and management mark (for OC). The latter ignores here marketing work referred to as narrow definition, see Appendix A. Information and communication technology (ICT) is from ICT services and related experts. After elaboration of the intangibles labor input from the related occupations the second task is to evaluate the worktime share spent on innovative work. Overheads should cover other factor inputs such as intermediate and tangible inputs used in construction of IA investment. The method is described in greater detail in Appendix A.

Following the micro analysis in the EU Horizon 2020 GLOBALINTO project, organizational capital investment is measured using management and marketing work based on linked employer-employee data that includes full occupational data of employees in Finland, see Isco three-digit code occupation list in Appendix A. Organizational capital investment is defined as the labor cost of management and marketing jobs, with a multiplier on the share of management and marketing work intended for long-term planning (30%) and associated nonlabor cost shares (55%) yielding a combined multiplier 1.55; see Piekkola and Rahko (2020) for analogous earlier methods and multipliers based on the earlier FP7 INNODRIVE project from 2008-2011. Multiplying OC occupation labor costs by this combined multipler gives OC capital investment. We similarly measure R&D capital investment through the labor costs of R&D-related work. Here, 50% of work is assumed to be intended for long-term planning, and the associated nonlabor cost share is 77% over labor costs with combined multiplier of 1.53.

The nonlabor cost shares are based on figures averaged over the EU countries and taken from the Eurostat national accounts data using Nace 2-digit intangible asset producing industries (Nace M72 for R&D, Nace M69-M70, M73 for OC).[4] Other variables include the number of employees, measures of innovation cooperation, and industry and year dummies.

We include the manufacturing and energy sector in our sample. Firms with fewer than 10 employees and more than 5000 employees are not included in the data[5]. Appendix B Table B.2 presents the 16 industries represented in our sample. Table 1 below presents some descriptive statistics for the variables used in the empirical analysis. Monetary values have been deflated to 2015 prices using the industry-level producer price index and investment price index.

Table 1. Descriptive statistics

| Variable | mean | sd | p50 | N |
|---|---|---|---|---|
| Product innovation | 0.506 | 0.5 | 1 | 5552 |
| EI | 0.568 | 0.495 | 1 | 5552 |
| EI res | 0.505 | 0.5 | 1 | 5552 |
| EI pol | 0.488 | 0.5 | 0 | 5552 |
| EI pol only | 0.080 | 0.271 | 0 | 5552 |

[4] IC-producing industries use intermediate inputs from other industries intensively, and hence only half of intermediate use is taken into account in assessing capital and intermediate input for one unit of labor costs.

[5] This restriction follows Marin (2014). The argument for this restriction is that that the innovation patterns in the smallest and largest firms are likely to be very different.

| | | | | |
|---|---|---|---|---|
| EI reg | 0.274 | 0.446 | 0 | 5552 |
| EI res regulation | 0.243 | 0.429 | 0 | 5521 |
| EI pol regulation | 0.232 | 0.422 | 0 | 5521 |
| Cooperation with group firms | 0.21 | 0.407 | 0 | 5552 |
| Cooperation with suppliers | 0.262 | 0.44 | 0 | 5552 |
| Cooperation with customers | 0.281 | 0.45 | 0 | 5552 |
| Cooperation with consultants | 0.143 | 0.35 | 0 | 5552 |
| Coop. with universities, research institutes | 0.314 | 0.645 | 0 | 5552 |
| R&D/L survey | 9.8 | 17.1 | 4.5 | 2773 |
| Share of firms with positive R&D survey | 0.499 | 0.5 | 0 | 5552 |
| R&D/L broad | 9.1 | 7.6 | 6.9 | 5134 |
| Share of firms with positive R&D broad | 0.925 | 0.264 | 1 | 5552 |
| OC/L | 2.75 | 2.599 | 2.151 | 4435 |
| Value added/L | 114 | 383 | 84.791 | 5552 |
| Employment L | 161 | 375 | 51 | 5552 |
| Capital/L | 37 | 40 | 26.313 | 5552 |
| Material/L | 0.241 | 0.525 | 0.14 | 5552 |
| Export/Sales | 0.444 | 0.388 | 0.371 | 5552 |
| Part of group | 0.549 | 0.498 | 1 | 5552 |
| Foreign | 0.198 | 0.399 | 0 | 5552 |
| R&D subsidy share | 0.167 | 0.373 | 0 | 5552 |

Notes. In sample OC/L is set at zero if missing. In thousand 2015€.

Broad R&D and survey R&D investments per employee are around 9-10 thousand € per employee in firms that have them, while OC investment per employee is 2.8 thousand € per employee. About one third of firms co-operate and 14% with consultants. 20% are foreign owned and majority are part of a group.

# 4 CDM model

The CDM model introduced by Crépon et al. (1998) is an empirical structural model that has been widely used and analyzes the innovation patterns of firms. In the context of the Porter hypothesis, Marin (2014), Van Leeuwen and Mohnen (2017) and Yuan and Xiang (2018), for example, have applied the CDM model. The model consists of three steps. The first phase estimates the firm's decision regarding whether to invest in R&D or not and subsequently estimates the firm's decision about the intensity of R&D investments.

The second step of the model is innovation, or a knowledge production function, in which the predicted R&D investment intensity, along with other explanatory factors, is used to predict innovation success. Using the predicted values is an instrumental variable approach to control for the endogeneity of R&D investment decisions. The third step of the model estimates the production function. The last step uses the predicted values of innovation success from the previous step as instruments for innovation variables.

