

Kurz, Antonia; Rubínová, Stela

Working Paper

Trade effects of carbon pricing policies

WTO Staff Working Paper, No. ERSD-2024-08

Provided in Cooperation with:

World Trade Organization (WTO), Economic Research and Statistics Division, Geneva

Suggested Citation: Kurz, Antonia; Rubínová, Stela (2024) : Trade effects of carbon pricing policies, WTO Staff Working Paper, No. ERSD-2024-08, World Trade Organization (WTO), Geneva

This Version is available at:

<https://hdl.handle.net/10419/308083>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

World Trade Organization

Economic Research and Statistics Division

TRADE EFFECTS OF CARBON PRICING POLICIES

Antonia Kurz* and Stela Rubínová†

Manuscript date: 19 December 2024

Disclaimer: "The opinions expressed in these papers are those of the authors. They do not represent the positions or opinions of the WTO or its Members and are without prejudice to Members' rights and obligations under the WTO. Any errors are attributable to the authors."

* Deutsche Institut für Wirtschaftsforschung (DIW) Berlin, Tinbergen Institute, and Vrije Universiteit Amsterdam. E-mail: akurz@diw.de.

† Economic Research and Statistics Division, World Trade Organization, Rue de Lausanne 154, 1202 Geneva. E-mail: stela.rubanova@wto.org.

Trade Effects of Carbon Pricing Policies *

Antonia Kurz[†] and Stela Rubínová[‡]

December, 2024

Abstract

Policies that affect the cost of using fossil fuels in production have a complex impact on the economy. In this paper, we focus on the role of these policies for the pattern of comparative advantage through their effect on production costs in manufacturing industries. Using data on carbon prices and fossil fuel subsidies, we show that less stringent carbon pricing policies increase comparative advantage in carbon intensive industries. In the first step, we use a fixed-effects gravity model of trade to estimate the export capabilities that determine the pattern of comparative advantage. In the second step, we regress the change in export capability of a country in an industry on the change in the country's carbon pricing policy, interacted with the carbon intensity of the industry, controlling for country and industry fixed effects. Our results suggest that a 10% increase in carbon price is associated with a decline in export capability in the most carbon-intensive industry by 0.3% to 0.7%. On the other hand, industries with low carbon intensity are barely affected. Overall, we estimate that changes in all the policy instruments combined can explain up to 1.2% of the changes in export capabilities in the periods 2012-2015 and 2015-2018. We then use the econometric results to illustrate the potential impact of removing fossil fuel subsidies on the pattern of comparative advantage in carbon intensive industries. Furthermore, we extend our analysis to consider potential policy spillovers along the supply chain. The results suggest that carbon pricing policies compound along the domestic supply chain so that an industry's export competitiveness increases when its carbon intensive domestic suppliers face lower carbon prices or higher fossil fuel subsidies. We also find some limited empirical support for supply chain spillovers of foreign carbon prices.

Keywords: Carbon Pricing, Fossil Fuel Subsidies, Fossil Fuel Taxes, Comparative Advantage, Competitiveness

JEL classifications: F18, Q48, Q56, Q58

*The opinions expressed in this paper are those of the authors. They do not represent the positions or opinions of the WTO or its members and are without prejudice to members' rights and obligations under the WTO. Any errors are attributable to the authors. We are grateful for the comments and support by Gregoire Garsous, Carolyn Fischer, Hans Koster, Konstantinos Theodoropoulos, Gerard van der Meijden, and the participants of the OECD's Applied Economics Work-in-Progress Seminar May 2022, the Dutch Economists' Day 2022, the Dutch Environmental Economics Day 2023, EAERE 2023, the World Bank/IMF/WTO workshop 2023, and VU Amsterdam EUREKA seminars.

[†]DIW Berlin, Tinbergen Institute, & Vrije Universiteit Amsterdam; e-mail: akurz@diw.de

[‡]World Trade Organization, Economic Research and Statistics Division; e-mail: stela.rubanova@wto.org

1 Introduction

Fossil fuels are still the most important source of energy in the world. Policies that target fossil fuel prices are therefore widespread, both as a means of taxing the negative externalities created by their combustion and as a means of subsidising certain production activities or households. Policies that increase the cost of carbon facilitate the green transition: instruments like fuel excise taxes, carbon emission taxes, or emission permit systems have been put in place to reduce climate change inducing emissions from fossil fuel combustion. Despite increasing efforts to price carbon emissions worldwide, many governments continue with their support for fossil fuels through exemptions from excise taxes or direct transfers of government funds to producers and consumers of fossil fuels. Policies that increase the cost of using fossil fuel for combustion, therefore, coexist with policies that lower this cost.

