Policy mix or policy mess? Effects of cross-instrumental policy mix on eco-innovation in German firms

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Abstract

This paper evaluates the effectiveness of a policy mix between general innovation policies and environmental policies in fostering the adoption of global warming-related eco-innovations both in the short term and long term. Focusing on process eco-innovations, we investigate whether the combined impact of general innovation and environmental policy instruments, which we term a cross-instrumental policy mix, is greater than their individual impact. We examined data from the Mannheim Innovation Panel on German firms, investigating both cross-sectional data from 2015 and longitudinal data from two waves of the survey conducted in 2009 and 2015. We apply two models, based respectively on a matching analysis and a panel analysis. We find that cross-instrumental policy mix has a stronger positive effect on process eco-innovations than the impact of general innovation policy instruments alone, both in the short and long term. In contrast, although we expected the greater impact of a cross-instrumental policy mix relative to environmental policy instruments, this argument is not supported by our empirical results. Our study offers policy implications concerning the coordination of innovation and environmental policies in achieving an optimal policy mix.

Keywords: Cross-instrumental policy mix; Process eco-innovation; Innovation policy; Public subsidy; Regulation; Climate change; Global warming; Environmental policy

1. Introduction

This study evaluates how the policy mix between innovation and environmental policies incentivises process eco-innovation (EI) to mitigate global warming. According to the Intergovernmental Panel on Climate Change (IPCC), climate change poses a formidable threat to humankind, causing 95% of negative environmental changes since the beginning of the twentieth century (IPCC, 2014). Innovation activities and large-scale adoption of greenhouse gas (GHG)-reducing technologies are necessary to stabilise atmospheric carbon dioxide (CO_2) concentrations (IPCC, 2007) and contain global warming. The innovations needed to address climate change pertain to energy efficiency, renewable energy, switching fuel from coal to oil and gas, nuclear power and CO_2 capture and storage (Newell, 2009). These innovations with a strong link to environmental issues are known as EIs. Amongst the many definitions offered for EI in the literature (for a review, see Carrillo-Hermosilla et al., 2010), one of the most comprehensive was proposed by Kemp and Pearson (2007, p. 7) as 'the production, assimilation or exploitation of a product, production process, service or management or business method that is novel […] and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives'. EI can address climate change-related challenges, especially in the industry sector, which is responsible for 30% of GHG emissions (IPCC, 2014). However, two types of market failure affect EI, causing a double externality problem (Rennings, 2000). First, as in any type of innovation, EI is subject to market failures caused by knowledge spillovers, which may lead firms to underinvestment in research and development (R&D) and innovation. Second, innovations aimed at addressing environmental issues are generally undersupplied since a whole society benefits from them, while the costs are borne by the innovator (Beise and Rennings, 2005). This type of market failure is known as an environmental externality. Hence, EIs are socially desirable due to the positive impact upon the environment, but firms' return on R&D in EI is less than its social return (Ozusaglam, 2012). Consequently, firms' responses to social challenges such as climate change cannot gather momentum without the support of policymakers (George et al., 2016).

Policymakers can contribute to reduced innovation costs – especially in the invention phase – through innovation policy actions. Furthermore, policymakers can promote environmental policies focused on the diffusion phase of the innovation to balance the competition from firms that offer more convenient but less eco-friendly alternatives. Multiple policy instruments can be combined, giving birth to a 'policy mix' (Borrás and Edquist, 2013;

Crespi et al., 2015). Policy mixes can arise from both the combination of different policy instruments that belong to the same policy area (e.g. environmental regulation and environmental taxes) or those that belong to different policy areas (e.g. environmental taxes and R&D subsidies). As suggested by Bouma et al. (2019), the interaction between different instruments may lead to positive, negative or neutral effects. Indeed, a policy mix can become a 'policy mess' (Sorrell, 2003) when the mix of instruments lacks an overall coherence (i.e. when different instruments with different goals are not coordinated properly) (Beise and Rennings, 2005; Crespi et al., 2015; Kemp and Pontoglio, 2011; Rennings, 2000). Therefore, an evaluation of policy mix effects is pivotal to understanding whether policies are welfare-enhancing (Bouma et al., 2019). However, such an evaluation is complex (Bouma et al., 2019; Goulder and Parry, 2008), and empirical research on the topic is scarce (Trencher and van der Heijden, 2019). Furthermore, very few articles have analysed policy mix within the realm of environmental policy (e.g. Costantini et al., 2017; Crespi et al., 2015; Haščič, 2012). Moreover, to the best of our knowledge, no previous study has empirically analysed the effectiveness of a policy mix including two policy areas – environmental innovation policy and innovation policy – for innovation activities in general (i.e. not necessarily EI).

In this study, we will refer to this particular type of policy mix as a *cross-instrumental policy mix*. The lack of empirical studies on a cross-instrumental policy mix constitutes a remarkable gap since many countries have various policy instruments to sustain 'general' innovation and EI. Still, they are not coordinated, and their combined effect on the actual development of EI remains largely unverified. Furthermore, there is a lack of evidence on the temporal effects, that is, whether the theorised positive impact of a cross-instrumental policy mix on EI occurs in the short term only or if it persists in the long term as well. Therefore, the two research questions explored in this study are: *Is the effectiveness of a cross-instrumental policy mix greater than the effectiveness of individual innovation and environmental policies? Is the effectiveness of such a policy mix sustained in the long term?*

We respond to the research questions by analysing the Mannheim Innovation Panel (MIP), which is the German part of the Community Innovation Survey (CIS) conducted by the *Leibniz-Zentrum für Europäische Wirtschaftsforschung* [Leibniz Center for European Economic Research] (ZEW). The short-term policy effects are examined using the survey conducted in 2015 and by estimating a multilevel treatment model. The long-term effects are explored using two survey waves from 2009 and 2015 and estimated using a random-effects probit model. Empirical findings show that the cross-instrumental policy mix is more effective in stimulating process EI relative to the individual effects of public support for general innovation (GI).

However, the effects of a policy mix are absent when firms that are subject to environmental policy also receive support for GI. These results hold in the short term as well as in the long term.

The article is structured as follows. Section 2 reviews the literature on EI and environmental policy and formulates hypotheses. Section 3 provides an overview of innovation and environmental policies in Germany and describes the data, empirical strategy and estimated models. Section 4 presents the empirical results, while Section 5 discusses them. The final section provides some concluding remarks and policy implications.

2. Theoretical background

2.1. How EI can mitigate global warming

In recent years, climate change has become a key issue on the political agenda. Green technology, such as renewable energy technologies and energy efficiency, contributes to more than 60% of the CO_2 reduction foreseen by the International Energy Agency’s Scenario 450 (IEA, 2013). The consequences of global climate change have increased the need for technologies to reduce environmental costs, i.e. the need for EIs (Kula and Ünlü, 2019). According to Garetti and Taisch (2012, p. 1), new technologies should be ‘the cornerstones of the new sustainable world’. The Organization for Economic Co-operation and Development (OECD, 2019) reviewed several sectors to characterise current applications of EI in manufacturing. The EI examples examined by the OECD Project on Sustainable Manufacturing and EIs are summarised in Table 1.