## *5.1 R&D investment equation*

We apply first stage estimation to impute the predicted value of broad R&D ) to all CIS survey firms (in robustness check the predicted value of formal R&D, where half of the CIS sample firms did not enter the R&D survey). The R&D investment strategies of firms are modeled as a two-stage decision process, in which firms decide, in the first step, whether to perform any R&D investment and, in the second step, the intensity of these investments. The decision to invest or not can be modeled as follows:

$$D_{it} = 1 \quad \text{if} \quad D_{it}^{*} = Z_{1it}^{'}\alpha_1 + \varepsilon_{1it} \quad \text{and zero otherwise} \tag{1}$$

Firms conduct R&D investments if the latent value of investing, denoted by $D_{it}^{*}$, exceeds some threshold value, which for practical purposes can be set equal to zero. The indices i and t denote firms and time periods. $Z_1$ refers to the variables that determine the decision to invest. We include in these variables the lagged number of employees, lagged OC intensity, lagged intermediate input use, and export status as well as dummies for corporate group membership, foreign ownership, industrial sectors and years.

Furthermore, we also include cooperation in innovation activities as a control variable because we consider such cooperation important for the estimation of the knowledge production function and include them here to ensure a proper instrumentation approach for the second step. Following Piekkola and Rahko (2020), we consider OC as a significant explanatory variable for R&D since the two forms of structural intangible capital are interrelated. OC correlates strongly with R&D, and OC coverage is large and evaluated from register data, while R&D data are based on surveys.

Given the selection equation above, the firm will then decide on the intensity of investment, i.e., the R&D investment per employee. Investment intensity is modeled as follows:

$$\text{R\&D}_{it} = R\,\&\,D_{it}^{*} = Z_{2it}^{'}\alpha_2 \ + \varepsilon_{2it} \quad \text{if} \quad \text{D}_{it}\text{=1 and zero otherwise} \tag{2}$$

$R\,\&\,D_{it}^{*}$ is the unobserved latent variable accounting for the firm's R&D investment efforts. $Z_2$ refers to the variables determining the intensity decision. The error terms in (1) and (2) are assumed to be jointly normally distributed. The combined model is estimated as a Heckman sample selection model, also referred to as a tobit type II model. The R&D investment decisions are characterized by incidental truncation, with the decision to perform investments depending on their unobservable expected returns.

The intensity equation includes the same explanatory factors as the selection equation as well as a dummy for receiving R&D subsidies. This variable was not included in the selection equation because its value is zero for all firms that do not report R&D investments.

## 5.2 Innovation equations

The second step of the CDM model analyzes innovation success, which is explained by the predicted R&D investments and other firm resources. Prior applications of the CDM model have used various measures for innovation outcomes: patents, innovative sales or dummy variables for the introduction of innovations. Our innovation measures come from the CIS data and are binary variables. Whether we observe EI outcomes is determined by a selection process. First, the firm either innovates or does not. Only if the firm has innovated can we observe whether the innovation has environmental benefits, whether they are related to resource savings or pollution reduction and whether the innovation is motivated by regulation. We first estimate a firm's propensity to innovate with an ordinary probit model. However, when we analyze the EIs, we need to estimate a bivariate probit model a. Thus, in the second specification, we estimate:

$$produ_{it} = 1 \quad \text{if } produ^{*}_{it} = X^{'}_{1it}\beta_1 + \upsilon_{1it} > 0 \text{ and zero otherwise} \tag{3}$$

$$\mathrm{EI}_{it} = 1 \quad \text{if } \mathrm{EI}^{*}_{it} = X^{'}_{2it}\beta_2 + \upsilon_{2it} > 0 \text{ and zero otherwise} \tag{4a}$$

The variable *produ* refers to any product innovation. The variable *EI* is environmental innovation. The error terms, $\upsilon$, of the above equations are allowed to be correlated.

Furthermore, because we wish to compare not only environmental and nonenvironmental innovations but also different types of EIs, the second stage will be a trivariate model. Thus, equation 4a above is replaced by the following equations in specification 3[6]:

$$EI\_RES_{it} = 1 \quad \text{if } EI\_RES^{*}_{it} = X^{'}_{3it}\beta_3 + \upsilon_{3it} > 0 \text{ and zero otherwise} \tag{4b}$$

$$EI\_POL_{it} = 1 \quad \text{if } EI\_POL^{*}_{it} = X^{'}_{4it}\beta_4 + \upsilon_{4it} > 0 \text{ and zero otherwise} \tag{4c}$$

where the variable *EI_RES* refers to resource-saving EIs and *EI_POL* to pollution-reducing EIs. Again, the error terms, $\upsilon$, from equations 3, 4b and 4c are allowed to be correlated in a trivariate model. In our fourth specification, we wish to compare the effects of voluntary EIs and regulation-motivated EIs. Here, the corresponding dependent variables are *produ*, *EI* and *EI_REG*. In this specification, we actually observe regulation-induced EIs only if the firm has first introduced EIs. Thus, we allow a selection process in this specification, a Heckman probit model[7].

[6] This model is estimated in Stata using the cmp command by Roodman (2011).
[7] This model is also estimated with the cmp command.

From these models, we obtain the probability of each innovation type: innovation in general, EI vs. nonenvironmental innovation, resource-saving EI vs. pollution-reducing EI, and regulation-motivated EI vs. voluntary EI.

We consider innovation variables to be endogenous. The main explanatory variables in the second step of the CDM model are the predicted R&D investments and lagged OC investments per employee.

Intangible inputs in R&D and OC are expected to positively affect innovations in general. We do not include the intermediate input intensity, R&D subsidy dummy and group membership variables in the second step estimation. These variables are assumed to affect a firm's R&D investment decisions, but they are assumed to not have direct effects on firm innovativeness. Thus, these variables act as our instrumental variables. We find that these variables are highly significant in explaining R&D investments. However, because our first step estimation is a Heckman selection model, the common tests for instrument validity are not directly applicable. Nevertheless, if we estimate the first stage using simple OLS, we can perform a test for instrument validity. In this case, we find that the exogeneity of the instruments is not rejected. This supports our use of the abovementioned variables as instruments. We also use firm exports/sales ratio to separate product and EI innovations, because the ratio does not significantly explain the latter.

