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Environmental regulation and productivity growth in the euro area: testing the Porter hypothesis

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Abstract

This paper analyses the impact of changes in environmental regulations on productivity growth at country- and firm-level. We exploit several data sources and the environmental policy stringency index, to evaluate the Porter hypothesis, according to which firms' productivity can benefit from more stringent environmental policies. By using panel local projections, we estimate the regulatory impact over a five-year horizon. The identification of causal impacts of regulatory changes is achieved by the estimation of firms' CO2 emissions via a machine learning algorithm. At country- and firm-level, policy tightening affects high-polluters' productivity negatively and stronger than their less-polluting peers. However, among high-polluting firms, large ones experience positive total factor productivity growth due to easier access to finance and greater innovativeness. Hence, we do not find support for the Porter hypothesis in general. However for technology support policies and firms with the required resources, policy tightening can enhance productivity.

Keywords: Environmental regulation, Emissions, Porter hypothesis, Productivity, Euro Area

JEL Codes: O44, Q52, Q58

Non-technical summary

With climate change becoming an increasing threat to our society and economy, governments across Europe have been implementing measures to reduce greenhouse gas emissions. Environmental policies cover a broad range of tools, including CO_2 taxes, performance standards and research and development (R&D) subsidies for environmentally friendly technologies, all impacting the aggregate economy via changes in firms' behaviour. While these policies often achieve a pollution reduction, they also reduce the flexibility with which firms can operate and imply higher costs due to necessary adjustments.

The existence of a trade-off between a sustainable and prosperous economy is, however, questioned by Porter and van der Linde (1995). They argue that more stringent environmental regulations could increase productivity (output-to-input ratio) and competitiveness of firms by switching towards "green" materials or implementing more efficient processes. Thereby, the short-term adjustment costs could be compensated or even exceeded by benefits, so environmental regulations could reduce emissions and increase productivity in the long-term. This hypothesis, known as the Porter hypothesis, needs to be empirically tested to give reliable policy recommendations.

This paper tests the Porter hypothesis at the aggregate and also at the firm level. We use country-level data from 15 Euro Area (EA) member states and firm-level information of nearly three million firms from 6 EA countries over the period 2003 to 2019. We combine these data with the Environmental Policy Stringency (EPS) indicator of the OECD that allows us to compare the stringency of different types of environmental policies across countries and time. In addition, we estimate the CO_2 emissions of firms by a machine learning algorithm (XGBoost) so that we can distinguish between low and high polluting firms. This distinction is important, because high polluting firms can be expected to be more exposed to regulations and therefore, face higher costs. We estimate the impact of changes in environmental policies on productivity growth with a local projection approach that allows us to estimate the impact over different horizons (up to five years ahead), while we can still control for many other explanatory variables of productivity growth. Furthermore, we explore whether all environmental policies are similar in terms of impact, and whether there are differences in firms' responses depending on their characteristics.

We conduct our empirical investigation at country and firm level and find consistent results.

Highly polluting countries and firms are more negatively affected by more stringent regulations than their less polluting peers due to their larger regulatory exposure. Even after five years the costs faced by high polluting countries and firms are higher than their productivity gains. A large reform (one standard deviation shock) reduces high polluting firms' productivity growth by 1/3 on average over five years. Therefore, we have to reject the Porter hypothesis for the overall population of countries and firms. Note, however, that in a related paper we find that more stringent environmental policies increase firms' efforts in green innovation which could imply that it takes more than five years (the horizon analysed in this paper) for productivity gains to show up. Moreover, our results suggest that not all policies have the same productivity impacts. While non-market based tools (e.g. performance standards) reduce productivity growth of polluting firms significantly, market based instruments (e.g. taxes, permits and certificates) seem to be less harmful. In the case of technology support policies (e.g. green research & development subsidies), we observe only temporary adjustment costs for high (and low) polluting firms, before the subsidies enhance their productivity.

Not all firms are equally affected by policies. We find significant differences among highly polluting firms regarding their adjustment to more stringent policies. Firms have very different capabilities to deal with regulatory reforms and while the age of a firm does not seem to play a role, the size (in terms of number of employees) does. Very large firms even experience positive productivity growth three years after a change in environmental policy stringency. Two underlying factors potentially explain these different reactions. First, we show that firms with better access to financial markets, measured by the equity ratio, face lower losses in terms of productivity. Second, firms with more research experience, measured by the number of patents registered in the past, cope better with a changing regulatory environment. Thus, policy makers should consider the need for a balanced mix of environmental regulations and put in place research and development incentives so that greenhouse gas emissions decline and productivity losses are limited.

1 Introduction

In establishing the objective of reaching 'net zero' greenhouse gas emissions by 2050 and launching the Green New Deal, the EU has set a clear direction for the future. In addition to potent EU-level policies tackling climate change, such as the EU Emissions Trading Scheme (ETS), an increasing number of member state governments are signing up to their own greenhouse gas emission targets and adopting increasingly stringent policies to deliver on their ambitions at the national level. The policies implemented run the entire gamut of command-and-control, market-based and technology support options, from mandatory standards to carbon pricing and R&D subsidies. These policy changes are likely to trigger a wide-ranging transformation of the EU economy and re-allocation of resources between various sectors. This is especially true when combined with stimulus packages adopted in the wake of the COVID-19 crisis, which are also dedicated to supporting 'green' economic activities albeit to varying degrees. The economic effects of climate regulation and environmental regulation more generally are therefore of central interest to policy-makers both at the national and EU levels.

Regulation is traditionally seen as a hindrance to economic activity, at least in the short to medium term, as it raises costs without increasing output and restricts the set of available production technologies and outputs. In contrast to this view, the Porter hypothesis (Porter and Van der Linde, 1995) suggests that under certain conditions environmental policies can spur innovation and by doing so enhance productivity, which can offset or even outweigh the costs of the policy. As evident from the literature review, the number of existing empirical analyses regarding the validity of the Porter hypothesis is large but results remain inconclusive, with some studies suggesting it holds while others arguing the opposite. The majority of relevant studies are focused on single countries or industries and suffer from limited external validity, while potential endogeneity issues are rarely addressed in a robust manner.

This paper probes the link between environmental policy stringency and productivity growth in six euro area countries (Germany, Belgium, France, Italy, Spain and Portugal) in the period between 2003 and 2019. More specifically, we assess the dynamic impact of environmental regulation on euro area firms' total factor productivity (TFP) and labour productivity (LP) growth and its aggregate consequences on competitiveness. The use of firm-level data is fundamental to analyse heterogeneous impacts of policies across firms differing in size, innovativeness or financial resources. These heterogeneous effects are often hidden in aggregate data. The granular analysis is complemented with country-level insights to gauge the aggregate impacts of policies. Lastly, we explore the differences between different types of policy (market-based vs non-market-based vs technology-support) in their impact on productivity growth. We find that high-polluting countries and firms are affected differently than their low-polluting peers by an increase in environmental policy stringency. Generally, high polluters are affected more negatively, so we have to reject the strong Porter hypothesis for the overall population of firms. It is, however, important to distinguish between different policy types as they affect TFP growth differently. In case of high-polluting firms, technology support policies only have transitory negative effects before boosting TFP growth; market-based policies have small but negative effects; and non-market based tools reduce TFP growth the most. Among high polluting firms, the impact of policy tightening varies: more resources, as proxied by a higher equity ratio and more experience with patenting can ameliorate the negative impact of stricter environmental policies.

We contribute to the rich empirical literature examining the Porter hypothesis in two main ways. First, our panel data set spans multiple countries and sectors. We exploit a firm-level data set containing data about more than three million individual firms. Second, our contribution relies on a novel identification strategy based on the assumption that environmental policy is likely to affect firms differently depending on their exposure to regulation, with firm-level emissions used as a proxy for this exposure. A similar approach has been applied by Albrizio et al. (2017) albeit at the industry level. Scarcity of firm-level pollution data, especially for smaller firms, would normally hinder the deployment of this approach at firm-level. We overcame this problem by estimating emission equivalents using a Boosted Trees machine learning model based on firm-level financial account data. We then use local projections to estimate the non-linear impulse responses of TFP growth to a change in environmental regulation, defined as a positive change in policy stringency. This is motivated by the fact that environmental policies might have different short and medium-term impacts. The local projection methodology allows us to describe dynamic effects of changes in regulation and to capture heterogeneous impacts across firms, while remaining robust to miss-specifications.

The paper is structured as follows: Section 2 reviews the literature and the importance to control for endogeneity. Section 3 describes the macro and firm-level data as well as the emission estimates, which are used in the local projection framework explained in section 4. Section 5 presents the effects of different types of environmental policies on productivity growth at country and firm-level. Section 6 concludes.

2 Literature Review

The Porter hypothesis has a number of theoretical offshoots. The 'strong' version states that increases in environmental regulation stringency raise overall productivity, while the 'weak' version holds that optimally designed environmental regulation spurs innovation. The 'narrow' version predicts that market-based tools are more effective in boosting innovation than command-and-control policies. While we analyse the 'weak' version in a related paper (Benatti et al., 2023), the focus of this paper is on the evaluation of the strong (and narrow) version at country- and firm-level.

Various sources of endogeneity complicate the identification of a causal link between regulation and economic outcomes including productivity. A great concern is omitted variable bias, which can arise as a result of other regulations (e.g. labour or financial market), expenditure on R&D or trade that affects both TFP growth and decisions on environmental stringency. Moreover, Albrizio et al. (2017) point out that simultaneity issues may arise if, for instance, good environmental performance in given industries facilitates adoption of more stringent environmental policies or if firms that are performing poorly are able to successfully lobby against more stringent policies. The present section therefore reviews the most relevant literature with a particular focus on the identification strategy chosen by the authors.

Most prior studies examining the strong version of the Porter hypothesis do not sufficiently address potential endogeneity issues, which may result in biased estimates (Hille and Möbius, 2019; Brunel and Levinson, 2020). Cohen and Tubb (2018) also support this finding and qualify this in their meta-analysis by claiming that studies are more likely to yield evidence supporting the strong version of the Porter hypothesis when an instrumental variable is implemented for environmental regulation. Overall, the evidence presented is inconclusive both with regards to the significance and direction of the effect (Ambec et al., 2013; Kozluk and Zipperer, 2015; Cohen and Tubb, 2018).

The majority of studies exploring the relationship between environmental regulation and productivity focus on specific countries and industries and, in many cases, specific legislation. In general, these studies tend to exploit the introduction of a significant change in a particular environmental policy and a firm or plant inclusion threshold, and then gauge the effect of the policy on regulated firms though some version of the difference-in-differences approach. Among the studies investigating the impact of specific legislation on productivity are Berman and Bui

(2001) who report that refineries located in the Los Angeles area enjoyed significantly higher productivity than other US refineries despite the more stringent air pollution regulation in Los Angeles. Greenstone et al. (2012) find a negative effect of ozone and particulate emission regulation on productivity but no effect of sulphur dioxide regulation and a positive effect of carbon monoxide regulation.

More closely related to our inquiry are those contributions considering various aggregate measures of environmental policy stringency and which therefore cannot exploit inclusion criteria in specific policies. Many of these studies tend to avoid making strong claims about causality. Lanoie et al. (2008), for instance, analyse the relationship between the stringency of environmental regulation and total factor productivity (TFP) in the Quebec manufacturing sector. Their results suggest that the contemporaneous impact of environmental regulation on productivity is negative and turns positive in models using lagged measures of environmental policy stringency. Hamamoto (2006) finds that environmental command-and-control regulations led to an increase in innovation (proxied by R&D spending) and consequently to an increase in productivity growth in a sample of five Japanese manufacturing sectors over 20 years. He likewise refers to "positive association" rather than a clear causal relationship. More recently, a similar approach was taken by Lee and Lee (2022) who use a multilevel linear model and their results indicate that environmental protection expenditure has a negative correlation with TFP in Korea.

In terms of cross-country studies, the most notable contribution is that of Albrizio et al. (2017), which uses the Environmental Policy Stringency (EPS) composite index to measure the impact of environmental policy on total factor productivity growth. The study combines insights from firm- and industry-level analysis and finds that the tightening of environmental policy has a positive short-term effect on productivity growth at the industry level. At the firm-level, only a minority of the firms (the most productive ones) register productivity gains after a tightening of environmental regulation. They also find the temporary effects tend to differ by policy type, with market-based instruments having a more robust positive effect on productivity growth. Their identification strategy relies on the fact that environmental policy is likely to affect industry productivity heterogeneously depending on the industry's exposure to the regulation. A higher environmental dependence (proxied by pollution intensity) increases the industries' exposure to the country-level environmental policies and hence the potential economic effects. Thus, in their main empirical specification, the EPS index is interacted with the past pollution intensity of the industry.

