Erasmus University Rotterdam

The EU ETS: A boost for economic growth?

Testing the Porter Hypothesis for the European Union: the effects of environmental policy on innovation and productivity growth[*]

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Abstract:

This study aims to evaluate the effects of environmental policy on innovation and productivity growth in the European Union, over the period 2008 to 2017. During this period, the third phase of the EU Emissions Trading Scheme has come into effect. The starting point in this study is the Porter hypothesis on environmental regulations (Porter, 1991). The general idea of this hypothesis, related to the argumentation of Hicks (1932), is that increasing costs accompanying the environmental regulations will spur innovation activity towards economizing and improving the production processes. Hence, the Porter hypothesis suggests that environmental regulations stimulate productivity growth through increasing innovation, induced by the regulations. First, this paper uses a regular OLS-estimation panel regression to study this Porter hypothesis for the mining and manufacturing industries in the EU. Moreover, this study recognizes the accompanying endogeneity issues and adopts an instrumental variable approach to overcome biased estimates. Innovation activity is proxied by R&D expenditures and the measure of productivity growth is TFP growth. This study finds some evidence supporting a positive impact of environmental regulations in the EU on industry-level R&D expenditures but finds no evidence for a productivity growth effect through R&D activity induced by the regulations.

Keywords: *EU ETS, environmental policy, economic performance, innovation, productivity*

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1 Introduction

With the 2030 Climate Target Plan, the European Union has set important goals to cut greenhouse gas emissions by 55 percent below 1990 levels before the year 2030. This is an appropriate and much-needed plan when looking at the raging floods and astonishing heat records that we have seen in 2021. Since January 2021, phase four of the EU Emissions Trading System (EU ETS) has launched in order to achieve these ambitious 2030 targets. The EU ETS is the cornerstone of the environmental policy in the European Union, aiming at fighting climate change and reducing greenhouse gas emissions cost-effectively. Under the so-called ‘cap and trade’ system, installations buy or receive a number of allowances for their greenhouse gas emissions, which are tradable on a carbon market. The cap of emission allowances has been reduced over the years, through the different phases of the system, to lower the overall emissions (European Commission, 2015). As the number of emission allowances is limited in supply and decreasing over the years, we have seen that by the end of August 2021 the EU carbon price has reached a new record by jumping above 60 euros per tonne carbon dioxide (Hook, 2021). The prices have surged significantly, setting record after record, as it is expected that the supply of carbon allowances will further decrease over the coming years to meet the ambitious climate targets of 2030.

These increasing carbon prices represent the increasing levels of stringency of the environmental policy in the European Union. Changes in the stringency of EU’s environmental regulations are subject to research and debate regarding the impact of the regulations on economic performance. The head of the International Energy Agency finds the increasing carbon price an excellent development that will stimulate a rapid transition towards clean energy and technologies, as companies are incentivized to invest in innovation (Sheppard & Hodgson, 2021). On the other hand, industry associations of pollution intensive industries are less optimistic towards the recent developments and raise concerns regarding the competitiveness of companies under the EU ETS, referring to global competitors that are subject to less stringent environmental regulations (Sheppard & Hodgson, 2021). The debate surrounding the economic effects of EU’s environmental policy is important looking at the recent surge in the carbon price. Although the primary objective of EU’s carbon market program is to reduce the greenhouse gas emissions, it is from an economic perspective crucial that the environmental policy provides incentives for technological change and innovation, since this leads to productivity growth and reduces the long-run costs of pollution control (Calel & Dechezleprêtre, 2016; Acemoglu et al., 2012). The ability of an environmental policy to stimulate innovation, through which productivity growth can be reached, is an important criterion on which to judge its success (Calel and Dechezleprêtre, 2016).

The economic outcomes of environmental policies have been studied extensively since the first major environmental regulations in the 1970s (Dechezlepretre & Sato, 2017). The literature can be distinguished between two different theories: the pollution haven hypothesis and the Porter hypothesis. The pollution haven hypothesis suggests that due to asymmetries in the stringency of environmental regulations a competitive disadvantage will arise in the global market, as pollution-intensive firms in countries with strict regulations face larger costs. (Dechezleprêtre and Sato, 2017). Therefore, enterprises will shift production towards the pollution havens with less stringent environmental regulations. This concept is called carbon leakage. The Porter hypothesis, first established by Porter in 1991 and further specified in Porter and Van der Linde (1995), relates back to the argumentation of Hicks (1932), suggesting that strict environmental policies will spur innovation activity directed towards clean technologies and cost-cutting efficiency improvements, that will overcome the additional cost-burden accompanying the environmental regulations. Through this induced innovation, productivity growth will arise. The Porter hypothesis is the starting point of this study in aiming to investigate the effects of environmental regulations in the European Union on industry-level economic performance outcomes, measured by innovation activity and productivity growth. We measure innovation activity by the country-sector level research and development (R&D) expenditures, and productivity growth by country-sector level annual TFP growth ratios. The research question is the following:

Does environmental policy in the European Union induce industry-level investment in research and development and consequently increase productivity growth of the mining and manufacturing sectors in the European Union over the period 2008 to 2017?

The Porter hypothesis has been studied extensively in the United States, but empirical literature is relatively scarce for the European Union. For the United States, Jaffe and Palmer (1997) finds a small positive effect of environmental policies on industry-level R&D expenditures, and Barbera and McConnell (1990) finds a negative effect on productivity growth. Hamamoto (2006) finds a positive relationship between environmental policy and R&D expenditures. For European manufacturing industries, Rubashkina et al. (2015) finds no significant relationship between environmental regulations and R&D expenditures or productivity growth.

We investigate the Porter hypothesis using a cross-country sector-level panel data set containing 14 mining and manufacturing industries for 18 countries in the European Union over the period 2008 to 2017. The activities in these sectors, and the accompanying emissions, are all subject to EU's environmental regulations. Evaluating the economic effects of environmental regulations requires a proper measure for the stringency of the regulatory measures. Although the market-based carbon price follows the stringency of the environmental regulations in the European Union accurately, these price levels are the same for all countries and industries, providing only time-variant variation in the data. Therefore, this study uses country-sector level environmental protection expenditures aimed at pollution control as a proxy for the stringency of the environmental policy in the European Union. The assumption is that larger environmental protection expenditures are induced by more stringent environmental regulations (Koźluk & Zipperer, 2015). However, this measure for the stringency of EU's environmental policy may be subject to reverse causality bias and other endogeneity issues. In line with De Vries and Withagen (2005), Rubashkina et al. (2015) and Hille and Möbius (2019), this study recognizes these endogeneity issues, by adopting an instrumental variable approach. The pollution control environmental protection expenditures (EPE) are instrumented by the average share of pollution control expenditures over value added of the industry's adjacent sectors, excluding the industry itself: $\frac{EPE}{VA}_{-j}$. We argue that industries with similar pollutive behavior have strongly correlated environmental protection expenditures as a response of more stringent environmental policy. Therefore, the EPE-intensity of the industry's adjacent sectors with similar pollution ratios serves as a good predictor of the EPE-intensity of the industry under consideration. Only a few papers have recognized these endogeneity issues properly. Not accounting for the endogeneity of the environmental protection expenditures leads to biased estimates of the innovation and productivity effects (Hille & Möbius, 2019).

This study is subdivided into the innovation effect and the productivity effect. We find evidence for a positive impact of environmental regulations in the EU on industry-level R&D expenditures, when using our IV-approach, supporting a positive innovation effect. The impact on productivity growth is more complex. We find an indication for a negative direct effect of EU's environmental regulations on TFP growth. Furthermore, we cannot support the presence of a positive impact of innovation, induced by environmental regulations, on productivity growth, as suggested by the strong version of the Porter hypothesis.

As this paper provides evidence on the effects of environmental regulations in the European Union during the period of the second and third phase of the EU ETS, the results will strengthen and complement discussions regarding the economic outcomes of the current surge of the EU ETS carbon price in the fourth phase. Moreover, we contribute to the literature by providing a comprehensive overview of both the innovation and productivity effect of the environmental regulations in the EU for the more recent years.

The paper proceeds as follows. Chapter 2 discusses the theoretical framework, including a brief description of the EU ETS, a theoretical background and the empirical findings in previous literature on the innovation and productivity effects of environmental regulations. In respectively chapter 3 and 4, this paper presents the methodology and data of the empirical estimation. Chapter 5 evaluates the results subdivided into the innovation effect and productivity effect. Chapter 6 concludes, mentions some important limitations to the study and provides further research avenues.

2 Theoretical Framework

2.1 – Climate action

2.1.1 – Climate change

Article 1 of the United Nations Framework Convention on Climate Change (UNFCCC) defines climate change as ‘a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods’ (United Nations, 1992). This definition distinguishes between climate change attributable to human activities and climate variability attributable to natural causes (UNFCCC, 2011).

The Intergovernmental Panel on Climate Change (IPCC)[1] states that the CO_2 concentrations in the atmosphere of 2019 were higher than at any time in at least the last 2 million years (IPCC, 2021). Global warming, originated from the greenhouse gas emissions from human activities, has large effects on the weather, food production and human health (IPCC, 2021). The average temperatures are rising and in 2021 only, we have seen raging floods and astonishing heath records that have destroyed lives (Mellen, 2021). Many changes in the global sea, ocean and icesheet levels are irreversible for centuries to millennia due to past and future greenhouse gas emissions (IPCC, 2021). Solving these climate change problems requires strong action on a global scale (UNFCCC, 2010).

Countries have acknowledged the climate change issues in the Kyoto Protocol, which was adopted in 1997. The Kyoto Protocol operationalizes the United Nations Framework Convention on Climate Change by committing industrialized countries and economies in transition to limit and reduce the greenhouse gas emissions and environmental pollution ratios (United Nations, 1997). The Kyoto Protocol has set multiple different national environmental regulations into operation and the signing countries of the convention have increased their national expenditures on environmental protection.

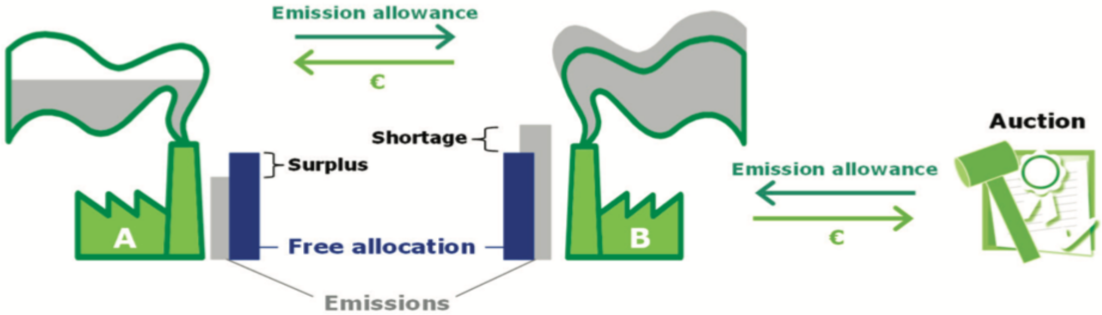
2.1.2 – The EU Emissions Trading System

Through national and harmonized environmental regulations, the European Union is striving to make Europe the first climate-neutral continent (European Commission, 2019). The EU Emissions Trading Scheme was introduced in 2005. Ever since, the EU ETS has undergone

[1] The IPCC is created in 1988 by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP) with the objective to provide governments and institutions with scientific information that can be used to develop climate policies (IPCC, 2021).

several changes in the stringency of the regulations and is the world's largest and longest running international system for trading emissions allowances (European Commission, 2015). The first phase ran from 2005 to 2007, following with the second phase from 2008 to 2012. The third phase began in 2013 and was followed by the fourth phase since 2021. The EU ETS is a 'cap and trade' system. A specific cap is set on the total amount of greenhouse gas emissions allowed for a specific installation. Within this cap, enterprises buy or receive allowances for their emissions, which are tradable on the carbon market against a carbon price. The cap has reduced over the years, through the different phases of the system, to lower the overall emissions (European Commission, 2015). As the number of emission allowances is limited in supply and decreasing over the years, the carbon price has shown a surge in the last years (Hook, 2021). This 'cap and trade' system provides market-based flexibility which ensures that overall emissions are cut where it costs least to do so (European Comission, 2015). The increasing prices on the carbon market in turn provide a representation of the changes in the stringency of the environmental policy. Figure 1 provides an overview on how the EU ETS operates. Policymakers have envisioned that the market-scheme will be a driving force of innovation and economic growth (Calel & Dechezleprêtre, 2016).

Figure 1: the EU Emissions Trading Scheme (European Commission, 2015)



2.2 – Theoretical background

2.2.1 – The role of environmental policy on international competitiveness

Since the first major environmental policies were established in the 1970s, a large debate has arisen regarding the potential competitiveness concerns of regulations directed towards environmental objectives. These concerns originate from the fact that there are large asymmetries worldwide in the stringency of such environmental regulations. Over the years, two main theories have evolved: the pollution haven hypothesis and the hypothesis of Porter. The theories do not have to rule each other out and can be complimentary, as they are both based on different definitions of an economy's international competitiveness.

First, the pollution haven hypothesis is based on trade theory. International competitiveness that relies on the Ricardian trade theory, is defined as a country's comparative advantage over other countries. The real effective exchange rate (REER) can serve as an indicator for this widely applied definition of international competitiveness. The REER compares the value of a nation's currency against a weighted average of currencies of a country's major trading partners. An increase in a nation's REER indicates that the exports become more expensive in relation to the country's imports, which in turn implies a loss in international competitiveness. In a world that is increasingly characterized by the integration of trade and capital flows, industries and policymakers foresee that environmental policy asymmetries could potentially shift production of pollution-intensive enterprises towards countries with less stringent regulations (Dechezlepretre & Sato, 2017). The increasing costs from complying with environmental policies, such as environmental taxes and prices on carbon emissions, create a comparative disadvantage for firms in comparison to their foreign rivals that are not bounded to these regulations. This can induce pollution-intensive firms to shift production towards low-cost regions (Naegele & Zaklan, 2019). The low-cost regions become pollution havens where enterprises can pollute freely since no additional costs are enforced.

The pollution haven hypothesis foresees a negative impact of environmental regulations on both the climate and an economy's international competitiveness. First, the shift of production only moves carbon leakage elsewhere which ultimately offsets the initial abatement efforts of lowering global levels of CO_2 pollution. Second, environmental regulations cause changes in a country's market-share in pollution-intensive industries. The domestic firms lose their market-share to unregulated foreign competitors, who do not have to bear the additional cost burden of strict environmental regulations (Naegele & Zaklan, 2019). The (neo-)classical Ricardian trade theory argument behind the pollution haven hypothesis argues that countries loose comparative advantage in pollution intensive industries by enforcing environmental regulations. Following this theory, the REER increases due to environmental regulations, as the domestic production costs increase, and hence the exports become more expensive in comparison to the imports.

The hypothesis of Porter (Porter, 1991; Porter and Van der Linde, 1995) is based on the definition of international competitiveness as the productivity level that companies located in the country can achieve (Ketels, 2006). Porter suggests that stricter environmental regulations and constraints promote cost-cutting efficiency improvements and induce firms to invest in innovation and clean technologies, increasing overall productivity. In this study, the Porter hypothesis serves as the starting point. Therefore, the next section will dive deeper into the formulation and theory behind this hypothesis.

2.2.2 – The Porter Hypothesis

Michael E. Porter is a professor in business strategy economics at Harvard Business School. In 1991, thirty years ago, he established a conventional theory on the impact of environmental policy. He states the following:

> *"The conflict between environmental protection and economic competitiveness is a false dichotomy. Strict environmental regulations do no inevitably hinder competitive advantage against foreign rivals; indeed, they often enhance it. However, properly constructed regulatory standards, which aim at outcomes and not methods, will encourage companies to re-engineer their technology. The result in many cases is a process that not only pollutes less but lowers costs or improves quality"* (Porter, 1991).

While the pollution haven, market-share-based, hypothesis defines competitiveness as the ability to sell on international markets and is fundamentally concerned with the sustainability of an economy's overall external balance, Porter defines the competitiveness of a location as the productivity level that companies located there can achieve (Ketels, 2006). It is important to emphasize that it is a false dichotomy to always see both hypotheses as opposing theories.

Porter's initial line of thinking is based on anecdotical evidence. During the 80s and 90s, both Germany and Japan had tough environmental regulations, while both countries continued to surpass the United States in GDP and productivity growth. Furthermore, Porter saw that Japan had become a world-leader in developing more efficient processes (Porter, 1991). He found that the "Chicken-Little" mind-set and lobbying gibberish, that environmental regulation inevitably leads to costs, must be discarded. Porter argues that environmental regulations can be a win-win strategy: stimulating better environmental quality and creating higher overall firm productivity (Ambec et al., 2013). The general idea behind this hypothesis is related to the argumentation of Hicks (1932), which suggests that a change in the relative prices of the factors of production will spur innovation directed to economizing the use of this relatively expensive factor. In the context of environmental regulations, Porter (1991) and Acemoglu et al. (2012) have restated this theorem by Hicks (1932), suggesting that when regulated firms face higher costs on emissions relative to other production factors, they are inclined to invest in reducing the emission intensity of their output and part of this new investment will be directed towards developing and commercializing new emissions-reducing technologies (Calel and Dechezleprêtre, 2016).

Following the framework of Acemoglu (2002), technical change is in most situations not neutral: *'technological change benefits some factors of production, while directly or indirectly reducing the compensation of others'* (Acemoglu, 2007). The direction of technical change is determined by the relative profitability of the different types of technologies (Acemoglu, 2002). The presumption is that the same profit incentives that affect the amount of technical change will also shape the direction of this technical change, and therefore determine the equilibrium bias of technology (Acemoglu, 2002). Innovation-induced technological change is one of the most common approaches used to endogenize technological change (Popp et al., 2010). Two competing forces dictate the relative profitability of innovation: the price effect and the market-size effect. Following the price effect, firms are encouraged to innovate in technologies directed at the more expensive, scarce factors (Acemoglu, 2002). The market-size effect incentivizes firms to invest in technologies that use the more abundant factor (Acemoglu, 2002). The framework of Acemoglu (2002) shows that the elasticity of substitution of the factors of production determines the relative strengths of both effects. Therefore, factoring in directed technical change implies that, when inputs are sufficiently substitutable, firms can be nudged and directed towards innovation of a certain factor through temporary policy intervention (Acemoglu et al., 2012). Regarding the environmental context, policy stimulates cost-cutting efficiency improvements and fosters innovation in new technologies, that may reduce or even offset the costs accompanying the environmental regulations (Dechezlepretre & Sato, 2017). Also, evidence in the environmental context suggests that technology is directed towards the activities with greater profitability (Acemoglu et al. 2012). Newell, Jaffe and Stavins (1999) find that increasing energy prices encourage the direction of technological change in air conditioning and Popp (2002) relates energy prices and innovation directed towards energy saving.

Hence, Porter's hypothesis suggests that environmental regulations stimulate and foster innovation directed at clean energy and production, which in turn may reduce or even offset the costs of compliance (Porter, 1991). The assumption is that there are certain profitable opportunities for improvement that firms do not fully make use of already. The implementation of new environmental policies provides firms the push to do so. (Koźluk & Zipperer, 2015). A clear-cut question in this case is why policymakers can better understand where certain win-win areas lie than firms themselves. After all, if there are certain profitable opportunities, profit maximizing firms would already have adopted them (Ambec et al., 2013). Porter and Van der Linde (1995) argues that due to the existence of market failures, such as information asymmetries and imperfect competition, enterprises see no reason to or are unable to start a risky process, even though there are net expected gains. This is also related to the question of factoring in state and path dependency in the model of directed technical change. Past innovations complementing an 'environmental dirty' production factor make current innovations directed at that factor the cheaper choice (Acemoglu et al, 2012). In other words, the direction of technical change is dependent on the path firms are following. Enterprises that have innovated in dirty technologies in the past, see more profitability in innovating in these dirty technologies in the future (Calel and Dechezleprêtre, 2016). Acemoglu et al. (2012) shows that path dependency in combination with the environmental externality, if firms do not take in account a potential loss in aggregate productivity or consumer utility induced by environmental degradation, will lead to a *laissez-faire* economy where enterprises will innovate too much in dirty technologies in comparison to the social optimum (Aghion et al., 2016). Therefore, government intervention through environmental regulations is needed to redirect the technical change, provided that the factors are substitutable (Acemoglu et al., 2012). Another argument in favor of Porter's hypothesis is that managers are risk averse, myopic or rationally bounded to react on profitable opportunities and need a push from policy makers to redirect technical change (Koźluk & Zipperer, 2015). Effective policies, such as a carbon tax, R&D subsidy or tradable emissions, can help reinforce the growth of clean innovation (Acemoglu et al. 2012; Aghion et al., 2016). The objective of environmental policy is to reduce carbon emissions, but seen from an economic perspective, it is crucial that policy also provides incentives for technological change, since this may reduce the long-run costs of abatement (Calel & Dechezleprêtre, 2016).