## *5.3 Production function*

The final step of the CDM model consists of estimating the effect of reported innovation on firm productivity. Following the prior literature, we apply a Cobb-Douglas production function, where the dependent variable is labor productivity (log value-added per employee).

$$y_{it} = \delta_0 + \delta_k k_{it} + \delta_{OC} oc_{it} + \delta_l l_{it} + \sum\nolimits_{z=produ,EI} \delta_z p_{zit} + C_{it}^{'} \delta + u_{it} \tag{5}$$

In the equation above, $y$ refers to log value-added per employee, $k$ to log investment per employee, oc to log OC per employee (zero if missing), and $l$ to the log number of employees, and the input variables (capital intensity, OC intensity and labor). $p$ are the innovation variables, and $C$ is a vector of additional control variables.

Control variables include controls for industry, year and firm export status, as they are expected to affect labor productivity. We do not include innovation cooperation variables or R&D intensity in the productivity estimation. Thus, these variables act as instruments for the innovation variables. They are assumed to influence labor productivity only through firm innovativeness. However, because we use probit estimations in the earlier step, we cannot directly use the predicted values in our third-step regression. In this case, following van Leeuwen and Mohnen (2017) and Piekkola and Rahko (2020), we can use the predicted values as instruments for the innovation variables (Wooldridge 2010, p. 937-945). . Furthermore, we also include lagged values of input variables as instruments.

Because we use the predicted value of the innovation variable as an instrument, the production function equations are always just-identified, and thus, we do not have overidentification restrictions to test. However, if we were to use a linear probability model with the above listed instrumental variables, the equations would be overidentified. In this case, we can test for the exogeneity of the instruments. Indeed, such tests do not reject the validity of the predicted R&D or innovation cooperation variables as instruments but do reject the validity of predicted R&D intensity when resource-saving and pollution-reducing EIs are considered in the same specification (third estimation).

Only about 5% of firm observations have resource-saving EIs without pollution-reducing EIs and only 6% have pollution-reducing EIs without resource-saving innovations, so these types of innovation are hard to disentangle. The last two estimations consider these innovation types one at a time, and the exogeneity of instruments is validated. The key insight of the CDM model is to use the R&D to instrument for innovation output and then to explain productivity using innovation outputs and further by using OC because of the general nature of management and marketing in output decisions.

# 5 Results

In this section, we present and discuss the results of the modified CDM model. The results of the first step are presented in Table 2. The correlation between the error terms of the two equations, rho, is reported at the bottom of the table.

Stage 1: Table 2. Heckman model on R&D intensity and selection.

| | R&D intensity | Selection |
|---|---|---|
| ln(OC/L) t-1 | 0.108*** | 0.044 |
| | (0.015) | (0.040) |
| ln(Material) t-1 | 0.203*** | 0.258*** |
| | (0.021) | (0.046) |
| ln(L) t-1 | 0.073*** | 1.072*** |
| | (0.014) | (0.073) |
| Export /sales | 0.026 | 0.008 |
| | (0.038) | (0.090) |
| Part of group | 0.102** | 0.07 |
| | (0.037) | (0.108) |
| R&D subsidy | 0.143*** | |
| | (0.034) | |
| Cooperation with group firms | 0.109** | 0.134 |
| | (0.038) | (0.212) |
| Cooperation with suppliers | -0.054 | -0.079 |
| | (0.036) | (0.139) |
| Cooperation with customers | 0.04 | 0.073 |
| | (0.036) | (0.161) |
| Cooperation with consults | 0.005 | -0.11 |
| | (0.038) | (0.193) |
| Cooperation with universities, research | 0.062** | 0.136 |

| | | |
|---|---|---|
| institutes | (0.024) | (0.118) |
| Foreign owned | 0.139*** | 0.247 |
| | (0.038) | (0.216) |
| Constant | 2.252*** | -1.594*** |
| | (0.093) | (0.301) |
| Log pseudo-likelihood | -6602 | |
| Rho | 0.090 | |

Notes. 5552 observations. All estimations include year and industry dummies. Cluster robust standard errors in parenthesis.

Looking at the selection equation, we can see that firms with more employees and intermediate input use invest more often in R&D. Turning to R&D intensity equation, we notice that number of employees, OC intensity and intermediate input use increase R&D intensity. Additionally, receiving R&D subsidies and foreign ownership positively affect R&D investment intensity. Some of the innovation cooperation variables are also positively related to the intensity of R&D investments. From these results, we obtain the predicted value of R&D intensity, which we also calculate for firms that do not have reported R&D investments.

Table 3 presents the results for the second step of the CDM model, where the important input variables of capital, OC and labor are again taken not from the CIS but from financial accounts or from occupational employee data. Here, we report the results from five different specifications. First, we estimate a model with only a single innovation outcome variable: whether the firm has introduced any product innovation. Second, we estimate the probability of product innovation and the probability of engaging in EI. Third, we separately estimate the probability of developing resource-saving EIs and pollution-reducing EIs. In columns four to six, we report the results from separately analyzing the regulation induced EIs compared to all EIs (column 4), to resource-saving EI (column 5)or to pollution reducing EI (column 6). For example, resource-saving EIs motivated by regulations can be categorized from the 5th estimation of column by predicting resource saving EI without regulations (but possibly with product innovations) and EI resource saving with regulations (but possible with product innovations). These predicted values can then be used is stage 3 as instruments for respective innovation occurences. We report the correlation between the error terms, rho, at the bottom of the table.