The benefits deriving from these EI initiatives comprise both product and process innovations that address a reduction of CO_2 emissions, an increase of energy efficiency and a reduction of air pollution. Thus, firms play an important role in achieving environmental performance results through their efforts to introduce a more sustainable process and product innovations (Lee, 2009). We conclude that EIs are likely to contribute to addressing the problem of global warming.

Table 1.
Examples of EI in different manufacturing sectors.

Industry	Company/Association	EI product/process
Automotive and transport sector	The BMW Group	Improving the energy efficiency of automobiles
	Toyota	Sustainable plants
	Michelin	Energy-saving tyres
	Vélib’	Self-service bicycle sharing system
Iron and steel sector	Siemens VAI	Alternative iron-making processes
	ULSAB-AVC	Advanced high-strength steel for automobiles
Electronics sector	IBM	Energy efficiency in data centres
	Yokogawa Electric	Energy-saving controller for air conditioning water pumps
	Sharp	Enhancing the recycling of electronic appliances
	Xerox	Managed print services

Source: OECD (2009).

2.2. *The rationale of policy instruments for GI and EI*

Public organisations use policy instruments as tools to influence innovation processes (Borrás and Edquist, 2013). Conventionally, policy instruments for innovation – in this study we term them ‘general’ innovation policies – are classified as supply-side-oriented or demand-side-oriented (OECD, 2011). Governments have long promoted innovation activities by focusing on the supply-side policy instruments, such as R&D subsidies, R&D tax credits, the protection of intellectual property rights and the support for collaborative innovation activities (Edler et al., 2012; Radicic, 2019). Such policy instruments are considered important in addressing the market failure associated with knowledge spillovers (Jaffe et al., 2005).

Moreover, the GI policy often neglects the fact that new technologies can be deeply embedded in persistent environmental and social problems (Schot and Steinmueller, 2018). Arguably, some policy instruments can foster innovation that eventually harms the environment. Furthermore, other policy instruments are needed to overcome the second type of market failure that relates to the environmental externalities stemming from unpriced environmental impacts. Therefore, the economic argument justifying public intervention to enhance EI refers to the double externality problem associated with the two types of market failures discussed above (Cantner et al., 2016; Kemp and Pontoglio, 2011; Rennings, 2000; Rogge and Schleich, 2018). Various uncoordinated policy instruments have been applied to overcome the double externality problem. While GI policies tackle the knowledge spillovers issue, environmental policies aim to address the issue of environmental externalities (Foxon and Pearson, 2008).

Most previous empirical studies have investigated the effectiveness of a single policy instrument (Crespi et al., 2015; del Río et al., 2015; Demirel and Kesidou, 2011; Horbach et al., 2012; Rennings and Rexhauser, 2011). Demirel and Kesidou (2011) found that environmental regulation motivated British firms to introduce end-of-pipeline technologies, to invest in environmental R&D and, to a lesser extent, to develop integrated cleaner technologies. In contrast, the effect of environmental taxes was found to be negligible. Horbach et al. (2012) analysed a German sample and found a positive effect of current and future regulations and environmental subsidies on different types of process EIs, including those related to global warming (i.e. reduced CO_2 emissions and reduced emissions of other air pollution). Crespi et al. (2015) analysed the effect of (future and existing) regulations on pollution and grants (or subsidies) as drivers to innovation on nine different process EIs in European firms. They found, somewhat surprisingly, that existing taxes and regulations have a marginal role (that is, a positive impact only on two EIs), as opposed to future regulations (a positive impact on six types of EI). Overall, firms adopting EI aimed at reducing CO_2 emissions were influenced by future regulations only, but not by the existing ones nor by grants.[1] Del Río et al. (2015) found that public subsidies and compliance with environmental, health and safety regulations had a positive effect on Spanish firms' propensity to introduce environmental innovation. Finally, Rennings and Rexhauser (2011) studied the effect of different types of environmental regulations (end-of-pipe, circular-flow economy, and climate policy) on different types of EI in German firms. They found a few statistically significant results, including a positive effect of climate policy on EIs aimed at reducing CO_2, and a negative effect of a circular-flow-economy regulation on EIs aimed at reducing other air pollutants.

To the best of our knowledge, two empirical studies explored the effectiveness of a cross-instrumental policy mix. The first, a micro-level study by Veugelers (2012), found a

[1] However, Crespi et al. (2015) did not model specific policy interactions, which means that a cross-instrumental policy mix was not investigated.

complementarity between environmental regulations and taxes on the one hand, and innovation subsidies on the other hand, in promoting two types of EIs (those that reduce CO_2 emission and those that reduce energy use). The second, a macro-level study by Costantini et al. (2017), investigated 23 OECD countries and concluded that a more balanced and comprehensive policy mix had greater positive effects on EI. In contrast, the indiscriminate addition of instruments could be detrimental. However, Costantini et al. (2017) assessed the count of patent applications, which is an intermediate innovation outcome, but neglected an important outcome: the introduction of EI. In the Discussion section, we will compare our findings with the findings from these two studies.

2.3. Hypotheses development

The implementation of policy instruments aimed at a single policy target can be explained using the theory of the second best. Namely, traditional environmental economics suggests that a single policy instrument, such as taxes, should be used in tackling one market failure, such as pollution (Tinbergen, 1952). However, the theory assumes that there is only one type of market failure (i.e. pollution) and that a certain policy can be implemented at a zero cost (Lehmann, 2012). Consequently, the one instrument-one target rule cannot be used if these assumptions do not hold, either because there are multiple market failures (as in the case of EI due to the double externality issue) or because the implementation of the policy is costly due to government failures or political constraints. Therefore, since the double externality problem characterises EI, a government should use multiple policy instruments to overcome multiple market failures (Bennear and Stavins, 2007; Lipsey and Lancaster, 1956). Another implication from the theory is that such policies need to be coordinated to achieve an efficient outcome (Bennear and Stavins, 2007). Indeed, the literature suggests that a conflict between environmental objectives and competitiveness can be mitigated by integrating environmental policies with GI policies (Crespi et al., 2015). When firms that engage in EI benefit from both environmental and GI policies, termed above as a cross-instrumental policy mix, they can increase the speed of technological change in developing alternative technology scenarios (van den Bergh, 2013).