The Porter hypothesis can be subdivided into three versions, first differentiated by Jaffe and Palmer (1997): the weak, strong and narrow version. The weak version argues that there is a positive effect of environmental regulations on innovation, even though the opportunity costs might initially exceed the benefits of innovation (Rubashkina et al., 2015). Profit maximizing firms will find the most cost-effective alternatives to comply with the new established regulations, by investing in innovative activities. Secondly, the strong version postulates the idea that environmental policy will lead to increasing productivity, through channels of increasing innovation activity. Environmental regulations stimulate firms to rethink their production processes, leading to improvements that offset the regulatory costs from compliance (Koźluk & Zipperer, 2015). The third, most narrow hypothesis focuses on the type of policy, stating that environmental policy that is designed to target the environmental outcome rather than the type of production processes, is expected to better stimulate innovation and economic performance. Hence, according to the narrow hypothesis, market-based and flexible instruments of environmental policy, are more likely to stimulate innovation and productivity growth in comparison to command-and-control regulations (Hille & Möbius, 2019; Koźluk & Zipperer, 2015). As we do not explicitly distinguish between different type of policies, this study will only investigate the weak and strong version of Porter's hypothesis: the innovation effect and the productivity effect.

2.2.3 – The Determinants of Economic Performance

Porter defines international competitiveness by an economy's productivity level. Productivity was one of the key pillars in the agenda of the European Union for 2020 (NIESR, 2016). This is not different for 2021 or the upcoming years as productivity is widely recognized as a key mechanism for increasing living standards. Productivity is the quantity of output that can be produced using a certain level of input factors (Hall, 2011). There is renewed interest in understanding why some nations are leading the race on productivity growth against countries with otherwise similar levels of economic development (NIESR, 2016).

Government programs and policies affect productivity growth, i.e. higher taxes reduce productivity growth of industries, through increased costs (Eichler et al., 2006). The traditional view of environmental policy suggests a direct negative impact on productivity growth, through increased production costs. Moreover, indirect negative effects may arise, through increased input prices resulting from changes in the stringency of environmental policies (Barbera & McConnell, 1990). As an example, the EU ETS imposes an additional production related cost-burden for an initially free product, which in turn decreases productivity growth. However, another key determinant of productivity growth is innovation. Through innovation, environmental regulations can have a positive indirect effect on productivity growth. Innovation induced productivity growth, originated from environmental policy, is the concept on which Porter primarily relies in his hypothesis.

The relationship between innovation and productivity has always been a predominant aspect of economic growth literature. Schumpeter (1942) characterizes innovation as the engine of productivity growth. The OECD and Eurostat define innovation, in the notorious Oslo Manual for innovation, as follows:

"Innovation is the implementation of a new or significantly improved product or process (or combination thereof), that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)." (Oslo Manual (OECD/Eurostat 2018) - 4th edition, p. 20)

This definition suggests that innovation can be both product- and process-based. The implementation of new products in the market will create new sources of demand, which can influence rising economies of scale in the production (Mohnen & Hall, 2013). Moreover, new implemented products might require lower amount of production inputs. This implicitly indicates that implementing new products improves the production process, providing a clear-cut connection with process innovation. Innovating and renewing processes is often undertaken to reduce production costs by saving on the more costly inputs (Mohnen & Hall, 2013). Empirical findings over the past 20 years confirm a positive impact of both product and process innovation on productivity growth (Hall, 2011; Mohnen & Hall, 2013). Griffith et al. (2006) find a positive role for innovation in affecting productivity growth for European countries.

It is hard to get a good grasp on measuring innovation perfectly, but it can be proxied among others by R&D expenditures and patent applications. Both measures do not fully represent the definition of innovation as stated by the Oslo Manual, as they ignore the importance of the fact that R&D expenditures and patents need to be exploited well to be qualified as innovation. However, as no perfect measures exist, this study uses the sectoral R&D expenditures to proxy for innovation. R&D expenditures are well known to have two faces: stimulating innovation and enhancing technology transfers (Griffith et al., 2004). R&D can directly increase productivity growth through development of new products and more efficient production processes, but larger R&D expenditures may also boost productivity growth indirectly, as R&D enhances the assimilation of technologies from foreign economies (Jacobs et al., 2002). Assuming all else equal, if environmental policy such as the EU ETS stimulates R&D expenditures, it can have a positive impact on productivity growth, through innovation and technology spillovers. Finally, there are of course other important key determinants of productivity growth, such as trade, human capital and sustainable management, which the Porter hypothesis does not directly account for.

To estimate the effect of environmental policy on productivity growth, this paper uses total factor productivity (TFP) growth. TFP growth is the fraction of production output growth that cannot be attributed to the primary input factors of production and their respective nominal shares (Stehrer et al., 2019). Let the production function be given by:

$$Y_{jt} = f_{jt}\,(I_{jt}, L_{jt}, K_{jt}, T_{jt})$$

where Y_{jt} denotes the production output of sector *j* at time *t*. This output is equal to the function (f_{jt}) of the input factors: intermediate input (I_{jt}), labor (L_{jt}) and capital (K_{jt}). Moreover, T_{jt} represents the (unobserved) level of technology (Stehrer et al., 2019). The production function assumes constant returns to scale with respect to the primary and intermediate inputs (Jacobs et al., 2002). Furthermore, the function displays a competitive product and factor market with full input utilization (Stehrer et al., 2019). TFP growth is described as the output growth due to technological innovation growth (Schumpeter, 1942). Using a log transformation, similar as in Stehrer et al. (2019), it can be derived as:

$$\Delta \ln TFP_{jt} = \Delta \ln Y_{jt} - \vartheta_{I,jt}\,\Delta \ln I_{jt} - \vartheta_{L,jt}\,\Delta \ln L_{jt} - \vartheta_{K,jt}\,\Delta \ln K_{jt}$$

where $\Delta \ln TFP_{jt}$ denotes the TFP growth and $\Delta \ln Y_{jt}$ equals $\ln Y_{jt} - \ln Y_{jt-1}$ (similar for the inputs *I*, *L* and *K*). The nominal shares of the input factors in gross output are denoted by ϑ_{jt}.[2]

In this study however, TFP growth is defined as the fraction of value-added growth that cannot be attributed to the primary input factors of production and their respective nominal shares. In line with the forementioned total output function, a production function using value added has the following form, where a separability assumption between the intermediate inputs and primary inputs is required:

$$Y_{jt} = f_{jt}\,\left(I_{jt}, g_{jt}\,(L_{jt}, K_{jt}, T_{jt})\right)$$

[2] We use the Divisia Index, $\vartheta_{jt} = \frac{fp_{jt}F_{jt}}{P_{jt}Y_{jt}}$, where F_{jt} equals the input factors *I*, *L* and *K*. The gross output price index is denoted by P_{jt}, while the production factor input prices are denoted by fp_{jt}. Due to the assumption of constant returns to scale the sum of all factors' nominal shares are equal to 1 (Stehrer et al., 2019).

In this function, output (Y_{jt}) is equal to the function (f_{jt}) of the intermediate input (I_{jt}) and the function (g_{jt}) of the primary inputs and technology (L_{jt}, K_{jt}, T_{jt}). The second function (g_{jt}) represents value-added production, which equals:

$$VA_{jt} = g_{jt}\left(L_{jt,}\, K_{jt,}\, T_{jt}\right)$$

Following this, TFP growth can be derived as follows.[3]

$$\Delta \ln TFP_{jt} = \Delta \ln VA_{jt} - \vartheta_{L,jt}\, \Delta \ln L_{jt} - \vartheta_{K,jt}\, \Delta \ln K_{jt}$$

where $\Delta \ln TFP_{jt}$ denotes the TFP growth and $\Delta \ln VA_{jt}$ equals $\ln VA_{jt} - \ln VA_{jt-1}$ (similar for the inputs L and K). The nominal shares of the input factors are denoted by ϑ_{jt}. According to the above established conceptual framework of productivity growth, TFP growth captures technological change. However, in practice, TFP also expresses efficiency change, economies of scale, variations in capacity utilization and measurement errors (Rubashkina et al., 2015).

2.2.4 – The measures of environmental policy stringency

This study investigates the innovation- and productivity growth impact of EU's environmental policy on regulated sectors. Unfortunately, we do not have data of a fictional control group that captures what would happen if the regulated sectors would not be regulated, all else equal (Dechezlepretre & Sato, 2017). This is called the fundamental problem of causal inference. Therefore, we require a proxy for the stringency of the environmental policy to identify the effects of changes in the stringency on economic outcomes (Kozluk & Zipperer, 2014). These measures of environmental stringency provide a convenient source of variation in comparison to country-industry-invariant carbon prices (Dechezlepretre & Sato, 2017). However, finding an appropriate measure for the stringency of environmental policies is difficult and has played a prominent role in environmental research over the past twenty years (Brunel & Levinson, 2013). Although there are various approaches to measure the stringency of environmental policy, all are likely to be fraught with measurement errors (Dechezlepretre & Sato, 2017). The challenges of finding an appropriate measure relate not solely to data collection and the scarcity of adequate resources but derive from a much deeper set of conceptual econometric problems, such as multidimensionality and simultaneity (Brunel & Levinson, 2016).

A variety of approaches have been used to measure the stringency of environmental policy. Continuous efforts are being undertaken by the OECD to help with the further development of environmental policy indicators (OECD, 2005). A common source is the

[3] This study uses the annual TFP growth contributions to value added growth in percentages to measure the economic outcomes of environmental regulations.

OECD Environmental Policy Stringency index (Botta & Koźluk, 2014). Unfortunately, these data are only available until 2014. Also, the shadow prices of energy have been interpreted as a measure of the stringency of both environmental (Van Soest et al., 2006) and climate policy (Hille 2018). Khademvatani and Gordon (2013) defines the shadow price of energy as the price reflecting the willingness to pay for one more unit of energy input. As environmental regulations have a direct and indirect effect on the price of emissions-relevant energies, shadow prices reflect the stringency of the regulations (Hille & Möbius, 2019). The advantage of using the shadow price of energy is that it converts a muldimensional environmental policy into a single measure of costs (Brunel & Levinson, 2016). However, shadow prices can also reflect changes in the stringency of other non-environmental policies that influence the price of the polluting input energy (Althammer and Hille, 2016). Shadow prices are not necessarily the result of regulatory stringency (Brunel & Levinson, 2016). Alternative studies have used environmental performance data, such as energy-intensity (Harris et al., 2003) or pollution intensity rates (Brunel & Levinson, 2013), as proxy for environmental stringency. Lanoie et al. (2011) uses data on the perception of firms regarding environmental stringency. Alternatively, studies using difference in difference estimations use a more event-study based approach to measure the effects of an environmental policy (Van der Vlist et al., 2007). Some studies use even the voting-records of state representatives in congress regarding pro-environmental topics as proxy for environmental stringency (Gray, 1997), while some other empirical papers look at the frequency of environmental related inspections (Brunnermeier & Cohen, 2003). All different methods have certain drawbacks and research on finding the appropriate measure is still present.

This study applies the measure of environmental policy stringency that has been predominantly adopted in empirical literature: the pollution abatement and control expenditures (PACE). Sectoral pollution abatement and control expenditures in principle measure the compliance costs of sectors following the environmental regulation. The earliest and most comprehensive PACE data origins from the US Census Bureau survey, that was annually conducted since the 1970s (Brunel & Levinson, 2013). Many researchers have used this survey to construct a proxy for environmental policy stringency. In Europe and Asia-Pacific similar surveys have been conducted since the 1990s (Dechezlepretre & Sato, 2017). For the European Union, we use industry-level data on environmental protection expenditures, which are defined by the OECD as 'the expenditures on purposeful activities aimed directly at the prevention, reduction and elimination of pollution arising as a residual of production processes' (OECD, 2005). These expenditures are interpreted as being induced by the environmental regulations and hence destined to proxy for the stringency of the regulations (Koźluk & Zipperer, 2015). The country-sector level variability of these data makes it a good proxy for this study. The assumption is that more stringent regulations, including the stringency of the EU ETS over the years, force firms to increase their pollution control expenditures. Unfortunately, this proxy goes hand in hand with certain econometric drawbacks, such as poor comparability over time, the self-reporting nature, and problems with defining what part of the expenditures are induced by the environmental policy (Koźluk & Zipperer, 2015). Higher pollution control expenditures may arise predominantly from older firms, instead of from the stricter policies (Ambec et al., 2013). Moreover, the issue of simultaneity comes to place with using this measure of environmental policy stringency. We try to address these endogeneity issues by adopting an instrumental variable approach.

2.3 – Empirical findings

The economic effects of environmental policy have gained the interest of environmental economists over the past thirty years, due to the worldwide adoption of different environmental regulations. This resulted in a vast literature on the Porter hypothesis. This study emphasizes on both the weak and the strong version of the Porter hypothesis. Therefore, we divided this section into the 'innovation effect' (weak Porter hypothesis) and the 'productivity effect' (strong Porter hypothesis). Respectively appendix 2A and 2B present an overview of the important empirical findings in table form. Based on these findings and all theory discussed above, we construct our hypotheses for the innovation and productivity effects of EU's environmental policy.

2.3.1 – Environmental regulations and innovation

The literature on the innovation effect, dating back to Hicks (1932), is vast and most of the empirical findings are in line with the weak hypothesis of Porter. The ability of an environmental policy to direct technological change towards clean energy is one of the most substantial criteria on which to judge the success of the regulations (Calel & Dechezleprêtre, 2016; Acemoglu et al., 2012). For this reason, many empirical studies have investigated the capacity of environmental regulations to encourage innovation. Research and development expenditures and patent applications provide the straightforward proxies for innovation activity in most studies.

A first descriptive analysis study using a simple time-series correlation by Lanjouw and Mody (1996) finds that the increasing interest in environmental protection over the 1970s and

1980s has led to the development of new pollution control technologies and innovation, measured by patents and R&D spending, in Japan, Germany and the United States. Moreover, the study by Jaffe and Palmer (1997) is an important forerunner of the innovation effect. They adopt a panel regression study using industry-specific fixed effects, whereby PACE data of U.S. manufacturing industries serves as the measure of environmental policy stringency. Jaffe and Palmer (1997) finds a significant positive relationship between the regulatory compliance expenditures and R&D, but the magnitude of the effect is small. However, the study finds no significant effect when proxying innovation by the amount of patent applications in the U.S. The results of Jaffe and Palmer (1997) are consistent, although limited, with Porter's weak hypothesis and suggest that environmental policy stimulates certain forms of innovation. In line with Jaffe and Palmer (1997), Brunnermeier and Cohen (2003) used PACE data to proxy for environmental stringency and found a positive effect on environmental innovation measured by the number of successful environmental patent applications granted. However, the magnitude of the effect is relatively small, with a 0.04 percentage increase in the number of patents per one-million-dollar additional pollution abatement expenditures (Brunnermeier & Cohen, 2003). Moreover, the study finds no evidence for increasing monitoring and enforcement activities being an incentive to conduct in innovative activities. The internationally competitive industries were the most eager to adopt environmental innovation, according to Brunnermeier and Cohen (2003). For Japan's five most pollution intensive industries, Hamamoto (2006) finds a positive relationship between pollution control expenditures and R&D expenditures. Popp (2002)[4] and Newell et al. (1999) relate innovation activity to changes in energy prices and find evidence for the fact that innovation increases in the period following a duration of high energy prices. This empirical evidence indicates that changes in the relative price of energy impact the direction of technical change (Acemoglu et al., 2012). Moreover, the results suggest that innovation is a response of environmental concerns (Newell et al., 1999). A similar positive relationship is found between environmental taxes and R&D expenditures (Lanoie et al., 2011; Johnstone & Labonne, 2006). Furthermore, Arimura et al. (2007) contributes to the empirical literature on the innovation effect by providing evidence for a positive impact of survey data, that measures the perception of environmental stringency, on environmental R&D expenditures.

[4] Popp (2002) emphasizes on the necessity of including the knowledge quality of firms to avoid biased results, as new innovations build on past achievements, which is the reason for including our knowledge stock variable into our regression.

For the European Union, empirical literature is more scarce. Rubashkina et al. (2015) investigates the weak and strong version of the Porter hypothesis for a panel of European manufacturing industries between 1997 and 2009, using an instrumental variable approach to account for potential endogeneity of the PACE variable. The explanatory variable, environmental policy stringency, is instrumented by the average share of PACE intensity of adjacent industries within the same country, excluding the measured sector: $PACE/VA_{-j}$ (Rubashkina et al., 2015). The paper argues that there is a strong correlation between environmental regulations applied to different sectors within the same country, suggesting that therefore the PACE intensity of adjacent sectors is strongly correlated with the measured sector's PACE intensity (Rubashkina et al., 2015). Additionally, this instrument ($PACE/VA_{-j}$) is interacted with pre-sample sectoral energy intensity, since within the countries the environmental regulations of energy-intensive sectors might differ from those of less energy-intensive sectors, according to Rubashkina et al. (2015). All in all, the idea is that these instruments are strong predictors of the sectoral PACE variable, but are not directly correlated with unobserved factors impacting innovation, and therefore help avoiding biased results caused by the endogeneity issues surrounding the PACE variable (Rubashkina et al., 2015). The postestimation IV-tests confirm the relevance and validity of the instruments. We discuss this approach in more detail in the methodology section, as our instrument follows a similar approach. The results of this paper by Rubashkina et al. (2015) indicate that environmental policy induces innovation, when measured by patent applications. However, the authors find no significant effect when measuring innovation by R&D expenditures. Xing and Kolstad (2002) also adopted an instrumental variable approach in their estimation on the relationship between FDI in the U.S. and environmental regulations of foreign countries. Their instrument consists of all the exogenous variables and two external exogenous variables: infant mortality and population density. The infant mortality variable serves as an indicator for social consciousness, which is likely to influence the stringency of environmental regulations (Xing & Kolstad, 2002). The more conscious a country is towards social issues, the stricter the environmental regulations will be. Population density serves as an indicator of congestion and the ability of pollutants to naturally disperse away from population centers (Xing & Kolstad, 2002; De Vries & Withagen, 2005). The idea is that when the population density is high, stricter environmental regulations are needed. De Vries and Withagen (2005) adopts a similar approach as Xing and Kolstad (2002) to investigate the weak Poter hypothesis for 18 OECD countries and finds a significant and large positive effect of environmental regulations on environmental patents. Unfortunately, both studies fail to provide details and arguments on the validity of their instrument (Koźluk & Zipperer, 2015). Finally, Kneller & Manderson (2012) finds evidence for a positive relationship between environmental protection expenditures and environmental R&D, for manufacturing industries in the United Kingdom. However, a similar relationship was not found for total R&D spending.

Although Rubashkina et al. (2015) and Kneller and Manderson (2012) find no effect when proxying innovation with overall R&D spending, all other empirical findings discussed above and the theoretical background has led us to the following hypothesis on the innovation effect of EU's environmental policy:

Hypothesis 1:

Environmental policy in the European Union, including the major flexible market-based EU Emissions Trading Scheme, has a positive impact on industry-level innovation activity proxied by total R&D expenditures for the period 2008 to 2017, consistent with the weak hypothesis of Porter.