In this paper, we consider a range of indicators to measure carbon pricing policies, relying on data from the World Carbon Pricing Database (WCPD), the Organization for Economic Co-operation and Development (OECD)’s Effective Carbon Rates (ECR) as well as its Inventory of Support Measures for Fossil Fuels. These indicators include both fossil fuel subsidies (direct transfers of government funds or tax expenditures) and carbon prices (carbon emission taxes, emission permit prices, and fossil fuel excise taxes). For ease of exposition, in what follows, we refer to all the policy instruments that affect the cost of using fossil fuels for combustion as “carbon pricing policies”.

We study how domestic carbon pricing policies alter international competition, focusing on their effects as subsidies/taxes on inputs into industrial production.¹ A lower cost of carbon gives a competitive advantage to industries that use fossil fuels more intensively in their production than other domestic industries, and skews the economic structure toward carbon intensive activities. On international markets, the competitive advantage gained from cheaper cost of production translates into larger exports and a distorted pattern of comparative advantage. Our analysis captures both a direct exposure to carbon pricing policies through the use of fossil fuels as a production input, as well as an indirect exposure through the use of intermediate inputs that themselves are produced by carbon intensive activities.

Our estimates rely on a two-step empirical approach. First, building on [Eaton and Kortum \(2002\)](#) and [Costinot, Donaldson and Komunjer \(2012\)](#), we obtain theory-consistent estimates of export capability – an indicator of production factor costs and production efficiency – from a structural gravity equation following the methodology introduced in

¹The direct impact of fossil fuel subsidies on the competitiveness in international fossil fuel markets would concern only a handful of countries that are large producers of fossil fuels. On the other hand, the impact of fossil fuel subsidies as input subsidies to downstream sectors has the potential to distort international competition more broadly ([Burniaux, Chateau and Sauvage, 2011](#)). Therefore, we focus on the latter channel and exclude fossil fuel producing sectors from our analysis.

[Egger, Larch, Nigai and Yotov \(2021\)](#). In a second step, we regress the estimated export capability on a measure of a country’s carbon pricing policies interacted with the industry’s carbon intensity, controlling for country and industry fixed effects. Additionally, we analyse potential spillover effects along the supply chain by using an indirect exposure to domestic and foreign carbon pricing policies through purchases of carbon intensive intermediate inputs. We obtain a country-industry’s indirect exposure by calculating its dependencies on all other country-industries, using the inverse (local) Leontief matrices, similar to [Wang, Wei, Yu and Zhu \(2017\)](#).

Our results suggest that a 10% increase in a country’s carbon tax (10% decrease in fossil fuel subsidies) is associated with a 0.3% (0.6%) decline in export capability in the most carbon (fossil fuel) intensive industry and a 0.008% (0.06%) decrease in export capability in the least carbon (fossil fuel) intensive industry.

Previous studies have demonstrated that energy prices influence trade and production in energy-intensive industries ([Sato and Dechezleprêtre, 2015](#); [Aldy and Pizer, 2015](#); [Arezki, Fetzer and Pisch, 2017](#); [Misch and Wingender, 2024](#)). In particular, [Sato and Dechezleprêtre \(2015\)](#) evaluate how countries’ industry-level energy prices influence bilateral trade flows. By using a panel dataset with 42 economies and 62 manufacturing industries from 1996 until 2011, they find that “changes in relative energy prices have a statistically significant but very small impact on imports”. The effect is larger for energy-intensive industries, but even then, differences in energy prices cannot explain more than 0.01% of trade flows’ variation. Using a 35-year panel of approximately 450 US manufacturing industries, [Aldy and Pizer \(2015\)](#) find that an increase in energy prices results in a decrease in production and an increase in net imports for energy-intensive manufacturing industries compared to non-energy-intensive ones.

Whereas the aforementioned studies connect trade flows with energy prices, we connect them with a set of government policies, similar to [Aichele and Felbermayr \(2015\)](#) who analyse the effect of the Kyoto Protocol. While the latter is found to have triggered a pollution haven effect, the introduction of the EU Emission Trading System (ETS) seems to not have done so ([Branger, Quirion and Chevallier 2016](#); [Naegele and Zaklan 2019](#); [Dechezleprêtre, Gennaioli, Martin, Muûls and Stoerk 2022](#); [Colmer, Martin, Muûls and Wagner 2024](#)), possibly by not altering production costs enough to affect production location decisions.²

From a methodological perspective, we improve on previous studies by separating the component of trade flows that is driven by comparative advantage from the components that are driven by import demand and trade costs. Focusing on the comparative advantage component, we identify the impact of policies on international competition through their impact on domestic production costs. This is important especially in the

²All those studies results are mostly based on the EU ETS Phase 1 (2005-2007) and/or Phase 2 (2008-2012), with only [Dechezleprêtre et al. 2022](#) analysing data until 2014.

context of carbon pricing policies that may impact trade flows also through the costs of transportation.