The identification approach taken by Albrizio et al. (2017) is common in the analysis of impacts of national-level policies of all types and developments at the industry and firm-levels and was popularised by Rajan and Zingales (1998), who explored the role of financial development using industry-specific financial dependence as the exposure variable. They argue that since financial markets and institutions help a firm overcome problems of moral hazard and adverse selection and thus reduce the firms costs of raising money, financial development should disproportionally help firms or industries that depend on external finance for their growth. Another notable recent study is that of Hille and Möbius (2019) who tackle endogeneity by using fixed effects and a dynamic panel generalized method of moments (GMM) estimator. Their positive regulatory effects on productivity change to insignificant effects once simultaineity is controlled for.

3 Data

Our analysis combines a variety of data sources to describe the effects of changes in environmental regulation on productivity. These include aggregate indicators from the OECD and Eurostat to describe macroeconomic changes and environmental policies as well as granular firm and emission data from ORBIS, iBACH and Urgentem. Our data set spans the period from 2003 to 2019 and includes 15 EA countries for the aggregate analysis and firms from 6 EA countries for our firm-level analysis.[1]

3.1 Measuring environmental policy stringency

In order to capture the development of environmental regulation, we use the index of environmental policy stringency (EPS) developed by the OECD (Botta and Koźluk, 2014; Kruse et al., 2022). The current version of the EPS index covers 34 OECD countries over the period 1990–2020 and summarizes environmental policy stringency across selected instruments. The indicator consists of three components: a market-based, a non-market based and a technology support sub-indicator. The market-based component groups instruments which assign an explicit price to externalities (taxes: CO_2, SO_X, NO_X, and diesel fuel; trading schemes: CO_2, renewable energy certificates and energy efficiency certificates). The non-market component clusters performance standards (emission limit values for SO_X, NO_X and PM, limits on sul-

[1] Austria, Belgium*, Estonia, Finland, France*, Germany*, Greece, Ireland, Italy*, Luxembourg, the Netherlands, Portugal*, Slovakia, Slovenia and Spain* - * indicates availability of firm-level data

fur content in diesel). Finally, technology-support policies capture green R&D subsidies (per GDP) and adaption support measures like feed-in-tariffs. All indicators range from 0 to 6 with higher numbers being associated with more stringent environmental policies. This implies that higher taxes, lower limits and more subsidies increase the indicator values. Figure 1 provides an overview of the evolution of the EPS index as well as the three sub-indices in the countries relevant for the firm-level analysis. While we observe a trend towards more stringent policies, there is substantial heterogeneity across countries and sub-indicators.

Figure 1: EPS index

Note: Development of the EPS index and its sub-indicators (market, non-market and technology support) between 2003 and 2019. Range between 0 and 6, 6 represents the most stringent policies among OECD countries since 1990.

The intention of the EPS index is to proxy the environmental policy stringency of the whole economy, although several environmental regulations are sector specific. Botta and Koźluk (2014) focus on regulations of the energy and transport sector curbing greenhouse gas emissions and air pollution. These two sectors are present and important in all countries, face high pollution intensity and are regulated by well known instruments over a reasonable long time period. By capturing regulations of upstream activities that impact other sectors indirectly, Botta and Koźluk (2014) argue that the policy stringency measured by the EPS is a reliable proxy for the overall aim to reduce negative emission externalities. Comparing the EPS indicator to other environmental policy stringency indices, like the economy-wide stringency indicator of World Economic Forums Executive Opinion Survey, supports this argument.

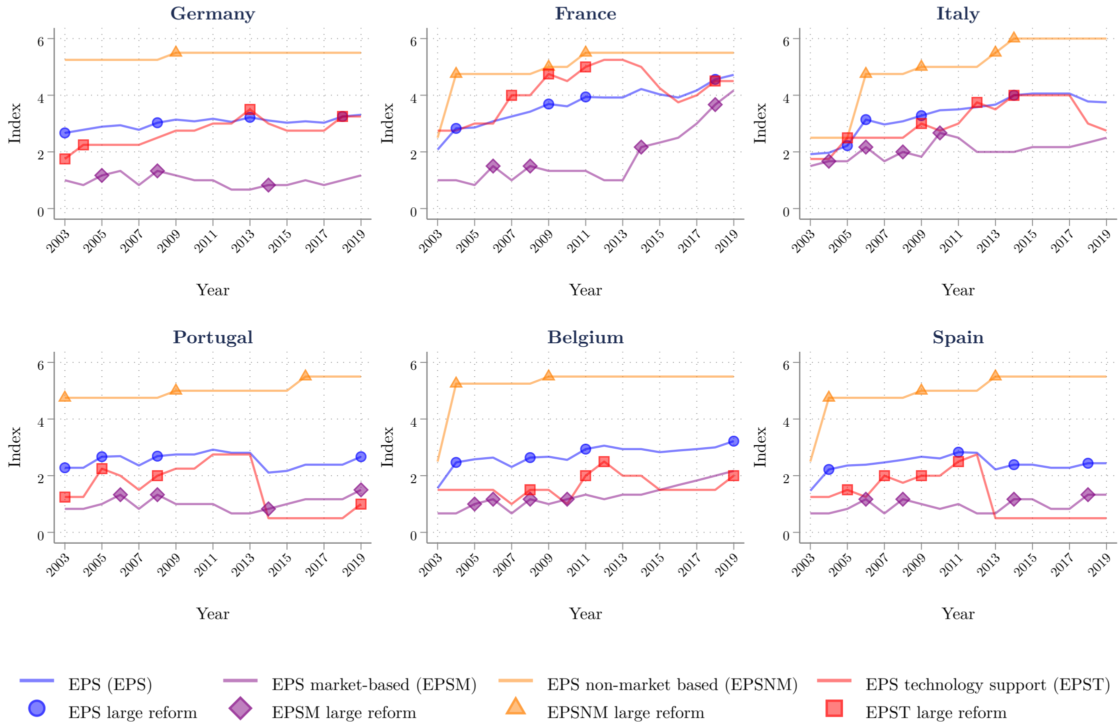
Similarly to Albrizio et al. (2017) and De Santis et al. (2021), our study uses the change in the EPS indicator rather than levels, given that new investments into abatement technology are more likely to be spurred by a substantial change in regulatory stringency. Furthermore, EPS (sub-indicator) levels are partly non-stationary, while first differences are stationary, thus facilitating empirical analysis. Since the Porter hypothesis concerns the effects of more stringent policies, we specifically focus on positive changes of the indicator to remove potential asymmetric effects of policy softening. In particular, we consider the annual changes of the overall index and its sub-indicators and replace all negative changes with zero. As a robustness exercise, we use a binary variable as our treatment which takes the value one if the increase in stringency is among the largest 25% of changes. Thereby, we remove all negative and small changes and focus on the salient regulatory changes where reactions by firms are expected to be more likely. The figure below (figure 2) shows these large reforms for each sub-indicator in each of the six countries in our data set, along with the year in which they occurred.[2] We also test for serial correlation of the positive and large changes in the EPS indicators using the bias-corrected Born and Breitung (2016) Q(p)-test. We find no serial dependency, except for positive changes in the technology support sub-indicator, which might stem from the serial correlation of GDP used as denominator to R&D subsidies. Hence, we argue that the changes in EPS indicators can be interpreted as independent shocks.

3.2 Firm-level data

Our firm-level analysis is based on firm data from six euro area countries – Belgium, France, Germany, Italy, Portugal and Spain - covering the period from 2003 to 2019. We are using the Bureau Van Dijk's ORBIS and the European Committee of Central Balance Sheet Data Offices' BACH (Bank for the Accounts of Companies Harmonised) data sets, which report balance sheet and profit-and-loss data for both listed and unlisted companies (BACH, 2015). A well-known concern regarding firm data is the lack of representativeness for some sectors and

[2] At EU level (affecting all six countries), major market policy reforms are the introduction of the ETS (2005) and large changes in certificate prices (2006, 2018). A non-market regulation to limit sulphur came into place in 2009. Country specific reforms are, among others, higher solar energy subsidies in Germany (2004), Portugal, Italy (2005) and France (2006-2012), NOx and PM emission limit reductions in Portugal (2003), Belgium, Spain and France (2004) or the introduction of CO_2 taxes in Spain and France (2014).

Figure 2: Large EPS changes



Note: Occurrences of large changes in the EPS sub-indicators in the six countries used in the firm-level analysis. A change is considered large if it is among the top 25% of the country's EPS change distribution.

countries. Therefore, we use historical vintages of ORBIS and organise the data to improve the representativeness and reduce the sampling bias, as explained in Kalemli-Ozcan et al. (2015).[3] Additionally, for the five countries where iBACH data is available - France, Spain, Italy, Portugal and Belgium - the ORBIS and iBACH data sets are merged to improve coverage. Whenever a duplicate firm is observed, we keep the one from ORBIS. Data for Germany is retrieved only from ORBIS. We do not weight the data as the number of firms per country-sector-size-year cell is only available from 2009 onwards in the Structural Business Statistics from Eurostat and Bajgar et al. (2020) report that weighting does not solve potential representativeness issues. By restricting the sample to the best-covered European countries, imputing value added and focusing on firms above 10 employees the Orbis data are broadly representative (Bajgar et al., 2020). By including iBACH data, we improve the coverage of small firms.

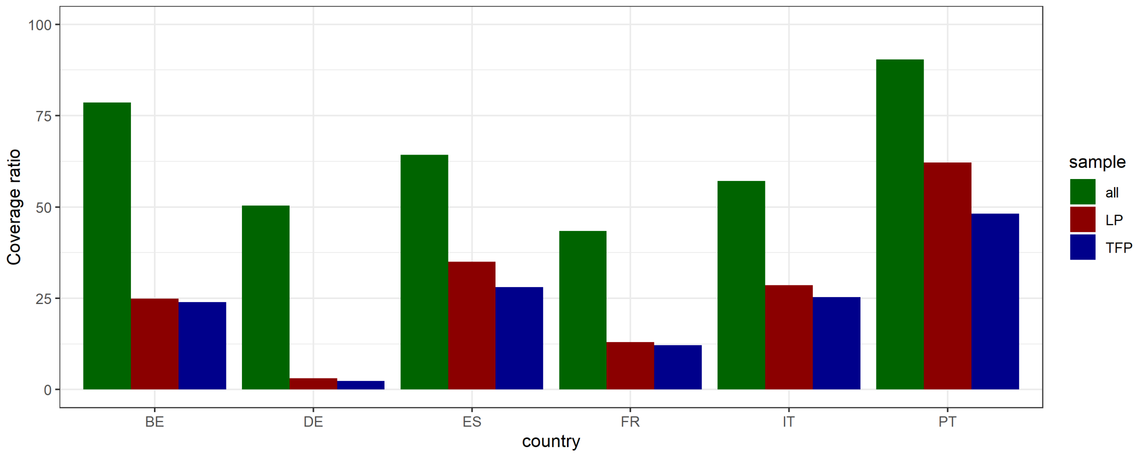
For the construction of our data set, we closely follow Kalemli-Ozcan et al. (2015) and Gopinath et al. (2017) to pursue a standard cleaning procedure. In particular, we keep only unconsol-

[3] Kalemli-Ozcan et al. (2015) argue that following their guidelines, there is no need to re-weigh the data to obtain nationally representative firm-level data sets.

idated accounts and remove sole proprietorships.[4] We restrict our analysis to non-financial and non-governmental sectors, and remove firms in the mining, energy and real estate sectors (NACE Rev. 2 codes C to N except K and L) to obtain reliable TFP values. In addition, we remove firm-year observations with less than one employee, negative value added and inconsistent balance sheet or income statement relations, including those with negative asset holdings.

Furthermore, we keep only firms with at least two consecutive years of reporting to be able to create growth rates. Finally, all balance sheet variables are winsorised at the 1st and 99th percentiles to limit the influence of outliers. The resulting data set covers three million firms (2.5 million with sufficient information to estimate Total Factor Productivity) with, on average, 10 years of information each. These are more than 22 million (18 million with TFP) firm-year observations from the covered six euro area countries. This represents about one-quarter of all firms with employees operating in the analysed sectors, but with important country differences: the coverage ratio ranges from 50% in Portugal, taking into account only firms for which we can estimate TFP, to less than 3% in Germany (Figure 3).

Figure 3: Firm data coverage



Note: Comparison of the number of firms in the data to the actual number of firms per country according the Eurostat. The bars LP (labour productivity) and TFP (total factor productivity) compare firms with productivity information to the actual number of firms.

Labour Productivity is computed as the real value added of the firm divided by the number of employees, where nominal value added is deflated with the 2-digit sector value added deflator. (Revenue) Total Factor Productivity takes into account the simultaneity bias arising from the fact that firms choose the optimal quantity of inputs given available information (to the firm,

[4]The inclusion of consolidated accounts would combine the financials of subsidiaries across different countries and industries and thus complicate comparisons across countries and sectors.

not to the econometrician) on firm productivity and it is estimated following Ackerberg et al. (2015). For more details, refer to the Appendix.