2.3.2 – Environmental regulations and productivity

Productivity effects can originate from changes in stringency of environmental regulations both through a direct and indirect effect (Barbera & McConnell, 1990). Although environmental policy may positively impact the long-term sustainability of our economies, traditional views tend to see the regulations as an extra cost-burden that negatively impacts the short and medium-term productivity (Koźluk & Zipperer, 2015). On the other hand, theory argues in favor of innovation induced economic growth, through directed technical change encouraged by environmental regulations (Porter, 1991; Acemoglu et al., 2012).

With regards to the direct effect, the study by Gray (1987) tried to find a relationship between the U.S. productivity slowdown of the 70s and environmental regulations. Gray (1987) found a strong negative correlation between productivity and pollution abatement and control expenditures for 450 U.S. manufacturing industries, but these findings disappeared upon the inclusion of relevant controls or the elimination of outliers (Gray, 1987; Koźluk & Zipperer, 2015). Barbera and McConnell (1990) and Dufour et al. (1998) found a similar negative relationship between environmental regulations and productivity, but these studies are suffering from serious identification issues. Barbera and McConnell (1990) studied the cost elastictity of pollution abatement requirements and found that these environmental abatement requirements lower productivity in the five most pollution-intensive industries, accounting for 10 to 30 percent of the decline in productivity. However, the study lacked to control for industry fixed characteristics. Furthermore, Dufour et al. (1998) found that environmental regulation has led to a reduction in productivity growth, but used a very small sample of the Quebec (Canada) manufacturing industry. At the firm and plant level the effects of environmental policy on TFP growth are either negative but small (for the Canadian brewing industry: Smith & Sims, 1985) or positive but insignificant (for oil refineries: Berman & Bui, 2001). Furthermore, Conrad and Wastl (1995) found pollution abatement costs to reduce the level of total factor productivity for ten pollution intensive German industries, when looking at the effect in terms of cost diminution.

In Lanoie et al. (2008), the stringency of environmental policy in Canada is measured by the ratio of pollution-control investment to total costs. The panel regression results show a negative effect of this ratio on total factor productivity (Lanoie et al., 2008). Interestingly, the study finds the negative effect of investment in pollution control equipment on TFP growth to disappear after three years. This suggests that productivity effects may arise with some delay and are characterized by an dynamic aspect. Yang et al. (2012) finds even a positive direct effect of PACE on TFP after the second year for Taiwanese manufacturing industries. However, it is important to emphasize that using a lag structure can introduce all kinds of problems and biases. A lag-structure is almost never the solution to endogeneity issues, but merely moves the channel through which endogeneity biases arise (Bellemare et al., 2017; Reed, 2015). The conditions for achieving a causal identification, while using lagged explantory variables, are that there is serial correlation in the endogenous independent variable, but no serial correlation among the unobserved variables (Bellemare et al., 2017). Hence, the identification assumption purely shifts from “selection on observables” to “no dynamics among the unobservables” (Bellemare et al., 2017). Therefore, it is hard to capture the real long-term dynamic effects of environmental policy (Koźluk & Zipperer, 2015).

Based on all of the above our hypothesis for the direct productivity effect is:

Hypothesis 2A:

Environmental policy in the European Union, including the major flexible market-based EU Emissions Trading Scheme, has a negative direct effect on industry-level productivity growth through the added cost-burden accompanying compliance with the policy.

However, empirical literature also investigated the strong Porter hypothesis, related to the question if innovation, induced by environmental regulations, can more than fully offset the costs of compliance and enhance productivity (Calel & Dechezleprêtre, 2016). Although the literature does suggest that the costs of environmental regulations are smaller than anticipated, due to induced innovation (Calel & Dechezleprêtre, 2016; Acemoglu et al., 2012), the empirical findings are not conclusive with regards to this strong version of the Porter hypothesis.

Many researchers have investigated innovation-induced productivity growth by estimating the effects of R&D spending, induced by environmental policy, on TFP growth. Using the fitted values of the estimated results of the innovation effect, Hamamoto (2006) finds empirical evidence for the fact that increases in R&D expenditures stimulated by regulatory stringency (measured by pollution control expenditures) have a significant positive effect on the TFP growth rate. This implies that the burden of environmental compliance gives firms an incentive to innovate directed towards cleaner production technologies, which improves overall productivity (Hamamoto, 2006). Additionally, through a fixed-effect panel regression, Yang et al. (2012) finds a positive effect of induced R&D on productivity levels. On the other hand, however, Lanoie et al. (2011) finds no support for the strong version of the Porter hypothesis. The authors argue that the direct negative effect of environmental stringency on economic performance is greater in size than the indirect positive effect through channels of innovation (Lanoie et al., 2011). Also, the more recent paper by Hille and Möbius from 2019 finds no support for a R&D-induced positive productivity effect of environmental regulations, measured by the shadow prices of energy. This study emphasizes that disregarding endogeneity concerns will significantly alter the productivity growth effects of environmental regulations, leading to biased estimates (Hille and Möbius, 2019). First, the fixed-effects estimates show a significantly positive effect of changes in the environmental policy stringency on productivity growth, but after taking simultaneity issues in account, using a dynamic panel generalized method of moments (GMM) estimator, the coefficient estimates are shown to be insignificant and partly negative (Hille and Möbius, 2019). Furthermore, Rubashkina et al. (2015) finds no evidence for the strong Porter hypothesis. As discussed in the previous section, Rubashkina et al. (2015) adopts an instrumental variable approach and in line with Hille and Möbius (2019), the study argues that not controlling for endogeneity of the environmental policy stringency measure delivers biased results. Alternatively, using the OECD environmental policy stringency index, Martínez-Zarzoso et al. (2019) finds evidence for a positive impact of environmental stringency on productivity growth in the long-term.

As shown, the empirical findings are inconclusive. In line with the theoretical hypothesis that innovation, induced and directed by environmental regulations, can more than fully offset the costs of compliance and enhance productivity, we adopt the following hypothesis:

Hypothesis 2B:

Environmental policy in the European Union, including the major flexible market-based EU Emissions Trading Scheme, has a positive impact on industry-level productivity growth through channels of R&D expenditures induced by environmental policy, for the period 2008 to 2017, which is consistent with the strong hypothesis of Porter

3 Methodology

In this paper, we empirically investigate the weak and strong version of the Porter Hypothesis for the manufacturing and mining sectors in 18 countries of the European Union. The manufacturing and mining industries are direct and/or indirectly affected by EU's environmental regulations, as a transformation of the industrial sector is required to reach the climate targets of the European Union. The EU ETS covers the CO_2-pollution of energy-intensive industry sectors, including oil refineries, steel works, and production of iron, aluminum, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals (European Commission, 2015).[5] This includes most of the mining and manufacturing sectors within our sample. Moreover, the greenhouse gas emissions associated with combustion activities in the food and drink sector are covered by the EU ETS (European Commission, 2015). In 2021, the food, drink and tobacco sector is the fifth largest greenhouse gas emitter in the manufacturing industry (Cameron et al., 2021). Additionally, energy efficiency and CO_2 reduction, in relation with the EU ETS, are of critical importance for the textile and clothing industry (European Commission, 2015). The level of aggregation of the sectors, following the NACE revision 2 industry classification, is based on data availability of the TFP growth ratios and the environmental policy stringency variable. Appendix 1A and 1B provide a compact overview of the countries and sectors within the sample.

The first estimation component within this study investigates the effect of environmental policy on innovation activity, measured by industry-level R&D expenditures. The second component estimates both the direct effect of environmental regulations on industry-level productivity growth and the indirect, innovation induced productivity growth effect.

Both components rely primarily on finding an appropriate measure that determines the stringency of environmental policy across countries within the European Union over the period 2008 to 2017. The complexity of measuring environmental stringency is one of the main challenges in empirical research on the competitiveness effects of environmental policies (Botta & Koźluk, 2014). We use data on Environmental Protection Expenditures (EPE), in empirical research commonly defined as Pollution Abatement and Control Expenditures (PACE), at the country-sector level, to proxy for the stringency of environmental regulations in the EU. The

[5] The Annual European Union greenhouse gas inventory 1990-2018 and inventory report 2020 presents the activities covered by the EU ETS summarised for the different sectors. This contains an elaborate greenhouse gas inventory report by the European Environmental Agency (EEA).

EPE variable is defined as expenditures directly aimed at the prevention, reduction and elimination of pollution, arising as a residual of production processes or the consumption of goods and services (OECD, 2005). The idea is that these expenditures reflect the changes in the stringency of environmental regulations. The more stringent the regulations, the higher the environmental protection expenditures. Through this expenditures variable we identify the effects of environmental stringency changes on innovation activity and productivity growth. Although this measure is not the ideal proxy for environmental stringency, alternative measures all have significant shortcomings (Brunel & Levinson, , 2013). Moreover, the EPE variable fits the research question due to its cross-country sector-level variation. In aggregate terms at the sector-level, the environmental protection expenditures vary over time and across sectors and countries in ways that are consistent with intuition (Brunel & Levinson, 2016). Finally, the data are predominantly available for all countries and sectors within the sample. However, we do address some econometric drawbacks in section 3.3.

The OECD's data on environmental protection expenditures can be subdivided into investment in plant and equipment for pollution control and investment in plant and equipment linked to cleaner technology. Instead of using the aggregate level of the environmental protection expenditures, the EPE variable in the regressions solely consists of the pollution control expenditures, as measure for the stringency of EU's environmental policy (Hamamato, 2006). We do include in the regressions a variable containing industry-level investment in cleaner technology to control for its effect on R&D spending and productivity growth. Larger investment in already existing cleaner technology will probably lower the R&D expenditures directed towards developing new clean technologies.

The remainder of this chapter will discuss the baseline specification for estimating the innovation effect and the productivity effect in respectively section 3.1 and 3.2. Section 3.3 describes the identification assumptions and endogeneity problems related to the EPE variable. We use an instrumental variable approach to overcome these endogeneity issues.

3.1 – The innovation effect

The 'weak' hypothesis of Porter suggests that stricter environmental regulations enhance and stimulate innovation. To investigate this first component of Porter's hypothesis, we conduct a panel data regression, using a log-log structure to reduce skewness in the data, as adopted originally by Jaffe and Palmer in 1997. Ever since, this log-log structure is used in most empirical studies (Brunnermeir & Cohen, 2003; Hammamoto, 2006; Rubashkina et al., 2015). Therefore, the baseline specification has the following expression:

$$\ln R\&D_{ijt} = const + \alpha_{ij} + \mu_t + \beta \ln EPE_{ijt} + \varphi \ln KS_{ijt} + \gamma \ln X_{ijt} + \varepsilon_{ijt} \qquad (1)$$

where *ln* $R\&D_{ijt}$ denotes the log of the R&D expenditures of country *i*, in industry *j* at period *t*, with *t* in years since the dataset consists of annual data. The R&D expenditures serve as a proxy for cross-country sector-level innovation activity. The variable *const* denotes the regression constant, whereas α_{ij} and μ_t represent respectively country-sector- and year fixed effects. The main variable of interest is the log of environmental protection expenditures directed at pollution control, indicated by *ln* EPE_{ijt}, as proxy for the stringency of EU's environmental regulations. We also include the log of KS_{ijt} that represents the country-sector level knowledge stock, capturing the previous innovation activity. Popp (2002) argues that including such a knowledge quality variable is necessary to avoid biased results. Additionally, this study includes a vector of country- and industry specific control variables, denoted by X_{ijt}. All main- and control variables that are in euro's have been adjusted to dollars with OECD's purchasing power parities to correct for inflation and exchange rate variation across the countries within the sample (European Union & OECD, 2012). Purchasing power parities (PPPs) are currency conversion rates that equalize the level of purchasing power between countries, by eliminating the differences in price levels (European Union & OECD, 2012) and are measured in terms of Euro per US dollar.[6] Finally, all regressions use heteroskedasticity robust standard errors.

When estimating the innovation effect, an important role is played by industry-specific technology levels from the past, the so-called technology push factors or knowledge spillovers (Rubashkina et al., 2015; Horbach et al., 2012). As Caballero and Jaffe phrase it in 1993: 'innovators rely and build on the insights embodied in previous ideas; they achieve their success by standing upon the shoulders of giants'. Therefore, when estimating the effect of environmental policy on innovation, it is important to include a knowledge stock variable, capturing previous R&D expenditures. The underlying assumption here is that R&D expenditures create an industry-level stock of knowledge that has a positive impact on future innovative practices. The knowledge stock variable is constructed by using the workhorse of R&D capital estimation, the perpetual inventory method:

$$KS_{\mathrm{ijt}} = (1-\delta)KS_{\mathrm{ijt-1}} + R\&D_{ijt} \qquad (2)$$

[6] In the euro area, the price levels differ significantly. Therefore, PPP adjustments are still necessary to revalue the expenditures at a uniform price level. (European Union & OECD, 2012)

where KS denotes the knowledge stock and δ is a suitable chosen depreciation rate. The knowledge stock of industry *j*, in country *i*, at time *t*, consists of the previous year's knowledge stock (times $(1 - \delta)$) plus the current R&D expenditures. This means that each year's knowledge stock is dependent on the knowledge stock of previous years. For this reason, we need an initial benchmark knowledge stock to start off from. We set the benchmark year to be 2007, the year before the estimation period (2008-2017), and the initial benchmark knowledge stock is calculated as follows:

$$KS_{ijt0} = \frac{R\&D_{ijt0}}{\delta + g_{ij}} \qquad (3)$$

where t_0 represents the benchmark year 2007 and g_{ij} is the sector-country specific average R&D expenditures growth rate of the three years preceding the benchmark (2004 to 2006). After constructing the sector-country specific knowledge stock benchmark through equation (3), we have determined the sector-country level knowledge stocks for the years 2008 to 2017 by using equation (2). Finally, choosing the suitable depreciation rate plays a prominent role in empirical research on innovation.[7] The depreciation rate represents the rate at which the private returns to past R&D investments decline if no further R&D is undertaken (Hall & Rosenberg, 2010). Several empirical papers find depreciation rates for R&D capital to lie between 10% and 30% (Nadiri & Prucha, 1996; Bosworth, 1978; Hall, 2005; Pakes & Schankerman, 1984). Therefore, to empirically assess the relationship between environmental policy and innovation, this study conducts estimations with the 20 percent depreciation rate knowledge stock variable but checks for robustness of the results against using 10% and 30% levels of depreciation, in section 5.3.

Furthermore, the baseline specification consists of a vector of control variables, which includes gross value added (VA) as scaling variable; the cross-country sector-level birth- and death rate; the country-sector level export intensity and import intensity rates; and country-specific government budget allocation for R&D targeting the socio-economic objective of the environment. First, to control for variation in the industry size, the variable value added is included, which measures the contribution of sector *j* to overall GDP of country *i*. It is important to control for the industry size, as larger industries are likely to have the resources necessary to bear the risks involved with investment in innovative activities (Rubashkina et al., 2015). As

[7] Determining the exact depreciation rate is demanding and nearly impossible, as the industry-level depreciation rate is endogenous to enterprises' behaviour and dependent on the progress of public research and science, generating the question if it is constant over time and across industries (Hall & Rosenberg, 2010). Moreover, identifying this depreciation rate separate from the return on R&D requires establishes a lag structure of R&D in generating returns (Hall & Rosenberg, 2010; Hall, Griliches, & Hausman, 1986).

pointed out by Jaffe and Palmer (1997), value added is the appropriate size-scaling variable in this model, because the R&D-to-sales ratios across sectors are distorted by the industries' positions in the value-added chain at the country level.

Second, we include country-sector level industry birth and death rates to control for structural changes (affected by environmental policy) that influence the industry's innovation activity. The birth rate is defined as the number of new enterprises over the total of active enterprises at time *t*, for industry *j* in country *i*. The death rate represents the opposite: the number of enterprises that had to shut down their operations divided by the sector's total active enterprises. The number of structural changes in an industry, measured by firm entry and survival rates, represent the stability of an industry. Following Schumpeter's patterns of innovation, innovative activities are characterized by high degrees of concentration and stability (Malerba & Orsenigo, 1995). Hence, economic theory suggests that high birth- and death rates imply a high rate of turbulence and low stability, which negatively impacts total industry-level R&D (Malerba & Orsenigo, 1995). The survival rate of firms might also affect our EPE variable. When the enterprises most burdened by stricter environmental policy shut down or relocate their operations, the industry-level environmental protection expenditures are likely to decrease (Rubashkina et al., 2015).

Third, the model includes both country-sector level import and export intensity rates at the European level, that measure respectively an industry's external competition and participation in European trade. Additionally, these variables capture market concentration and competition intensity. The variables are defined as the number of importing respectively exporting enterprises over the number of active enterprises (including non-traders). The Schumpeterian hypothesis postulates a positive effect of market concentration on innovation, as a more concentrated market is more stable and contains of larger enterprises with less uncertainty, which in turn stimulates innovation (Schumpeter, 1942). On the other hand, Levin et al. (1985) suggests that a concentrated market lacks competitiveness which does not stimulate investment in renewed processes and innovation. Furthermore, Porter and Van der Linde (1995) argues that enterprises within international competitive industries have more incentives to invest in innovative activity as a response of stricter environmental regulations, since world demand and enterprise valuation shift towards pollution-clean processes and products. Hence, enterprises in internationally competitive industries stand to benefit more from investment in innovation. Furthermore, Brunnermeier and Cohen (2003) suggests that foreign competition spurs innovation. Overall, it is difficult to predict the sign of the coefficients accompanying the import and export intensity variables. However, we do expect the innovation activity effects to be larger for the international competitive industries.

Finally, the vector of controls includes government budget allocation expenditures that target the environmental issues to control for the impact of government R&D spending on private industry-level R&D. Government support and stimulation of research and development has shown to have a positive impact on industry-level R&D adoption and speeds up the adoption of foreign technologies through R&D spillovers (Jacobs et al., 2002).

Besides controlling for observed heterogeneity by including a vector of control variables, this paper adopts a panel data fixed effects (FE) estimation technique to account for unobserved heterogeneity across countries and sectors. The fixed effects control for country-industry specific time-invariant characteristics that affect R&D. Additionally, we include year-specific dummies to control for time fixed effects. In this way, we control for certain year-specific shocks and characteristics that affect overall innovation activity in the EU. Not including country-sector fixed effects and year fixed effects creates biased estimates as the unobserved variables affecting R&D are not accounted for (Hille & Möbius, 2019).

Finally, the baseline specification in equation (1) is not in the form of a one-year lagged structure as originally suggested by Jaffe and Palmer (1997), since more recent literature argues that changes in the stringency of environmental regulations instantaneously induce innovation effects, when proxied by R&D expenditures (Rubashkina et al., 2015; Brunnermeier & Cohen, 2003). However, the analysis does control for a potential dynamic effect in section 5.1.2 using a one-year lagged structure of equation (1). It is important to note that including a lagged structure provides a new set of econometric issues and biases.

3.2 – The productivity effect

First, we study the direct effect of environmental regulations on annual TFP growth without including a potential innovation-induced indirect effect. The baseline specification for the direct effect has the following expression:

$$\begin{aligned} TFPgrowth_{ijt} &= const + \alpha_{ij} + \mu_t + \beta \ln EPE_{ijt} + \varphi \, TFPGleader_{jt} + \theta \ln TFPgap_{ijt} + \gamma \ln X_{ijt} \\ &+ \varepsilon_{ijt} \end{aligned} \tag{4}$$

where *TFPgrowth*$_{ijt}$ denotes the annual total factor productivity growth rates based on value added, as conceptually defined in section 2.2.3, for industry *j*, in country *i* at time *t*. Furthermore, this specification uses a constant (*const*), country-sector fixed effects (α_{ij}), time-fixed effects (μ_t), and *ln* EPE_{ijt} to proxy for the stringency of environmental regulations in the EU. $TFPGleader_{ijt}$ denotes the TFP growth rate of the 'leading country', the country with the highest TFP-level in industry *j* at time *t*. $TFPgap_{ijt}$ denotes the difference between the TFP-level of country *i* and the 'leading country' in industry *j* at time *t*. Similar as for the innovation effect, a vector of control variables ($ln\, X_{ijt}$) is included. Moreover, all estimations are conducted using robust standard-errors and all variables in euro's have been PPP-adjusted.