In summary, given that the development of EIs is subject to the double externality problem, it is unlikely that environmental policy alone can create enough incentives to develop EI. Rather, the optimal combination of public policies should also include instruments designed to promote GI (Jaffe et al., 2005), which leads us to hypothesise the following:

H1a. *In the short term, a cross-instrumental policy mix has a greater impact than general policy instruments on the introduction of process EIs related to global warming.*

H1b. *In the short term, a cross-instrumental policy mix has a greater impact than environmental policy instruments on the introduction of process EIs related to global warming.*

A cross-instrumental policy mix may favour the emergence of affordable breakthrough technologies that have a longer-term impact on society (van den Bergh, 2013). Innovation policies that facilitate firms' technological exploration can help them to escape technological lock-ins and to foster the development of green technologies in the long term (Crespi et al., 2015). This is justified by the concept of behavioural additionality, which posits that innovation policy may change firms' behaviour during or after project implementation. Such additionality may originate from the new knowledge obtained by firms on the occasion of an innovation project (Clarysse et al., 2009).

A large body of literature has investigated the persistence of innovation over time (Guarascio and Tamagni, 2019; Peters, 2009; Suárez, 2014), namely, innovating firms are more likely to continue innovating in the future (Ayllón and Radicic, 2019; Roper and Hewitt-Dundas, 2008). Strong persistency was recently observed by Segarra-Blasco and Jove-Llopis (2019) regarding the adoption of energy efficiency and renewable energy measures in European firms. Once public support induces firms to start investing in EI, they will likely maintain this behaviour over time. Therefore, public support can change firms' behaviour in the long term (Čadil, 2019). For instance, Rennings and Rexhauser (2011) discussed the long-term effect of environmental regulation on EI in German firms. However, Carrión-Flores and Innes (2010) found a modest impact of environmental policy on long-term emissions. To the best of our knowledge, no previous study has investigated the impact of a cross-instrumental policy mix in the long term.

We suggest that a cross-instrumental policy mix may be more effective than isolated policy instruments to persistently modify firms' set of routines (companies' forms, rules, procedures and strategies) and develop 'greener behaviours' that can last in the long term. Thus, we hypothesise:

H2a. *In the long term, a cross-instrumental policy mix has a greater impact than general policy instruments on the introduction of process EIs related to global warming.*

H2b. *In the long term, a cross-instrumental policy mix has a greater impact than* *environmental policy instruments on the introduction of process EIs related to global warming.*

3. Methodology

3.1. Context of the study

EI has been defined as '*the key to Europe's future competitiveness'* (European Commission, 2013). Hence, the European Commission set up the Eco-Innovation Action Plan, a programme aimed at reducing the impact on the environment through innovation in the framework of the Europe 2020 strategy (Triguero et al., 2013). This study focuses on firms based in Germany, a country that has been consistently amongst the European EI leaders ever since the Eco-Innovation Index was introduced in 2010. The development of the green economy is a long-term political goal in Germany (Hommes et al., 2011). The promotion of German innovation capacity relies on financial support for research through project funding, institutional funding and departmental research (BMBF, 2020).

Germany has historically used strict environmental policy to encourage innovation and improve environmental quality while pursuing economic objectives, the first set of environmental policy instruments dating back to 1970s to reduce airborne pollutants emissions from power plants (Haščič, 2012). An important feature of German environmental policy is the absence of an explicit carbon tax, which normally sets an energy tax rate based on carbon content. In fact, in 2015, German carbon rates consisted principally of specific taxes on energy use and, to a limited extent, permit costs imposed by the EU emission trading system (OECD, 2018). However, in September 2019, a comprehensive climate policy package was presented by the German government, also including a new CO_2 pricing system from 2021 (Reuters, 2019).

Renewables and advanced transportation policies introduced in Germany are two 'technology forcing' policy mixes. Both are characterised by the implementation of diffusion incentives and R&D support measures (Haščič, 2012). In summary, the German context is characterised by remarkable and continuous policymakers' attention to EI, together with well-developed and innovative industries, thus representing an ideal context for this study.

3.2. Sample characteristics

The MIP data sets used in this study were collected by the Centre of European Economic Research together with the Fraunhofer-Institute for System and Innovation Research and the Institute for Applied Social Sciences on behalf of the German Federal Ministry for Education and Research (BMBF). The MIP is an annual innovation survey based on a panel sample of German firms that constitutes the German contribution to the European Commission's Community Innovation Survey (CIS). The MIP does not specifically aim to explore EI, but the MIP2009 innovation survey contained detailed questions on the topic (Behrens et al., 2017), which were replicated and extended in MIP2015. These are the only two surveys to date that have included questions on EI. The surveyed companies from both manufacturing and service sectors have at least five employees, which makes it possible to overcome the constraint identified by Lichtenberg (1984), according to which the results of the evaluations are often biased because the data used include mainly observations on large companies. To estimate short-term treatment effects, we use the MIP 2015 survey data, while for the estimation of the long-term effect, we merge MIP 2009 and 2015 survey data.

We first discuss summary statistics for cross-sectional data from MIP2015. Although the whole sample includes 5,445 firms, because of missing values, the effective sample consists of 2,053 firms. Regarding the treatment variable, the largest number of firms did not receive support for GI, and these firms were not treated by any measure of environmental policy (*treatment* = 0 for 1,083 firms or 52.8%). The number of firms that only received support for GI (*treatment* = 1) was 159 or 7.7%, whereas the number of firms that only received support for EI (*treatment* = 2) was 612 or 29.8%. Finally, 199 firms or 9.7% received both support for GI and EI (*treatment* = 3).

In terms of variables measuring EI (see Table 2), the largest number of firms introduced EI that focused on reduced energy use (47.7%), while a quarter of firms introduced EI with reduced CO_2 emission (25.4%) and the smallest number of firms focused on reduced air pollution (16.7%). Focusing on matching (control) variables, the modal firm had an average of 32 employees and 27.2% labour productivity. The average share of exports on total turnover was 15.8%. Concerning the variables measuring absorptive capacity, 54.5% of firms were continuously investing in R&D, while the share of R&D personnel in total employment was 3.6% on average.

Summary statistics for the panel data are quite similar to summary statistics for the cross-sectional data (see Table 2).

3.3. Model specification

The questionnaire items related to EI refer to product and process innovations. From these, we select variables that represent process EI directed towards tackling global warming. Indeed, EI can achieve positive outcomes when a change in the resource bases and capabilities induces the redesign of the production process (Russo and Fouts, 1997). Our choice is consistent with the evidence from several large companies' strategies for initiating major process innovations to mitigate global warming (Lee, 2013; Linstone, 2011).

Below are variables that are termed outcome variables in a multiple treatment model. In a panel data analysis, they represent dependent variables (see Table 2 for variable definitions and descriptive statistics).