We further contribute to the literature by accounting for supply chain linkages which may cause policy spillovers between sectors and countries. Previous work has shown that subsidies can lead to the expansion of downstream industries (Lane, 2024) and, in the context of carbon pricing policy, that the introduction of an emission trading scheme can have a negative short-term effect on downstream firms' performance (Jia, 2023). Similarly, we complement earlier case study approaches (e.g., OECD, 2019) by testing the impact of policies that may act as input subsidies in a comprehensive analytical framework.

The rest of the paper is organised as follows. In Section 2, we describe how we measure carbon pricing policies. In Section 3, we set out our estimation methodology and dataset construction. We present our results in section 4. Section 5 concludes.

2 Measuring carbon pricing policies

Carbon pricing policies consist of various instruments that vary along a number of dimensions, such as whether they are linked to carbon emissions or fossil fuel consumption, and, in the latter case, whether they target consumers or producers of fossil fuels, and which fuels in particular. In this study, we focus on policy instruments that target all types of fossil fuel consumption in the industrial sector, as well as the resulting emissions. We use three different databases that, combined, provide information on carbon taxes, carbon emission permit prices, fossil fuel excise taxes, exemptions from these three types of taxes, and direct subsidies for fossil fuel consumption.

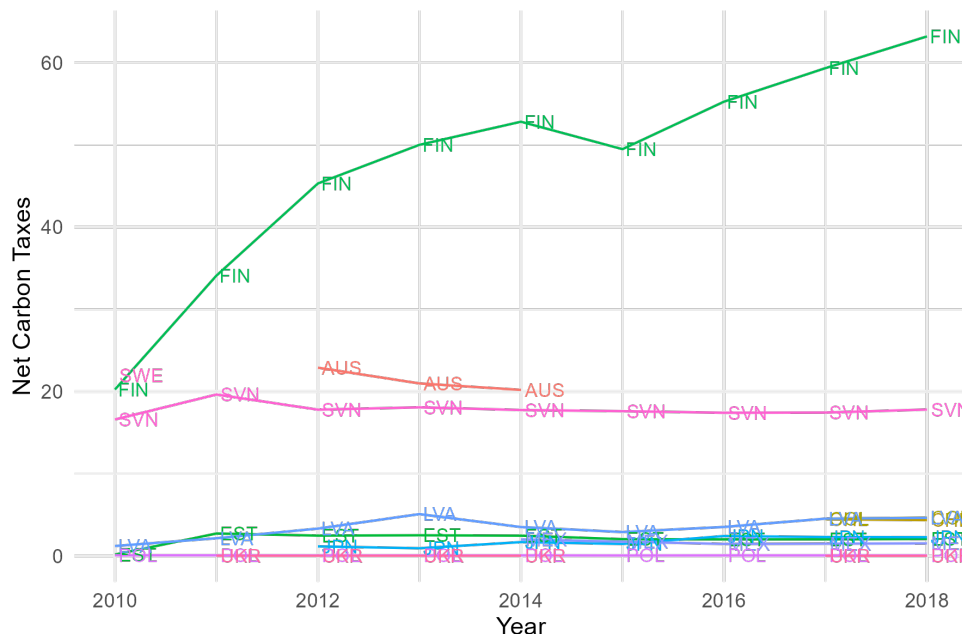
2.1 Carbon Prices

The World Carbon Pricing Database (WCPD) by Dolphin and Xiahou (2022) provides a detailed annual record of carbon prices from carbon pricing systems implemented in different jurisdictions.³ The database includes information on carbon taxes and their exemptions. It also includes permit prices in emissions trading systems (ETS) but this information has three main drawbacks in the context of our analysis. First, it does not include free permit allowances, which were important in the period of our study (2010-2018). Second, the variation in the ETS permit prices stems from only four permit systems (the European Economic Area, Korea, New Zealand and Switzerland), see visualisation in Figure A.1. Finally, since the permit price formation within an ETS depends on the level of economic activity (demand for permits), the resulting permit prices have a component that is endogenous in our model of export capability. We therefore restrict our analysis to the carbon taxes instrument in the WCPD.

³See <https://www.rff.org/publications/data-tools/world-carbon-pricing-database/>

The database is available at 4-digit Intergovernmental Panel on Climate Change (IPCC) classification. In our empirical analysis we focus on the industrial sector (excluding energy mining and producing industries) where carbon taxes (including exemptions) recorded in the WCPD did not vary across the IPCC industries.⁴

Figure 1: Carbon taxes in the industrial sector



Note: Carbon taxes in the industrial sector (excluding energy extraction and production) from the World Carbon Pricing Database (Dolphin and Xiahou, 2022) for 2010-2018 in nominal USD per ton of CO₂. See Table A2 for economy codes.