In empirical literature, the *TFPG-leader* and *TFP-gap* variables are identified as important determinants of industry-level productivity growth. The technological frontier country is defined as the country within our sample with the highest level of TFP within industry *j* at time *t*. Theory argues that production efficiency of this country stimulates the productivity growth in other countries through productivity spillovers, with the frontier country setting an example for the "catching-up" countries (Griffith et al., 2004). Evidence suggests that productivity spillovers and the adoption of foreign technologies from the most advanced country, influence productivity growth levels of other countries within the same industry (Griffith et al., 2004). With including the *TFPG-frontier* variable, we capture the effect of such efficient technology transfers from the frontier country to country *i*. Moreover, the *TFP-gap* variable controls for the difference between the TFP-level of country *i* and the technological leader. Economic theory suggests that the potential gains from productivity spillovers are larger when the country is further behind the frontier country in terms of TFP, inducing higher productivity growth levels (Rubashkina et al., 2015). Moreover, Griffith et al. (2004) find evidence that the further a country lies behind the technological frontier the greater the potential innovation induced TFP growth.

The vector of control variables does not include gross value-added as scaling variable, as the industry-level value added is already incorporated into the construction of the TFP growth rates. Therefore, $ln\, X_{ijt}$ includes only the country-sector level birth- and death rate and the export intensity and import intensity rates. Industry structural changes including enterprise creation and exits, measured by the birth- and death rates of firms, influence sectoral productivity. A high birth rate represents the entry of new entrepreneurs which increases competition and incentivizes firms to increase productivity, while a low birth rate helps shielding the position of unproductive firms. Holtz-Eakin and Kao (2015) find evidence for the fact that government policies, such as environmental regulations, increase the entry of new firms, which in turn leads to higher productivity levels. On the other hand, additional environmental costs might discourage entering a certain market, reducing the industry's market competition, which in turn helps shielding and protecting the position of unproductive firms, leading to lower productivity growth levels (Mohr & Saha, 2008). Furthermore, environmental costs, associated with more stringent policies force less productive firms to exit the market, which likely increases aggregate industry level productivity (Koźluk & Zipperer, 2015). Finally, firm entry and exit represent and amplify the productivity effects of aggregate shocks (Clementi & Palazzo, 2016).

We add industry-level export intensity rates because the learning by exporting hypothesis suggests that enterprises participating in foreign trade have larger productivity growth (Crespi et al., 2008). The import intensity rates reflect industry-level external competition, which stimulates productivity growth as firms need to continuously improve to compete with international competitors. Empirical evidence proofs that productivity effects are particularly stronger in internationally competitive industries (Lanoie et al., 2008; Koźluk & Zipperer, 2015). Besides, potential technology spillovers, that increase productivity, may arise from the reversed engineering of imported products (Griffith et al., 2004).

Second, we study Porter's strong hypothesis, suggesting that innovation activity induced by environmental policy drives productivity growth. We incorporate the log of R&D and the interaction term of the log of EPE and the log of R&D for country *i*, in sector *j* at time *t* into equation (4) to obtain equation (5).

$$\begin{aligned} \ln TFPgrowth_{ijt} &= const + \alpha_{ij} + \mu_t \\ &+ \beta \ln EPE_{ijt} + \eta \ln R\&D_{ijt} + \lambda (\ln EPE_{ijt} * \ln R\&D_{ijt}) + \varphi \, TFPGleader_{jt} \\ &+ \theta \ln TFPgap_{ijt} + \gamma \ln X_{ijt} \\ &+ \varepsilon_{ijt} \end{aligned} \tag{5}$$

The interaction term represents the indirect productivity effects of environmental policy driven by R&D. In some of the models all independent variables are lagged using a one-year lagged structure, as some empirical findings argue that R&D induced productivity growth effects have shown to come with a lag of one year (Koźluk & Zipperer, 2015; Ambec et al., 2013; Rubashkina et al., 2015). However, this lagged structure is associated with additional endogeneity issues and biases, which makes a causal relationship in these regressions difficult to identify.

Besides using equation (5), we adopt a two-stage least squares instrumental variable approach to estimate the innovation induced productivity effects of environmental policy. We instrument the R&D expenditures with the EPE variable to make the R&D variable more exogenous, allowing for a more causal interpretation. During the first stage, the effect of environmental policy stringency on R&D expenditures is estimated, whereas the second stage uses the fitted values of the first stage to estimate the effect of R&D expenditures, induced by the environmental policy, on TFP growth. However, we do not perform the estimation in two stages because the second stage will in that case yield the wrong residuals (Woolridge, 2015). This paper uses the direct two-stage instrumental variable regression[8], providing the following expression.

$$\ln TFPgrowth_{ijt} = const + \alpha_{ij} + \mu_t + \beta \ln R\&D_{ijt} + \varphi\, TFPGleader_{jt} + \theta \ln TFPgap_{ijt} + \gamma \ln X_{ijt} + \varepsilon_{ijt} \qquad (6)$$

where $ln\ R\&D_{ijt}$ is instrumented by the environmental protection expenditures, identifying the effect of R&D spending, induced by environmental policy stringency, on productivity growth. All other variables are the same as in equation (4) and (5).

Finally, we incorporate sector-country fixed effects and time-fixed effects into model (4), (5) and (6) to control for unobserved heterogeneity. Ignoring sector-country specific and year-specific characteristics that alter the productivity growth rates within our sample, creates biased results. Therefore, we adopt a fixed effects (FE) estimation approach when estimating the direct and indirect productivity effects of EU's environmental regulations.

3.3 – Identification

This study aims to estimate the causal relationship between environmental policy stringency in the EU and innovation and productivity growth. As Brunel & Levinson (2016) phrases it: 'the environment is a complex multidimensional issue, and so are its associated regulations'. Environmental regulations are not easily comparable across countries and industries over time. In an ideal world, suppose Y_{ijt} represents i.e. TFP growth rates for industry *j*, in country *i* at time *t*. Then, the impact of environmental regulation (ER) on TFP growth would be determined through the following equation:

$$ImpactER = Y_{ijt}\,(T) - Y_{ijt}\,(C) \qquad (7)$$

where $Y_{ijt}\ (T)$ denotes the TFP growth of industry *j* subject to environmental policy (the treatment) and $Y_{ijt}\ (C)$ denotes TFP growth without environmental policy (the control), all else equal. In this case, we would just estimate the difference between the treated TFP growth ratios

[8] STATA's direct two-stage iv regression method for panel data, *xtivreg*, is adopted.

and the control TFP growth ratios. However, it is impossible to construct this object as we can only observe one of the TFP growth values for each country-specific industry at time *t*. This is called the fundamental problem of causal inference. Therefore, identification of the true effect is a challenging task. Moreover, the simultaneous implementation of other measures related to the environmental policy further complicates a proper identification of the initial effect and attributing an observed economic outcome to the policy (Koźluk & Zipperer, 2015). For example, the EU ETS is accompanied by additional mitigating measures, designed to soften adverse impacts of the regulations, such as the promotion of environmental action in other countries, border tax adjustments and special treatment for installations considered at a significant risk of carbon leakage (European Commission, 2014).

For this reason, assessing the impact of EU's environmental policy requires a measure of the relative stringency of the environmental regulations over time and across different countries and industries. We measure the stringency of EU's environmental policy by environmental protection expenditures (EPE) directed towards pollution control, relying primarily on the identification assumption that higher pollution control expenditures are induced by more stringent environmental policy. Enterprises are expected to have higher pollution control expenditures when they encounter more strict regulatory measures. We argue that these reported pollution control expenditures are a suitable measure for this study as they vary over time and across industries and countries (Brunel & Levinson, 2016). The idea is that the industry-level EPE variable represents the stringency of EU's environmental policy for these industries, influencing innovation and productivity growth.

However, this concept faces certain econometric specification drawbacks. First of all, the identification assumption might be too strong as it is difficult to distinguish if the environmental expenditures are driven only by the regulatory measures or also by environmental sentiment or even residual profits. Although this is of relevant concern, Becker (2005) finds evidence that supports the fact that changes in regulations are reflected in reported pollution control expenditures. An additional concern is that certain unobserved industry and country-specific characteristics can alter both the pollution control expenditures and innovation and/or productivity growth. We hope to solve this by conducting a FE-estimation using country and sector-specific fixed effects.

Additionally, our EPE variable might be subject to measurement error problems, due to its self-reporting characteristic (Brunnermeier & Cohen, 2003). This could lead to both upward and downward bias of our coefficients. Firms could face difficulties in identifying which portion of the total expenditures are associated with pollution control and related to compliance with EU's environmental regulations (Rubashkina et al., 2015). Moreover, firms might attempt to gain a greener image by attributing irrelevant expenditures to their environmental protection expenditures (Brunnermeier & Cohen, 2003). However, as we use aggregate industry-level environmental protection expenditures, we hope that the measurement error at the industry-level will be on average close to zero.

Furthermore, to obtain unbiased estimates in the OLS-regressions, we require that the EPE variable is uncorrelated with the error-term. However, our regressions may be subject to reverse causality or simultaneity bias. While we seek to assess the effects of policy stringency on innovation activity and productivity growth, both outcome variables may simultaneously influence the stringency of EU's environmental policy (Brunel & Levinson, 2016). This would result in our EPE variable being correlated with the error term, leading to biased estimates. Simultaneity in the innovation effect regressions may arise as regulation-induced R&D expenditures will be designed as such to lower the costs of pollution control (Kneller & Manderson, 2012; Rubashkina et al., 2015). Hence, not only pollution control expenditures impact R&D but also R&D influences the amount of pollution control expenditures. This simultaneity relation could bias downward the coefficient of the pollution control EPE variable. Reverse causality may also arise in the productivity effect, following the theory of the environmental Kuznets curve, suggesting that economic growth can spur the demand for environmental quality (Koźluk & Zipperer, 2015). The opposite may also be true, industries with low productivity growth decide to lower their pollution control expenditures to cut costs (Hille & Möbius, 2019). Hence, stricter environmental regulations, measured by our EPE variable, might be influenced by TFP growth, whereas this study tries to estimate the opposite relationship. This could result in an upward bias of our estimates. Furthermore, omitted variable bias can occur when certain unobserved effects are correlated with both the stringency of environmental regulations and innovation or productivity growth. For both the innovation and productivity effect, this suggests that our EPE variable may be subject to endogeneity. Many prior studies do not sufficiently address this potential endogeneity of the pollution control expenditures (except: Hille & Möbius, 2019; Rubashkina et al., 2015 and De Vries & Withagen, 2005).

To overcome these potential issues regarding endogeneity of our EPE variable, we adopt next to the OLS-estimations, an instrumental variable (IV) approach. The idea of IV-estimation is to find a variable that is strongly correlated with the EPE variable, but uncorrelated with our measures of innovation and productivity growth, except indirectly through the EPE variable, and use this instrumental variable to estimate the causal relationship. Rubashkina et al. (2015) uses the average share of EPE divided by value added (EPE intensity) for the adjacent sectors of sector *j*, excluding sector *j*, as instrumental variable: $\frac{EPE}{VA}_{-j}$. The authors argue that there is a strong correlation between environmental policy applied to different industries within the same country, suggesting a strong correlation between a sector's EPE intensity and the EPE intensity of the adjacent sectors within the same country (Rubashkina et al., 2015). Hence, the average share of EPE intensity of adjacent sectors influences the EPE intensity of sector *j*, but does not directly impact innovation or productivity growth, except through its relationship with the EPE intensity of sector *j*.

We use an instrumental variable that follows a similar structure: the average share of the EPE intensity of the adjacent sectors, excluding sector *j*. However, we specify the definition of the adjacent sectors. We argue that that there is a strong correlation between the stringency of EU's environmental policy applied to different industries with similar pollution intensity ratios, which is reflected in the EPE variable. Industries with production processes that are strongly reliant on greenhouse gas emissions are more affected by increasing stringency of environmental policies, whereas less pollutive industries need fewer investment in pollution control. The opposite also holds, industries with similar reliance on greenhouse gas emissions receive similar amounts of freely allocated emissions under the EU ETS and therefore have strongly correlated (lower) environmental protection expenditures. Hence, we argue that industries with similar pollutive behavior have strongly correlated environmental protection expenditures as a response of more stringent environmental policy. Therefore, we have divided the industries within our sample into four different country-specific groups, based on similar average pollution intensity ratios. These pollution intensity ratios are calculated using country-industry specific greenhouse gas emissions from the European Industrial Emissions Portal divided by the industry's gross output. The industry division appeared naturally as we found a distinct difference between average industry-level pollution ratios. The sample consists of 14 different industries and both the most pollutive and least pollutive groups contain four sectors, whereas the other two contain each three industries. Appendix 3A provides an overview of this pollution intensity industry division.

The adjacent sectors of sector *j*, within our definition of the instrument ($\frac{EPE}{VA}_{-j}$), are the industries that are in the same pollution intensity group as sector *j*. Hence, our instrumental variable is defined as the average EPE intensity of sector *j*'s adjacent sectors within the same 'pollution group', for country *i* at time *t*. The identification assumption is that this variable is a strong predictor of the EPE intensity of the sector under consideration, which serves as our measure for environmental policy stringency, impacting the innovation activity and productivity growth. We adopt some important postestimation IV-tests to support the validity of the instrument.

The second requirement for the instrumental variable is that the instrument is uncorrelated with innovation activity and productivity growth. We argue that the average share of EPE intensity of the adjacent sectors has no direct impact on sector *j*'s innovation and productivity, but only through its relationship with sector *j*'s own EPE intensity. The environmental protection expenditures of other industries do not directly affect R&D or TFP growth of the industry under consideration, but *only* through the above discussed relationship with the sector's own environmental protection expenditures. The word '*only*' requires the assumption that conditional on using fixed effects and all control variables within our models, the instrument is not correlated with unobserved factors that influence R&D and TFP growth. A similar assumption has been adopted by Rubashkina et al. (2015).[9] However, we do note that the EPE of adjacent sectors influences the productivity level of these adjacent sectors, through its additional costs component. Hence, if there are potential productivity spillovers within the pollution intensity industry groups, this last assumption may be weak. This would namely suggest that our instrument is correlated with unobserved productivity spillover effects that influence sector *j*'s productivity growth and potentially even innovation activity.

[9] Rubashkina et al. (2015) does include an additional instrument where EPE intensity of adjacent sectors is interacted with pre-sample energy intensity of industry *j*. However, as this energy intensity variable is time-invariant, it would drop out when including year fixed effects, due to collinearity. We argue that the use of year-specific fixed effects is preferred over interacting our instrument with pre-sample sectoral energy-intensity.

4 Data

4.1 – Sources

The main variable of interest in our regressions is the stringency of EU's environmental policy proxied by environmental protection expenditures (EPE). These expenditures have been collected from the *Eurostat* database *Environmental Protection Expenditures by Environmental Domains*, using the NACE revision 2 industry classification. The EPE variable is split into investment in equipment and plant for pollution control and investment in equipment and plant linked to cleaner technology. Our measure for environmental policy stringency is the first investment post: pollution control expenditures. R&D expenditures data at the industry-level are taken from the *OECD Analytical Business Enterprise R&D* (*ANBERD*) database for the period 2004 to 2017. The R&D expenditures of the years 2004 to 2007 have been used for the construction of the knowledge stock variable. Government R&D expenditures aimed at environmental objectives are collected from the *Government Budget Allocations R&D* (*GBARD*) database of OECD. Annual TFP growth ratios, defined as the fraction of value-added growth that cannot be attributed to the primary input factors of production, have been collected from the *EU KLEMS Release 2019 Growth Accounts* database that uses the growth accounting techniques discussed in section 2.2.3 (Stehrer et al., 2019; Adarov & Stehrer, 2019). Moreover, the *EU KLEMS Release 2019* database is used to construct the TFPG-leader and TFP-gap variables to control for technology spillovers from the technology-leading country.

Data on our scaling variable gross value added (VA) are collected from the *OECD National Accounts database - Value added and its components by activity (*ISIC revision 4*).* Additional control variables include the country-sector specific birth- and death rates that control for industry stability and structural changes. These business demography indicators are collected from *OECD Structural and Demographic Business Statistics* (*SBDS*), at the ISIC revision 4 industry classification level. The OECD Trade by Enterprise Characteristics provided us with data on the number of exporting and importing firms by industry (within EU trade). Using the number of active enterprises from the *OECD Structural and Demographic Business Statistics* (*SBDS*) database, the EU export and import rates have been constructed following that the export/import ratios equal: exporting/importing firms divided by active firms. For the construction of the instrumental variable, we constructed pollution ratios using data from *Eurostat Air Emissions Intensities*, by NACE Rev. 2 activity, provided by the *European Industrial Emissions Portal*. The production output data are collected from the *EU KLEMS Release 2019, National accounts* database.

Finally, the environmental protection expenditures, R&D expenditures, government R&D expenditures, knowledge stock variable and gross value-added variable have been transformed from euros to PPP adjusted dollars, using the *OECD PPPs and exchange rates* dataset containing the PPP adjusted euro/U.S.-dollar rates. Across all data sources, the aggregation by industrial sectors varied. Therefore, a long process of data construction, merging and adaption was needed to merge all data into the large panel data set, following the NACE revision 2 industry classification.

4.2 – Descriptive Statistics

The balanced panel data set contains of 2520 observations for 14 different mining and manufacturing industries of 18 countries in the European Union between 2008 and 2017. The sample has been selected based on the availability of data of our explanatory EPE variable and the TFP growth ratios, following the NACE revision 2 industry classification. The dataset initially consisted of 22 countries, but large gaps of missing values in the EPE variable forced the exclusion of Denmark, Estonia, Ireland and the United Kingdom from the sample. Appendix 1A and 1B provide a detailed overview of all final countries and sectors in the estimation. The period 2008 to 2017 covers the transition period of the EU ETS second phase into the third phase, which fully began to operate in 2013. Therefore, it is an interesting period to investigate the effects of EU's environmental policy.

Table 1 shows a sectoral breakdown of the means of the main variables: environmental protection expenditures, R&D expenditures and TFP growth ratios. Moreover, table 1 shows the pollution intensity rates of all 14 sectors. The more pollution intensive industries, such as *manufacturing of rubber and plastic products, and other non-metallic mineral products* (C22-C23) and *manufacturing of chemicals and chemical products* (C20) show relatively higher levels of investment in pollution control. However, the relatively pollution intensive *mining and quarrying* industry (B) has relatively lower investment in pollution control, suggesting lower stringency of environmental policy. This might be the result of the old-fashioned characteristics of the mining industry and the industry's reliance on pollution intensive processes. Furthermore, table 1 shows that the highest R&D expenditures in absolute numbers comes from *manufacturing of transport equipment* (C29-C30). However, the 2405.69 million dollars in R&D account for only 8.33% of the industry's value added. The *manufacturing of computer, electronic and optical products* (C26) industry spends the most on R&D relative to value added, on average 1228.59 million dollars, which denotes for 16.76 percent of value added. The fact that the computer and electronic industry is continuously developing and modernizing, is expectedly the main reason for this relatively large investment into research and development. The *manufacturing of basic pharmaceutical products and pharmaceutical preparations* industry (C21) comes second with 13.44 percent R&D spending over value added. Interestingly, both industries have the highest average annual productivity growth, respectively 1.97% (C26) and 1.94% (C21), suggesting a relationship between innovation and productivity growth. The lowest average TFP growth is shown in the *manufacturing of coke and refined petroleum products* industry (C19), an industry largely affected by regulations and environmental sentiment.