Based on the results in Table 3, we can see that the predicted R&D intensity has a statistically significant positive effect on the probability of engaging in EIs. OC intensity has instead no significant effects. We thus find little evidence that EIs are sensitive to organizational efficiency. Firm size is primarily measured by the number of employees, which tends to increase the occurrence of all kinds of innovations. Innovation cooperation increases the probability of innovations in general. Cooperation with consultants especially drives EI, so that consulting and external help are needed to carry out EI. Cooperation with universities and research institutes is notrelevant for regulation driven EIs (columns 4-6).The results indicate that environmental innovation activities are somewhat supported by different innovation cooperation patterns than other types of innovation. Similar findings have been reported by Horbach et al. (2013), where cooperation with universities was not important for EIs in Germany, whereas it was in France. It is possible that the insignificance for Germany is also driven by them being more regulation driven where consultant help is relatively more needed.

Stage 2: Table 3. Innovation output equations in probit, biprobit, and trivariate models

| | 1 | 2 | | 3 | | | 4 | | | 5 | | | 6 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Product | Product | EI | Product | EI res | EI pol | Product | EI | EI_reg | Product | EI res | EI reg | Product | EI pol | EI reg |
| ln(R&D/L broad ) predicted | 0.743*** | 0.764*** | 0.545*** | 0.746*** | 0.457*** | 0.502*** | 0.754*** | 0.540*** | 0.379** | 0.728*** | 0.435*** | 0.454*** | 0.735*** | 0.490*** | 0.484*** |
| | (0.142) | (0.143) | (0.138) | (0.141) | (0.134) | (0.133) | (0.142) | (0.137) | (0.165) | (0.141) | (0.132) | (0.133) | (0.141) | (0.131) | (0.134) |
| ln(K/L) t-1 | -0.009 | -0.008 | 0.545*** | -0.01 | 0.030** | 0.005 | -0.008 | 0.018 | -0.002 | -0.008 | 0.033** | 0.005 | -0.009 | 0.006 | 0.007 |
| | (0.014) | (0.014) | (0.138) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.018) | (0.014) | (0.014) | (0.015) | (0.014) | (0.014) | (0.015) |
| ln(OC/L) t-1 | 0.014 | 0.015 | 0.019 | 0.015 | -0.05 | -0.04 | 0.018 | -0.037 | -0.043 | 0.018 | -0.048 | -0.051 | 0.015 | -0.035 | -0.057 |
| | (0.036) | (0.036) | (0.014) | (0.036) | (0.033) | (0.033) | (0.036) | (0.034) | (0.041) | (0.036) | (0.033) | (0.035) | (0.036) | (0.033) | (0.035) |
| ln(L) t-1 | 0.100** | 0.097** | -0.041 | 0.103** | 0.082** | 0.105*** | 0.100** | 0.105** | 0.045 | 0.107** | 0.087** | 0.063** | 0.104** | 0.108*** | 0.062** |
| | (0.034) | (0.034) | (0.034) | (0.034) | (0.030) | (0.032) | (0.034) | (0.033) | (0.035) | (0.033) | (0.030) | (0.030) | (0.034) | (0.031) | (0.030) |
| Export sales share | 0.029 | 0.064 | | 0.044 | | | 0.063 | | | 0.054 | | | 0.04 | | |
| | (0.066) | (0.057) | | (0.058) | | | (0.057) | | | (0.059) | | | (0.059) | | |
| Cooperation with group firms | 0.273** | 0.275** | 0.098** | 0.258** | 0.457*** | 0.502*** | 0.274** | 0.179* | 0.161* | 0.258** | 0.105 | 0.183** | 0.262** | 0.133 | 0.178** |
| | (0.093) | (0.089) | (0.033) | (0.088) | (0.134) | (0.133) | (0.089) | (0.096) | (0.090) | (0.089) | (0.084) | (0.080) | (0.089) | (0.084) | (0.080) |
| Cooperation with suppliers | 0.321*** | 0.311*** | 0.184* | 0.282*** | 0.030** | 0.005 | 0.309*** | 0.681*** | 0.225** | 0.296*** | 0.557*** | 0.352*** | 0.275*** | 0.519*** | 0.363*** |
| | (0.083) | (0.080) | (0.097) | (0.080) | (0.014) | (0.014) | (0.080) | (0.082) | (0.096) | (0.080) | (0.074) | (0.073) | (0.081) | (0.074) | (0.072) |
| Cooperation with customers | 0.832*** | 0.824*** | 0.692*** | 0.812*** | -0.05 | -0.04 | 0.828*** | 0.627*** | 0.352*** | 0.822*** | 0.537*** | 0.449*** | 0.818*** | 0.539*** | 0.453*** |
| | (0.082) | (0.079) | (0.082) | (0.079) | (0.033) | (0.033) | (0.079) | (0.081) | (0.092) | (0.079) | (0.071) | (0.073) | (0.079) | (0.071) | (0.073) |
| Cooperation with consultants | -0.006 | 0.005 | 0.608*** | 0.004 | 0.082** | 0.105*** | 0.01 | 0.239** | 0.248** | 0.004 | 0.166* | 0.268*** | 0.02 | 0.177* | 0.248** |
| | (0.101) | (0.097) | (0.082) | (0.094) | (0.030) | (0.032) | (0.096) | (0.108) | (0.088) | (0.094) | (0.091) | (0.081) | (0.095) | (0.092) | (0.081) |
| Cooperation with universities, | 0.151** | 0.143** | 0.229** | 0.152** | 0.111 | 0.145* | 0.146** | 0.117* | 0.051 | 0.154** | 0.163** | 0.06 | 0.153** | 0.155** | 0.058 |
| research institutes | (0.062) | (0.060) | (0.109) | (0.059) | (0.083) | (0.085) | (0.060) | (0.062) | (0.055) | (0.059) | (0.056) | (0.051) | (0.060) | (0.054) | (0.050) |
| Log-likelihood | -2827 | -5138 | | | -7341 | | | -7110 | | | -7615 | | | -7507 | |
| Rho12 | | 0.751 | | | 0.645 | | | 0.749 | | | 0.662 | | | 0.662 | |
| Rho13 | | | | | 0.671 | | | 0.311 | | | 0.490 | | | 0.490 | |
| Rho23 | | | | | 0.874 | | | 0.518 | | | 0.778 | | | 0.778 | |

Notes. 5552 observations. Product=Product innovation, EI=environmental Produvation, EI res=resource-saving EI, EI pol =pollution-reducing EI, EI reg= regulation-driven EI. All estimations include year and industry dummies. Cluster robust standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Next, we analyze labor productivity effects. In Table 4, the dependent variable is labor productivity, measured as log value-added per employee. The innovation variables are instrumented with the predicted probabilities obtained from the corresponding second-step estimates of our CDM model.