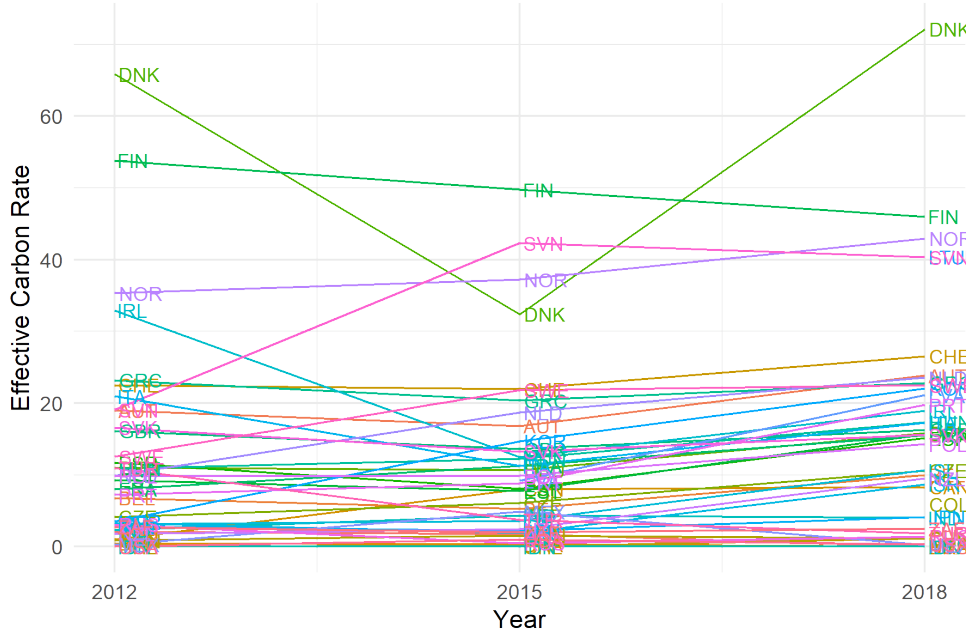
Figure 1 shows the evolution of carbon taxes in the non-energy industrial sector in the economies that imposed them in the period 2010-2018. Finland was the first in the world to introduce a carbon tax in 1990 and keeps standing out as the economy with by far the highest level⁵, followed by Slovenia which introduced one in 1996. Sweden was the second country in the world to introduce a carbon tax in 1991, but applied it to the non-energy industrial sector only until 2010, while Australia abolished its carbon tax in 2014, two years after its introduction. Only three other countries imposed a carbon tax of at least 5 USD – Latvia’s carbon tax has gradually increased over the period, reaching above 5 USD in 2018 while Argentina and Chile introduced a 5 USD carbon tax in 2018 and 2017, respectively. Colombia, Estonia and Japan had a carbon tax that varied between 1 and 3 USD while Mexico, Poland and Ukraine maintained a tax of less than 1 USD.

Another source of information on carbon prices is the OECD’s dataset on Effective

⁴In our sample of 45 economies in the period 2010-2018, Sweden is the only country with an exemption.

⁵In 2013, its carbon price was a combination of the carbon tax and energy tax (Khastar, Aslani and Nejati, 2020) which together considerably increased from 2010-2018. In the WCPD, they are jointly considered as carbon tax.

Figure 2: Effective carbon rates in the industrial sector



Note: Effective carbon rates (ECR) in the industrial sector from the OECD for 2012, 2015 and 2018 in nominal EUR per ton of CO₂. The ECR consists of the explicit carbon price plus the fuel excise tax – Figure A.2 in Section A.3 visualises both components. See Table A2 for economy codes.

Carbon Rates (ECR). In addition to explicit carbon prices (emission permit price and carbon tax), this dataset includes also fuel excise taxes which are an important instrument to implicitly tax carbon emissions, especially in emerging economies. Similar to the WCPD, the effective carbon rates are reported net of tax exemptions and, in addition, take into account free emission allowances.

The ECR dataset comes with two drawbacks. First, it is only available for three years within the period of our analysis – 2012, 2015 and 2018. Second, the publicly available ECR data is aggregated to the level of ‘the industrial sector’ using industry-level emissions as weights. If effective carbon rates vary across industries, changes in the composition of industries within the sector can therefore affect the ECR independently of changes in the underlying rates.