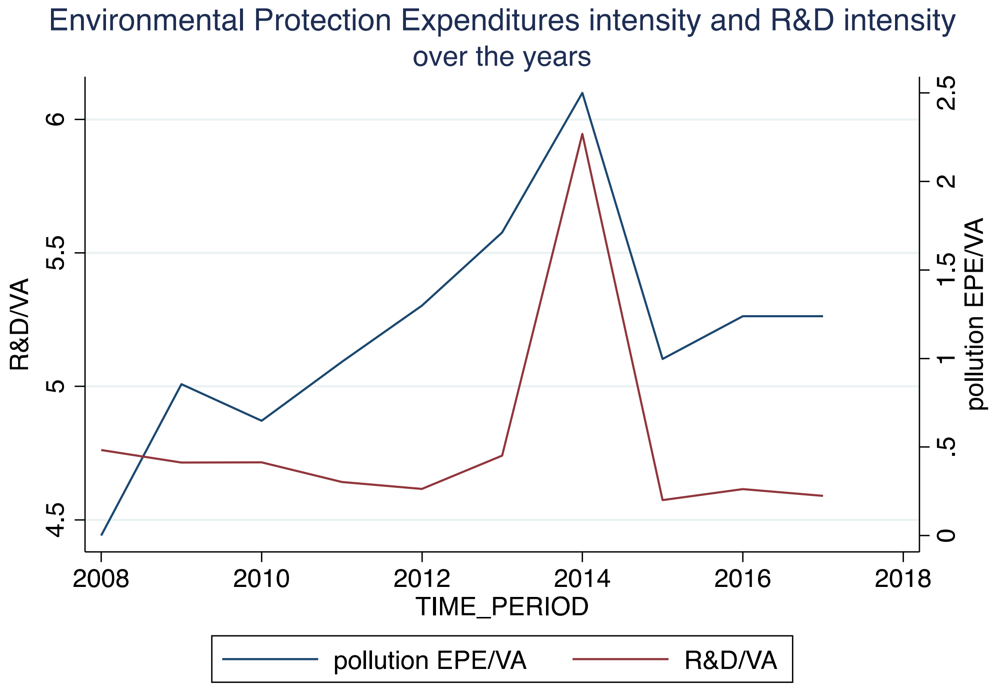
Based on the comparison of the means of the pollution control EPE/VA and R&D/VA in table 1, we do not see a direct relationship between environmental protection expenditures and innovation. However, graph 1, shows that both variables follow a similar trend over the estimation period. More specifically, pollution control investment and R&D expenditures over

Table 1: Summary statistics: sectoral breakdown – pollution intensity and means of main variables

Industry (NACE Rev. 2)	Pollution Intensity	Investment in Pollution Control (million dollars)	Investment in Cleaner Technology (million dollars)	R&D (million dollars)	Pollution EPE/VA (%)	R&D/VA (%)	Average annual TFP growth rate
Mining & quarrying	863.70	48.79	16.07	17.13	1.05	0.99	0.02
Manufacturing of:							
Food & Drinks	77.27	103.48	24.99	136.88	0.15	1.04	-0.35
Textile & leather	41.04	4.48	1.66	83.46	0.05	1.69	-0.13
Wood & paper products	326.86	95.25	31.61	65.95	0.19	0.89	1.26
Coke & refined petroleum	423.80	83.64	36.92	42.45	4.87	4.98	-1.70
Chemicals & chemical products	607.10	201.56	46.77	503.48	0.50	4.75	1.84
Pharmaceutical products	53.57	38.51	12.78	719.17	0.08	13.44	1.94
Rubber & plastics	1204.03	83.28	52.30	262.68	0.22	2.34	1.10
Metals & metal products	684.72	83.10	30.72	305.49	0.28	1.99	0.82
Electronics	20.03	7.25	2.46	1228.59	0.03	16.76	1.97
Electrical equipment	242.24	30.75	9.00	410.65	0.06	8.15	1.64
Machinery	38.03	25.47	13.49	824.36	0.05	5.49	-0.01
Transport equipment	40.38	43.92	28.99	2405.69	0.06	8.33	1.61
Other manufacturing	66.63	5.77	3.77	222.80	0.04	1.59	-0.54

value added increased significantly around 2013/2014, which marks the beginning of the third phase of the EU ETS. This would suggest that stricter environmental policy induces investment into research and development.

Graph 1: Environmental protection expenditures (pollution control) intensity and R&D intensity over the years 2008 to 2017.



Appendix 4A and 4B present the scatterplots of the pollution EPE variable against respectively R&D expenditures and TFP growth. These scatterplots are also presented by industry. Based on these scatterplots, a similar indication is given that there is a potential positive relationship between the pollution EPE variable and sectoral R&D expenditures. In the sectoral scatterplots, the fitted lines all show a positive trend, whereby the Food & Drinks sector is shown to have the strongest positive correlation between pollution control EPE and R&D. The scatterplots of the relationship between the pollution EPE variable and TFP growth provide less of an indication. Both no strong positive or negative correlation can be determined. In the sectoral scatterplots, some industries show a small positive correlation and others a small negative correlation.

Table 2 provides a correlation matrix of the main variables and shows that R&D is positively correlated with the pollution EPE variable. The same holds for the cleaner technology EPE variable. TFP growth on the other hand is negatively correlated with these environmental cost variables, indicating a potential negative relationship. However, the sectoral scatterplots provide no strong indication for such a negative relationship between pollution EPE and TFP growth. Therefore, a regression analysis is needed. Additionally, table 2 shows that R&D expenditures and TFP have a positive correlation, in line with the theory that innovation stimulates productivity growth (Schumpeter, 1942). Finally, more summary statistics of the total sample, including all regression variables are tabulated in appendix 3B.

Table 2: Correlation matrix of the main variables

	Pollution EPE	**Cleaner Technology EPE**	**R&D**	**TFP**
Pollution EPE	1.0000			
Cleaner Technology EPE	0.7321	1.0000		
R&D	0.2144	0.1391	1.0000	
TFP	-0.1218	-0.0394	0.1204	1.0000

5 Empirical Results

The first part of this section discusses the relationship between EU's environmental regulations and innovation activity, following with some robustness checks of the main results. In the second part, we present the results of the relationship between EU's environmental regulations and productivity growth. We conclude with some robustness checks for this productivity effect.

5.1. – The innovation effect: environmental policy and R&D

5.1.1 – Baseline estimation results

We first estimate the innovation effect using a standard panel data OLS-estimation with the dependent variable being the log of country-sector level R&D expenditures, as presented in equation (1) of the methodology. Table 3 presents the results. The regressions in column (1) to (3) do not control for country-sector and year fixed effects, whereas in column (4) to (6) we conduct a fixed effects estimation. We include country-sector fixed effects in column (4) and (5) and in column (6) both country-sector and year fixed effects are accounted for. Without controlling for the fixed effects, a strongly significant but small positive relationship between pollution control environmental protection expenditures and R&D expenditures is shown in column (1) to (3). As expected, an industry's past R&D investment, measured by our knowledge stock variable, has a strongly significant positive impact on R&D in the present. When including the vector of controls, the model improves as shown by an increasing test-statistic and R-squared. The decreasing coefficient shows that the control variables play a role in explaining the variation in the R&D expenditures, which was in column (1) partly incorporated in the coefficient of the EPE variable. Government R&D is shown to have a strongly significant positive effect on R&D, indicating that Government R&D decisions impact the R&D investment of the private sector, as expected from the literature. Moreover, the birth rate is shown to play a key role in the regressions. A higher industry-level birth rate negatively influences R&D expenditures, as presented in the coefficient (-0.165) significant at the 1% level. This is in line with the Schumpeterian theory that innovation activity is negative related with industry instability and turbulence (Malerba & Orsenigo, 1995).

However, the coefficient of the EPE variable lowers and becomes insignificant, when including country-sector fixed effects and the vector of controls, as presented in column (5). In this model, all time-invariant industry and country variation in R&D expenditures is captured in the country-industry specific fixed effects. Hence, the coefficient related to the EPE variable

Table 3: Innovation effect – R&D expenditures panel regression results of EU's environmental policy

R&D expenditures	(1)	(2)	(3)	(4)	(5)	(6)
ln EPE	0.042***	0.036***	0.025**	0.022*	0.010	0.007
(*Pollution control*)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)
ln EPE	-0.002	-0.007	-0.008	-0.005	-0.004	-0.003
(*Cleaner Technology*)	(0.010)	(0.010)	(0.011)	(0.010)	(0.693)	(0.010)
ln Knowledge Stock	0.632***	0.591***	0.586***	0.430***	0.413***	0.412***
	(0.050)	(0.053)	(0.060)	(0.055)	(0.060)	(0.145)
ln Government R&D		0.112***	0.115***	0.060	0.033	0.041
		(0.036)	(0.038)	(0.039)	(0.039)	(0.040)
ln Value Added			0.033		0.308***	0.240
			(0.021)		(0.088)	(0.103)
ln Birth Rate			-0.165***		-0.086*	-0.099**
			(0.037)		(0.045)	(0.042)
ln Death Rate			-0.019		-0.020	0.011
			(0.053)		(0.057)	(0.053)
ln EU-export rate			0.108		0.043	0.019
			(0.101)		(0.100)	(0.108)
ln EU-import rate			-0.075		-0.040	-0.024
			(0.092)		(0.094)	(0.102)
Constant	5.139***	4.107***	3.813***	8.572***	2.593	4.125
	(1.078)	(0.936)	(1.030)	(1.301)	(2.142)	(2.636)
Country-sector FE	No	No	No	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes
Test	χ^2 = 164.92***	χ^2 = 279.43***	χ^2 = 453.14***	F = 16.91***	F = 12.59***	F = 14.13***
No. Observations	1679	1430	1141	1430	1141	1141
Within R^2	0.382	0.914	0.911	0.911	0.448	0.557

Notes: The dependent variable is the log of R&D expenditures; logging values equal to zero creates missing values, lowering the number of observations and extra control variables reduce the number of observations further due to less data availability; robust standard errors are in parentheses
*** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level

only reflects the relationship between R&D expenditures and the EPE variable within industry and country, across the time dimension. Since the coefficient becomes insignificant, the results indicate that there are certain unobserved country-sector specific characteristics, which are constant over time, that are correlated with both the EPE variable and R&D expenditures. The inter- industry and country differences, such as for example technological opportunities, and the vector of controls, play a major role in explaining the variation in R&D expenditures. Including time fixed effects in column (6), further lowers the coefficient and takes out all the variation in the EPE variable. This potentially also has something to do with the characteristics of the EU ETS. The stringency of the EU ETS comes from the changes in the carbon price, which varies over the time. However, including time fixed effects takes out all time variation and we may have overcontrolled in our estimations, losing all variation in our explanatory variable. However, all in all, based on the OLS-estimation, we find no evidence supporting a relationship between environmental policy stringency, measured by pollution control expenditures, and innovation.

An alternative on the log-log structure would be to regress R&D intensity (R&D/VA) on EPE intensity (EPE/VA). However, a big part of the relationship would then originate from the value-added variable. Moreover, as Jaffe and Palmer (1997) suggests, measurement error in value added will cause this ratio-structure to exhibit spurious correlation. Therefore, most empirical literature uses the log-log structure instead of R&D/VA on EPE/VA (Jaffe & Palmer, 1997; Hammamoto (2006); Rubashkina et al., 2015; etc.).

When using OLS-estimation techniques and proxying the stringency of EU's environmental policy by pollution control environmental protection expenditures, we primarily rely on the identification assumption that higher pollution control expenditures are induced by more stringent environmental policy in the European Union. As extensively discussed in section 3.3, this concept faces certain drawbacks in the econometric specification and our EPE variable is subject to endogeneity issues (Hille & Möbius, 2019; De Vries & Withagen, 2005; Rubashkina et al., 2015). To overcome potential issues with the endogeneity of our explanatory variable, we conduct in table 4 a two-stage least squares instrumental variable estimation to study the innovation effect. Pollution control EPE is instrumented by the average share of pollution control EPE intensity of industry *j*'s adjacent sectors following the pollution intensity group division as shown in appendix 3A. In all six IV regressions, we use the FE-estimation to control for unobserved heterogeneity.

In column (1) to (3) of table 4, we adopt the log-log specification using the instrumental variable. In comparison to table 3, there is a strong significant positive relationship shown between EU's environmental stringency and R&D. When including all control variables in the fixed effect estimation, the positive coefficient is significant at the 1% level. Moreover, when also accounting for unobserved year specific characteristics the positive relationship is still statistically significant at the 5% level. This indicates that the results in table 3 were downward biased due to endogeneity issues, related to the simultaneity bias. R&D investment lowers the pollution control expenditures, whereas we simultaneously tried to estimate the opposite relationship. This reverse causality biased our results in table 3.

Table 4 provides a comprehensive series of postestimation tests for the validity of the instrument. First, to test for identification of the instrument, we use the Kleibergen-Paap rank LM-statistic test. The null hypothesis is that the instrument is uncorrelated with the pollution

Table 4: Innovation effect – 2SLS Instrumental variable approach - panel regression results of environmental policy in the European Union.

	R&D expenditures			**R&D intensity (R&D/VA)**		
2SLS IV - estimation	(1)	(2)	(3)	(4)	(5)	(6)
EPE	**0.194****	**0.321*****	**0.296****	0.113	0.250	0.399
(*Pollution control*)	**(0.083)**	**(0.102)**	**(0.146)**	(0.137)	(0.255)	(0.395)
EPE	-0.017	-0.019	-0.014	0.022	0.018	0.022
(*Cleaner Technology*)	(0.012)	(0.018)	(0.019)	(0.019)	(0.020)	(0.027)
Knowledge Stock	0.496***	0.545***	0.448***	0.362***	0.265**	0.424**
	(0.061)	(0.091)	(0.137)	(0.097)	(0.116)	(0.168)
Government R&D	0.013	-0.008	0.004	0.223**	0.123	0.136
	(0.038)	(0.054)	(0.058)	(0.110)	(0.076)	(0.102)
Value Added	0.219	0.548**	0.452*	-	-	-
	(0.140)	(0.234)	(0.247)			
Birth Rate		-0.138*	-0.168*		-0.173**	-0.206*
		(0.076)	(0.093)		(0.081)	(0.117)
Death Rate		0.004	0.042		-0.005	-0.049
		(0.078)	(0.075)		(0.070)	(0.098)
EU-export rate		0.003	0.003		0.016	-0.035
		(0.120)	(0.122)		(0.129)	(0.146)
EU-import rate		0.098	0.068		-0.094	-0.051
		(0.132)	(0.134)		(0.158)	(0.181)
Constant	5.565**	2.655	4.747	0.358	0.042	0.277
	(2.348)	(3.350)	(0.242)	(0.216)	(0.247)	(0.385)
Country-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	No	No	Yes
Test	F = 20.73***	F = 10.70***	F = 13.38***	F = 22.42***	F = 13.04***	F = 14.13***
No. Observations	1430	1121	1121	1430	1141	1141
Within R^2	0.805	0.710	0.667	0.871	0.872	0.863
Identification						
K-P Wald rank LM-statistic	18.599	19.302	11.181	6.883	5.053	5.332
p-value	0.001	0.001	0.004	0.009	0.041	0.038
Weak instrument						
K-P Wald F-statistic	9.613	12.929	10.944	9.135	10.271	9.130
15% level (Stock & Yogo)	11.59	11.59	11.59	8.96	8.96	8.96

Notes: FE-estimation; the dependent variable is R&D expenditures in regression 1 to 3 and R&D intensity in regressions 4 to 6; the pollution control EPE variable is instrumented by EPE/VA_{-j}; robust standard errors are in parentheses; logging values equal to zero creates missing values, lowering the number of observations and extra control variables reduce the number of observations further due to less available data.

*** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level

control expenditures of industry *j* (Aiyar, 2012). The test-statistics in column (1) to (3) show that we can strongly reject the null hypothesis, suggesting that the instrument correctly identifies our explanatory variable. Furthermore, to test if the instrument is sufficiently strong, we conduct the Kleibergen-Paap Wald F-test, with the null hypothesis that the instrument is weak. The Cragg-Donald Wald test is more conventional, but when using heteroskedastic robust standard errors this test is invalid (Aiyar, 2012). In empirical literature the rule of thumb of the Kleibergen-Paap Wald F-test is an F-statistic above 10 to support having used a strong instrument. Therefore, the null hypothesis of a weak instrument can be strongly rejected in column (2) and (3). Moreover, in column (2) the F-statistic is above the weak IV critical value of 15% relative IV-bias toleration, following Stock and Yogo (2005). Unfortunately, as we include only one instrument, we cannot test for overidentification using the Hansen J-test to further support the exclusivity assumption that the instrument is uncorrelated with the error term and affects R&D expenditures only through its impact on sector *j*'s pollution control expenditures.

Based on column (3), we can conclude that a 1 percent increase in pollution control expenditures is on average associated with a 0.296 percent increase in R&D expenditures. As mentioned in the methodology, we cannot control for potential productivity spillover effects that impact the exclusivity of our instrument. Hence, a part of the strong positive relationship found in column (1) to (3) of table 4 might be the result of our instrument being positively correlated with these productivity spillovers effects. However, the results do suggest that when accounting for endogeneity issues, the coefficient changes significantly. Conclusive, our results do indicate but not strongly support evidence for a positive relationship between EU's environmental policy and R&D expenditures.

In column (4) to (6), we measure, through IV-estimation, the effect of EPE intensity on R&D intensity. We find still positive coefficients, but they are all insignificant. The Kleibergen-Paap Wald LM-statistical values suggest a significantly strong identification of our instrument. Furthermore, the instrument seems to be significantly strong in column (5) according to the rule of thumb of the Kleibergen-Paap F-statistic. In all three columns the F-statistics is larger than the Stock and Yogo (2005) 15% critical value. The sign of the effect is positive in all regressions using R&D/VA on EPE/VA, indicating that there might be a positive relationship.

Furthermore, also in column (1) to (6), we can attribute a strong impact of R&D variation to an industry's birth rate, suggesting that high industry instability is an indicator for lower R&D. Finally, the results in this paper show no strong significant relationship between R&D expenditures and the EU-Export intensity and EU-import intensity rates.

5.1.2 – Robustness checks

We conduct robustness checks of the results, presented in section 5.1.1, focused on the following concerns: a dynamic innovation effect; the sensitivity to different depreciation rates of the knowledge stock variable; and the measure of innovation activity.

First, the innovation effect might be subject to a dynamic effect, requiring us to apply a one-year lagged structure to the regressions in table 3 and 4. In all regressions we find a similar qualitative positive relationship between pollution control environmental protection expenditures and innovation activity, however in most cases statistically insignificant and small. Therefore, we cannot conclude that environmental policy has a positive impact on innovation activity when applying a lag structure to the regressions. It is important to note, that these results are subject to other biases accompanying a lagged structure, as it requires the assumption that there is no serial correlation among the unobservable variables (Bellemare et al., 2017). For space reasons, we do not include a table of the results, but they are nevertheless available upon request.

The second robustness check focuses on the construction of the knowledge stock variable, which relies on the choice of the depreciation rate. The depreciation rate represents the rate at which the impact of past R&D investments on the knowledge capital declines if no further R&D related activity is undertaken (Hall & Rosenberg, 2010). Empirical literature finds depreciation rates of R&D capital to lie between 10 and 30 percent (Nadiri & Prucha, 1996; Bosworth, 1978; Hall, 2005; Pakes & Schankerman, 1984). Appendix 5A.1 shows the estimation results using different depreciation levels in the construction of the knowledge stock variable. We conduct the regressions of column (6) of table 3, and column (2) of table 4 with knowledge stock depreciation rates varying between 10, 20 and 30 percent. Note that in the baseline specification we used the 20% depreciation rate, but these coefficients are included in appendix 5A.1 to provide a clear comparison. The results show that the positive relationship, found in table 4 is robust against different depreciation rates of the knowledge stock variable. The '*10% and 30% regressions'* follow a similar pattern as when using a 20% depreciation rate. More specifically, for the IV-estimation, the coefficients of the EPE variable equal respectively 0.231, 0.321 and 0.367 for the 10, 20 and 30 percent depreciation rates, all statistically significant.