Stage 3: Table 4. GMM Productivity estimates

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ln(K/L) | 0.216*** | 0.208*** | 0.145** | 0.214*** | 0.220*** | 0.220*** |
| | (0.017) | (0.018) | (0.050) | (0.018) | (0.020) | (0.019) |
| ln(OC/L) | 0.141*** | 0.149*** | 0.175*** | 0.144*** | 0.136*** | 0.139*** |
| | (0.017) | (0.019) | (0.041) | (0.019) | (0.021) | (0.018) |
| ln(L) | 0.011 | 0.003 | 0.03 | -0.001 | -0.001 | 0.003 |
| | (0.013) | (0.012) | (0.029) | (0.012) | (0.014) | (0.013) |
| Product | 0.072 | | | | | |
| | (0.057) | | | | | |
| Product no EI | | -0.538 | -2.094* | -0.271 | | |
| | | (0.431) | (1.147) | (0.481) | | |
| EI | | 0.118** | | | | |
| | | (0.058) | | | | |
| EI res only | | | 3.578** | | | |
| | | | (1.767) | | | |
| EI pol | | | -0.12 | | | |
| | | | (0.166) | | | |
| EI vol | | | | -0.048 | | |
| | | | | (0.100) | | |
| EI reg | | | | 0.221** | | |
| | | | | (0.100) | | |
| Produ no EI res | | | | | 0.161 | |
| | | | | | (0.422) | |
| EI res voluntary | | | | | -0.132 | |
| | | | | | (0.161) | |
| EI res regulation | | | | | 0.263** | |
| | | | | | (0.114) | |
| Product no EI pol | | | | | | 0.074 |
| | | | | | | (0.293) |
| EI pol voluntary | | | | | | -0.243** |
| | | | | | | (0.120) |
| EI pol regulation | | | | | | 0.278** |
| | | | | | | (0.092) |

Notes. 5552 observations. All estimations include year and industry dummies. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

In specification 1, we surprisingly observe that engaging in product innovation does not improves firm labor productivity. In the second specification, we distinguish between EIs and product innovations with no environmental benefits. We observe that the effect of EI is positive and statistically significant, whereas the

This project has received funding from the *European Union's Horizon 2020 The mechanisms*

effect of nonenvironmental product innovations is insignificant negative. The category of other innovations includes product innovations without EIs as well as EIs that have only pollution-reducing benefits in column 5 or only resource-saving benefits in column 6. Product innovations alone do not enhance productivity in any of the estimations, when also EIs are considered.

In the third specification, we separate out firms that have resource-saving only orpollution-reducing EIs (with or without resource-saving EIs). We find that EIs improve productivity except when firm has only resource saving EIs. We find regulation induced EIs to improve productivity regardless of whether the EI is voluntary or regulation induced (columns 4 through 6). When regulation is the primary driver of innovation, both resource-saving and pollution-reducing innovations improve productivity and the same is found when they considered together in column 4. This is different from earlier results, where Rennings and Rammer (2011) find a that regulation only improves the positive performance effect of EIs related to the German vehicle industry, while in general has negative effects.

One limitation of our empirical data is that we cannot distinguish whether firms that EIs also have nonenvironmental innovations. Moreover, firms with regulation-induced EIs may also have other voluntary EIs. In interpreting our results, it should also be noted that the effects estimated by our identification strategy could be interpreted as local average treatment effects (LATEs) (Imbens and Angrist, 1994). Because our instrumental variables affect only certain firms, we are identifying the causal effect of innovation for those firms whose innovation activities are influenced by the instruments. If the innovations have heterogeneous productivity effects, the effects identified here are for the type of innovations induced by the instruments used.

As a robustness check, we use formal R&D investments from R&D survey. We follow a similar procedure as before using the Heckman model to predict the value of the R&D investments. The results for stages 1 through 3 are reported in Tables C.1-C.3 in the Appendix. Our main interest is in the analysis on regulation driven EIs. The results are the same as before in productivity estimates of EIs in stage 3 However, product innovations are now improving productivity and also when considered alone in columns 2-6. The only reason for difference is the use of survey R&D rather than broad R&D,

Survey R&D also has stronger positive effects on regulation-driven voluntary EIs than broad R&D in Table C.3 columns 4-6. In most studies R&D is from R&D survey which cannot be lagged to reduce its endogeneity since CIS is done every second year (except in Germany). Based on Table C.1 firms reporting R&D are more likely to be large, while the amount of R&D is decreasing in firm size. The R&D survey hence pick relatively more small firms with high R&D intensity so that the sample of small firms can be biased to those firms. Finally, R&D intensity increases in export per sales for survey R&D and not for broad R&D. The larger exposer to trade may explain both the increase in R&D and occurrence of product innovation, which bias the results.

# 6 Conclusion

This paper has added to the literature by examining the environmental innovations of Finnish manufacturing and energy sector firms as part of overall firm innovation activity and by testing the Porter hypothesis. We contribute to the extensive prior literature by comparing the productivity effects of nonenvironmental innovations and different types of environmental innovations and by using an extended CDM panel model with instrumental variables that can better address endogeneity. Finally, determinants of innovation input include organizational capital, which is found to be a relevant explanatory factor for R&D activity while also having an independent, significant effect on productivity.