- *Reduced energy use*: a dummy variable (DV) equal to 1 if a firm introduced process innovations that reduce energy use, and 0 otherwise. As energy-intensive industries emit the majority of industrial GHG emissions (IEA, 2011), the reduction of energy use should be considered as a key EI to address global warming. CO_2 from energy production accounts for about 80% of global GHG emissions due to human activities (Quadrelli and Peterson, 2007). Furthermore, energy consumption in manufacturing industries grew by 61% from 1971 to 2004 and accounted for almost a third of current global energy consumption (IEA, 2007). According to the Eco-Innovation Observatory (EIO), the reduction of energy use per unit of output is one of the EI challenges (EIO, 2011).
- *Reduced CO_2 footprint*: DV equal to 1 if a firm introduced process innovations that reduce the CO_2 footprint, and 0 otherwise. Fossil fuel combustion, with the accompanying CO_2 production, is the largest human influence on climate change (Crowley, 2000; Quadrelli and Peterson, 2007). At the United Nations Conference on Climate Change in Paris in 2015, 195 countries approved a plan to reduce emissions of CO_2 and other GHGs, intending to limit the increase in global temperature to below 2°C (Anderson et al., 2016). Scientists attribute the trend of global warming to the expansion of the 'greenhouse effect' (Bostrom et al., 1994) that occurs because certain gases in the atmosphere – such as CO_2 – block heat from escaping.
- *Reduced air pollution*: DV equal to 1 if a firm introduced process innovations that reduce air pollution, and 0 otherwise. Experts have noticed that the combined climate effect of increasing concentrations of trace gases may rival or even exceed that of increasing CO_2 concentrations (Lashof and Ahuja, 1990). Together with other factors, Sulphur oxide (SOx) and nitrogen oxide (NOx) are two of the main causes of air pollution (OECD, 2013). SOx and NOx have a localised impact on environmental pollution, while CO_2 emissions are linked to a more diffused impact (Defra, 2006). Thus, the reduction of air pollution is a major purpose of EI (Rennings, 2000).

Concerning policy mix, below are variables measuring innovation policy (*GI support*) and three instruments of environmental policy (*Legal requirements*, *EI support*, and *Env. taxes*):

- *GI support:* DV equal to 1 if a firm received public financial support for innovation projects from 2012 to 2014 (including grants, subsidised loans, equity or loan guarantees), and 0 otherwise (other studies using this variable are Cantner et al., 2016; De Marchi, 2012; Horbach et al., 2012).
- *Legal requirements:* DV equal to 1 if a firm responded that existing environmental regulations were important factors in driving their decision to introduce EI, and 0 otherwise (other studies using this variable are Crespi et al., 2015; Demirel and Kesidou, 2011; Horbach et al., 2012; Veugelers, 2012).
- *EI support:* DV equal to 1 if a firm responded that government grants and subsidies were important factors in driving their decision to introduce EI, and 0 otherwise (other studies using this variable are Crespi et al., 2015; Horbach et al., 2012, Veugelers, 2012);
- *Env. taxes:* DV equal to 1 if a firm responded that existing environmental taxes, charges or fees were important factors in driving their decision to introduce EI, and 0 otherwise (see e.g. Demirel & Kesidou, 2011).[2]

These variables are used differently in our models. In the panel data analysis, to test for a cross-instrumental policy mix, we model a three-way interaction term amongst *GI support*, *Legal requirements* and *EI support*. In the cross-section analysis, using a multiple treatment model, a single treatment variable reflects different combinations of innovation and environmental instruments. This *treatment* variable is defined as follows:

- *Treatment* equal to 0 if the firm did not receive support for GI and was not treated by any environmental policy instrument during 2012 to 2014 (*GI support* = 0 and *Legal requirements* = 0 and *EI support* = 0 and *Env. taxes* = 0) (1,083 firms).
- *Treatment* equal to 1 if the firm only received support for GI from 2012 to 2014 (*GI support* = 1 and *Legal requirements* = 0 and *EI support* = 0 and *Env. taxes* = 0) (159 firms).
- *Treatment* equal to 2 if the firm was only treated by any environmental policy instrument during 2012 to 2014 (*GI support* = 0 and *Legal requirements* = 1 or *EI support* = 1 or *Env. taxes* = 0) (612 firms);

[2] This variable is not available in MIP 2009 survey; thus, it is not included in panel data models.

- *Treatment* equal to 3 if the firm received support for GI and was treated by any environmental policy instrument during 2012 to 2014 (*GI support* = 1 and *Legal requirements* = 1 or *EI support* = 1 or *Env. taxes* = 1) (199 firms).

The following variables serve as matching variables in the cross-section analysis and as control variables in the panel analysis. To control for firms' absorptive capacity (Cohen and Levinthal, 1990), we include two variables: *Continuous R&D*, which is a categorical variable equal to 1 if a firm was continuously engaged in R&D activities between 2012 and 2015, and 0 otherwise (see e.g. De Marchi, 2012; Hottenrott and Rexhäuser, 2015), and *R&D personnel* which is measured as the share of R&D personnel in total employment (De Marchi, 2012).[3] In the literature on the determinants of EI, R&D activities are categorised as a 'technology-push' driver along with knowledge capital endowment and managerial capabilities (Ghisetti and Pontoni, 2015; Hojnik and Ruzzier, 2016; Horbach, 2008). Absorptive capacity, which encompasses R&D investment, enables firms to absorb and exploit knowledge and opportunities that result in EI (Díaz-García et al., 2015). Consequently, R&D investment is amongst the most important technology-push determinants of EI (Ghisetti and Pontoni, 2015).

Firm characteristics are controlled by the inclusion of the following variables. The variable *Size* measures the number of employees (in natural logarithm). Large firms are more likely to engage in EI than smaller firms as they possess greater human and financial resources as well as absorptive capacity (in particular when a dedicated R&D department exists), and they can reap the benefits of economics of scale. In contrast, smaller firms face difficulties due to their limited resources, access to information flows and subsidies (del Río et al., 2016; Díaz-García et al., 2015). We model export intensity (*Exports*) as a continuous variable calculated as the turnover from abroad divided by total turnover. Exporting firms might have more incentive to innovate as a result of competitive pressure on international markets (Busom and Fernández-Ribas, 2008). A similar argument can be extended to EI, since international demand for greener products, even in the absence of domestic demand, can spur domestic firms to eco-innovate (Brunnermeier and Cohen, 2003; del Río et al., 2015). We also include the variable *Productivity*, which measures labour productivity (turnover divided by the number of

[3] In the panel data analysis, we did not have information about R&D personnel, as this variable was not included in the MIP2009 survey.

employees), as more productive firms have a higher probability of pursuing environmental objectives (Demirel and Kesidou, 2011).

To control for industry heterogeneity, based on the Statistical Classification of Economic Activities in the European Community (referred to as NACE) at the 2-digit industry level, we include four sector DVs: research-intensive industries, other industries (the base category), knowledge-intensive services, and other services (see Table 2 for the variables' definitions). Table 3 summarises the main characteristics of the two estimated models.

Table 2.
Variable description and summary statistics.