Finally, we rely in the main results on R&D expenditures as proxy for innovation activity, but it is of concern that this is not a perfect measure of innovation. Although it is hard to get a good grasp on finding a proper measure for innovation, we conduct regressions using an alternative measure of innovation: the number of patent applications at the European Patent Office (EPO). The patent application data are collected from the *OECD patent statistics* database and are only available for the years 2008 to 2013. We conduct regressions of the OLS-estimator and IV-approach using the log of the number of patent applications as dependent variable. Appendix 5A.2 presents the results. All coefficients are insignificant, but we find a sign switch in the IV-estimation, suggesting a negative relationship between pollution control expenditures and the number of EPO patents.Therefore, we do see some concerns regarding the robustness of the main results to different measures of innovation, but further research is required. Hence, our baseline results only apply to R&D expenditures as measure of innovation.

5.2. – The productivity effect: environmental policy and TFP growth

5.2.1 – Baseline estimation results

Both through a direct and indirect effect, new or more stringent environmental regulations can have impact on productivity growth (Koźluk & Zipperer, 2015). We begin this section with the results on the direct effect of EU's environmental policy on TFP growth, presented in table 5. Unfortunately, the countries Greece, Hungary, Lithuania, Poland, Portugal and Slovenia dropped out of the sample due to not enough available TFP growth data.

Since the TFP growth rates are already based on value added production growth, no additional value-added control variable is included in the regressions. Column (1) to (6) show the results of the regressions using the OLS-estimator, whereas the regression results in column (7) and (8) originate from the two-stage least squares instrumental variable estimation. The IV-approach is adopted to overcome endogeneity issues and uses the same instrument as applied to the innovation effect. In column (1) to (3), the OLS-estimator provides no significant effect of environment related pollution control expenditures on TFP growth. When controlling for unobserved country-sector fixed effects, we find a large statistically significant negative effect, as presented in column (4) and (5). This indicates that the negative productivity growth effect comes from within-industry and country variation. Not controlling for unobserved country-sector specific characteristics results in biased estimates. Column (5) indicates that a 1 percent increase in pollution control expenditures, measuring the stringency of EU's environmental regulatory measures, decreases annual productivity growth with 0.649 percentage point. A strong productivity growth effect can be attributed to structural changes in industry characteristics, as measured by the birth- and death rate variables. A high birth rate indicates the entry of new entrepreneurs, which increases competition and stimulates firms to increase productivity, while a low birth rate helps shielding the position of unproductive firms. This is shown in the results, indicating that a 1 percent increase in the birth rate is associated with an annual productivity growth of 1.467 percentage point. The negative coefficient of the death rate variable is surprising as it is expected that the unproductive firms do not survive, which would suggest an increase in overall industry productivity.

When including international competitiveness proxied by import intensity, export intensity controlling for the learning by exporting hypothesis and year-specific unobserved characteristics, the coefficient of the EPE variable becomes statistically insignificant, although still negative of sign (column (6)). The impact of time fixed-effects suggests that all variation in productivity growth related to the EPE variable comes from time variation. This might be related to the EU ETS characteristics whereby most stringency variation is time related. The sign of the coefficient remains negative.

The instrumental variable estimation also provides a negative coefficient accompanying the EPE variable, although highly insignificant, as presented in column (7) and (8). Postestimation IV- tests support the use of the instrumental variable in the productivity effect, but the support is less strong than for the innovation effect. We can reject the null hypothesis that the instrument is uncorrelated with the endogenous regressor, according to the Kleinbergen-Paap Wald LM-statistic. Moreover, although the Kleinbergen-Paap Wald F-statistic does not present a value higher than the rule of thumb value of 10, the F-statistic in column (8) is higher than the 15% critical value of IV-bias tolleration (Stock & Yogo, 2005).

Conclusive, we do not find a strong signficant direct effect of EU's environmental policy on productivity growth, but the negative coefficient signs in all regressions, and the significant coefficients in column (4) an (5)) do indicate that there might be a negative relationship. This would be in line with the traditional theory that the environmental policy creates an additional cost-burden to the production process that negatively impacts productivity growth.

Furthermore, the results of column (1) to (5) find no significant impact of the TFP growth rate of the technology leader and the TFP-distance with this country on productivity growth. In regression (6) to (8), the TFP-gap variable is found to have a negative impact on productivity growth. This suggests that there are no larger productivity growth gains from adopting efficient technologies in case a country and its sector lies further behind the technology leader (Griffith et al., 2004). Even more, the results suggest that the further a country is behind the technology leader, the lower the productivity growth.

Table 5: Productivity effect – Direct effect – OLS & 2SLS IV-estimation – panel regression results of environmental policy in the European Union.

TFP growth	**OLS-estimation**						**2SLS IV-estimation**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln EPE	-0.067	-0.020	-0.004	-0.826**	-0.649*	-0.256	-2.594	-0.962
(*Pollution control*)	(0.216)	(0.195)	(0.231)	(0.378)	(0.384)	(0.368)	(5.872)	(2.005)
ln EPE	0.169	0.319	0.373	-0.401	-0.116	-0.395	-0.147	-0.327
(*Cleaner Technology*)	(0.253)	(0.232)	(0.244)	(0.461)	(0.449)	(0.376)	(0.819)	(0.816)
TFPG - leader	-0.015	0.003	0.015	-0.007	0.017	0.001	-0.009	0.001
	(0.020)	(0.026)	(0.033)	(0.020)	(0.025)	(0.029)	(0.022)	(0.030)
ln TFP - gap	-0.315	-0.323	-0.393	-0.055	-0.392	-2.189***	-1.792***	-2.126***
	(0.326)	(0.405)	(0.416)	(0.525)	(0.523)	(0.674)	(0.674)	(0.586)
ln Birth Rate		0.835***	0.766***		1.467**	0.518		0.429
		(0.163)	(0.143)		(0.429)	(1.125)		(1.124)
ln Death Rate		-0.546***	-0.778***		-1.497***	0.792		0.746
		(0.114)	(0.179)		(0.295)	(1.561)		(0.771)
ln EU-export rate			0.812			0.434*		0.815
			(0.974)			(0.219)		(1.223)
ln EU-import rate			-0.824			-0.534**		-0.145
			(0.809)			(0.186)		(0.727)
Country-sector FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes	Yes	Yes
Test	$\chi^2 = 2.57$	$\chi^2 = 15.67$**	$\chi^2 =22.16$***	F = 1.51	F = 2.76**	F = 13.16***	F = 19.32***	F = 13.51***
No. Observations	1108	1061	1026	1108	1061	1026	1085	1003
Within R^2	0.128	0.128	0.045	0.017	0.022	0.317	0.249	0.318
Identification								
K-P Wald rank LM -statistic	-	-	-	-	-	-	3.514	3.793
p-value							0.051	0.056
Weak instrument								
K-P Wald F-statistic	-	-	-	-	-	-	8.723	9.831
15% level (Stock & Yogo)							8.96	8.96

Notes: The dependent variable is TFP growth and in regression 1 to 6 the OLS-estimator is used, whereas in 7 and 8 an IV-approach is used: the pollution control EPE variable is instrumented by EPE/VA_{-j}; robust standard errors in parentheses; logging values equal to zero creates missing values, lowering the number of observations; extra control variables reduce the number of observations further due to less available data.

*** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level

The exclusion of certain innovation measures may have led to omitted variable bias, as the potential indirect effect of EU's environmental policy through innovation channels on productivity growth is not captured (Hille & Möbius, 2019). Porter's strong hypothesis suggests a positive relationship between environmental policy and productivity growth through increasing innovation, induced by the policy. First, we estimate this indirect effect of the stringency of EU environmental policy by using an interaction term of country-sector R&D expenditures and the pollution control EPE variable in OLS estimation regressions. The results are presented in table 6 in column (1) to (4). The variable of interest is the interaction term of R&D and EPE. All regressions are conducted using fixed effect estimation. The coefficient in column (2) shows a small positive relationship between the interaction term and TFP growth, suggesting environmental policy to have a positive effect on TFP growth through R&D channels. However, the coefficient is small and statistically insignificant. As expected, the not interacted R&D expenditures positively influence productivity growth, although insignificant.

When estimating the indirect productivity effects, empirical literature advocates for a lag structure in the econometric specification to capture potential time-dimension differences in the relationship between environmental policy and productivity growth, since R&D induced productivity effects may arise with some delay (Yang et al., 2012; Lanoie et al., 2008). In column (3) and (4) of table 6, we include a one-year lag structure of the variables. We find a statistically significant negative coefficient of the interaction term. Moreover, we do observe a strong statistically significant positive coefficient of the pollution control EPE variable. However, these results need to be taken lightly as the associated estimates are inconsistent and biased, as we cannot assume that there is dynamics among the observables but no dynamics among the unobservable variables (Reed, 2015).

Alternatively, this study instruments the R&D expenditures with the pollution control EPE variable, allowing for a more causal interpretation of a R&D-induced productivity effect, since the R&D variable becomes more exogenous. Column (5) to (8) of table 6 show the coefficients of the effect of R&D expenditures stimulated by EU's environmental policy on TFP growth. Without using a lag-structure, the coefficient is negative but statistically insignificant. Although, the negative coefficient turns significant at the 10% level when using a one-year lagged structure, the coefficient becomes strongly insignificant when adding relevant control variables and year fixed effects, as presented in respectively column (7) and (8). It is noteworthy to mention that, in comparison to the negative coefficient in table 5, the industry-level death rate is found to have a statistically significant positive impact on TFP growth when including R&D expenditures, as shown in column (6) and (8). The coefficient associated with the birth rate remains positive when controlling for R&D effects.

Although we cannot develop direct conclusions from the results presented in table 6, the direct negative effect of EU's environmental policy appears to be greater in size than a potential positive innovation induced productivity effect. Hence, this study finds no significant evidence in favor of the strong hypothesis of Porter. We find no support for the fact that environmental regulations stimulate technical change directed towards technologies that positively impact productivity growth and offset the additional costs of compliance. Due to large econometric drawbacks of adding lagged structures, we cannot study the medium to longer-term innovation induced productivity effects. Further research is required to investigate these longer-term sustainability effects of environmental policy in the European Union.

5.2.1 – Robustness checks

Lanoie et al. (2008) finds a positive R&D induced productivity effect of environmental regulations for the less pollution intensive industries but not for the more pollution intensive industries. Therefore, we conduct several regressions to find if our baseline results are following a similar pattern or if they are robust against such a segregation of the sample. We have constructed a dummy variable that equals one for the subsample of the seven more pollution intensive industries and zero for the other seven less pollutive industries. The more pollution intensive industries are group 1 and 2 and the less pollution intensive industries are group 3 and 4, following the instrumental variable pollution intensity classification, as presented in appendix 3A.

Appendix 5B.1 presents the results for the direct effect regressions, using all relevant control variables and country-sector and time fixed effects. In line with the main results, we find for the more pollution intensive industries a coefficient of -0.973, significant at the 10% level, suggesting a negative direct effect of environmental regulations on productivity growth. On the other hand, for the less pollution intensive industries, the coefficient is smaller and insignificant (-0.138). Moreover, the instrumental variable approach even suggests a potential sign switch for the less pollution intensive industries, but these coefficients are not significant. All in all, we can conclude from these results that the negative direct productivity effect, applies to the more pollution intensive industries.

Appendix 5B.2 presents the results for the indirect productivity effect, when using the pollution intensity dummy variable, for the models without a lag structure. For the more pollution intensive industries, the interaction term in the OLS-estimation has a coefficient equal

Table 6: Productivity effect –Indirect effect – OLS & 2SLS IV-estimation with R&D instrument – panel regression results of environmental policy in the EU

TFP growth	**OLS-estimation**				**2SLS IV-estimation**			
	Not lagged		**One-year lags**		**Not lagged**		**One-year lags**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln EPE	-3.824	-1.575	0.894*	1.641***	-	-	-	-
(*Pollution control*)	(5.562)	(5.532)	(0.433)	(0.475)				
ln R&D Expenditures	0.542	1.274	1.945	1.746*	-	-	-	-
	(0.614)	(4.874)	(1.223)	(1.007)				
(ln R&D * ln EPE (*pc*))	**0.147**	**0.065**	**-0.579***	**-0.655*****	-	-	-	-
	(0.288)	**(0.288)**	**(0.274)**	**(0.227)**				
R&D instrumented by EPE	-	-	-	-	**-0.348**	**-1.388**	**-3.156***	**-1.999**
					(0.390)	**(2.232)**	**(1.824)**	**(1.578)**
ln EPE		-0.548		-0.014	0.037	-0.026	0.024	0.003
(*Cleaner Technology*)		(0.376)		(0.347)	(0.097)	(0.063)	(0.081)	(0.072)
TFPG - leader		0.032		0.052	-0.008	-0.006	-0.001	-0.001
		(0.023)		(0.013)	(0.008)	(0.010)	(0.008)	(0.004)
ln TFP - gap		-0.631***		2.744***	0.032	-0.014	0.134	0.266**
		(0.175)		(0.801)	(0.134)	(0.096)	(0.136)	(0.119)
ln BR		0.933		-0.915**		0.838**		0.578
		(1.025)		(0.318)		(0.335)		(0.392)
ln DR		0.393		2.214		0.539*		0.819**
		(0.474)		(2.208)		(0.322)		(0.345)
ln EU-export rate		0.193		1.549		-0.470		-0.082
		(0.358)		(1.154)		(0.597)		(0.440)
ln EU-import rate		-0.678*		-0.896		0.005		0.098
		(0.492)		(0.825)		(0.789)		(0.398)
Country-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Test	F = 5.01***	F = 13.13***	F = 7.76***	F = 11.64***	F = 3.36***	F = 5.23***	F = 4.29***	F = 5.48***
No. Observations	1224	1012	1105	916	1080	1012	980	916
Within R^2	0.011	0.329	0.020	0.321	0.028	0.137	0.044	0.123

Notes: The dependent variable is TFP growth; Regression 1 to 4 use the OLS-estimator with the explanatory variable being the interaction term R&D * EPE. In regression 4 to 8, the R&D expenditures are instrumented by the pollution control EPE; robust standard errors are in parentheses; logging values equal to zero creates missing values, lowering the number of observations and extra control variables reduce the number of observations further due to less available data.

*** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level

to 0.709, significant at the 10% level, which suggests that there is a positive effect of R&D, induced by environmental regulations, on productivity growth. On the other hand, an opposite relationship can be found for the less pollution intensive industries. Here, the coefficient of the interaction term is -0.732, significant at the 5% level. However, these striking opposing results between pollution intensity groups do not hold when adopting an IV-estimation approach for which the R&D variable becomes more exogenous.

This segregation in the sectors provides no strong evidence, but some of the OLS-estimation results do indicate a difference between the more pollutive industries and the less pollutive industries for both the direct productivity effect and the innovation-induced productivity growth effect. This suggests that the more pollutive industries are more negatively affected on productivity growth by changes in the stringency of environmental regulations in comparison to the less pollutive industries. However, these pollutive industries do benefit more from innovation induced by environmental regulations, contrary to the findings of Lanoie et al. (2008), indicating that the strong Porter hypothesis is more relevant for the more polluting industries.

Finally, the exclusion of the aggregate and more old-fashioned mining and quarrying sector from our sample does not alter qualitatively the empirical results and the conclusions reached from the baseline estimations.

6 Conclusion

This study has given new econometric evidence on the nexus between environmental policies and economic performance, measured by innovation and productivity growth. The results have shed further light on the renowned Porter hypothesis, in both the innovation effect (weak version) and productivity effect (strong version), using an industry-level panel data analysis of the mining and manufacturing industries in the European Union over the period 2008 to 2017. As this paper provides evidence for the economic effects of environmental regulations in the EU during the period of the second and third phase of the EU ETS, this study has provided a comprehensive overview containing further empirical evidence that strengthens the political debate on the economic performance effects of the EU ETS, in times of increasing carbon prices. The ability of an environmental policy to influence technological change and stimulate innovation, through which an industry can reach higher productivity growth, is an important criterion on which to judge a policy's success (Calel and Dechezleprêtre, 2016).

In line with De Vries and Withagen (2005), Rubashkina et al. (2015) and Hille and Möbius (2019), this study recognizes the endogeneity issues accompanying the OLS-estimation using the environmental protection expenditures as a proxy for the stringency of environmental regulations. To account for reverse causality bias and other endogeneity issues, this paper has adopted an instrumental variable approach. The pollution control environmental expenditures are instrumented by the average share of pollution control expenditures over value added of the industry's adjacent sectors, excluding the industry itself: $\frac{EPE}{VA}_{-j}$. The instrumental variable follows a similar structure as the instrument of Rubashkina et al. (2015), but we include pollution intensity ratios to define the adjacent sectors.

With regards to the innovation effect of environmental regulations, this study finds empirical evidence for a positive relationship between the environmental regulations in the European Union and industry-level research and development expenditures, when accounting for endogeneity of the stringency measure. The results are robust against using different knowledge stock variables, but do not hold when using patent applications as measure for innovation. Although we do appoint certain issues with our instrumental variable, we argue that this study has provided supporting evidence for the existence of a positive innovation effect in line with the weak version of the Porter hypothesis. Hence, hypothesis 1 can be accepted. However, it is important to further foster innovation activity and increase the ability of EU's environmental policy to direct technical change through the establishment of innovation stimulating incentives and programs, to insure the innovation effect over the years.

Regarding the productivity effects, this study finds some significant negative direct effect of environmental regulations in the EU on productivity growth. However, this significant effect disappears with the inclusion of time-fixed effects and when accounting for endogeneity issues regarding the environmental stringency measure. As the sign of coefficient remains negative, we cannot reject hypothesis 2A.

Additionally, the strong hypothesis of Porter postulates the idea that environmental policy will lead to increasing productivity-levels, through channels of increasing innovation activity induced by the environmental regulations and directed to economizing and improving the production processes. This study finds no strong evidence supporting such a positive indirect effect on productivity growth in the European Union. The additional cost-burden accompanying the tradable emission permits of the EU ETS seems to negatively impact productivity growth, and this effect is larger than the potential growth from the increased innovation activity induced by the policy. Therefore, we reject hypothesis 2B.

Using the OLS-estimation, a strong negative direct effect and positive indirect effect is found for the more pollution intensive industries. This indicates that that the more pollutive industries are more negatively affected by changes in the stringency of environmental regulations in comparison to the less pollutive industries. However, these pollutive industries do benefit more from innovation induced by the environmental regulations, as the R&D-induced productivity growth effect is positive. We do suggest that further research is necessary to better determine this distinguishable difference between the productivity effects of the more pollutive industries and the less pollutive industries.

This study contains certain limitations that are noteworthy. First of all, the assumption that, conditional on using fixed effects and all control variables within our models, the instrumental variable is not correlated with unobserved factors that influence R&D expenditures and TFP growth, might be weak. Although a similar assumption is made by Rubashkina et al. (2015), we do note that the EPE of adjacent sectors influences the productivity level of these adjacent sectors, through its additional costs component. Hence, if there are potential productivity spillovers within the pollution intensity industry groups, this would suggest that our instrument is correlated with unobserved productivity spillover effects that influence sector *j*'s productivity growth and potentially even innovation activity. Second, the overall negative productivity effects originate partly from the nature of our productivity growth measure. Per definition, TFP growth does not take environmental effects and pollution into account (Koźluk & Zipperer, 2015). Adjusted TFP, or "green" TFP measures include environmental services as an omitted output or input of the productivity definition (Koźluk & Zipperer, 2015). Third, besides the endogeneity issues regarding reverse causality of the main explanatory variable, some of the other variables in the vector of controls may be subject to simultaneity bias. For example, the export intensity ratios, that are included to control for the learning by exporting hypothesis, may increase when productivity growth is higher, as productivity growth may stimulate exporting activity. Finally, this study does not account for the potential that environmental policies may foster the creation of industries and activities that would not exist without the implementation of the policy. This makes the overall productivity effects of environmental policies more complex and uncertain a priori (Koźluk & Zipperer, 2015).