Our empirical analysis shows that both regulation driven resources saving and pollution reducing environmental innovations enhance productivity, which contrasts the findings in the recent literature that finds the relation to be positive only for resource savings environmental investments; see Rexhäuser and Rammer (2014) and Ghisetti and Rennings (2014) in Germany. Earlier survey by Ambec et al. (2013) also found regulation effects to be negative in general. However, they also showed that most previous studies have no panel data and can't take into account the dynamic dimensions of the Porter Hypothesis that regulation affects firm behavior in lag. Rubashkina et al. (2015) finds still no effect on productivity in with panel data in 17 European countries.

Our results are thus more positive in the European context also for pollution reducing environmental innovations. In Nordic countries in Norway regulation in cutting emissions has also improved environmental performance (Bye and Klemetsen, 2018). It appears that environmental regulations has had more widely positive effect in Nordic countries Finland and Norway than in Europe as a whole. We can offer a few practical conclusions. The strategy of introducing new environmental regulations will increase innovativity, which in turn leads to improved firm performance that can apparently cover all of the costs from regulation. Nordic firms may also have benefitted from a first-mover advantage by becoming "green" in many industries, a reason for good performance suggested initially by Lieberman and Montgomery (1988). This is evidently driven by regulation that has become more stringent especially in last observation year 2014 so that the shares of environmental innovations driven by regulation have increased over time.

It is clear that EIs require cooperation with consultants, while they are unrelated to organizational change or even negatively to OC. The organizational structure within firms is less important than the ability to be connected with experts and consultants who can enable firms to fulfill the targets set by environmental regulations. Future research must more deeply analyze the interactions of EIs with organizational and process innovations.

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# Appendix A.

Occupation data are used to evaluate the innovative labor input in intangible activities. These intangible-related labor are assumed to be produced with similar share of other factor inputs as in intangible producing services, such as OC producing business services (Legal and accounting activities M69, Head office M70, Architectural and engineering activities M71, Advertising and market research M73). The method is analogous for measuring "overheads" in OECD (2010); a method applied to evaluate "software and database expenditures" ICT from related labor costs. [8] Real expenditure-based investments of type IA = OC, R&D, ICT is given by (industry j in year t suppressed):

$$P\ N_{IA} \equiv z^{IA} l^{IA} P^{IA} L^{IA}, \tag{A.1}$$

where $l^{IA}$ is the innovation labor share of type IA and $z^{IA}$ is time invariant factor multiplier. The benchmark factor multipliers that represent the entire EU27 area from IA-producing upstream industries IA=OC, R&D, ICT. The shares $l^{IA}$ are considered the same in all countries and the combined multiplier $z^{IA} l^{IA}$ is 1.55 for OC wage expenses, 1.53 for R&D wage expenses, and 1.7 for ICT wage expenses. The factor multiplier includes half of intermediate input and all capital input per one unit of labor costs given that IA producing industries are more intermediate input intensive than other industries on average. Table 1 summarizes the combined multiplier $z^{IA} l^{IA}$ (the product of the share of work effort assumed to be in related occupations to be devoted to IA production and the factor multiplier).

Table A.1 Combined multipliers for OC, R&D and ICT

| | OC | R&D | ICT |
|---|---|---|---|
| Employment shares $l^{Y}$ | 30% | 50% | 50% |
| Factor multiplier $z^{IA}$ | 1.55 | 1.53 | 1.7 |
| Combined multiplier $z^{IA} l^{IA}$ (rounded) | 45% | 77% | 85% |

[8] Office for National Statistics (ONS) evaluate ICT factor input from 72.2. industry (Research and experimental development on social sciences and humanities) and not from J62-J63 (Computer programming, consultancy and related activities and information service activities) as done here. Intermediates are further deducted by those used for resale without further processing, road transport, computer services, advertising and marketing costs and depreciation of vehicles. They are added by total taxes and levies and total depreciation. Estimate of the rate of return on capital is excluded. They end up with non-labor cost share of 80% which is close to CHAMBERLIN, G., CLAYTON, T. & FAROOQUI, S. 2007. New measures of UK private sector software investment. *Economic & Labour Market Review*, 1, 17-28..

The following shows the innovation occupations chosen using ISCO08 3-digit coding in Globalinto in a narrower version of OC occupations excluding marketing workers.

**ICT work**

Information and communications technology services managers 133

Information and communications technology professionals 25 (software and applications developers and analysts 251 and database and network professionals 252)

Information and communications technology professionals 35 (Information and communications technology operations and user support 351, telecommunications and broadcasting technicians 352)

**Organizational work**

Business Services and Administration Managers 121

Sales and marketing managers 1221, Advertising and public relations managers 1222,

Production managers in agriculture, forestry and fisheries, 131

Manufacturing, mining, construction and distribution managers 132

Professional services managers 134

Finance professionals 241, Administration professionals 242

**R&D work**

Research and development managers 1223

Physical and earth science professionals 211, Engineering professionals 212, Life science professionals 213, Engineering professional (excluding electrotechnology) 214 , Electrical engineering 215

Architects, planners, surveyors and designers 216

Health professionals: Medical doctors 221, Nursing and midwifery professionals 222, Other health professionals 226

Physical and engineering science technicians 311, Life science technicians and related associate professional 314, Medical and pharmaceutical technicians 321

Physical and engineering science technicians 311, Life science technicians and rel. associate professionals 314