3.3 Emission estimation

One of the novel features of this paper is the estimation of CO_2 equivalent emissions for all firms in our sample using machine learning. Unfortunately, the availability of firms' emission data is very limited and biased towards large firms. However, financial and non-financial information can be used to infer CO_2 equivalent emissions. This effectively fills the data gap for firms which do not report emissions in order to support the analysis. Moreover, this synthetic data set can be used to monitor the exposures of the markets to polluting firms in an extensive number of other applications. The algorithm relies on emissions data provided by commercial providers for a sample of large listed firms, associated with the balance sheet information of those companies. The relevant quantities can then be predicted for non-reporting firms by applying the observed statistical relationships between the CO_2 equivalents emitted, the sector, the country and their financial information.

More specifically, we use Urgentem data on Scope1+Scope2 CO_2 equivalent emissions and link these with ORBIS/iBACH information to produce a sample of 35,000 firms. In order to simplify potential non-linearities in the relationship between emissions and financial information, we opted for creating ten emission quantity classes (bins) based on the distribution in our sample. This also simplifies the calibration of the model. For the estimation of the data generation model we use a machine learning algorithm called Extreme Gradient Boosting (XGBoost), which is one of the most successful models used in machine learning in the past years, based on ensembled trees. The model selects the regressors (via lasso algorithm) and finds the best non-linear patterns (tree) to estimate the dependent variable, then it averages them.

The confusion matrix below (figure 4) shows how well XGBoost is able to estimate CO_2 emissions based on ORBIS/iBACH for firms never seen by the model before. Since most observations in the confusion matrix are at or close to the main diagonal, it shows that actual and estimated emission bins are closely related and our algorithm works well. As we only need to split firms into high and low polluters for our empirical identification approach, the estimation accuracy is sufficient for our purpose. The bar plot in figure 5 depicts the mean of the absolute SHAP (SHapley Additive exPlanations) values for each regressor. The SHAP value captures how much a single regressor affected the prediction of an observation and this is summarized by taking the average over the sample (Lundberg and Lee, 2017). Employment, turnover, tangible and intangible fixed assets as well as the sector are the most important variables to determine CO_2 emissions of a firm. It is difficult to asses ex-post the accuracy of classifications done on million of firms that do not report CO_2 but the relationships between sector, size and emissions follows our expectations. As additional check, we estimated our model (in section 4) only with large firms, comparable to the Urgentem firms, and the results are consistent with those of the overall sample.

Figure 4: Confusion matrix

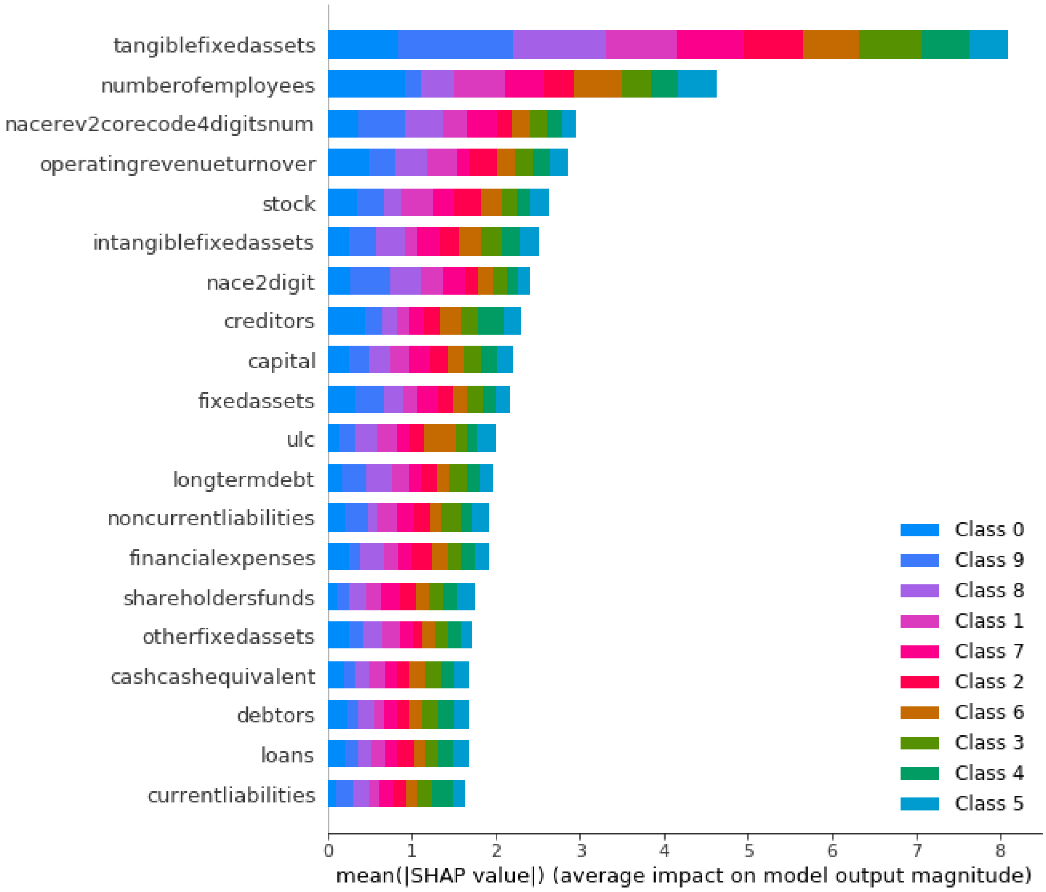
	Re 1 2									
A	0	1	2	3	4	5	6	7	8	9
0	168	88	30	31	18	8	5	7	6	3
1	56	117	54	22	21	13	10	3		2
2	29	68	87	44	28	42	17	7	11	
3	11	28	57	65	62	49	28	7	10	1
4	13	14	51	55	72	53	28	27	26	9
5	6	21	21	45	47	72	35	29	22	9
6	8	10	15	20	39	57	61	64	21	5
7	4	2	5	9	25	32	72	96	69	29
8	2	6	4	6	7	13	38	39	99	42
9	3	1	1	2	4	6	4	27	58	202

Note: Each row of the matrix represents the instances in an actual class while each column represents the instances in a predicted class. The matrix shows to which extent the algorithm "confuses" two classes. A large accumulation at the main diagonal show the fit of the estimation.

4 Empirical Strategy

Describing the causal impact of a regulatory reform over time poses various challenges, as described in the literature review. First, policy reforms create a dependency with business cycle dynamics and their impact could be heterogeneous reflecting macroeconomic or firm-specific conditions. Furthermore, policy and productivity changes could be jointly determined by many, sometimes unobserved, variables. Second and regarding environmental policies, Brunel and Levinson (2020) point to the problem of simultaneity, since not only environmental reforms affect macroeconomic outcomes but also macroeconomic conditions influence the implementation of reforms. Third, in a cross-country analysis we have to deal with different industrial compositions. Inferences can be incorrect, because even identical laws have different effects when the average manufacturer face different environmental costs across countries. Hence, in this section, we explain how we estimate the regulatory effects and how we deal with these concerns.

Figure 5: Importance of balance sheet variables - SHAP values



Note: Importance of variables in the machine learning algorithm, measured by the mean of the absolute SHAP value, starting with the most important and going to the least important.

Our analysis builds on two layers. We start with the analysis of the impact of environmental policies on aggregate productivity growth (at the country-level) to capture the effects on the whole economy. In a second step, we explain our aggregate findings and deal with potential endogeneity concerns by looking at the effects on firm-specific productivity growth. Since we expect that effects of regulatory changes occur with some delay, we apply an econometric approach that allows to capture effects at different horizons. Local projections (LP), introduced by Jordà (2005), calculate impulse responses directly by estimating regressions at each period of interest rather than extrapolating into increasingly distant horizons. This technique is based on sequential regressions of the endogenous variable shifted forward in time onto its lags and therefore has much in common with direct multi-step forecasting. Cette et al. (2020, p.7) describe the method as the "differences between two forecasts - the first corresponding to a situation with the shock and the second to the same situation without this shock." Compared to Vector Autoregressions, LP are less prone to miss-specifications (Li et al., 2022) and more flexible regarding the analysis of non-linear and state-dependent impacts, while still able to deal with endogeneity issues (Bordon et al., 2018). As it disentangles the economic effects of policy compared to background shifts in the economic environment, LP have been recently widely applied in the study of the economic impacts of structural reforms (Bordon et al., 2018) and fiscal consolidation measures Jordà and Taylor (2016); Owyang et al. (2013). We will apply this approach to capture the effects of environmental policy changes.

Our identification strategy is based on the idea that environmental policies affect firm productivity differently depending on the firms' exposure to environmental regulation. Due to different technologies, firms produce with different emission intensities which lead to heterogeneous adjustment needs in case of regulatory changes. Therefore, high-polluting firms are expected to face higher productivity losses in reacting to increased policy stringency compared to their low-polluting peers. We test this hypothesis to evaluate the underlying mechanism that explains the intended direction and excludes reversed causality (from productivity growth to regulatory changes).[5] This approach, to describe the causal impact of country-level policies on industries or firms, was popularized by Rajan and Zingales (1998) analysing the impact of financial development on output growth using external financial dependence as exposure variable. Beside many other applications, Albrizio et al. (2017) use the industrial-level pollution intensity to analyse the effects of environmental reforms. In our empirical setting this approach implies that the environmental regulation indicator is interacted with a pollution indicator of countries or firms. Beside the assumption that different technologies lead to variations in emissions and hence to different adjustment costs, the identification is based on the assumption that the exposure variable (emissions) is exogenous to regulatory changes. Hence, it is crucial for this approach to use pre-determined (lagged) emission indicators that are unlikely to be affected by current changes in environmental regulation. In addition, we tested whether an increase in regulatory stringency affects the probability of being a high-polluting firm and we find no significant impact. Firms being among high-polluters might reduce their pollution, but remain among high-polluters up to five years after the reform. In a similar way, most high polluting countries remain in this group over the whole period, although they introduced environmental policies. This supports the validity of our identification scheme.

The dependent variable of our empirical model is the cumulative change in productivity, measured as labour productivity or total factor productivity, between year h after the reform and

[5]This logic can also be applied to the countries instead of firms.

the pre-reform year, in percentage points (pp). The main regressor ($EPS_{i,t}^{j}$) is the positive change in the EPS index or the positive change in one of its sub-indicators j. We interact the policy index with a dummy ($CO2$) indicating if the country or firm was among the top most polluting ones of its peer group in the year before the regulatory reform. By using the change in the EPS index between $t-1$ and t, we limit the problem of simultaneity as it is unlikely that future TFP changes affect past regulatory changes.[6] More specifically, the baseline specification for our aggregate analysis looks as follows:

$$\begin{aligned} ln(y_{i,t+h}) - ln(y_{i,t-1}) = \alpha_{1,i}^{h} + \alpha_{2,t}^{h} + \beta_{1}^{h} CO2_{i,t-1} + \beta_{2}^{h} EPS_{i,t}^{j} + \beta_{3}^{h}(EPS_{i,t}^{j} * CO2_{i,t-1}) + \\ + \gamma_{1}^{h} X_{i,t} + \varepsilon_{i,t+h} \qquad h = 0, 1, ..., 5 \end{aligned} \tag{1}$$

where $y_{i,t+h}$ is the productivity variable (TFP or labour productivity) of country i in year t; h represents years after the reform. $\varepsilon_{i,t+h}$ captures the idiosyncratic error. X captures country controls including the cyclical position of the country's economy, country TFP frontier growth, labour market regulation, startup costs, governmental R&D expenditure and the level of economic development, following Albrizio et al. (2014) if the variables are available. The last four controls are included as first lags (before the reform) so that they can be interpreted exogenously and not as an outcome of the environmental policy change. The cyclical position of the country measured by the output gap controls for business cycle dependencies of productivity growth and new regulations. The TFP frontier growth captures common trends and technology spillovers among countries or firms. The employment protection legislation indicator and startup costs approximate supply side policies at the labour and product market. Governmental R&D expenditure controls for another potential omitted variable bias as it influences both firm productivity as well as decisions on green subsidies. These macro indicators are also included in the firm-level local projections. Additionally, we add lagged firm characteristics Z (before the reform) as control variables: age, size, return-on-assets, distance to sector frontier and TFP growth of sector frontier. A detailed description of the variables can be found in the Appendix. At the firm-level, the specification includes firm-specific productivity changes $y_{f,t}$ and $CO2_{f,t-1}$ indicators:

$$\begin{aligned} ln(y_{f,t+h}) - ln(y_{f,t-1}) = \alpha_{1,t}^{h} + \alpha_{2,s}^{h} + \alpha_{3,f}^{h} + \beta_{1}^{h} CO2_{f,t-1} + \beta_{2}^{h} EPS_{i,t}^{j} + \\ + \beta_{3}^{h}(EPS_{i,t}^{j} * CO2_{f,t-1}) + \gamma_{1}^{h} X_{i,t} + \gamma_{2}^{h} Z_{f,t} + \varepsilon_{f,t+h} \qquad h = 0, 1, ..., 5 \end{aligned} \tag{2}$$

We use country fixed effects (α_i) to capture the different institutional settings across countries,