This study provides stimulus for additional further research. First, as it is necessary to account for endogeneity issues accompanying the environmental protection expenditures, further research could focus on finding a better suited instrumental variable or adopt a different estimation strategy to overcome biased estimates. Furthermore, when specifically looking at the market-based EU ETS, it is interesting to apply different measures for the stringency of the environmental policy. Instead of using the pollution control environmental protection expenditures as a proxy, a difference in difference method or carbon price analysis can be conducted. However, a carbon price analysis is a difficult approach since the carbon price does not contain country-sector specific variation. Alternatively, further research can study the relationship between environmental policy and R&D expenditures directed specifically towards environmental objectives. Furthermore, the longer-term sustainability and overall productivity effects of environmental policy in the EU are subject to further research. However, longer time-horizon effects are hard to capture and may depend on the specific policy design (Koźluk & Zipperer, 2015). Therefore, studies that are directed towards the different innovation and productivity effects of different policy designs (market-based; monitoring policies; waste-water management, etc.) are required.

To conclude in a nutshell, this study finds that environmental regulations in the European Union, including the EU ETS, have a positive impact on industry-level innovation activity, supporting the weak version of the Porter hypothesis. This study finds no supporting evidence for a positive indirect productivity effect through innovation channels, as suggested by the strong version of the Porter hypothesis.

7 Bibliography

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8 Appendices

Appendix 1A – Alphabetic country list

Country list	
Austria	Lithuania
Belgium	The Netherlands
Czech Republic	Poland
Finland	Portugal
France	Romania
Germany	Slovak Republic
Greece	Slovenia
Hungary	Spain
Italy	Sweden

Appendix 1B – Industry list

Industry	**NACE Revision 2**
Mining and Quarrying	B
Manufacturing of food products, beverages and tobacco	C10-C12
Manufacturing of Textiles, wearing apparel, leather and related products	C13-C15
Manufacturing of wood and paper products; printing and reproduction of recorded media	C16-C18
Manufacturing of coke and refined petroleum products	C19
Manufacturing of chemicals and chemical products	C20
Manufacturing of basic pharmaceutical products and pharmaceutical preparations	C21
Manufacturing of rubber and plastic products, and other non-metallic mineral products	C22-C23
Manufacturing of basic metals and fabricated metal products, except machinery and equipment	C24-C25
Manufacturing of computer, electronic and optical products	C26
Manufacturing of electrical equipment	C27
Manufacturing of machinery and equipment n.e.c.	C28
Manufacturing of Transport equipment	C29-C30
Manufacturing of Other manufacturing; repair and installation of machinerey and equipment	C31-C33

Appendix 2A – Empirical findings – Innovation Effect

Paper	Dependent variable	Sample	Environmental Stringency	Methodology	Result
Lanjouw & Mody (1996)	Patents & R&D spending	United States, Germany, Japan 1970-1980	Pollution Abatement Control Expenditures/ Interest in environmental protection	Descriptive analysis – simple time series correlation	Increasing interest in environmental protection correlates with innovation
Jaffe & Palmer (1997)	R&D expenditures & U.S. patent applications	U.S. manufacturing industries 1975-1991	Pollution Abatement Control Expenditures	Panel regression using industry fixed effects	- A small positive relationship between PACE and R&D (0.131 significant at 5%) - No significant relationship with patent applications
Brunnermeier & Cohen (2003)	Successful Environmental patent applications	U.S. manufacturing industries 1983-1982	Pollution Abatement Control Expenditures / monitoring and enforcement activities	Panel regression	- PACE influences environmental innovation (0.0125 significant at 1% level) - Monitoring and enforcement activities are no incentive to innovate
Hamamoto (2006)	R&D expenditures	Five heavy pollutive industries in Japan	Pollution Control Expenditures	Panel study	Positive effect on R&D expenditures in Japan (0.195 significant at the 5% level)
Popp (2002)	U.S. patents	United States 1970-1994	Energy prices	Regression analysis	Energy prices have a positive effect on innovation
Newell et al. (1999)	Product innovation	Product specific	Energy prices	Panel regression	Energy price changes induce innovation activity
Lanoie et al. (2011)	Environmental R&D expenditures	Survey data 7 OECD countries 2003	Environmental taxes	Probit Estimation	Positive relationship between environmental taxes and R&D (0.037 significant at 10% level)
Johnstone and Labonne (2006)	Environmental R&D expenditures	Survey data 7 OECD countries 2003	Environmental taxes	Probit estimation	Positive relationship between environmental taxes and R&D
Arimura et al. (2007)	Environmental R&D expenditures	Survey data 7 OECD countries 2003	Perception of environmental stringency	Tobit and bivariat probit estimation	- The perception of environmental stringency positively impacts R&D spending - No stronger effect for flexible market-based policy instruments
Rubashkina et al. (2015)	R&D expenditures & patent applications	European manufacturing sectors 1997-2009	Pollution Abatement Control Expenditures / ($PACE/VA_{-j}$)	Instrumental variable approach	- No relationship between PACE and overall R&D - PACE has a positive impact on patent applications (0.063 significant at 5% level)

Kneller and Manderson (2012)	R&D expenditures	UK manufacturing industries 2000-2006	Environmental Protection Expenditures (EPE)	GMM estimation	- Positive relationship between PACE and environmental R&D (0.163 significant at 1% level) - However, this is not true when using overall R&D spending
De Vries and Withagen (2005)	Environmental patents	14 OECD countries 1970-2000	Population density as instrument for environmental stringency	Instrumental variable approach	Only for the IV-model a positive relationship

Appendix 2B – Empirical findings – Productivity Effect

Paper	Dependent variable	Sample	Environmental Stringency	Methodology	Result
Gray (1987)	TFP growth	450 U.S. manufacturing industries 1958-1978	PACE	Regression analysis	- Negative effect of PACE on TFP growth. - Findings disappear when including appropriate controls
Barbera and McConnell (1990)	TFP growth	Five U.S. manufacturing industries 1960-1980	Abatement capital	Estimating cost elasticity of the abatement capital	Negative direct effect, but without controlling for industry characteristics. Environmental requirements account for 10-30% of decline in productivity
Dufour et al. (1998)	TFP growth	Canadian manufacturing industries 1985-1988	Investment in pollution control equipment over total input costs	GLS estimation	Negative direct effect, but small sample.
Smith & Sims, (1985)	TFP growth	Canadian brewing industry 1971-1980	Pollution charges/payment	Comparison of TFP growth between the unregulated and regulated firms	Small negative effect of pollution charges on productivity growth
Berman & Bui (2001)	TFP	Los Angeles oil refineries 1977-1992	Number of environmental regulations in place	Fixed effect estimation	Positive insignificant productivity effect
Conrad & Wastl (1995)	TFP growth	10 pollution intensive German industries 1975-1991	Pollution abatement costs	Look at the effect in terms of cost diminution	Negative direct effect Pollution abatement costs reduce TFP growth by 2.5%
Yang et al. (2012)	TFP	Taiwanese manufacturing industries 1997-2003	Pollution abatement fees & environmental regulation induced R&D spending	Fixed effect estimation including a lag structure	- Positive direct effect of environmental regulation on TFP (0.008 significant at 10% level) - Positive effect of induced R&D on TFP (0.011 at 5% level)

Lanoie et al. (2008)	TFP growth	Quebec (Canada) manufacturing industries 1985-1994	Investment in pollution control equipment over total input costs	GLS estimation including a lag structure	- Negative productivity effect disappears after three years. - This positive switch is only for the low pollutive industries and stronger for international competitive industries
Hamamoto (2006)	TFP growth	Five heavy pollutive industries in Japan	Pollution Control Expenditures	- Using an extended Cobb-Douglas production function, including R&D capital - Lag structure	Positive effect of induced R&D on TFP growth (0.282 at 5% significance level)
Lanoie et al. (2011)	Business performance dummy variable	Survey data of 7 OECD countries 2003	Environmental taxes	Instrumental variable probit Estimation	No support for strong version of Porter's hypothesis
Hille & Möbius (2019)	TFP growth	14 manufacturing sectors in 28 OECD countries 1995 - 2009	Shadow prices of energy	GMM and FE estimation	- No significant R&D induced productivity effect - Not controlling for endogeneity issues generates biased results
Martínez-Zarzoso et al. (2019)	TFP	14 OECD economies 1990-2011	OECD's Environmental Policy Stringency (EPS) index	Panel regression using a lag structure	Positive long-term effect of the EPS index on productivity
Rubashkina et al. (2015)	TFP level & TFP growth	European manufacturing sectors 1997-2009	PACE	Instrumental variable approach	No significant productivity effect of environmental regulations in the European manufacturing industries

Appendix 3A - Pollution intensity group division for the construction of the instrumental variable

NACE Revision 2	Pollution Intensity (Greenhouse Gas Emissions/Gross Output)	IV-Group
B	863.70	1
C20	607.10	1
C22-C23	1204.03	1
C24-C25	684.72	1
C16-C18	326.86	2
C19	423.80	2
C27	242.24	2
C10-C12	77.27	3
C21	53.57	3
C31-C33	66.63	3
C13-C15	41.04	4
C26	20.03	4
C28	38.03	4
C29-C30	40.38	4

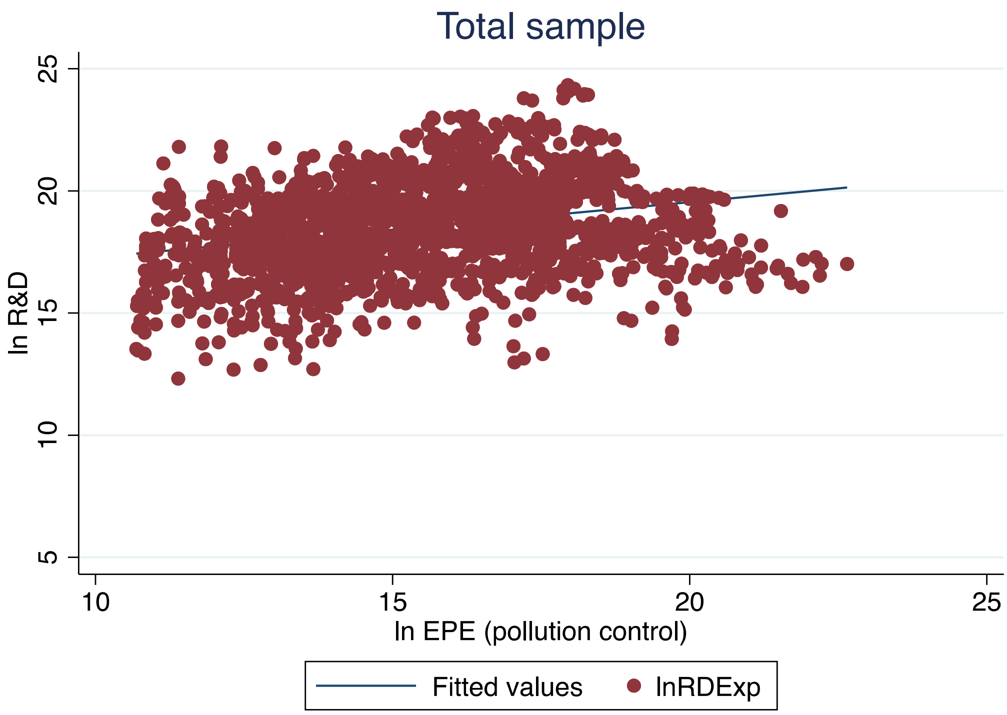
Appendix 3B – Summary statistics of all regression variables (2008-2017)

Summary statistics over the period 2008 - 2017

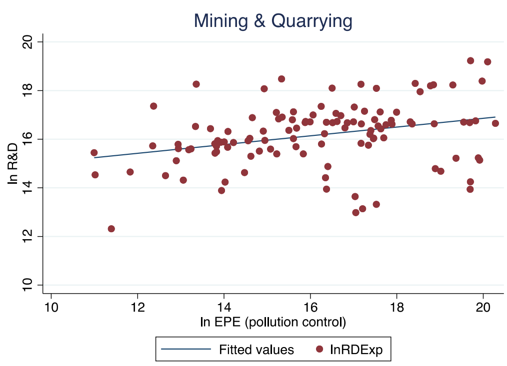
	Unit	Mean	Standard Deviation	Min	Max
Pollution EPE/VA	Percentage	0.32	1.47	0	42.50
Cleaner Technology EPE/VA	Percentage	0.17	0.62	0	11.00
R&D/VA	Percentage	5.12	7.92	0	79.69
ΔTFP	Percentage	1.61	13.69	-49.93	98.89
KS/VA	Percentage	29.34	40.61	0	193.55
Gov.R&D/VA	Percentage	4.37	7.42	0.01	83.36
Birth Rate	Percentage	8.17	7.07	0	76.00
Death Rate	Percentage	7.61	6.53	0	56.00
EU Export Rate	Percentage	27.46	17.71	0	97.00
EU Import Rate	Percentage	36.16	21.80	0.90	99.22

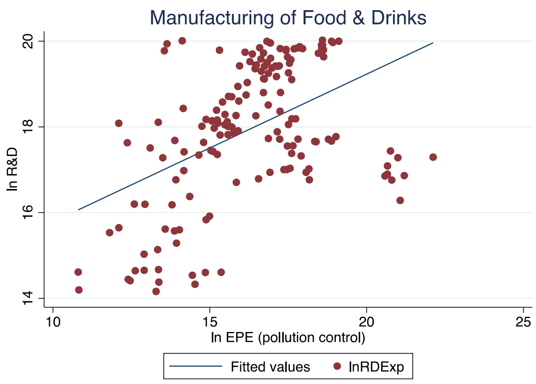
Appendix 4A – Scatterplots – R&D expenditures & EPE variable

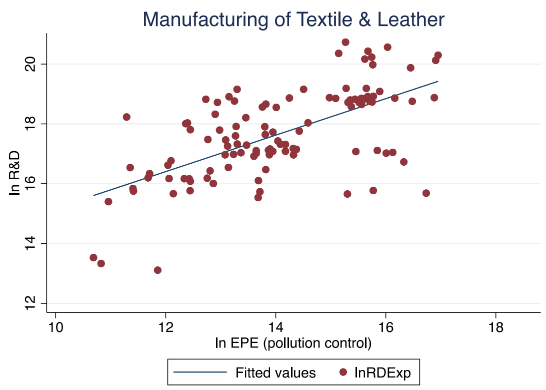
Total sample:

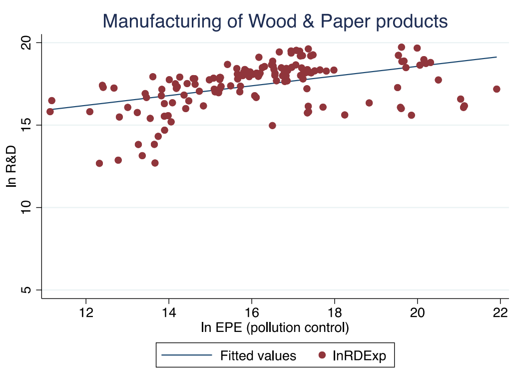


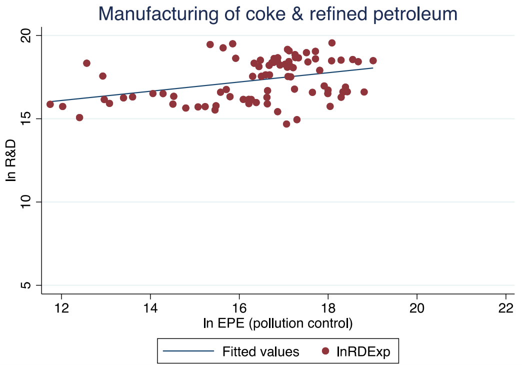
By industry:

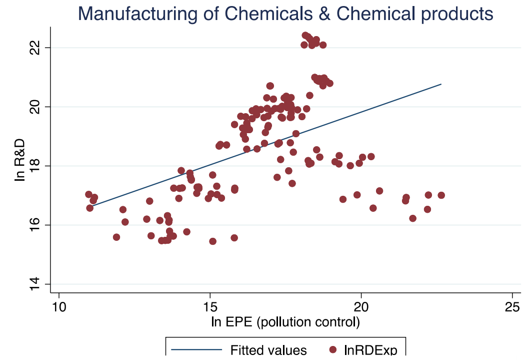


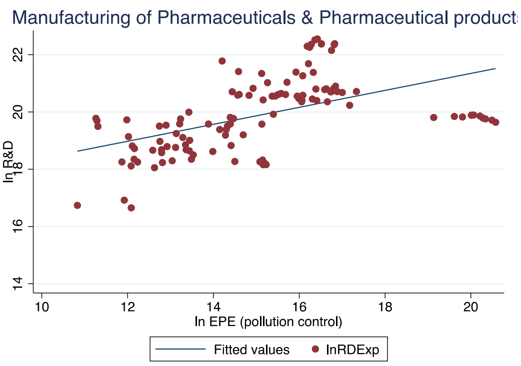


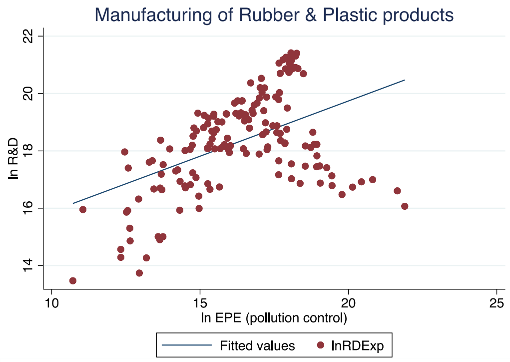


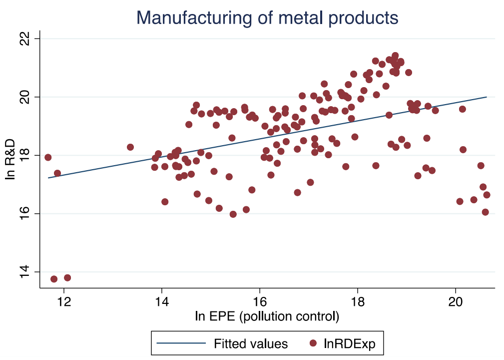


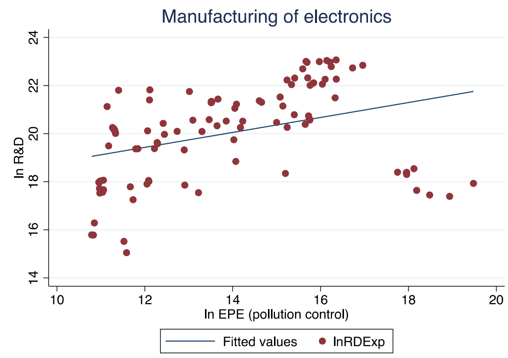

Manufacturing of coke & refined petroleum
ln R&D
5
10
15
20
12
14
16
18
20
22
ln EPE (pollution control)
Fitted values
lnRDExp

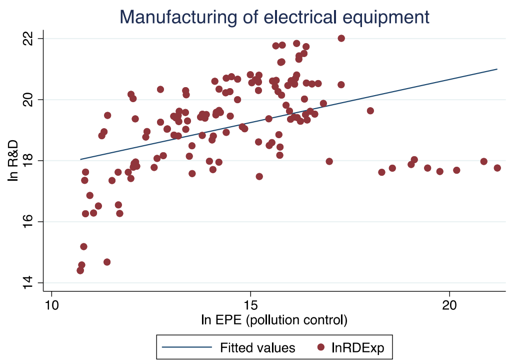

Manufacturing of Chemicals & Chemical products
ln R&D
14
16
18
20
22
10
15
20
25
ln EPE (pollution control)
Fitted values
lnRDExp

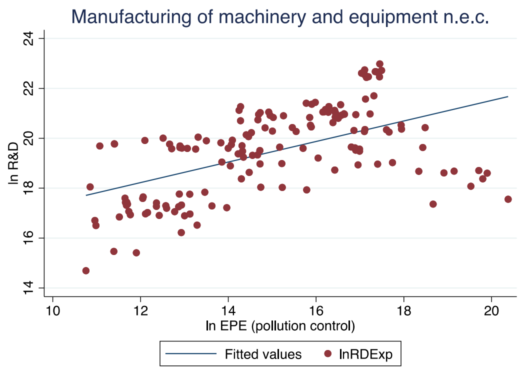

Manufacturing of Pharmaceuticals & Pharmaceutical product
ln R&D
14
16
18
20
22
10
12
14
16
18
20
ln EPE (pollution control)
Fitted values
lnRDExp