Most economies in our sample had a positive effective carbon rate between 2012 and 2018, see Figure 2. On average, effective carbon rates increased between 2012 and 2018 from 11.8 to 15.0 EUR per ton of CO₂ emissions, driven by an increase in the average explicit carbon price from 6.2 to 11.7 EUR in high-income economies. Fuel excise taxes, on the other hand, on average declined from 8.1 to 7.3 EUR in high-income economies and from 3.0 to 1.3 EUR in emerging economies. The two components of the ECR are visualised in Figure A.2. Overall, effective carbon rates increased in two thirds of economies in our sample.

2.2 Fossil Fuel Subsidies

Another dataset that is available to quantify carbon pricing policies is the OECD inventory of support measures for fossil fuels. The inventory collects data on measures that include direct budgetary transfers and tax expenditures (i.e. tax exemptions from value added or fuel excise taxes) which in some way provide a benefit for fossil-fuel production or consumption (OECD, 2015), see also Figure A.5. Other available measures of fossil fuel support, such as those published by the International Energy Agency or the International Monetary Fund, are calculated with a price-gap approach in which the end-use prices of fossil fuels are compared to their wholesale prices, assuming that the difference is a result of government support. One issue with this approach is that it may miss the forms of domestic support that do not depress current price levels of fossil fuels, such as direct transfers of funds from the government to firms to compensate for their fossil fuel expenses.

The inventory covers both primary fossil-fuel commodities (crude oil, natural gas, coal, and peat) and secondary refined or processed products (diesel fuel, gasoline, kerosene, and coal briquettes), as well as electricity produced by fossil fuels (OECD, 2015). In our analysis we focus on the support for primary and secondary fossil-fuel products excluding electricity support. The inventory also categorises support according to the beneficiary sectors: fossil fuel production, fossil fuel consumption, and so-called general services that typically include support to physical infrastructure or infrastructure services. In our empirical analysis we focus on the impact of carbon pricing on industries that consume fossil fuels and therefore on the support provided through consumption-related instruments, which also account for the majority of global fossil fuel support, see Figure A.6. The data is reported for four industry categories: transportation, residential, electricity generation, and other sectors that include industry. We focus on the latter in our analysis.

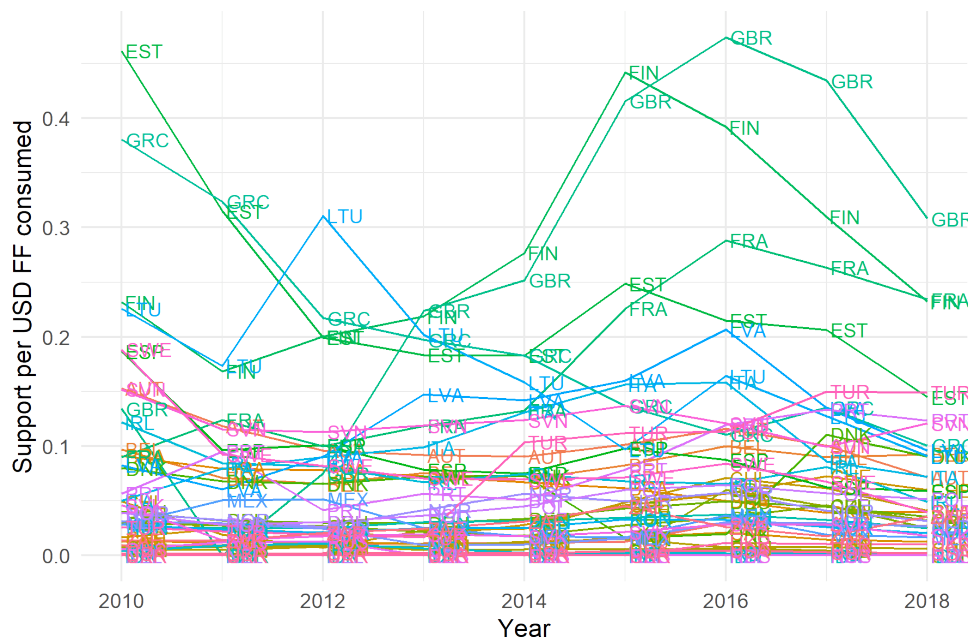
Fossil fuel support is expressed in total US dollars in the inventory. We construct a per-unit measure by dividing the total support by a country’s fossil fuel consumption in the relevant sectors.⁶ This subsidy per unit of fossil fuel consumption, through tax expenditures and direct transfers, is the main measure of fossil fuel subsidies used in our analysis.

Figure 3 shows that most economies provide some fossil fuel support to their industries. The level of support as well as its variation across economies and over time is predominantly driven by the tax expenditure component. Only eight economies in our sample provided direct subsidies for fossil fuel consumption (see Figures A.3 and A.4).