[6] To test for this form of endogeneity, we regress changes in the EPS index on past country TFP growth. The lags of TFP growth do not predict the changes in the EPS index independent of the inclusion of control variables.

as well as differences in corruption and climate that are potentially relevant to productivity. In addition, we include time dummies (α_t) to capture developments specific to a year but common to all countries or firms like the ECB's monetary policy or the occurrence of the global financial crisis. In the firm-level analysis, we replace country FE with more granular sector and firm FE (α_s, α_f) to control for unobserved heterogeneity across sectors and firms. The combination of sector, firm and time FE with a broad set of controls reduces a potential omitted variable bias drastically. Regarding the concern of industrial composition differences across countries, we add the industry share as control variable at the aggregate level and see no changes in the baseline results. This is not necessary in our firm-level analysis as it is not subject to the industrial composition problem by looking at each firms response separately. In order to control for potential anticipation effects of new policies, we additionally include next year's EPS change in the firm-level specification, assuming perfect foresight. As this is a strong assumption and the inclusion reduces the magnitude of our estimated effects only slightly, we decided not to include it in the baseline specification. The estimation of the local projections is done by using Stata's reghdfe command on the pooled sample of 15 countries in the aggregate analysis or about 2.5 million firms from six euro area countries in the firm-level analysis. The standard errors are clustered at country or firm-level respectively to allow for fully flexible time series dependence in the errors within each block.[7]

5 Results

In this section, we present the impact of changes in the environmental policy stringency on productivity growth. First, we describe the results at the aggregate level for a pooled sample of 15 countries to show the validity of our identification strategy and to get some intuition as to whether the strong version of the Porter hypothesis holds in the euro area. Second, we use firm-level data to control for potential sources of endogeneity and to explore the heterogeneity in the regulation impact along several dimensions. By analysing the aggregate country data, we consider the full firm population, including entry and exit, and the relative importance of effects across firms weighted by their size. This analysis may, however, suffer from aggregation and endogeneity bias. The firm-level analysis can address these problems, but has limitations in terms of population representativeness and tracking firm entry and exit dynamics.

[7] Given the national EPS indices and national institutions in charge of collecting the firm data, clustering SE at the country level would also be appropriate in the firm-level specification. Due to the low number of clusters (6) and the more relevant correlation among firm observations, we decided to use firm clusters. Country cluster SE estimates are robust and can be found in the Appendix.

5.1 Country-level analysis

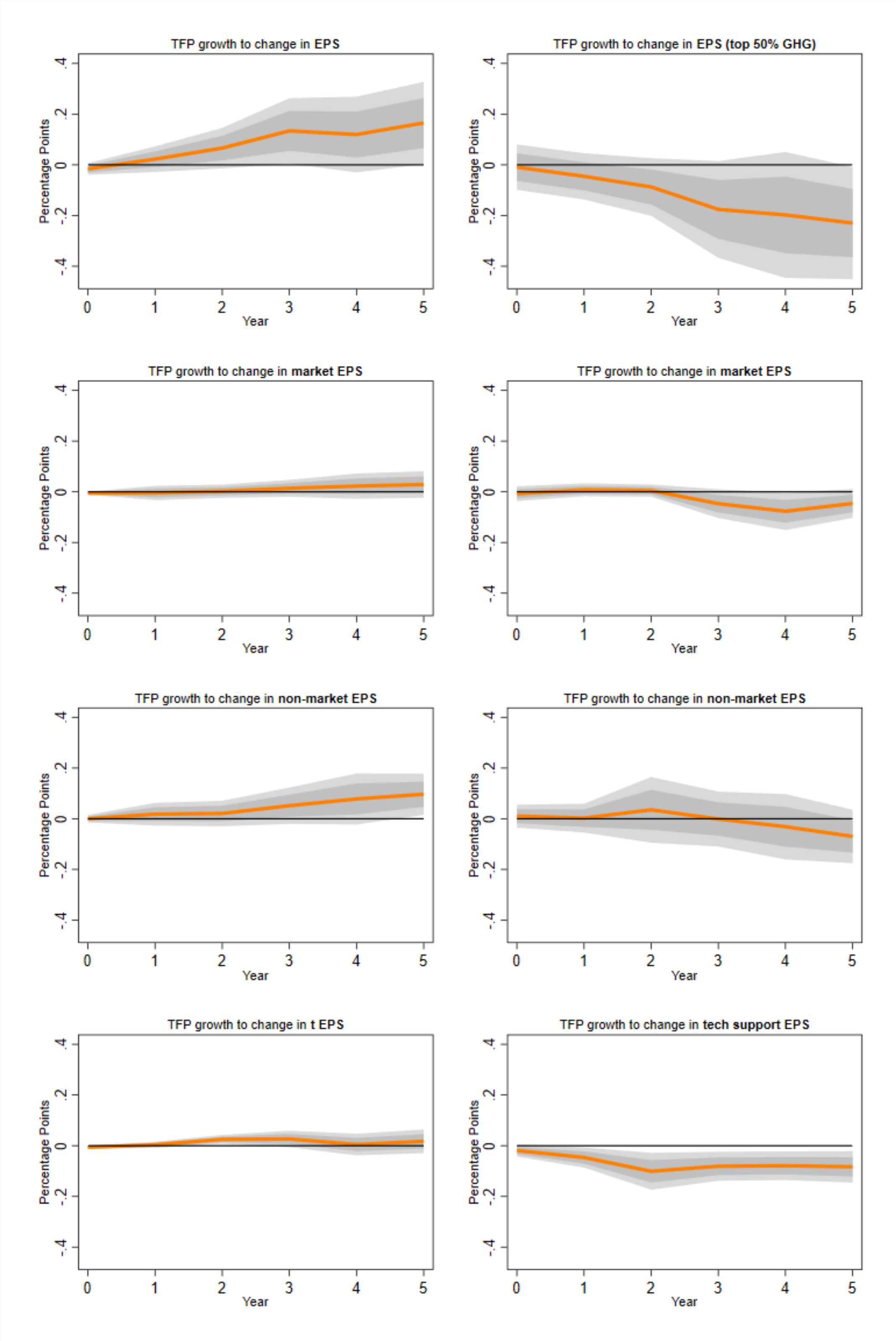
Figure 6 shows the impulse response functions (IRF) of the country-level analysis, using aggregate TFP growth as dependent variable. Results regarding the impact of environmental regulation on aggregate labour productivity are similar and shown in the Appendix (figure 10). The orange lines show the mean responses over the five year horizon and the grey bands depict the respective confidence intervals around the point estimations. While the dark grey area represents the 68% confidence bands, the light grey area show the 90% bands. In the left column of figure 6 we show the productivity responses of the countries with the lowest greenhouse gas (GHG) emissions per capita (bottom 50% of the sample). We contrast them to the responses of the high polluting countries (top 50%) in the right column.[8] In line with our identification assumption that high polluters are more vulnerable to changes in the stringency of environmental regulation, we find that aggregate TFP of highly polluting countries is affected negatively and more strongly than that of less polluting countries.

Based on our aggregate results, we have to reject the strong Porter hypothesis. While for the low-polluting countries the productivity effects of changes in the EPS index and its sub-indicators is close to zero or slightly positive, the regulatory impact on aggregate TFP growth of high polluters is significantly negative (at least at the 68% confidence level). The effect is negative for all sub-indicators, however, with different patterns. An increase in the stringency of the technology-support policies leads to a decline in productivity in the first two years which reverses afterwards to some extent. The effect is, however, significantly negative until the end of the horizon. In contrast, the effects of the market-based policy index and the non-market based policy index are muted in the short-run and show a declining trend only in the second half of the five year horizon, which drives the development of the overall EPS index. Hence, we do not find general support for the idea that a tighter environmental regulation leads to aggregate productivity increases that outweigh the costs of implementation, neither in the short-run, nor at the end of the projection horizon.

In order to evaluate the economic relevance of the regulatory impact, it is important to set the EPS shock size and the medium-term TFP development in perspective. The regulatory stringency shocks include small changes due to increases in CO_2 prices in the ETS or increases

[8] Belgium, Germany, Estonia, Finland, Ireland, Luxembourg and the Netherlands are in all years among the countries with above median pollution intensity, Greece in 8 years, Austria in 3 years.

Figure 6: Impulse response functions - country level



Note: Cumulative impulse responses of TFP growth to 1 pp EPS shocks (positive changes) over 5 years. Left column bottom 50% polluting countries, right column top 50% polluting countries. Orange line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

in green subsidies. At the same time, it also contains large changes caused by major reforms and price swings. While we plot the responses to a one percentage point increase in the EPS indicator, the mean change over all years and countries is around four pp for the overall indicator as well as its sub-indicators. A one standard deviation (SD) shock ranges between 13 pp for the overall indicator and 33 pp for the technology-support indicator. Hence, the effects of environmental policy reforms on TFP are larger in magnitude than depicted by the scale used in Figure 6. A one SD shock to the overall EPS indicator would result in an expected TFP decline of 2.8 percentage points after five years in high polluting countries. This is a large effect given the mean annual aggregate TFP growth rate of 0.48% (2.4% over five years) in all countries or 0.28% (1.4% over five years) in high polluting countries.

As we cannot rule out endogeneity issues completely, we repeat the exercise with a different kind of regulatory shock that is less persistent and hardly predictable. Instead of a time-series of positive changes in the EPS index, we use a dummy that equals one if a salient change takes place that is among the largest 25% of changes in a country within our period of observation. Figure 9 in the Appendix shows the respective IRFs. While the effects are slightly more positive for the low-polluters and generally larger, the difference for the high-polluters is the same as before and the overall pattern is remarkably similar. There is substantial heterogeneity among countries and their responses depend on their pollution intensity. Nonetheless, aggregate responses mask heterogeneous patterns across firms operating in a given country and sector as indicated by the large confidence bands. Moreover, there are still some remaining concerns about potential endogeneity at the aggregate level. For these reasons, the next section replicates the analysis at the firm-level.

5.2 Firm-level analysis

Granular firm-level data help to reduce aggregate uncertainty, to limit endogeneity concerns and to explain heterogeneity in the regulatory impact on productivity. Therefore, we present the productivity responses of up to three million firms to positive changes in the EPS indicators similar to the country-level analysis, before we explore the heterogeneity across firms in the next section in more detail.

Figure 7 shows the IRFs of firm productivity to a one percentage point increase in the EPS indicator and its sub-indicators. The blue lines represent the estimated coefficients β_2 and β_3

of equation 2 over a five year horizon and the grey areas represent the corresponding confidence intervals (68% and 90%). The significant differences between the left and right column confirm the validity of our identification approach. As at the country-level, highly polluting firms are affected differently and to a larger degree than low-polluting firms. In particular, we compare firms that are assigned to the bottom four emission bins by our machine learning algorithm to those assigned to the top six bins by our machine learning algorithm (as described in section 3.3). As there are less high polluting firms than low polluters, we decided for this unequal split, but robustness checks with different splits (top 4 vs bottom 6 or top 9 vs bottom 1) show similar results as shown in the appendix (figure 14). The large number of low polluting firms is also a reason for the more precise estimation of the impulse responses in the left column. The confidence bands are so tight that they are not clearly visible in the plots. In this specification, we make use of the granularity of the firm-level data to control for sector and firm fixed effects so that we capture a broad set of reasons for different TFP growth rates and reduce the omitted variable bias to a minimum. Detailed regression results, including the coefficients of the control variables, can be found in table 5 in the Appendix.

Qualitatively, the results are similar to the findings at country-level. The productivity of low-polluting firms is either not affected or slightly positively affected depending on the type of policy. In contrast, all policies affect highly polluting firms more negatively compared to the less polluting ones. The patterns of the various policies are, however, substantially different from each other. The negative productivity effects of technology-support policies are only temporary until firms adapt to the new conditions and make use of green R&D subsidies and feed-in-tariffs or auctions. Low-polluting as well as high-polluting firms benefit from subsidies in the long-run, while the latter go through a more painful transition. In contrast, the non-market based measures have no immediate impact but become more costly over time. Non-market based instruments generally offer less flexibility to firms and we observe a persistent impact on exposed firms that takes a long time to compensate.[9] Finally, market-based policies have a significantly negative impact on firm productivity over the whole horizon, but at a much lower level than the non-market based policies. This is in accordance with the 'narrow' Porter hypothesis that states that market based measures are more productivity friendly than non-market based measures. However, in contrast to the 'strong' Porter hypothesis, the market based tools still have negative productivity effects. Since all three sub-indicators have an averse impact on firm productivity of high polluting firms (at least temporarily), it is no surprise that the overall indicator points

[9]The peak in the fourth year of the IRF to EPS and non-market EPS changes is driven by large non-market policy reforms in Italy in 2005. Turning this effect off leads to similar but more muted results without a peak.