	Variables	Variable definition	Mean (standard deviation) for cross-sectional data from 2015	Mean (standard deviation) for panel analysis 2009 and 2015
Outcome variables	Reduced energy use	DV = 1 if a firm introduced innovations reducing energy use, 0 otherwise	0.477 (0.500)	0.406 (0.491)
	Reduced CO_2 footprint	DV = 1 if a firm introduced innovations reducing CO_2 footprint; 0 otherwise	0.254 (0.435)	0.249 (0.433)
	Reduced air pollution	DV = 1 if a firm introduced innovations reducing air pollution, 0 otherwise	0.167 (0.373)	0.158 (0.365)
Matching (control) variables	Size	Firm size as the number of employees (in natural logarithm)	3.479 (1.498)	3.320 (1.529)
	Continuous R&D	DV = 1 if a firm continuously engaged in R&D activities; 0 otherwise	0.545 (0.701)	0.381 (0.635)
	R&D personnel	Share of R&D personnel in total employment	0.036 (0.055)	-
	Exports	Share of turnover from abroad in total turnover	0.158 (0.253)	0.134 (0.234)
	Productivity	Labour productivity (turnover divided by the number of employees)	0.272 (0.177)	0.264 (0.169)
	Research-intensive industries	DV = 1 if a firm operates in NACE categories 20, 21 and 26 to 30, 0 otherwise	0.209 (0.407)	0.194 (0.396)
	Other industries (the base category)	DV = 1 if a firm operates in NACE categories from 5 to 19, from 22 to 25 and from 31 to 39, 0 otherwise	0.444 (0.497)	0.415 (0.493)
	Knowledge-intensive services	DV = 1 if a firm operates in NACE categories from 58 to 66, and from 69 to 73 (without 70.1), 0 otherwise	0.200 (0.400)	0.216 (0.412)
	Other services	DV = 1 if a firm operates in NACE categories 46, from 49 to 53, 74, and from 78 to 82, 0 otherwise	0.147 (0.354)	0.175 (0.380)

Table 3.
Models of the study.

	Model 1	Model 2
Time frame	Short term	Long term
Hypotheses	H1a & H1b	H2a & H2b
Sample period	2015	2009 → 2015
Method	Cross-section analysis using a multilevel treatment model	Panel analysis
Outcomes	Reduced energy use Reduced CO_2 footprint Reduced air pollution	Reduced energy use Reduced CO_2 footprint Reduced air pollution
GI policy variable/instrument	GI support	GI support
Environmental policy variables/instruments	Legal requirements EI support Environmental taxes	Legal requirements EI support

3.4. Econometric strategy

In assessing the *short-term* effectiveness of environmental and innovation policies, our empirical strategy encompasses the use of a multilevel treatment model, which is motivated by the endogeneity of public support due to the self-selection of firms for public support and the public agencies adopting a 'picking-the-winner' strategy (Radicic et al., 2016). To account for such endogeneity, the effect of any public support should be estimated as a treatment assignment, that is, the Average Treatment on the Treated (ATT) effect (see Equation 1). We follow the most common approach in this stream of research, which is to match the employed propensity scores of firms in the treatment group (denoted *m* in Equation 1) with firms in the comparison group (denoted *l* in Equation 1). Then, we estimate the difference between the probability of introducing EI for firms receiving a particular treatment, as the outcome of interest (Y_1), and the outcome for the comparison group of firms (Y_0) (Cerulli, 2010).

Given that environmental and innovation policies are provided simultaneously, we estimate treatment effects in the multi-treatment context. In this way, we can account for the presence of hidden treatment (Guerzoni and Raiteri, 2015), i.e. a simultaneous receipt of support from various sources (a policy mix). A matching approach with multiple treatments was first introduced by Lechner (2001). The approach considers M+1 treatments (in our case

3+1, see the *treatment* variable description in the previous section), whereby +1 refers to *treatment* = 0 (the non-participation in both environmental and innovation policies) (see e.g. Radicic and Pugh, 2017). Every firm has M+1 potential outcomes after receiving each of the M+1 treatments. For firm *i*, the potential outcome is denoted Y_i^T, where *T* denotes a treatment assignment. For each firm, the treatment effect (TE) of interest is the difference between the potential outcomes at different treatment levels, i.e. TE(*m,l*) = Y_i^m - Y_i^l, for all $m \neq l$. As Y_i^m and Y_i^l cannot be observed at the same time, the counterfactual outcome Y_i^l needs to be estimated. Then, to consider the treatment effect for all firms receiving treatment *m*, we estimate the ATT as follows:

$$ATT = E(Y^m|T = m) - E(Y^l|T = m), \quad (1)$$

where *m* denotes the treatment level, *l* represents the comparison group (the treatment level to which *m* is compared) and Y^m and Y^l denote outcomes in states *m* and *l*, respectively.

We employ the inverse probability of treatment weighting regression adjustment (IPWRA) estimator (Cattaneo, 2010). The IPWRA estimator belongs to a group of matching estimators that have a double-robust property. Double robustness implies that either the treatment model or the outcome model (or both) have to be correctly specified for the estimator to produce consistent treatment effects (Hirano et al., 2003).

The IPWRA estimator consists of three steps. First, for each firm in the sample, the treatment model estimates the propensity score, which is the probability for each firm that it received a particular type of support (i.e. treatment assignment). Given that we evaluate multiple treatment effects, the propensity scores are estimated by a multinomial logit model that incorporates all four treatment levels: no support from either environmental or innovation support (treatment = 0), support from GI policy only (treatment = 1), support from environmental policy only (treatment = 2) and support from both (treatment = 3). The choice of the model is motivated by the nature of our treatment variable, which has more than two outcomes with no natural ordering. The propensity scores enable firms to be matched within each treatment level. Second, regressions are estimated by the probit model because the outcome variables are binary indicators, in which the inverse of the estimated propensity scores are used as weights on covariates *X* and the treatment dummies. Third, from each of these regressions, the ATT effect is computed as the difference in the weighted averages of the predicted outcomes (for technical details, see Wooldridge, 2010).

Concerning the panel data analysis, the estimated programme effects are better identified, since we can control for unobserved firm characteristics that are time-invariant or slowly moving, whereas matching with cross-section data can control only for observable firm characteristics. Fixed effects (FEs) estimation is precluded because firms tend to either engage or not engage in particular types of EI throughout the sample period; hence, our binary dependent variables do not vary much over the sample period. Accordingly, we estimate a random-effects probit model, which takes into account both within- and between-firm variation and so retains the whole sample. The model can be presented as follows:

$$y_{it}^{*} = \beta_0 + \beta_1 GI\ support_{it} + \beta_2 Legal\ requirements_{it} + \beta_3 EI\ support_{it} + \beta_4 GI\ support_{it} * Legal\ requirements_{it} + \beta_5 GI\ support_{it} * EI\ supports_{it} + \beta_6 Legal\ requirements_{it} * EI\ supports_{it} + \beta_7 GI\ support_{it} * EI\ supports_{it} * Legal\ requirements_{it} + \beta Control\ variables_{it} + \vartheta_{it}$$

$$\vartheta_{it} = \alpha_i + u_{it}$$

$$y_{it} = 1\ if\ y_{it}^{*} > 0\ and\ zero\ else,$$

where the subscript *i* indexes each firm in the sample *I* = *1,2,…n*; the period t = 2009 and 2015; y_{it}^{*} denotes the unobserved latent variable; y_{it} is the observed binary dependent variable; the policy variables are *GI support, Legal requirements* and *EI support*; the vector *Control variable* includes matching variables from the cross-section analysis; α_i is the individual-specific unobserved effect; and u_{it} is the error term.