Fossil fuel support through tax expenditures can – by construction – be higher in economies with higher baseline taxation. For example, Finland registers high support

⁶We proxy fossil fuel consumption with the value of inputs sourced from industries that mine, extract and manufacture fossil fuel products (coal, lignite, crude petroleum, natural gas, coke and refined petroleum) reported in the ICIO tables, see Section on “Measures of carbon intensity”.

Figure 3: Fossil fuel support

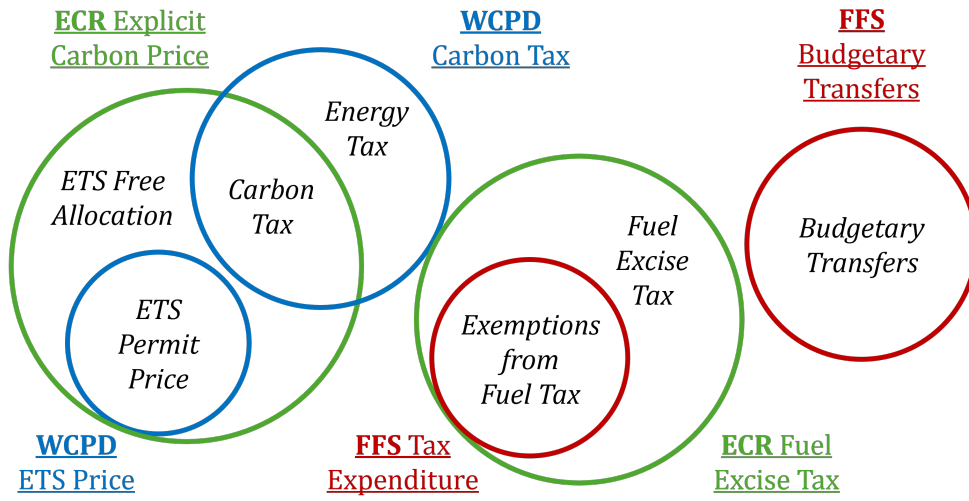


Note: Fossil fuel support (FFS) for fossil fuel consumption in sectors other than electricity generation, residential and transportation from the OECD's Inventory for Fossil Fuel Support measures for 2010-2018, in nominal USD per USD of fossil fuel consumed. FFS is provided through tax expenditures and direct transfers – Figures A.3 and A.4 in Section A.3 visualise both components. Please see Table A2 for economy codes.

to fossil fuel consumption by exempting it partially from their high energy tax (see discussion on Finnish carbon prices above). In our regression analysis we can control for this heterogeneity in the benchmark tax structure by including both the tax expenditures and the level of carbon taxes before exemptions.

As discussed above, tax expenditures due to exemptions from fuel excise taxes are also captured in the ECR. Figure 4 visualizes the coverage of the various carbon pricing instruments in the three databases and their overlap. It shows that the ECR has the broadest coverage while the WCPD covers only a subset of carbon tax instruments.

Figure 4: The coverage of carbon pricing policy instruments in the ECR, FFS, and WCPD databases



3 Methodology

Our methodological approach to estimating the trade effects of carbon pricing policies consists of two steps, similar to the approach in Costinot et al. (2012). In the first step, we use a gravity model to obtain an estimate of export capability of each country per industry. In the second step, we regress the export capability on a measure of carbon pricing policy in the economy interacted with carbon intensity of the industry, assuming that industries with a higher carbon intensity are the ones most affected. This two-step approach ensures that demand factors and trade costs are controlled for, thus allowing us to focus on the role of carbon pricing policies in distorting international competition through their effect on production cost. We first focus on the direct effect, taking into account only domestic policies and direct carbon emissions/fossil fuel use of the industry. Then we extend the analysis to account for potential policy spillovers along the supply-chain, both across industries and across countries, by including the upstream exposure to domestic/foreign policies.

3.1 Estimation of export capability

To identify export capabilities and the pattern of comparative advantage across countries and industries, we apply a fixed-effects gravity model to trade data from the OECD inter-country input-output (ICIO) tables. A broad range of theoretical trade models delivers a gravity equation that includes exporter- (γ_o), importer- (ν_d) and pair-specific (τ_{od}) determinants, leading to an interpretation of the exporter-specific determinants as reduced-form export capability (Head and Mayer, 2014). The gravity equation can be expressed in terms of country d 's imports from country o (x_{od}) as a share of country d 's overall expenditure (E_d), labelled as λ_{od} :

$$\lambda_{od} = \frac{x_{od}}{E_d} = \exp(\gamma_o + \nu_d + \tau_{od}). \quad (1)$$