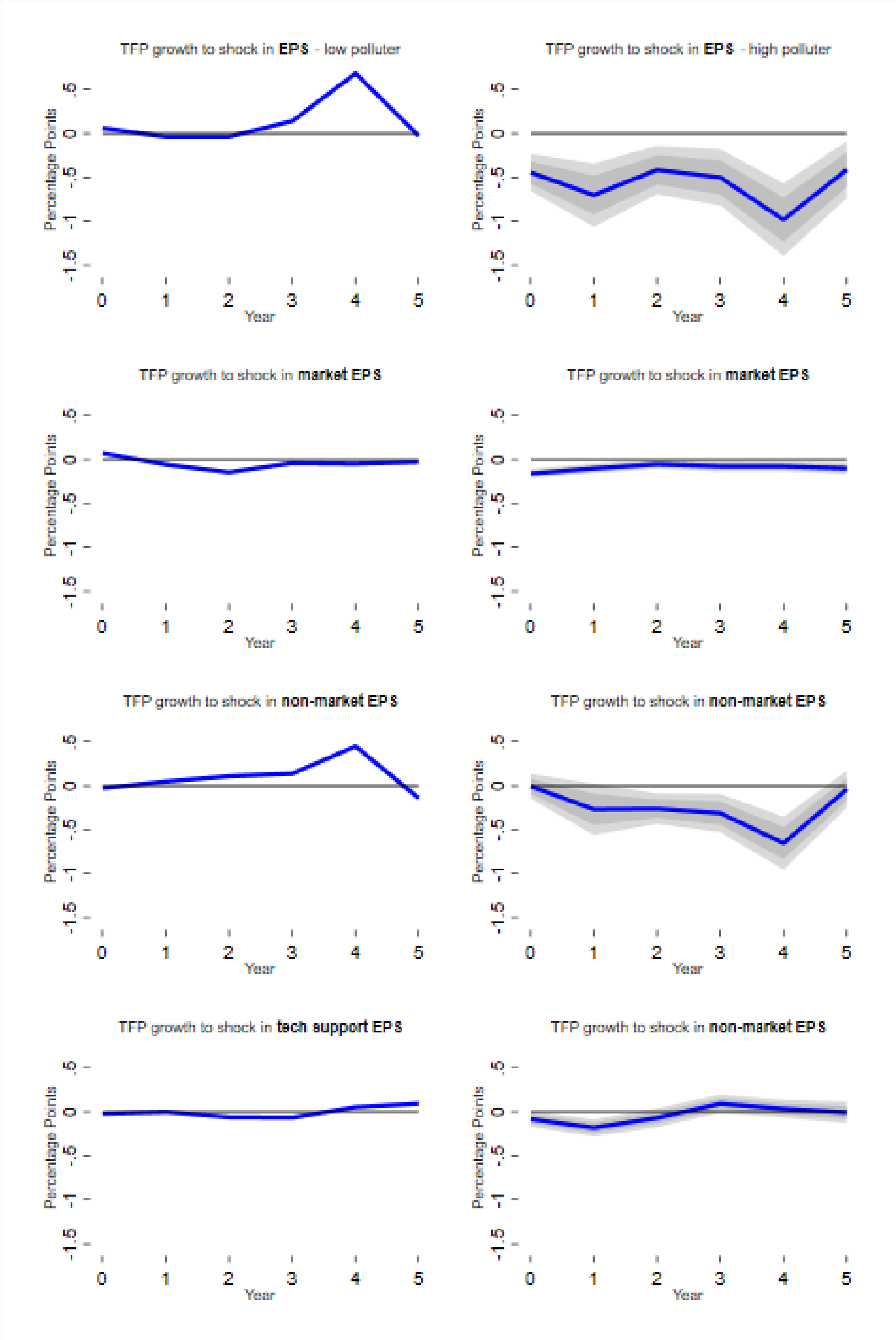
in the same direction. While the negative short-run impact is driven by market based and technology support measures, the negative effects at the end of the horizon is dominated by non-market measures. In accordance with our findings at the country-level, we have to reject the strong Porter hypothesis as soon as we consider pollution differences across firms. This finding is underpinned by the very similar responses of labour productivity to EPS shocks as shown in the Appendix (figure 13). Also controlling for a potential attrition bias, by analysing only firms with six observations or more, does not change our results and confirms their robustness.[10]

Again, we have to put the size of the regulatory impact in Figure 7 in perspective. While we plot the responses to a one percentage point increase in the EPS indicator, the mean change is around four pp for the indicators. As mentioned before, a one standard deviation shock ranges between 13 pp for the overall indicator and 33 pp for the technology-support indicator, so that a multiplication of the shock size by ten (or more) is necessary to capture the impact of large environmental reforms. A one SD EPS shock reduces firm TFP growth of high polluters by four pp after five years on average. Given the median annual TFP growth of 2.6% among high polluting firms, a one SD EPS shock reduces the TFP growth by one-third over five years. In contrast to the overall and the non-market policy indicator, the sub-indicator for market based policies shows smaller negative effects on polluting firms. After five years the TFP growth declines by 2.6 pp to a one SD market EPS shock, but this can be compensated by an average year of TFP growth. The median TFP growth of low polluting firms is significantly smaller (1.2%), but it is not negatively affected by more stringent environmental regulations. Using our dummy that equals one if a salient change takes place as our regulation indicator, we find robust results, but with different patterns for some sub-indicators (see figure 12). After four years TFP growth declines by four pp to large overall EPS changes and the negative impact of the technology support measures is only temporary as with the baseline reform indicator. However, the impact of the non-market policies becomes more temporary and large increases in market based policies seem to harm firm TFP growth relatively more.

While a detailed analysis of all potential spillover effects across firms and countries is out of the scope of this paper, we check the influence of European policies and general stringency changes across Europe. For this exercise, we use the country-specific EPS change and its interaction with the emission indicator in our local projections and add the average EPS change of the

[10] Unfortunately, entry/exit dynamics cannot be captured completely, as the incorporation date information in ORBIS (iBACH) suffers measurement issues. In addition, the firm may remain active even if it drops out of the sample.

Figure 7: Impulse response functions - firm-level



Note: Cumulative impulse responses of TFP growth to 1 pp EPS shocks (positive changes) over 5 years. Left column bottom 4 bins of polluting firms, right column top 6 bins of polluting firms. Blue line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

other five countries and the respective emission interaction. So, we can evaluate the impact of international regulations on high-polluting firms in addition to the national reforms. We find that country-specific reforms as well as reforms from abroad have a negative impact on polluting firms compared to low-polluting ones, however, with differences across policies. The negative effect of market policies stem exclusively from international reforms. This is not surprising since most of the observed variation in the EPS comes from the introduction and price changes of the ETS and many countries do not have own CO_2 taxes (or at a low level). In contrast, the negative non-market effects are mainly related to national reforms, which are less coordinated internationally.

5.3 Heterogeneity in firms' responses

Finally, we want to explore potential heterogeneities among firms, and in particular whether all high polluting firms are affected by more stringent environmental regulation in the same way. Therefore, we modify equation 2 to include a triple interaction effect to capture non-linearities in the regulatory shock on high polluting firms' TFP growth:

$$\begin{aligned} ln(y_{f,t+h}) - ln(y_{f,t-1}) = \alpha^h_{1,t} + \alpha^h_{2,s} + \alpha^h_{3,f} + \beta^h_1 CO2_{f,t-1} + \beta^h_2 EPS^j_{i,t} + \gamma^h_1 X_{i,t} + \gamma^h_2 Z_{f,t} + \\ + \beta^h_3 (EPS^j_{i,t} * CO2_{f,t-1}) + \beta^h_4 (EPS^j_{i,t} * CO2_{f,t-1} * T_{f,t-1}) + \varepsilon_{f,t+h} \qquad h = 0, 1, ..., 5 \end{aligned} \tag{3}$$

where $T_{f,t-1}$ is a standardized lagged variable which we use to differentiate among high polluting firms. As for the emission bins ($CO2$), we use the lagged value to keep it unaffected by the current EPS shock. We standardize the variables to ease the interpretation of variables with artificial measurement units (e.g. TFP) and to make the coefficients comparable to each other. The local projections also include the other two interaction effects $EPS * T$ and $CO2 * T$, but they are not shown to increase readability.

Capabilities to deal with a changing market environment are crucial to deal with climate change and new environmental legislation. These capabilities are often associated with more experience and resources. Therefore, we first distinguish the firms by size (number of employees), age (years since incorporation) and the current level of productivity (TFP). To reduce the dimensionality of our results, we focus on (overall) EPS shocks and their impact after three years. The results of our heterogeneity exercise are depicted in table 1. First, it shows that the pattern found in our baseline specification is robust to adding a triple interaction effect. The effect of an EPS shock on TFP growth remains positive and small for non polluting firms and significantly negative and large for high polluters. Second, considering the three firm characteristics size, age and productivity, we find that the number of employees and the TFP level are statistically relevant in explaining differences in the EPS's impact on productivity growth of polluting firms. Larger and more productive firms can handle regulatory changes more efficiently than the average high polluting firms. While a one SD larger firm (3,300 employees more) reduces the negative impact of policy tightening by only 0.05 pp, a one SD more productive firm reduces the negative impact by 1.08 pp. Therefore, starting from a higher productivity level seems crucial to deal with regulatory changes successfully.

We next explore why large and more productive firms are better off after a change in the environmental regulation relative to peers. In particular, we want to know to which extent the innovativeness of firms and their access to financial resources play a role in mitigating the costs of regulatory shocks. As proxy for innovativeness we use the amount of patent families created in the past[11] and financial resources are captured by the equity ratio. According to our estimation results (table 1), a larger equity ratio reduces the negative impact of an EPS shock on TFP growth. A one SD higher equity ratio (+31%) ameliorates the negative impact by a fifth. Similarly, having innovated in the past helps a firm to withstand negative effects of more stringent environmental policies. A one SD higher holding of patents (+37 patent families) reduces the negative impact experienced by high polluting firms by a tenth. Therefore, firms' innovativeness and access to finance are important mitigating factors of the short to medium-term negative impacts of stringent environmental policies.

[11] A patent family is a collection of patent applications covering the same or similar technical content. We use Orbis IP as our patent data source.

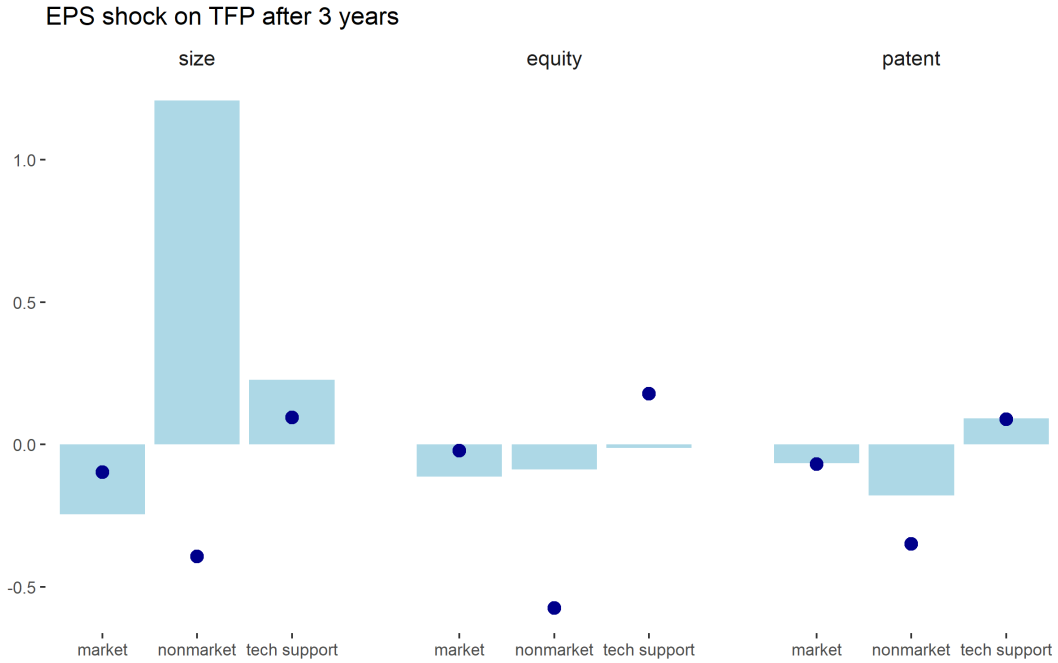
Table 1: Heterogeneity analysis - high polluting firms

	Dependent variable: 3 year ahead firm TFP growth					
	(1)	(2)	(3)	(4)	(5)	(6)
$CO2_{t-1}$	3.157	2.590	3.534	2.000	2.316	4.911**
	(2.031)	(2.185)	(2.322)	(2.323)	(2.160)	(2.087)
EPS shock	0.0141***	0.146***	0.136***	0.0567***	0.142***	0.142***
	(0.00573)	(0.006)	(0.0057)	(0.0104)	(0.0057)	(0.0057)
EPS shock * $CO2_{t-1}$	-0.499***	-0.591**	-0.415*	-0.391*	-0.548**	-0.493**
	(0.195)	(0.225)	(0.221)	(0.234)	(0.215)	(0.197)
EPS shock * $CO2_{t-1}$ * Employees		0.0524***				
		(0.01)				
EPS shock * $CO2_{t-1}$ * Age			-0.0076			
			(0.077)			
EPS shock * $CO2_{t-1}$ * TFP level				1.113**		
				(0.537)		
EPS shock * $CO2_{t-1}$ * Equity ratio					0.096**	
					(0.0177)	
EPS shock * $CO2_{t-1}$ * Cumulative Patents						0.0412***
						(0.0099)
Aggregate controls (Output gap, R&D, EPL, startup costs, TFP frontier)	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics (age, size, ROA, TFP gap)	Yes	Yes	Yes	Yes	Yes	Yes
Firm and sector F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
R^2 adjusted	0.57	0.57	0.57	0.42	0.57	0.57
N	6,081,287					

Note: Age, size and ROA are standardized in the local projections, TFP gap is not included in TFP level interaction regression. $CO2$ represents top 4 bins of polluting firms. Parentheses contain standard erros. $* < 0.1$, $** < 0.05$, $*** < 0.01$

This is supported by figure 8 where we distinguish between the impact of the EPS sub-indicators after three years. Their effects on TFP growth of high polluting firms are vastly different when we compare firms at the 10th percentile of the size, equity or patents distribution (dark blue dot) to their counterparts at the 90th percentile (light blue bar). While small polluting firms are negatively affected by more stringent non-market policies, large ones experience a TFP growth similar to low polluting firms. Stark differences in the effects of non-market policies can also be seen in case of different equity ratios and different patenting experience, however, at a lower level. The differences across firms are less relevant for market based policies. They have a negative but limited impact on the TFP growth of polluting firms with little differences across size, equity and patenting. It is important to see that technology support measures have already positive effects after three years, even for high polluting firms. The differences in innovativeness and financial resources matter only little for this policy type.