To test H3 and H4, we interact three policy variables so the coefficient of interest is β_7. If β_7 is positive and statistically significant, it would indicate that a cross-instrumental policy mix has a positive effect on the probability of process EI. However, to test whether a cross-instrumental policy mix is more effective than individual policies, we estimate marginal effects by creating the same treatment and comparison groups as in the case of a cross-sectional analysis.

4. Empirical results

In both cross-sectional and panel data analyses, two types of effects are estimated. Absolute effects refer to the effects of different treatment levels when the control group is treatment 0 (firms not benefiting from any policy measure). In contrast, relative effects are those effects of a treatment level when the control group is not level 0 (Radicic and Pugh, 2017). Given that our hypotheses are based on the assessment of the effects of the policy mix as opposed to individual policy instruments, our focus is on relative effects.

To test H1a and H1b, which state that, in the short term, a combined effect of environmental and GI policies is greater than the effect of individual policy types (general and environmental, respectively), we estimate Model 1 (see Table 4).[4] Relative effects measure a combined impact of public support for GI and any of the three instruments for EI respectively versus public support for GI (column 5) and versus any of the three instruments for EI (column 6).

The effects of the combined support relative to public support for GI (column 5) are positive and highly significant ($p < 0.01$) for each outcome variable. In the short term, the combined effect of GI and environmental policies is more effective in facilitating eco-innovative behaviour in firms than only receiving public support for GI. This suggests a complementary effect of the measures together and thus supports hypothesis H1b. As for the case of the policy mix relative to any of the three instruments for EI (column 6), the estimated treatment effects do not support H1a, as they are not statistically significant for any of the three outcome variables.

[4] Table A1 reports results for one output variable as an example, namely, from the multinomial logit model of *Reduced energy use*, in which the base is treatment at level 0. Results for the other multinomial logit models are not reported but are available upon request. Table A1 also reports the treatment model, which is the same for all the outcome variables. The treatment model shows the effect of covariates on the probabilities of different levels of treatment, whereas the outcome model estimates the impact of covariates on EI (in Table A1, *Reduced energy use*). Figure 1A in the Appendix shows the common support regions at different levels of treatment. Treatment effects of any matching estimator based on the propensity score are only estimated in the region of common support. Thus, it is necessary to check the overlap of the propensity scores at different treatment levels. The overlap plots reported in Figure A1 in the Appendix, reveal that the predicted probabilities are not concentrated near 0 or 1, which implies that the overlap assumption is not violated (Cattaneo et al., 2013).

Table 4.
Short-term effects of a policy mix between GI support (public support) and any three instruments for EI.

Outcome variables	Absolute treatment effects			Relative treatment effects	
	Public support for GI versus none (treatment = 0)	Any of the three instruments for EI versus none (treatment = 0)	The combined impact of public support for GI and any of the three instruments for EI versus none (treatment = 0)	The combined impact of public support for GI and any of the three instruments for EI versus public support for GI [H1a]	The combined impact of public support for GI and any of the three instruments for EI versus any of the three instruments for EI [H1b]
Column	*1*	*2*	*3*	*4*	*5*
Reduced energy use	0.127** (0.056)	0.382*** (0.057)	0.358*** (0.057)	0.183*** (0.055)	–0.011 (0.045)
Reduced CO_2 footprint	0.011 (0.046)	0.287*** (0.054)	0.204*** (0.053)	0.171*** (0.060)	–0.034 (0.051)
Reduced air pollution	0.014 (0.049)	0.138** (0.056)	0.157*** (0.056)	0.160*** (0.048)	0.056 (0.048)

Note: Robust standard errors in parentheses; ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

We estimate Model 2 (see Table 5) to test H2a and H2b, which state that, in the long term, the combined effect of environmental and GI policies is greater than the individual effect of individual policy instruments.[5] The effects of the combined impact relative to public support for GI (column 6) are positive and highly statistically significant ($p < 0.01$) for each of the three outcome variables. The estimated values show that firms that benefit from both innovation and environmental policy instruments have a higher probability of introducing EIs in the long term than firms that only received public support for GI, thus supporting hypothesis H2b.

[5] Table A2 in the Appendix shows the results of random-effects probit panel models with the three-way interaction terms including the treatment variables. The estimated marginal effects are reported in Table 5.

Table 5.
Marginal effects from random-effects probit panel models.

Outcome variables	Absolute treatment effects				Relative treatment effects	
	Public support for GI versus none	Legal require-ments for EI versus none	Public support for EI versus none	The combined impact of public support for GI and any of the two instruments for EI versus none	The combined impact of public support for GI and any of the two instruments for EI versus public support for GI [H2a]	The combined impact of public support for GI and any of the two instruments for EI versus legal requirements and public support for EI [H2b]
Column	*1*	*2*	*3*	*4*	*5*	*6*
Reduced energy use	0.758** (0.242)	1.930*** (0.253)	2.207*** (0.452)	2.737*** (0.439)	1.978*** (0.445)	0.659 (0.446)
Reduced CO_2 footprint	0.838 (0.296)	1.658*** (0.256)	1.407** (0.437)	2.965*** (0.421)	2.128*** (0.426)	0.806 (0.409)
Reduced air pollution	0.909* (0.308)	1.643*** (0.258)	1.602** (0.458)	2.663*** (0.379)	1.754*** (0.379)	0.641 (0.367)

Note: Robust standard errors in parentheses; ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

Finally, our results do not support hypothesis H2a, as the estimated relative effects in column 7 show that the policy mix and environmental policy instruments have qualitatively the same effect on the EI outcome variables (legal requirements and public support for EI), with the estimated treatment effects not being statistically significant.