Through the lens of the Eaton and Kortum (2002) model of Ricardian comparative advantage, the current workhorse model of international trade, the export capability γ_o reflects production factor costs (such as labour, capital and material costs) as well as the efficiency with which firms turn production factors into output (total factor productivity). As in Eaton and Kortum (2002), by normalising the expenditure share λ_{od} with the expenditure share on the output of domestic firms (λ_{dd}) and setting $\tau_{dd} = 1$, we obtain:⁷

$$\frac{\lambda_{od}}{\lambda_{dd}} = \exp(\gamma_o + \tau_{od} - \gamma_d). \quad (2)$$

Following the methodology introduced in Egger et al. (2021), we use the full ICIO tables structure and estimate the gravity model in terms of expenditure shares of firms in country d and industry j on output of firms in country o and industry i (λ_{od}^{ij}) normalised with their expenditure share on the output of domestic firms in industry i (λ_{dd}^{ij}). This allows us to estimate exporter-industry fixed effects while fully controlling for industry-specific bilateral trade frictions as well as other partner-specific supply or demand determinants of trade flows.⁸ For each year (hence, we suppress t in the presented notation), we estimate

⁷Using a normalised form of the expenditure shares reduces heteroscedasticity concerns raised in the context of empirical gravity models estimated in levels and reduces the number of parameters to estimate. Also note that consistent estimation of γ_o does not depend on the assumption of $\tau_{dd} = 1$.

⁸Using the ICIO tables has two advantages. First, they include both international trade flows and spending on domestically produced goods. Second, they include four dimensions: the sourcing country-industry and the using country-industry. The additional dimension of the using industry (that is not present in standard trade data) allows including both exporter-industry and exporter-importer-industry fixed effects in the empirical gravity model. The fixed effects structure allows us to separate export capability from the effects of trade costs and proximity to market demand on trade flows.

a stochastic, log-linear version of Equation (2) with a set of suitable constraints:

$$\ln\left(\frac{\lambda_{od}^{ij}}{\lambda_{dd}^{ij}}\right) = \gamma_o^i - \gamma_d^i + \tau_{od}^i + \varepsilon_{od}^{ij}, \text{ such that } \gamma_o^i = \gamma_d^i \quad \forall o = d \text{ and } i \neq j, \quad (3)$$

where ε_{od}^{ij} is an idiosyncratic stochastic term. Given the fixed effects structure, export capability is defined only up to an industry normalisation. We set up our exporter-industry fixed effects so that export capability in each industry is estimated relative to that of the United Kingdom.⁹

A double normalisation of the (exponential of) the estimated export capability $\hat{\gamma}_{o,t}^i$ yields a measure of comparative advantage (Hanson, Lind and Muendler, 2015). First, expressing the export capability relative to its global average within each industry yields the absolute advantage. This measure is net of worldwide industry supply conditions which makes it comparable across industries within a country. Second, expressing the absolute advantage relative to its country-wide average across all industries yields the comparative advantage. This normalisation removes the effect of countries' market size and thus makes the measure comparable across countries.¹⁰

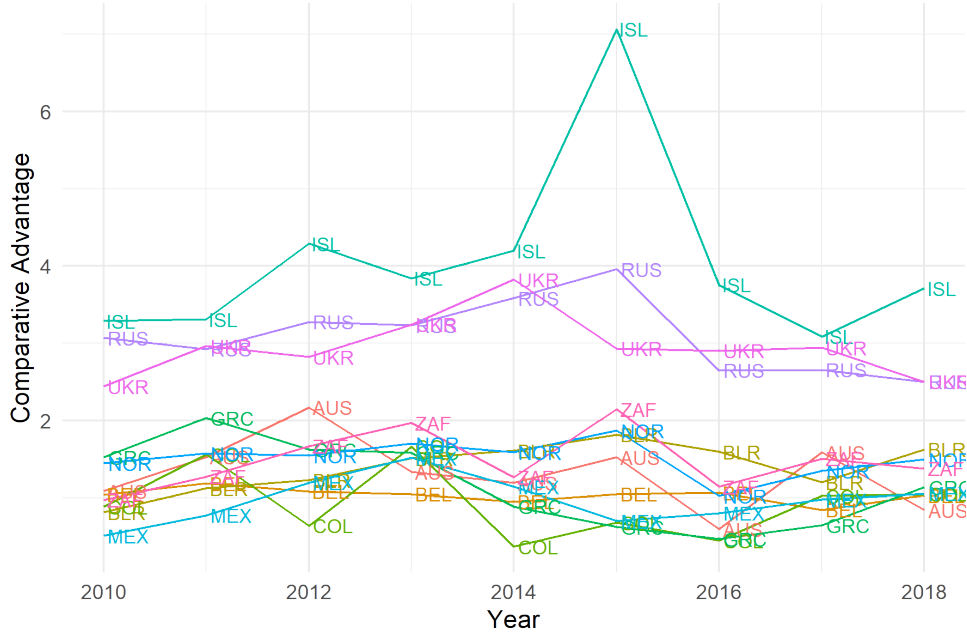
Figures 5 and 6 show the evolution of our estimated comparative advantages for the industries with the highest and the lowest fossil fuel intensity ("Basic Metals" and "Computer, electronic and optical equipment", respectively) and for economies which had comparative advantage in the respective industry at the beginning or at the end of the period.¹¹ Figure 5 shows that Iceland, Russia and Ukraine had the strongest comparative advantage in "Basic Metals", while Australia, Belgium, Belarus, Colombia, Greece, Mexico, Norway, and South Africa also had comparative advantage in the industry. In Figure 6, the Netherlands, and Israel show the strongest comparative advantage in "Computer, electronic and optical equipment" in 2018 while Slovakia lost the prime position it held at the beginning of the period, only to regain a third place in 2018. China, Mexico, Switzerland, and South Korea are among the other economies that had comparative advantage in this industry. Moreover, the figures show that while the set of economies with comparative advantage in an industry does not vary much, the strength of comparative advantage does. And for some economies, like Greece in "Basic Metals" and Slovakia in "Computer, electronic and optical equipment" these variations meant that they lost comparative advantage in the industry between 2010 and 2017. The variation in comparative advantage over time is important for our second-step econometric identification, as