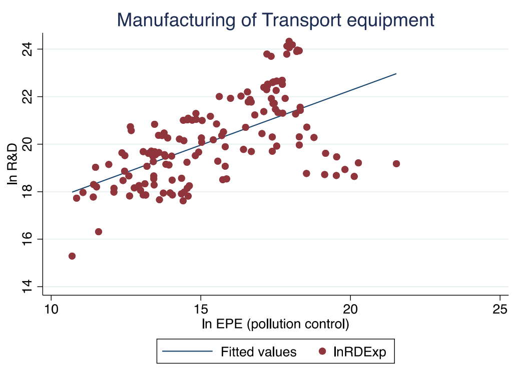

Manufacturing of Rubber & Plastic products
ln R&D
14
16
18
20
22
10
15
20
25
ln EPE (pollution control)
Fitted values
lnRDExp

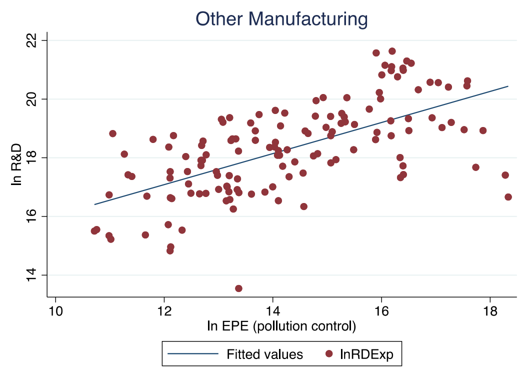

Manufacturing of metal products
ln R&D
14
16
18
20
22
12
14
16
18
20
ln EPE (pollution control)
Fitted values
lnRDExp


Manufacturing of electronics
ln R&D
14
16
18
20
22
24
10
12
14
16
18
20
ln EPE (pollution control)
Fitted values
lnRDExp


Manufacturing of electrical equipment
ln R&D
14
16
18
20
22
10
15
20
ln EPE (pollution control)
Fitted values
lnRDExp

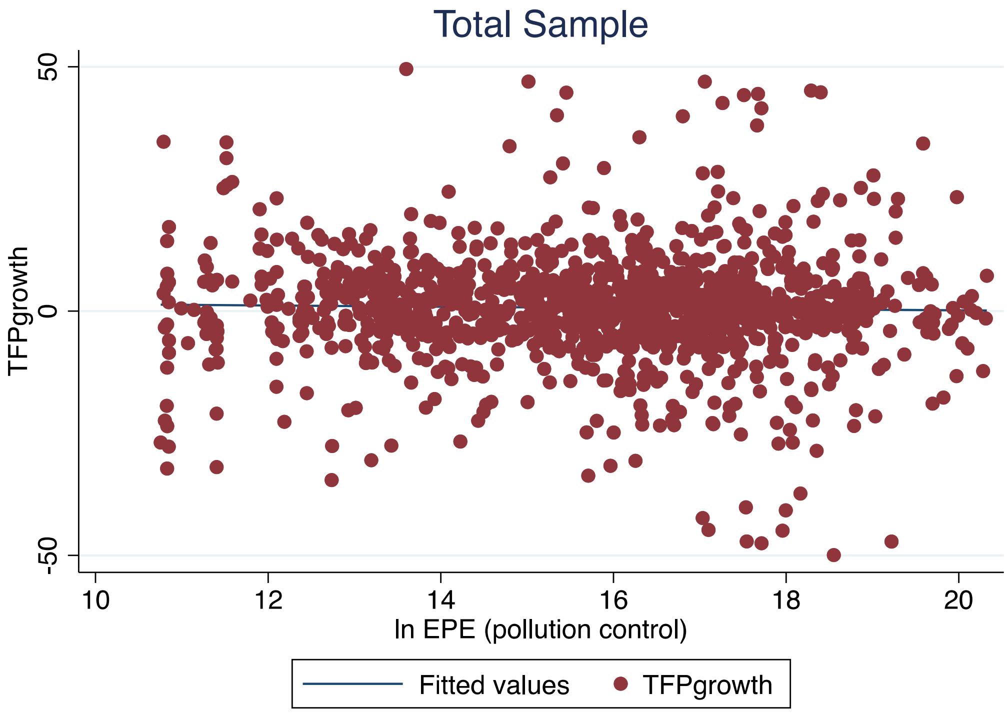

Manufacturing of machinery and equipment n.e.c.
ln R&D
14
16
18
20
22
24
10
12
14
16
18
20
ln EPE (pollution control)
Fitted values
lnRDExp


Manufacturing of Transport equipment
ln R&D
14
16
18
20
22
24
10
15
20
25
ln EPE (pollution control)
Fitted values
lnRDExp

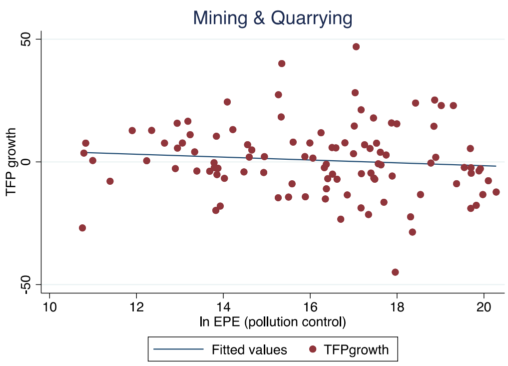

Other Manufacturing
ln R&D
14
16
18
20
22
10
12
14
16
18
ln EPE (pollution control)
Fitted values
lnRDExp

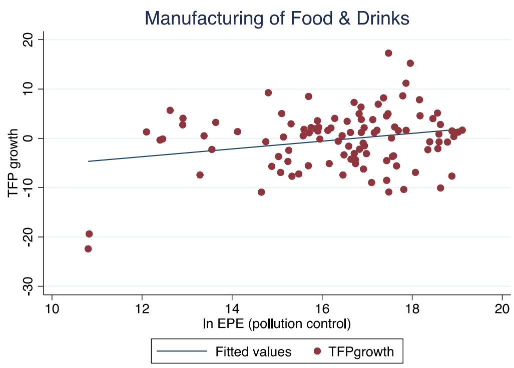
Appendix 4B – Scatterplots – TFP growth & EPE variable

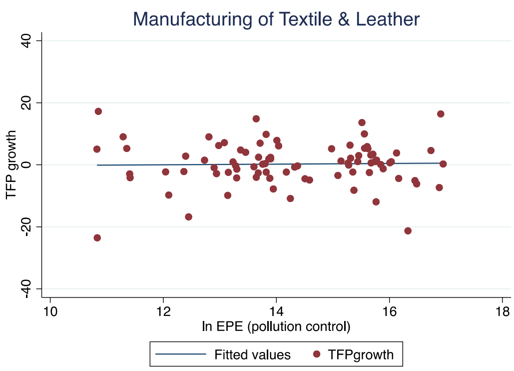
Total sample:

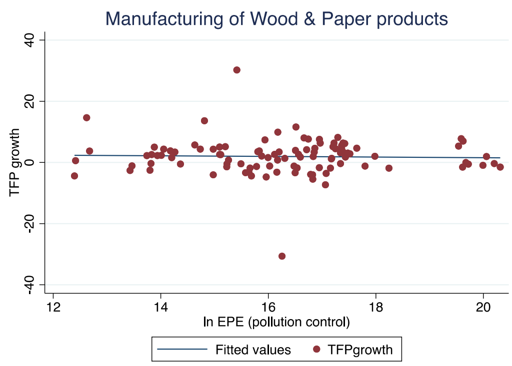


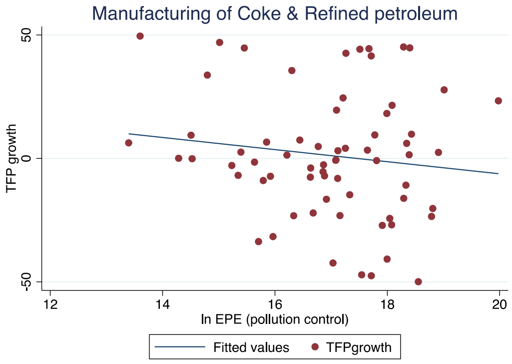
By industry:

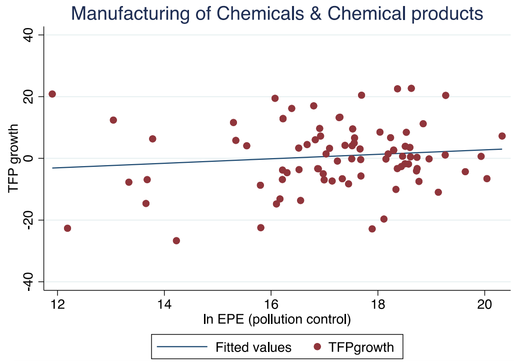


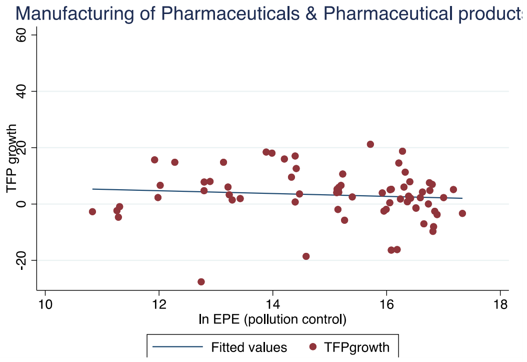


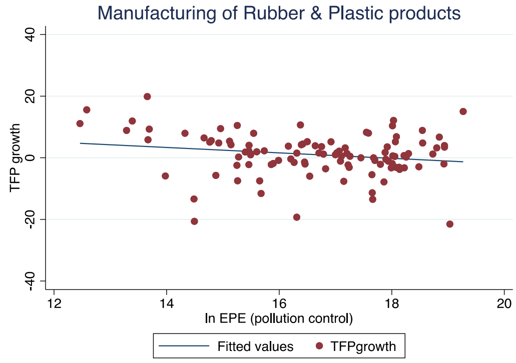


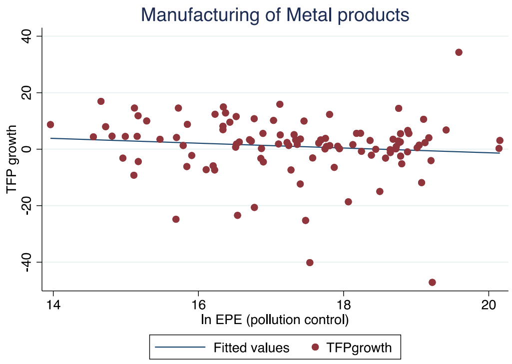


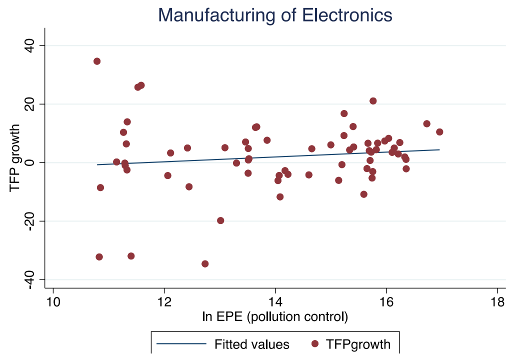

Manufacturing of Coke & Refined petroleum
TFP growth
-50 0 50
12 14 16 18 20
ln EPE (pollution control)
Fitted values TFPgrowth

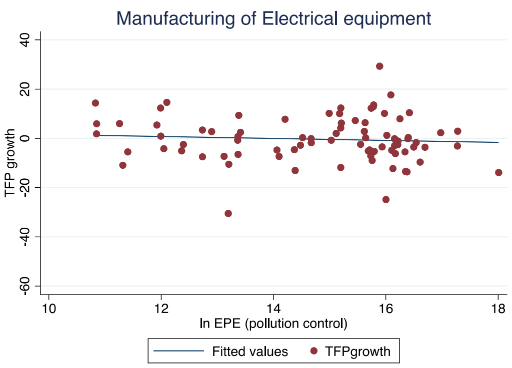

Manufacturing of Chemicals & Chemical products
TFP growth
-40 -20 0 20 40
12 14 16 18 20
ln EPE (pollution control)
Fitted values TFPgrowth

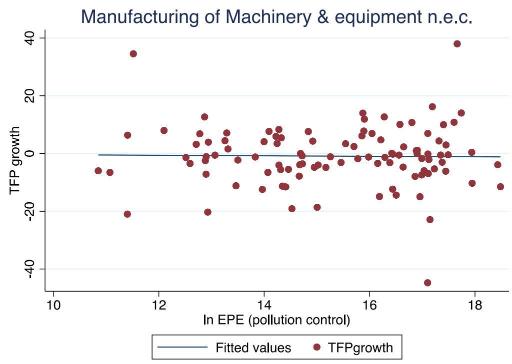

Manufacturing of Pharmaceuticals & Pharmaceutical product
TFP growth
-20 0 20 40 60
10 12 14 16 18
ln EPE (pollution control)
Fitted values TFPgrowth

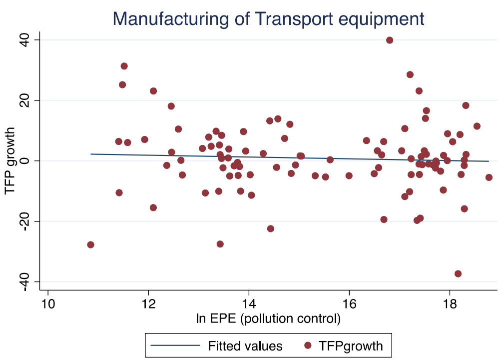

Manufacturing of Rubber & Plastic products
TFP growth
-40 -20 0 20 40
12 14 16 18 20
ln EPE (pollution control)
Fitted values TFPgrowth

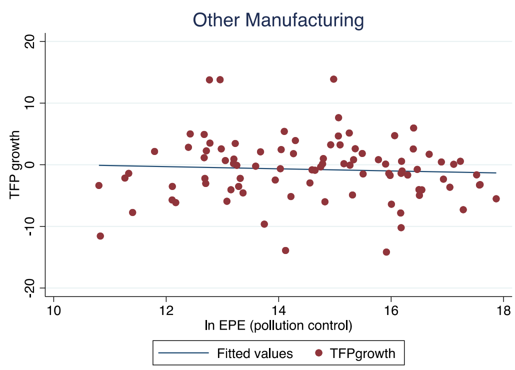

Manufacturing of Metal products
TFP growth
-40 -20 0 20 40
14 16 18 20
ln EPE (pollution control)
Fitted values TFPgrowth


Manufacturing of Electronics
TFP growth
-40 -20 0 20 40
10 12 14 16 18
ln EPE (pollution control)
Fitted values TFPgrowth


Manufacturing of Electrical equipment
TFP growth
-60 -40 -20 0 20 40
10 12 14 16 18
ln EPE (pollution control)
Fitted values TFPgrowth


Manufacturing of Machinery & equipment n.e.c.
TFP growth
-40 -20 0 20 40
10 12 14 16 18
ln EPE (pollution control)
Fitted values TFPgrowth


Manufacturing of Transport equipment
TFP growth
-40 -20 0 20 40
10 12 14 16 18
ln EPE (pollution control)
Fitted values TFPgrowth


Other Manufacturing
TFP growth
-20 -10 0 10 20
10 12 14 16 18
ln EPE (pollution control)
Fitted values TFPgrowth

Appendix 5A – The innovation effect robustness checks

Appendix 5A.1 – Different knowledge stock variables.

	OLS-estimation			**2SLS IV-estimation**		
	R&D expenditures			*R&D expenditures*		
	(1)	(2)	(3)	(4)	(5)	(6)
	δ = 10%	**δ = 20%**	**δ = 30%**	**δ = 10%**	**δ = 20%**	**δ = 30%**
EPE (*Pollution Control*)	0.005 (0.013)	0.007 (0.012)	0.007 (0.012)	0.231* (0.122)	0.321** (0.143)	0.367** (0.160)
Knowledge Stock	0.435*** (0.061)	0.412*** (0.145)	0.519*** (0.108)	0.577*** (0.073)	0.545*** (0.091)	0.559*** (0.082)
Const.	3.677* (2.144)	4.125 (2.636)	2.916 (2.291)	3.113 (2.721)	2.655 (3.350)	1.833 (3.589)
FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	No	No	No
Test	F = 16.51***	F = 14.13***	F = 16.82***	F = 18.06***	F = 10.70***	F = 17.28***
N	1141	1141	1141	1121	1121	1121
R^2	0.564	0.557	0.703	0.800	0.710	0.675

Notes: Regression (1) to (6) use the OLS-estimator, whereas regression (7) to (9) adopt a 2SLS IV-estimation. The dependent variable in regression (1) to (3) and (7) to (9) is the log of R&D expenditures. Regressions (4) to (6) uses R&D intensity (R&D/VA) as dependent variable. Independent variables are the pollution control (*PC)* EPE, cleaner technology (*CT)* EPE; knowledge stock (KS) using depreciation rates of 10%, 20% and 30% and a vector of controls as used in the main results, but for space reasons the coefficients are not presented; robust standard errors in parentheses.
Note that regression (2), (5) and (8) are already presented in the main results.
*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level

Appendix 5A.2 - Environmental policy and patent applications

Patent applications	**OLS-estimation** (1)	(2)	**2SLS IV-estimation** (3)	(4)
ln EPE	0.021	0.016	-0.138	-0.378
(*Pollution Control)*	(0.025)	(0.025)	(0.209)	(0.275)
Const.	2.810	-0.335	4.582	6.826
	(3.737)	(0.208)	(6.109)	(6.990)
FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Test	F = 1.18	F = 4.09***	F = 0.80	F = 1.68*
N	636	636	628	628
R^2	0.168	0.765	0.043	0.015

Notes: Regression (1) and (2) use the OLS-estimator, whereas regression (3) and (4) adopt a 2SLS IV-estimation. The dependent variable is the log of the number of patent applications at the European Patent Office. Independent variables are the pollution control (*PC)* EPE, cleaner technology (*CT)* EPE; knowledge stock (KS) and a vector of controls as used in the main results, but for space reasons the coefficients are not presented; robust standard errors in parentheses.
*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level

Appendix 5B – The productivity effect robustness checks

Appendix 5B.1 – The direct productivity effect using a pollution intensity dummy

TFP growth	**OLS-estimation**		**2SLS IV-estimation**	
	(1)	(2)	(7)	(8)
Pollution dummy	*More pollutive*	*Less pollutive*	*More pollutive*	*Less pollutive*
ln EPE	-0.973*	-0.138	-2.835	1.052
(*Pollution control*)	(0.517)	(0.438)	(4.388)	(3.448)
Country-sector FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Test	F = 8.81***	F = 8.13***	F = 3.22***	F = 8.93***
No. Observations	509	517	495	508
Within R^2	0.324	0.411	0.016	0.304

Note: the dependent variable is TFP growth; a dummy variable is included that equals one for the seven more pollution intensive industries and zero for the seven other less pollutive industries; the same vector of controls from the main results is used in all regressions of this table, but for space reasons the coefficients are not presented; robust standard errors are in parentheses.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

Appendix 5B.2 – The indirect productivity effect using a pollution intensity dummy

TFP growth	**OLS-estimation**		**2SLS IV-estimation**	
	(1)	(2)	(7)	(8)
Pollution dummy	*More pollutive*	*Less pollutive*	*More pollutive*	*Less pollutive*
R&D instrumented by EPE			-2.866 (4.900)	-0.362 (3.792)
(ln R&D * ln EPE (*pc*))	0.709* (0.376)	-0.732** (0.277)		
Country-sector FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Test	F = 13.15***	F = 7.00***	F = 4.85***	F = 9.54***
No. Observations	500	512	500	512
Within R^2	0.350	0.395	0.134	0.262

Note: the dependent variable is TFP growth; a dummy variable is included that equals one for the seven more pollution intensive industries and zero for the seven other less pollutive industries; the same vector of controls from the main results is used in all regressions of this table, but for space reasons the coefficients are not presented; robust standard errors are in parentheses.
*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level