Figure 8: Impact heterogeneity across firms



Note: Cumulative TFP growth response to an EPS shock (positive changes) after three years. Dark blue dots represent effects on a firm at the 10th percentile of the size (number of employees), equity (equity ratio) or patent (cumulative patent families) distribution. Light blue bars represent the effects on firms at the 90th percentile of the respective distribution.

Eventually, we also want to point to two other dimensions of heterogeneity: differences in the regulation stringency level and sector differences. So far, the analysis only captures the change of the EPS indicators and not the EPS levels. While we (and the literature) argue that regulatory changes are more important than their levels in explaining productivity growth, also the policy stringency level can have economic effects. Including the lagged EPS indicator (in levels) as additional control variable in equation 2 does not alter our results presented in figure 7. However, splitting the sample into high and low EPS level countries (FRA/GER/ITA vs BEL/POR/ESP) shows that the negative effects of more stringent policies on polluting firms are not statistically significant at the end of the horizon for the less regulated countries. It seems that less strict regulation allows firms to adapt quicker to new regulations, potentially by making use of the experience and technology of more regulated firms. Distinguishing between the industry and service sector leads to similar results regarding their vulnerability to more stringent environmental regulations. High polluting firms in both sectors face productivity growth losses due to changes in the EPS indicators. Interestingly, there is a difference regarding the market based indicator. While higher carbon prices have significantly negative effects on polluting firms in the industry sector, the service sector faces only small negative effects, neither statistically nor economically relevant.

6 Conclusion

Given the acceleration of climate change, governments all over Europe increased their efforts in limiting the emission of green house gas emissions by implementing a broad range of policies. While stricter regulation is usually associated with a decline in competitiveness, there is the hope that well designed environmental regulation boosts innovation and thereby counteracts negative economic effects. This idea became known as the Porter hypothesis.

In this paper, we evaluate the strong Porter hypothesis by analysing the impact of changes in environmental policy stringency on TFP growth of countries and firms. We combine macro indicators with firm-level data and estimate firm-specific emissions to identify more and less exposed firms to regulation. By estimating panel local projections on firm and country level, including a broad set of covariates and fixed effects, we confirm that high polluters are affected significantly different than low polluters. In general, the productivity growth of countries with high pollution intensity and firms with large CO_2 emissions are affected negatively by a change in environmental policies. Hence, we have to reject the strong Porter hypothesis that environmental regulation is productivity enhancing. It is, however, important to distinguish between different policy options. Green subsidies have negative effects on TFP growth only during a transition period, before becoming beneficial. Market based measures (taxes) reduce TFP growth of high polluting firms, but less than non-market based regulation (emission limits). In addition, it matters whether firms have access to finance or are innovative: a higher equity ratio and more expertise with patenting reduce the negative impact of environmental regulation.

Potentially, market and non-market regulations could boost productivity of polluting firms in the long run in a way comparable to the positive effects of subsidies after three years. This is hinted at in a related paper which finds that more stringent environmental regulation increases significantly the number of green patents over a five year horizon after the regulatory change. If we believe that new innovations need time to be adapted to different production processes and, therefore, render productivity gains, the strong version of the Porter hypothesis could be confirmed over a longer time horizon. Given our limited period of data, we are, however, only able to look five years into the future. Using a longer time series, including firms from more countries and having better firm-specific emission data could further improve the analysis, but is left for future research. Up to now, we have to dash the hope that environmental regulation has no economic costs, but we also show that the costs on TFP growth are limited and by choosing the right policies they can be minimized. We also show that better access to capital and innovativeness can mitigate the short to medium-term costs of adjusting to a greener way of producing.

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Appendix

TFP estimation

Total Factor Productivity at the firm-level is estimated following the approach of Ackerberg et al. (2015) building on Levinsohn and Petrin (2003) to correct for the so-called "simultaneity bias". This bias occurs when the firm's productivity is unknown for the econometrician but known to the firm before choosing optimally production inputs. The output measure used in the analysis is firm-level value added deflated with 2-digit industry deflators from the STAN database of the OECD. Intermediate inputs are used in the inverted policy function estimated in the first stage. The coefficients of the production function are estimated in the second stage by GMM at the 2-digit industry, pooling all countries together.

Descriptives

Table 2: Firm data coverage - iBACH/ORBIS (2003-2019)

Country	Population	All obs	Ratio all	TFP obs	Ratio TFP	LP obs	Ratio LP
BE	4,968,914	3,907,666	78.64	1,189,084	23.93	1,238,359	24.92
DE	11,670,030	5,875,611	50.35	272,223	2.33	357,360	3.06
ES	16,895,364	10,866,459	64.32	4,745,566	28.09	5,904,770	34.95
FR	21,839,701	9,478,328	43.40	2,643,235	12.10	2,823,961	12.93
IT	17,877,928	10,205,926	57.09	4,532,361	25.35	5,115,723	28.61
PT	5,087,249	4,596,188	90.35	2,448,580	48.13	3,165,136	62.22

Note: Population figures by Eurostat (structural business statistics), observations from merged data set - ORBIS and iBACH.

Table 3: Summary statistics - firm characteristics

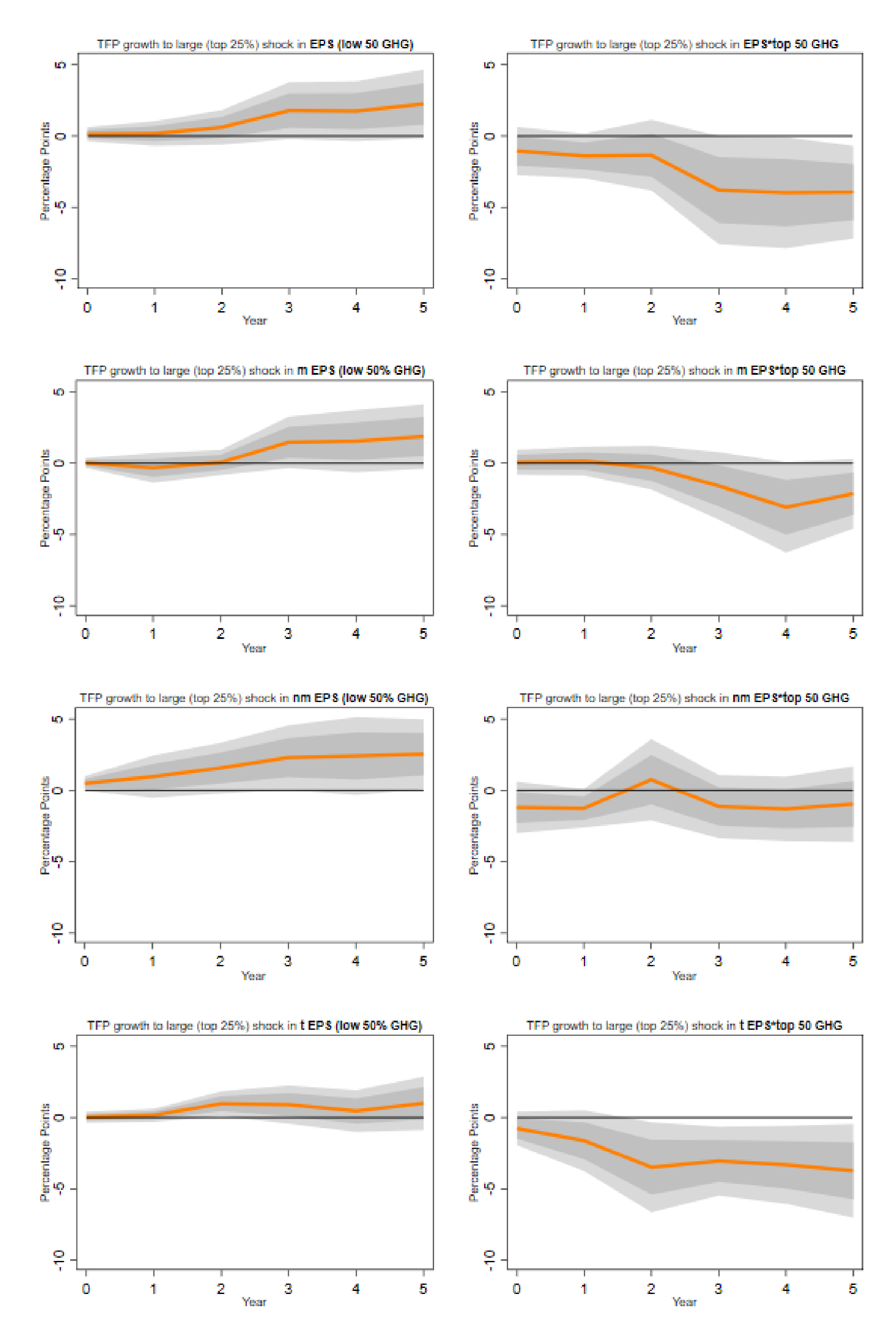
	Mean	SD	25th	Median	75th
Belgium					
TFP	1.16	0.81	0.73	0.97	1.34
Distance to TFP frontier	1.81	0.72	1.33	1.79	2.26
Labour prod	109,000.82	221,453.83	51,635.35	73,844.31	109,406.36
Distance to Lprod frontier	2.04	0.92	1.46	1.99	2.61
Employees	17.22	401.84	2.00	4.00	9.00
Firm age	21.55	13.49	12.00	19.00	27.00
ROA	14.63	15.51	6.08	12.56	21.21
Germany					
TFP	1.16	0.83	0.74	0.98	1.32
Distance to TFP frontier	1.88	0.69	1.40	1.85	2.33
Labour prod	116,644.23	219,176.73	58,899.91	83,144.93	119,460.07
Distance to Lprod frontier	2.17	0.86	1.61	2.15	2.71
Employees	58.52	908.50	4.00	13.00	35.00
Firm age	30.06	25.97	16.00	23.00	35.00
ROA	12.93	13.86	5.12	11.29	19.42
Spain					
TFP	1.32	1.49	0.64	0.90	1.35
Distance to TFP frontier	1.87	0.85	1.34	1.87	2.42
Labour prod	88,150.00	220,681.33	30,062.11	46,121.91	76,834.23
Distance to Lprod frontier	2.54	1.08	1.89	2.53	3.20
Employees	20.03	6,143.86	2.00	4.00	10.00
Firm age	16.32	9.81	9.00	15.00	21.00
ROA	20.65	75.48	1.85	6.70	14.64
France					
TFP	1.17	0.66	0.75	1.01	1.39
Distance to TFP frontier	1.77	0.71	1.27	1.72	2.22
Labour prod	72,004.61	91,730.05	38,492.93	56,565.88	82,407.70
Distance to Lprod frontier	2.31	0.89	1.71	2.23	2.85
Employees	29.40	599.24	2.00	5.00	12.00
Firm age	18.09	13.00	9.00	15.00	24.00
ROA	10.83	14.83	3.28	9.78	18.15
Italy					
TFP	1.78	3.00	0.56	0.84	1.43
Distance to TFP frontier	1.85	0.92	1.32	1.88	2.44
Labour prod	166,921.68	422,712.02	39,600.27	64,479.47	119,990.00
Distance to Lprod frontier	2.20	1.10	1.55	2.21	2.85
Employees	19.91	206.89	2.00	6.00	13.00
Firm age	20.95	13.09	12.00	18.00	28.00
ROA	33.20	83.89	4.15	8.67	17.89
Portugal					
TFP	1.24	0.89	0.73	1.05	1.50
Distance to TFP frontier	1.95	0.78	1.42	1.88	2.41
Labour prod	36,829.85	107,960.40	15,401.03	24,197.47	38,761.56
Distance to Lprod frontier	3.39	1.02	2.74	3.29	3.94
Employees	10.79	104.68	2.00	3.00	7.00
Firm age	20.28	14.14	11.00	17.00	25.00
ROA	6.52	23.79	0.96	6.67	15.05
All					
TFP	1.39	1.84	0.66	0.94	1.40
Distance to TFP frontier	1.85	0.83	1.33	1.84	2.37
Labour prod	100,967.75	267,763.09	31,020.16	51,867.29	86,211.59
Distance to Lprod frontier	2.47	1.10	1.78	2.43	3.13
Employees	23.68	3,438.03	2.00	5.00	12.00
Firm age	19.63	14.49	10.00	17.00	25.00
ROA	19.51	62.55	2.88	8.25	16.96