5. Discussion

Recently, scholars have recognised the importance of a cross-instrumental policy mix in supporting EI. However, the evidence for the effectiveness of such a policy mix is very limited (Crespi et al., 2015; Costantini et al., 2017; Veugelers, 2012) because of the complexity of this type of evaluation (Goulder and Parry, 2008). In estimating policy effects, we take into account the endogenous nature of policies, namely, the literature on public support of GI has long identified two sources of endogeneity (David et al., 2000). First, firms self-select themselves into public support programmes (in the case of R&D subsidies) and innovation activities (in the case of R&D tax credits). Second, government agencies might follow the ‘picking winners’ strategy, whereby firms that are more likely to be successful innovators are also more likely to receive government support. In contrast, endogeneity of environmental policy is often overlooked in quantitative evaluations (Ferraro, 2009; Nesta et al., 2014).. We modelled the endogeneity of environmental policy – in particular in the cross-section analysis – by employing a multilevel treatment model that accounts for the endogeneity of both innovation and environmental policies.

Our findings cannot be effectively compared with Costantini et al.'s (2017). Indeed, the authors examined the characteristics of the policy mix in the OECD countries and reported that a more balanced and a more comprehensive policy mix had a greater effect on EI. Their study was conducted at a macro-level (as opposed to our micro-level research), it considered an intermediate innovation outcome (as opposed to our final EI outcome) and did not identify specific policy interaction effects. Crespi et al.'s (2015) analysis of an aggregated measure of the policy instruments showed a positive impact on most EIs, which is consistent with our results, but their study did not model specific policy interactions. Therefore, the main results of our study cannot be compared with those found by Crespi et al. (2015). In contrast, our findings are comparable to and in line with those obtained by Veugelers (2012), whose empirical findings of the sample of Flemish firms suggested a complementarity between innovation and environmental policies, but only when the comparison group are firms that received support for GI.

This study empirically assesses whether a cross-instrumental policy mix has a higher probability of promoting EI against instruments belonging to either environmental or GI policy areas, both in the short and long term. By estimating treatment effects for environmental and GI policy areas, we can infer the potential complementary effects between them.

In the short term, a comparison between the effect of the cross-instrumental policy mix and the effect of GI policies indicates the existence of complementarity between environmental policy instruments (in the form of legal requirements, environmental taxes and public support for EI) and GI policy instruments (in the form of public support for GI). This finding is consistent with van den Bergh's study (2013), which showed that GI and environmental policy instruments play a complementary role. Indeed, adding GI policies to environmental ones helps to accelerate and lead technological change in a desirable direction towards alternative technological scenarios.

In the long term, positive synergies stemming from a cross-instrumental policy mix have a stronger effect on EI development than GI policy alone. The results confirm that complementary policy instruments are needed to provide a long-term political signal and thus trigger further technological development (OECD, 2009). This finding is in line with Rogge and Reichardt's article (2013), which argued that, in the context of environmental technological change, a policy mix should incorporate not only environmental policy instruments but also innovation instruments. Consequently, policymakers should focus on the coordination of such measures to promote EI and to address climate change. Given the long-term perspective inherent in the policy strategy (Hillman and Hitt, 1999), we conclude that the policy mix could play a crucial role in pursuing future environmental targets since it can correct for multiple failures of private governance structures, such as pollution externalities and technological spillovers (Lehmann, 2012).

We found no evidence that a cross-instrumental policy mix enhances the development of EIs more than environmental policy instruments alone, both in the short and long term. Within a policy mix, the co-existing instruments can interact (Nauwelaers et al., 2009). The combined effect of the instrument mix and the achievement of policy objectives may depend on the characteristics of single measures, i.e. their scope, the nature of their goals, their timing, and operation and implementation processes (Sorrell et al., 2003). Policy coordination failure (Schot and Steinmueller, 2018; Weber and Rohracher, 2012) can emerge at multiple levels, from the difficulty to horizontally coordinate different policy areas, such as the two investigated in this study, to the difficulties to coordinate local, regional, national and international policies.

Given that sustainability and climate change have a long-term dimension, innovating firms should persistently engage in environmental innovation (Jaffe et al., 2005). From a policymaking perspective, this argument posits the importance of long-term, persistent policy effects in incentivising environmental innovators (Le Bas and Poussing, 2018). Furthermore, radical EI entails a long-term investment and a high degree of uncertainty. Although we cannot distinguish in our data between radical and incremental EIs, our findings indirectly point to the issue of public support of radical innovation, i.e. radical innovation requires a long-term policy and a high degree of policy coordination (del Río et al., 2010; Kemp, 2011; Reichardt and Rogge, 2016). Consequently, if German firms want to focus on radical EI in the future, it is necessary to achieve better coordination between innovation and environmental policies.

In summary, the combined impact of the different instruments depends heavily on the choice of single instruments and their interdependencies. Thus, policymakers should consider these aspects and understand the mechanisms of policy interactions to create effective coordination between environmental and GI policies to foster EI and manage global warming.

6. Conclusions

This study investigates the effects of a cross-instrumental policy mix on firms' likelihood to introduce process EIs. To this aim, it analyses a large sample of German firms by estimating a cross-section multilevel treatment model as well as a panel data model to explore the effects of policy mix on EI in the short term and the long term. The results have theoretical, practical and policy implications.

6.1. Theoretical implications

Theoretical research on the policy mix concerning environmental innovation has grown considerably in recent years. However, studies focusing on the combined effects of GI policy and environmental policy (a cross-instrumental policy mix) are scarce (Costantini et al., 2017; Crespi et al., 2015; Veugelers, 2012). Our study fills this gap by estimating treatment effects of both types of policies. While accounting for the endogeneity of policies, our study also reports policy effects in both the short and long term. In this way, we can explore both whether policy effects have contemporaneous, short-term effectiveness in stimulating process EI and whether policy effects are of a prolonged nature. Empirical studies adopting this strategy are rare in both streams of research on the effectiveness of innovation policy as well as of environmental policy. Therefore, we encourage future research to unveil the differences between the short-term and long-term effects of policy instruments and policy mix on EI.

6.2. Practical implications

This study provides new evidence about the impact of policy mix on firms' EI behaviour. Our results show that the effect of a cross-instrumental policy mix is greater than the effect of GI policies in isolation, both in the short and long term. However, our study does not show any statistically significant difference between a cross-instrumental policy mix and the impact of single environmental policies, both in the short term and long term. Therefore, providing general support for innovation to firms already benefiting from environmental policies does not create any additional effects on process EI, which implies that there is no complementarity between these policy tools.

Our empirical findings indicate that environmental market failures could be larger than market failures arising from the public goods nature of new knowledge. In other words, once environmental policy addresses problems of environmental externalities, there are no additional effects on EI when firms receive support for tackling knowledge spillovers effects. This could be either because firms do not perceive knowledge spillovers as large enough to deter their investment in EI or firms can sufficiently protect their knowledge through the mechanism of intellectual property rights, so the issue of knowledge spillovers is eliminated.

An alternative explanation for our findings is that R&D subsidies stimulate the *invention* of new technologies, but do not provide incentives for the *adoption* of new, environmentally friendly technologies (Popp, 2006). Given that Germany is the leader in Europe in terms of sustainability and green technologies, it could be that German firms are less focused on the invention side of new technologies, and more focused on the adoption of new or existing green technologies. However, available information in our data set prevents us from exploring this argument empirically, and thus, we leave it as a suggestion for future research.