Medical and pharmaceutical technicians 321

# Appendix B.

**Table B.1** EI by year in the sample and in the CIS for manufacturing and energy sector firms.

| Sample | 2004 | 2006 | 2008 | 2014 |
|---|---|---|---|---|
| Product innovation | 0.499 | 0.510 | 0.480 | 0.518 |
| EI | 0.528 | 0.551 | 0.662 | 0.536 |
| EI res | 0.489 | 0.492 | 0.529 | 0.513 |
| EI pol | 0.473 | 0.495 | 0.615 | 0.376 |
| EI reg | 0.242 | 0.239 | 0.248 | 0.358 |
| EI res regulation | 0.226 | 0.218 | 0.168 | 0.348 |
| EI pol regulation | 0.235 | 0.236 | 0.167 | 0.278 |
| CIS survey | | | | |
| Product innovation | 0.367 | 0.372 | 0.371 | 0.398 |
| EI | 0.380 | 0.404 | 0.520 | 0.379 |
| EI res | 0.338 | 0.354 | 0.393 | 0.366 |
| EI pol | 0.328 | 0.352 | 0.476 | 0.249 |
| EI reg | 0.179 | 0.168 | 0.173 | 0.236 |
| EI res regulation | 0.161 | 0.147 | 0.120 | 0.228 |
| EI pol regulation | 0.167 | 0.160 | 0.120 | 0.179 |

EI=environmental innovation, EI res=resource -saving EI, EI pol=pollution-reducing Ei, EI reg=regulation-driven EU.

**Table B.2** Industry distribution in the sample.

| Industry | | Firms | % |
|---|---|---|---|
| Food and beverages | 10 | 165 | 7.7 |
| Textile | 13 | 69 | 3.22 |
| Leather and related products | 15 | 22 | 1.03 |
| Wood products and furniture | 16 | 225 | 10.5 |
| Pulp and paper | 17 | 64 | 2.99 |
| Chemical and chemical products | 20 | 82 | 3.83 |
| Rubber and plastic | 22 | 115 | 5.37 |
| Other non-metallic products | 23 | 105 | 4.9 |
| Basic metals | 24 | 48 | 2.24 |
| Fabricated metals | 25 | 363 | 16.95 |
| Computer, electronic and optical products | 26 | 106 | 4.95 |
| Electrical equipment | 27 | 81 | 3.78 |
| Machinery, equipment and their repair | 28 | 357 | 16.67 |
| Motor vehicles and other transport equipment | 29 | 101 | 4.72 |
| Other industries | 32 | 144 | 6.72 |
| Energy | 35 | 95 | 4.44 |
| Total | | 2142 | 100 |

# Appendix C.

**Stage 1:** Table C.1 Heckman model on R&D intensity and selection using R&D from survey data

| | R&D intensity | Selection |
|---|---|---|
| ln(OC/L) t-1 | 0.232*** | 0.113*** |
| | (0.035) | (0.031) |
| ln(Material) t-1 | 0.273*** | 0.190*** |
| | (0.053) | (0.040) |
| ln(L) t-1 | -0.100** | 0.599*** |
| | (0.039) | (0.037) |
| Export /sales | 0.400*** | 0.064 |
| | (0.113) | (0.073) |
| Part of group | 0.08 | 0.331*** |
| | (0.090) | (0.074) |
| R&D subsidy | 0.535*** | |
| | (0.061) | |
| Cooperation with group firms | 0.237** | -0.061 |
| | (0.075) | (0.086) |
| Cooperation with suppliers | -0.052 | 0.074 |
| | (0.067) | (0.082) |
| Cooperation with customers | 0.163** | 0.345*** |
| | (0.067) | (0.080) |
| Cooperation with consults | 0.183** | 0.092 |
| | (0.075) | (0.104) |
| Cooperation with universities, research institutes | 0.140** | 0.289*** |
| | (0.044) | (0.063) |
| Foreign owned | 0.105 | -0.062 |
| | (0.080) | (0.091) |
| Constant | 0.331 | -3.439*** |
| | (0.423) | (0.212) |
| Log pseudo-likelihood | -6394 | |
| Rho | 0.239 | |

Notes. 5552 observations. All estimations include year and industry dummies. Cluster robust standard errors in parenthesis.

**Stage 2:** Table C.2 Innovation output equations in probit, biprobit, and trivariate models using R&D from survey data.