Table 4: Variable description

Variable	Country	Firm	Description	Source
Total factor productivity	X		TFP index as derived by Eurostat, 2015 = 100, growth rate	AMECO
		X	Based on ORBIS/iBACH data, Petrison-Levin-Wooldridge approach (Ackerberg et al., 2015), growth rate	own calc
TFP frontier	X		TFP growth rate of the US	AMECO
		X	average TFP growth of top 5% most productive firms per (2-digit NACE) sector and year	own calc
Distance to TFP frontier		X	Difference between 95th TFP percentile (per sector and year) and individual TFP level	own calc
Labour productivity	X		GDP per hour worked, constant prices 2010 and PPPs, growth rate	OECD
		X	Value added / number of employees from ORBIS/iBACH data, growth rate	own calc
Labour productivity frontier	X		GDP per hour worked of the US, growth rate	OECD
		X	average labour productivity growth of top 5% most productive firms per (2-digit NACE) sector and year	own calc
Distance to Labour prod frontier		X	Difference between 95th labour productivity percentile (per sector and year) and individual labour productivity level	own calc
Environmental policy stringency	X	X	EPS index, values between 0 and 6 (least to most stringent), aggregate or sub-indicator, growth rate	OECD
Emission indicator	X		Green house gas emissions per capita, dummy variable equals one if country is among top (50 %) polluters	AMECO
		X	Dummy variable equals one if firm is among top X emission equivalence bins according to XGBoost classification, based on Urgentem data	own calc
Output gap	X	X	Cyclical component of real GDP	AMECO
Employment prot.	X	X	Strictness of employment protection legislation	OECD
Startup costs	X	X	Costs of starting a business for men as percentage of income per capita	World Bank
R & D spending	X		Research and Development investment as percentage of of GDP, measured in constant prices of 2015 and PPPs	OECD
Industry share	X		Gross value added industry (NACE section C+D+E) as percentage of gross value added overall	AMECO
Firm size		X	Number of employees, standardized	ORBIS/iBACH
Firm age		X	Years since formation of business, standardized	ORBIS/iBACH
Firm leverage		X	Debt as perctage of assets, standardized	ORBIS/iBACH
Return-on-assets		X	Profit as percentage of assets, standardized	ORBIS/iBACH
Equity ratio		X	Equity per total assets, standardized	ORBIS/iBACH
Patents		X	Cumulative number of patent families, standardized	Orbis IP

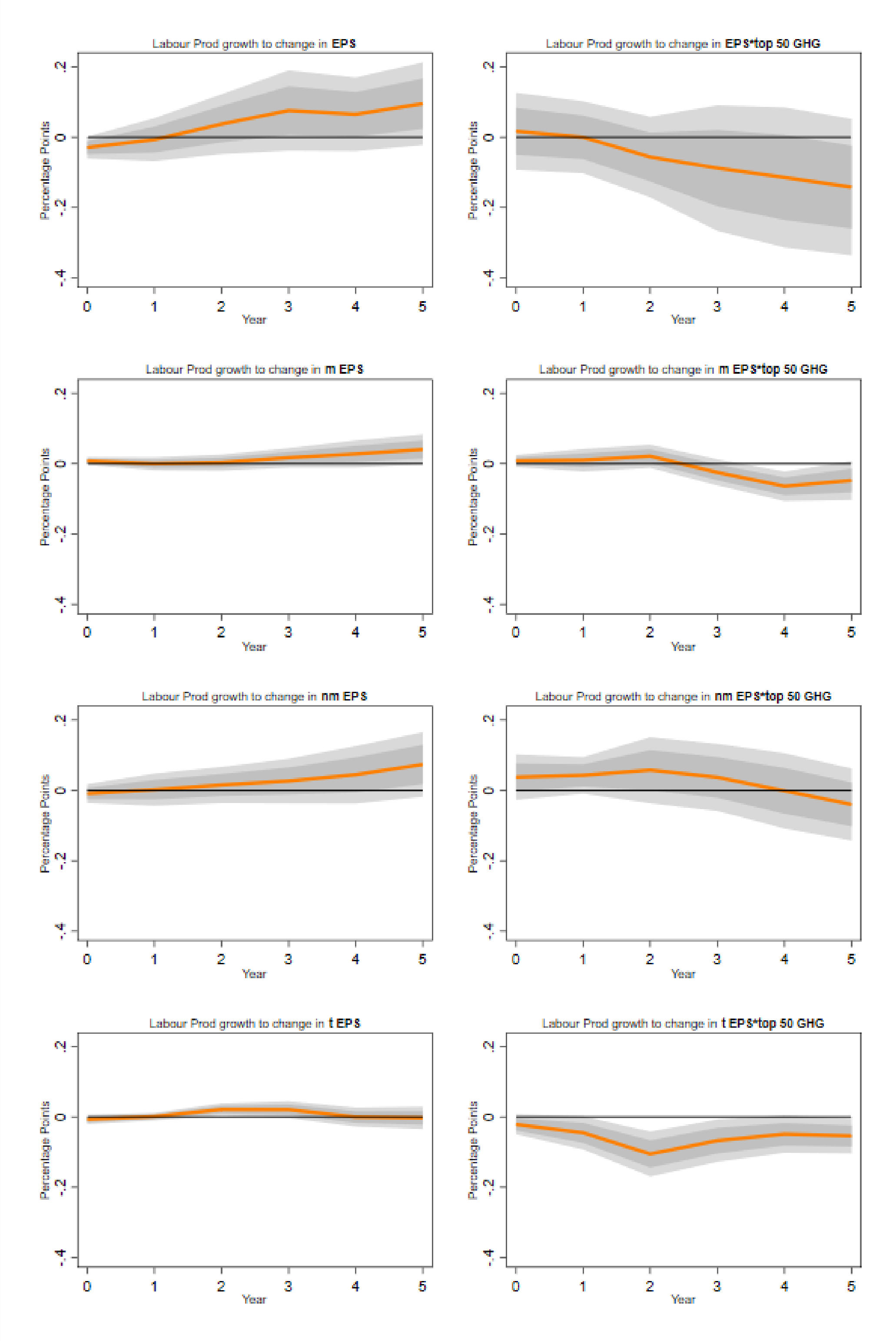
Additional results

Figure 9: Impulse response functions - country-level - large shock



Note: Cumulative impulse responses of labour productivity growth to 1 pp EPS shocks (top 25% changes) over 5 years. Left column bottom 50% polluting countries, right column top 50% polluting countries. Orange line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure 10: Impulse response functions - country-level - labour productivity



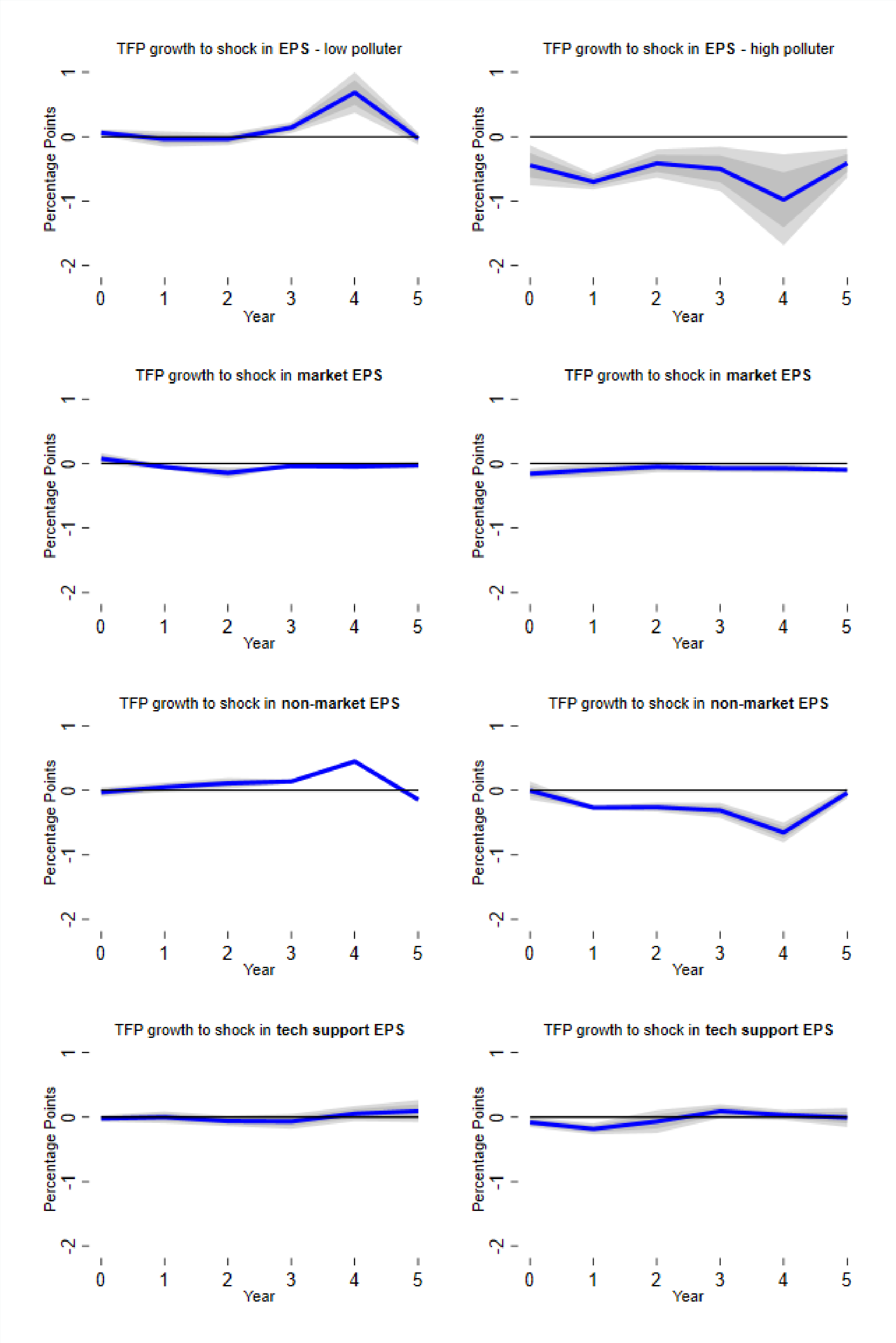
Note: Cumulative impulse responses of labour productivity growth to 1 pp EPS shocks (positive changes) over 5 years. Left column bottom 50% polluting countries, right column top 50% polluting countries. Orange line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Table 5: Detailed local projection results

	Country TFP growth		Firm TFP growth	
	(1y)	(5y)	(1y)	(5y)
$CO2_{t-1}$ indicator	-0.564	0.628	4.308***	3.902**
	(0.718)	(1.169)	(1.631)	(1.723)
EPS change	0.022	0.165	-0.038***	-0.028***
	(0.031)	(0.098)	(0.005)	(0.004)
$CO2_{t-1}$*EPS	-0.045	-0.230	-0.700***	-0.411**
	(0.055)	(0.135)	(0.219)	(0.198)
Output gap	0.469**	0.403	-1.645***	-2.529***
	(0.153)	(0.365)	(0.219)	(0.031)
GDP/capita	-24.49***	-81.551***	120.927***	134.780***
	(1.939)	(20.238)	(1.629)	(2.245)
EPL	8.029	17.823	-15.450***	-0.591
	(8.295)	(13.995)	(0.395)	(0.570)
Startup costs	-2.059**	-3.610*	-7.574***	-1.712***
	(0.942)	(1.732)	(0.108)	(0.113)
agg R&D	-2.094	4.398	-19.995***	8.581***
	(2.138)	(5.934)	(0.416)	(0.565)
agg TFP frontier	8.213***	-3.536		
	(1.239)	(12.052)		
sector TFP frontier			52.290***	57.033***
			(0.142)	(0.156)
Distance to frontier			81.598***	96.753***
			(0.075)	(0.893)
Size (employees)			-0.624***	-0.099***
			(0.172)	(0.096)
Return-on-Assets			-4.345***	-4.123***
			(0.051)	(0.058)
Age			9.374***	12.047***
			(0.497)	(0.808)
Country F.E.	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
Firm, sector F.E.	No	No	Yes	Yes
R^2 adjusted	0.04	0.01	0.43	0.54
N	182	134	8,206,621	4,422,580