6.3. Policy implications

The policy implications are twofold. First, providing general support for innovation to firms already benefiting from the support of environmental policies does not create any additional effects on the introduction of process EI, which implies that there is no complementarity amongst these policy tools. A cause of this issue could have been the lack of coordination amongst the public agencies responsible for implementing innovation and environmental policies. Under such circumstances, the policy mix could only arise by chance rather than by design. Consequently, to achieve complementarity, policymakers should coordinate their efforts in designing and implementing innovation and environmental policies.

Second, regarding the time frame under investigation, we obtained the same results in the short term and the long term. This leads us to assume that if policymakers achieve coordination in the short term, it is likely that such coordination will have positive effects in the long term as well. This consideration is based on two fundamental theoretical aspects: persistence of innovation and behavioural additionality. Indeed, if public support can change firms' behaviour in terms of their propensity to introduce EI, this will affect their behaviour in the long term. Furthermore, the pressing environmental issues, such as global warming, are of a long-term nature. This implies that firms have reasons to expect that the pressure and the incentives to invest in EI will persist. In other words, we argue, a core policy implication is that, once an initial effort is made to orchestrate the cross-instrumental policy mix, positive effects are likely to persist in the long term.

6.4. Limitations and future research

Although our empirical study is amongst the first to analyse the interaction between technological and environmental policies, it suffers from limitations that can serve as suggestions for future research. First, the information collected in the sample is restricted to German firms. Consequently, our findings represent country-specific results that may not be generalised to other countries. More evidence from other countries would enhance the understanding of the phenomenon. Second, future research could explore the effect of policy mix on firms' behaviour concerning EI (i.e. behavioural additionality). Third, this study explored the effect of policy mix on the process of EI. Besides process innovation, product and organisational EIs can have a major role in addressing the environmental challenges in the future (Borrás and Edquist, 2013; Cheng and Shiu, 2012; Ozusaglam, 2012; Pujari, 2006). Furthermore, future empirical studies on how policy mix can overcome the barriers to the adoption of EIs on the demand-side (Viardot, 2013) as well as on the increase of the demand for energy (Shi et al., 2017) would be extremely relevant. Finally, other metrics for both EI (e.g. novelty of innovations and their share in firms' sales) and policy mix (e.g. amount of funds obtained) would greatly enhance our understanding of the relationship between the two.

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Appendix

Table A1.

Estimation functions (the outcome and the treatment models) for the outcome variable *Reduced energy use* with treatment level 0 as the base (reference) category (N=2,053).

Independent variables	Outcome model				Treatment model		
	Potential outcome model for treatment=0	Potential outcome model for treatment=1	Potential outcome model for treatment=2	Potential outcome model for treatment=3	Treatment =1	Treatment =2	Treatment =3
Size	-0.128	0.618***	0.322*	0.142	0.509***	0.244***	0.682***
	(0.140)	(0.190)	(0.171)	(0.215)	(0.077)	(0.044)	(0.074)
Exports	-0.394	-0.280	-0.154	-0.356	0.352	0.235	0.804**
	(0.805)	(0.737)	(0.979)	(0.902)	(0.447)	(0.256)	(0.374)
Productivity	0.975	-0.701	-1.060	0.822	-2.781***	0.435	-0.787
	(1.195)	(1.587)	(1.364)	(1.614)	(0.793)	(0.312)	(0.613)
R&D intensity	0.321	-0.409	-0.131	0.169	0.883***	0.310***	0.743***
	(0.254)	(0.373)	(0.349)	(0.571)	(0.169)	(0.105)	(0.137)
R&D personal	-5.607	-0.147	-0.957	-4.723	22.456***	3.848**	20.210***
	(3.502)	(4.042)	(4.021)	(4.783)	(2.092)	(1.512)	(1.972)
Research-intensive Industries	-0.303	-0.504	-0.110	0.362	0.792***	-0.221	0.226
	(0.489)	(0.454)	(0.495)	(0.466)	(0.261)	(0.159)	(0.223)
Knowledge-intensive Services	-0.225	-0.826	0.194	0.604	-0.355	-1.231***	-1.101***
	(0.500)	(0.513)	(0.607)	(0.641)	(0.295)	(0.170)	(0.282)
Other services	-1.055**	-1.631	0.682	-1.971	-1.172*	-0.526***	-1.775***
	(0.495)	(1.074)	(0.591)	(1.208)	(0.624)	(0.157)	(0.621)
Constant	0.087	-1.163	0.386	0.274	-5.303***	-1.472***	-5.621***
	(0.612)	(1.171)	(0.834)	(1.318)	(0.376)	(0.180)	(0.374)
No of obs.	2,053	2,053	2,053	2,053	2,053	2,053	2,053

Note: Robust standard errors in parentheses; *** *p<0.01*, ** *p<0.05*, * *p<0.1;* the reference sector category is Other industries.

Table A2.

Results from random-effects probit panel models.

Independent variables	Reduced energy use	Reduced CO_2	Reduced air pollution
Legal requirements	1.930***	1.658***	1.643***
	(0.253)	(0.256)	(0.258)
EI support	2.207***	1.407***	1.602***
	(0.452)	(0.437)	(0.458)
Legal requirements * EI support	-2.059***	-0.905*	-1.222**
	(0.533)	(0.517)	(0.539)
GI support	0.758***	0.838***	0.909***
	(0.242)	(0.296)	(0.308)
Legal requirements * GI support	-1.795***	-1.370***	-1.092**
	(0.475)	(0.511)	(0.525)
EI support * GI support	-0.606	0.141	-0.314
	(0.652)	(0.665)	(0.634)
Legal requirements* EI support* GI support	2.301***	1.197	1.138
	(0.893)	(0.896)	(0.870)
Size	0.217***	0.278***	0.144**
	(0.052)	(0.061)	(0.060)
Exports	0.296	-0.081	-0.148
	(0.338)	(0.363)	(0.381)
Productivity	0.224	0.228	0.112
	(0.429)	(0.475)	(0.491)
R&D intensity	0.318***	0.050	0.252*
	(0.123)	(0.136)	(0.146)
Research-intensive industries	-0.269	-0.590***	-0.685***
	(0.196)	(0.224)	(0.240)
Knowledge-intensive services	-0.710***	-0.520**	-0.571**
	(0.194)	(0.221)	(0.239)
Other services	-0.715***	-0.271	0.139
	(0.208)	(0.224)	(0.228)
Constant	-1.875***	-3.043***	-3.300***
	(0.251)	(0.342)	(0.352)
No of obs.	1,828	1,810	1,800

*Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; the reference sector category is Other industries.*

Figure 1A. Checking the overlap assumption for the estimated models in Table 4