| | 1 | 2 | | 3 | | | 4 | | | 5 | | | 6 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Product | Product | EI | Product | EI res | EI pol | Product | EI | EI_reg | Product | EI res | EI reg | Product | EI pol | EI re |
| ln(R&D/L broad ) predicted | 0.540*** | 0.490*** | 0.302*** | 0.490*** | 0.208** | 0.295*** | 0.484*** | 0.300*** | 0.144 | 0.479*** | 0.195** | 0.184** | 0.494*** | 0.292*** | 0.192 |
| | (0.091) | (0.089) | (0.081) | (0.089) | (0.078) | (0.078) | (0.089) | (0.081) | (0.090) | (0.089) | (0.077) | (0.075) | (0.088) | (0.077) | (0.07 |
| ln(K/L) t-1 | -0.008 | -0.006 | 0.302*** | -0.008 | 0.033** | 0.007 | -0.006 | 0.02 | 0.001 | -0.006 | 0.036** | 0.008 | -0.008 | 0.008 | 0.01 |
| | (0.014) | (0.014) | (0.081) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.018) | (0.014) | (0.014) | (0.015) | (0.014) | (0.014) | (0.01 |
| ln(OC/L) t-1 | -0.03 | -0.01 | 0.021 | -0.013 | -0.042 | -0.05 | -0.007 | -0.042 | -0.027 | -0.01 | -0.039 | -0.035 | -0.016 | -0.046 | -0.03 |
| | (0.039) | (0.038) | (0.014) | (0.038) | (0.035) | (0.035) | (0.038) | (0.036) | (0.042) | (0.038) | (0.035) | (0.036) | (0.039) | (0.035) | (0.03 |
| ln(L) t-1 | 0.210*** | 0.212*** | -0.047 | 0.215*** | 0.150*** | 0.182*** | 0.213*** | 0.187*** | 0.098*** | 0.215*** | 0.152*** | 0.129*** | 0.213*** | 0.182*** | 0.132 |
| | (0.027) | (0.026) | (0.036) | (0.026) | (0.024) | (0.024) | (0.026) | (0.025) | (0.028) | (0.026) | (0.023) | (0.023) | (0.026) | (0.024) | (0.02 |
| Export sales share | -0.172** | -0.062 | | -0.089 | | | -0.061 | | | -0.091 | | | -0.097 | | |
| | (0.072) | (0.062) | | (0.064) | | | (0.062) | | | (0.065) | | | (0.065) | | |
| Cooperation with group firms | 0.233** | 0.251** | 0.183*** | 0.232** | 0.208** | 0.295*** | 0.251** | 0.173* | 0.182** | 0.232** | 0.117 | 0.203** | 0.233** | 0.12 | 0.202 |
| | (0.094) | (0.090) | (0.025) | (0.089) | (0.078) | (0.078) | (0.090) | (0.097) | (0.090) | (0.090) | (0.085) | (0.080) | (0.089) | (0.086) | (0.08 |
| Cooperation with suppliers | 0.313*** | 0.302*** | 0.178* | 0.274*** | 0.033** | 0.007 | 0.301*** | 0.679*** | 0.212** | 0.288*** | 0.549*** | 0.342*** | 0.269*** | 0.520*** | 0.351 |
| | (0.083) | (0.080) | (0.098) | (0.079) | (0.014) | (0.014) | (0.080) | (0.082) | (0.095) | (0.080) | (0.074) | (0.073) | (0.080) | (0.075) | (0.07 |
| Cooperation with customers | 0.759*** | 0.759*** | 0.688*** | 0.747*** | -0.042 | -0.05 | 0.764*** | 0.586*** | 0.336*** | 0.759*** | 0.514*** | 0.431*** | 0.753*** | 0.500*** | 0.434 |
| | (0.083) | (0.081) | (0.082) | (0.080) | (0.035) | (0.035) | (0.080) | (0.082) | (0.092) | (0.080) | (0.073) | (0.075) | (0.080) | (0.072) | (0.07 |
| Cooperation with consultants | -0.108 | -0.083 | 0.569*** | -0.087 | 0.150*** | 0.182*** | -0.077 | 0.186* | 0.224** | -0.085 | 0.134 | 0.238** | -0.072 | 0.125 | 0.217 |
| | (0.103) | (0.098) | (0.083) | (0.095) | (0.024) | (0.024) | (0.097) | (0.111) | (0.089) | (0.096) | (0.093) | (0.082) | (0.096) | (0.094) | (0.08 |
| Cooperation with universities, | 0.101 | 0.103* | 0.175 | 0.110* | 0.122 | 0.135 | 0.106* | 0.097 | 0.047 | 0.113* | 0.154** | 0.054 | 0.110* | 0.133** | 0.05 |
| research institutes | (0.063) | (0.061) | (0.111) | (0.060) | (0.083) | (0.086) | (0.061) | (0.063) | (0.056) | (0.060) | (0.057) | (0.052) | (0.061) | (0.055) | (0.05 |
| Log-likelihood | -2823 | -5139 | | | -7340 | | | -7112 | | | -7618 | | | -7507 | |
| Rho12 | | 0.750 | | | 0.645 | | | 0.641 | | | 0.661 | | | 0.748 | |
| Rho13 | | | | | 0.671 | | | 0.489 | | | 0.489 | | | 0.307 | |
| Rho23 | | | | | 0.874 | | | 0.779 | | | 0.779 | | | 0.507 | |

Notes. 5552 observations. Product=product innovation, EI=environmental innovation, EI res=resource-saving EI, EI pol =pollution-reducing EI, EI reg= regulation-driven EI. All estimations include year and industry dummies. Cluster robust standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

This project has received funding from the *European Union's Horizon 2020 The mechanisms to promote smart, sustainable and inclusive growth* under gr
agreement No 822259.

**Stage 3: Table C.3** GMM Productivity estimates using R&D activity from R&D survey data

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ln(K/L) | 0.180*** | 0.176*** | 0.207*** | 0.180*** | 0.233*** | 0.175*** |
| | (0.017) | (0.020) | (0.036) | (0.020) | (0.040) | (0.020) |
| ln(OC/L) | 0.097*** | 0.085*** | 0.058 | 0.082*** | 0.060* | 0.100*** |
| | (0.016) | (0.018) | (0.036) | (0.020) | (0.034) | (0.018) |
| ln(L) | -0.002 | 0.004 | -0.015 | 0.001 | -0.013 | 0.011 |
| | (0.012) | (0.013) | (0.023) | (0.013) | (0.023) | (0.014) |
| Product | 0.264*** | | | | | |
| | (0.052) | | | | | |
| Product no EI | | 1.185** | 2.373** | 1.328** | | |
| | | (0.395) | (1.026) | (0.473) | | |
| EI | | 0.240*** | | | | |
| | | (0.056) | | | | |
| EI res only | | | -1.939 | | | |
| | | | (1.188) | | | |
| EI pol | | | 0.374** | | | |
| | | | (0.123) | | | |
| EI vol | | | | 0.108 | | |
| | | | | (0.112) | | |
| EI reg | | | | 0.314*** | | |
| | | | | (0.091) | | |
| Produ no EI res | | | | | 2.158** | |
| | | | | | (0.751) | |
| EI res voluntary | | | | | -0.560* | |
| | | | | | (0.311) | |
| EI res regulation | | | | | 0.605** | |
| | | | | | (0.189) | |
| Product no EI pol | | | | | | 0.901** |
| | | | | | | (0.286) |
| EI pol voluntary | | | | | | 0.076 |
| | | | | | | (0.126) |
| EI pol regulation | | | | | | 0.289** |
| | | | | | | (0.096) |

Notes. 5552 observations. All estimations include year and industry dummies. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

This project has received funding from the *European Union's Horizon 2020 The mechanisms*