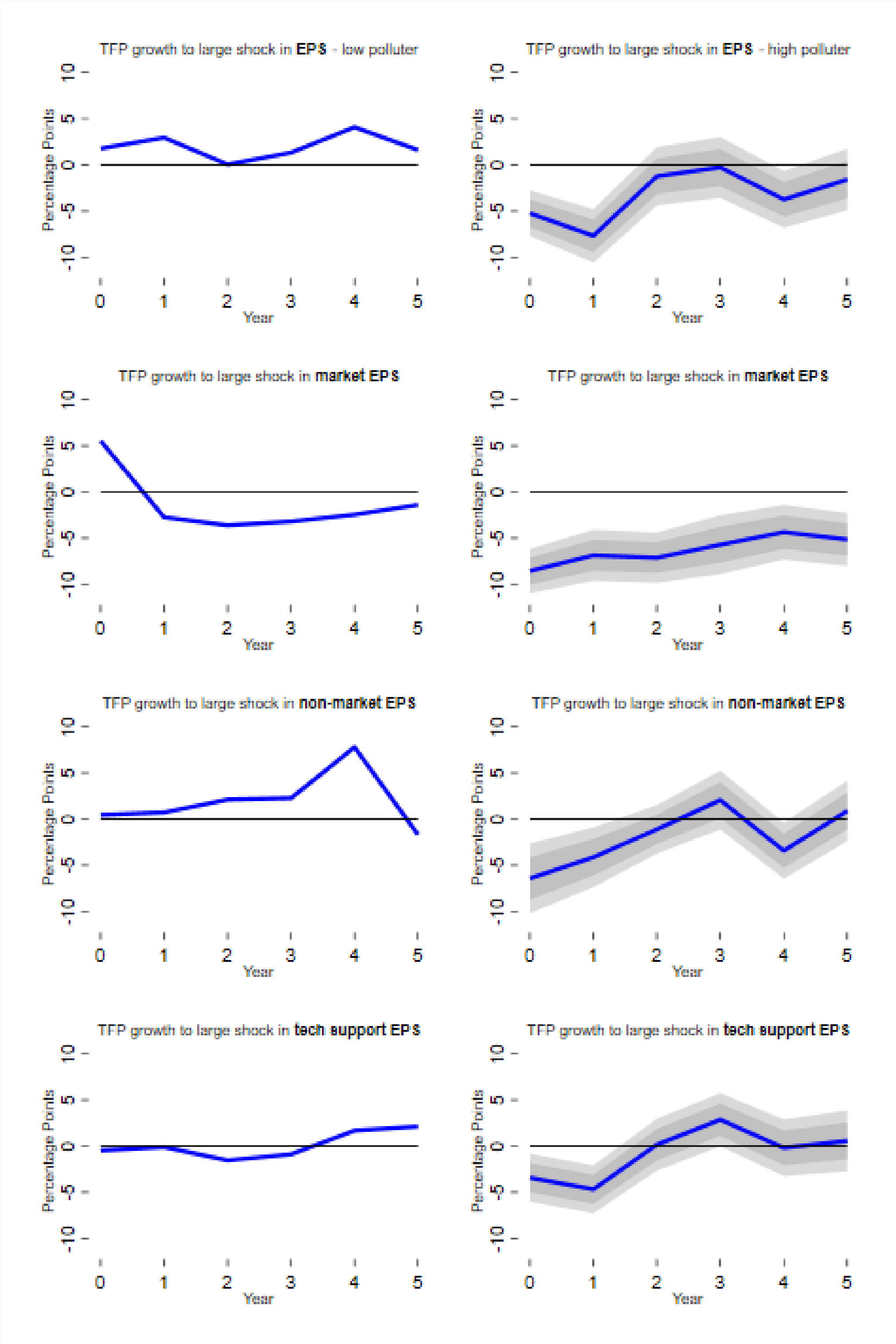
Note: Local projections with 1 and 5 year ahead cumulative TFP growth as dependent variable at country and firm level. CO2 indicator is top 50% of countries according to emission intensity or top 6 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardized. * < 0.1, ** < 0.05, *** < 0.01

Figure 11: Impulse response functions - firm-level - country cluster SE



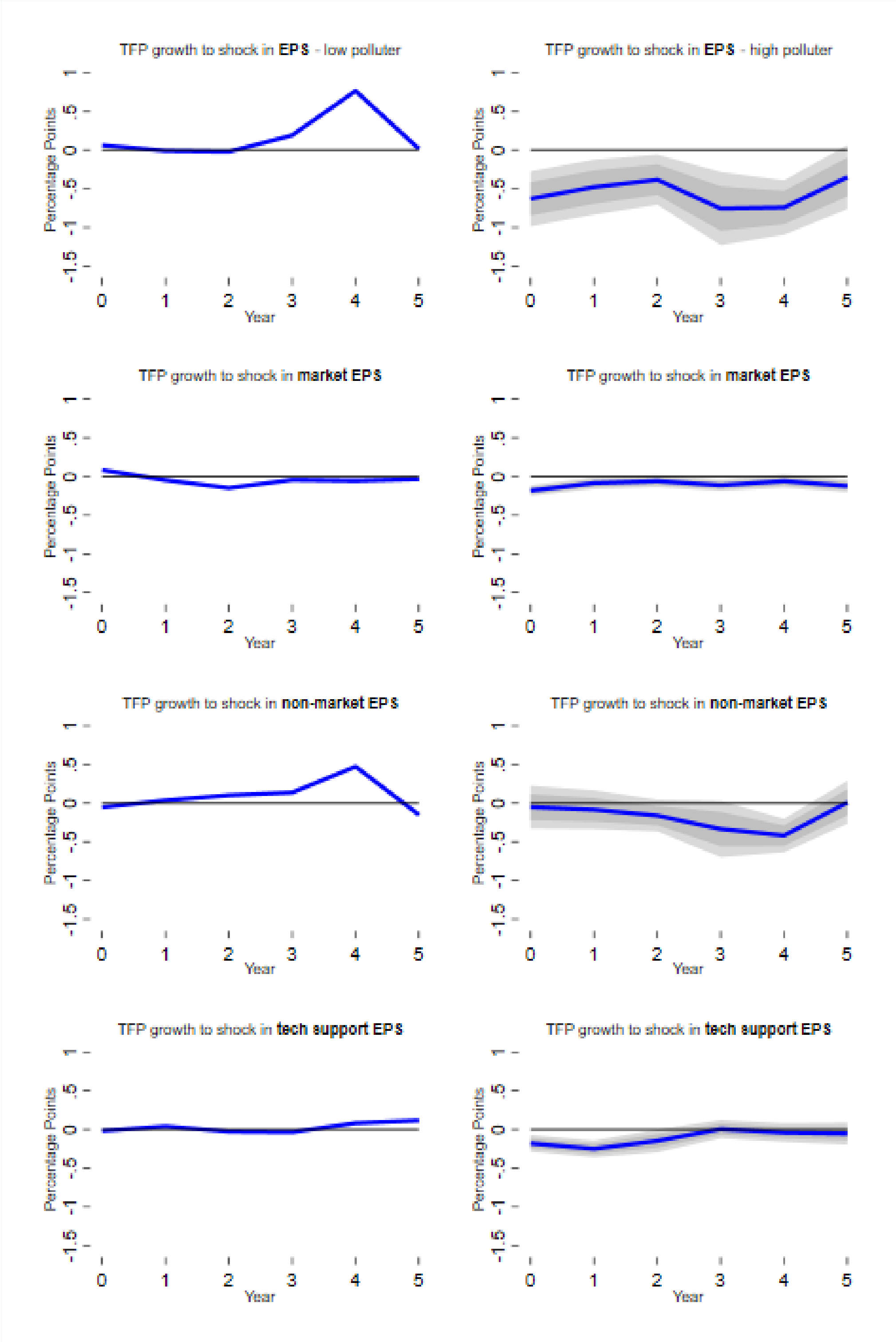
Note: Cumulative impulse responses of TFP growth to 1 pp EPS shocks (top 25% changes) over 5 years. Left column bottom 4 bins of polluting firms, right column top 6 bins of polluting firms. Blue line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands based on country-cluster standard errors.

Figure 12: Impulse response functions - firm-level - large shocks



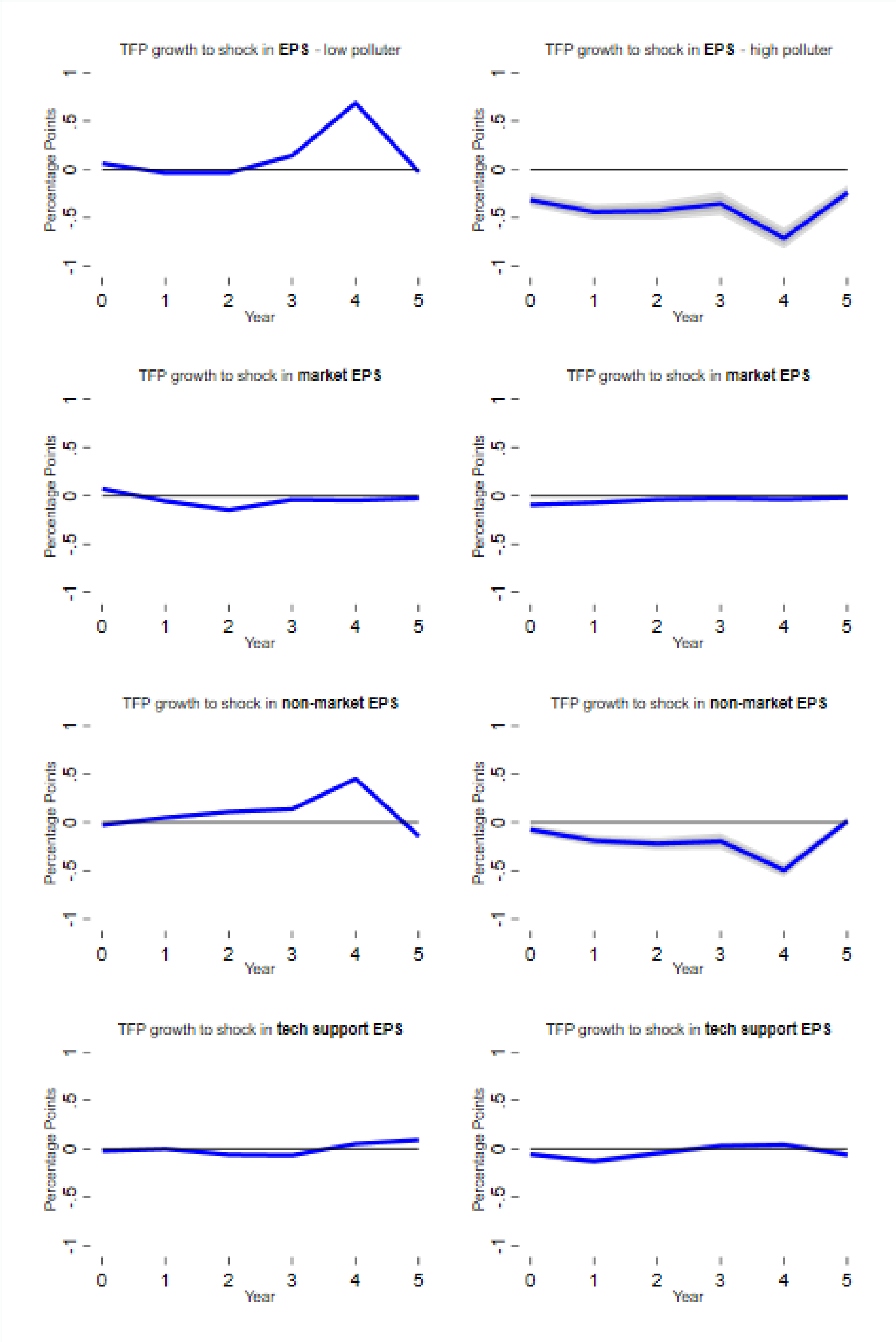
Note: Cumulative impulse responses of TFP growth to 1 pp EPS shocks (top 25% changes) over 5 years. Left column bottom 4 bins of polluting firms, right column top 6 bins of polluting firms. Blue line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure 13: Impulse response functions - firm-level - labour productivity



Note: Cumulative impulse responses of labour productivity growth to 1 pp EPS shocks (positive changes) over 5 years. Left column bottom 4 bins of polluting firms, right column top 6 bins of polluting firms. Blue line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure 14: Impulse response functions - firm-level - top 9 bins



Note: Cumulative impulse responses of TFP growth to 1 pp EPS shocks (positive changes) over 5 years. Left column bottom 1 bin of polluting firms, right column top 9 bins of polluting firms. Blue line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

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