⁹We employ the Abowd, Creedy and Kramarz (2002) algorithm to verify that the connectivity between importers and exporters in our data allows the estimation of all our exporter fixed effects in each industry.

¹⁰The resulting measure of comparative advantage is more refined than the traditional Balassa index of revealed comparative advantage (Balassa, 1965) because it corrects for distortions caused by trade costs and demand differences.

¹¹The comparative advantage is computed within the industrial sector excluding fossil fuel producing industries, which is the sample of industries used in our econometric analysis.

Figure 5: Comparative advantage in “Basic Metals” over time, for the economies with comparative advantage in the industry in 2010 or 2018



Note: Comparative advantage is the twice normalised estimated export capability. An economy has comparative advantage in an industry if the value is equal or larger than 1. Figure A.8 in Section A.4 visualises both the top 5 and the bottom 5 economies in 2010. Please see Table A2 for economy codes.

explained in the following section.

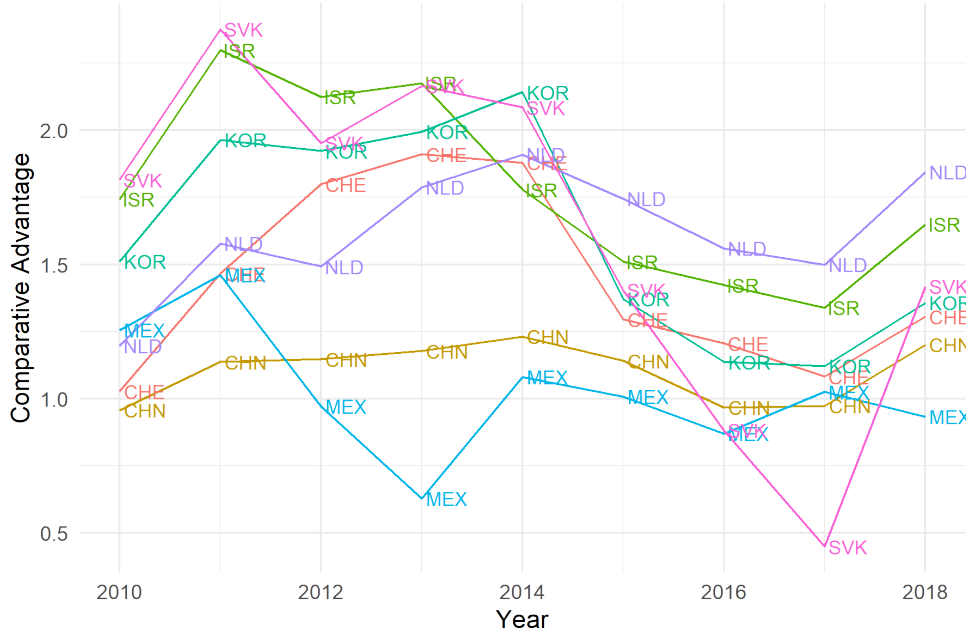
3.2 Estimation of the impact of carbon pricing policies

In the second step, we use our estimated export capability ($\gamma_{o,t}^i$) to assess whether it is affected by carbon pricing policies. We assume that subsidies/taxes on the use of fossil fuels affect industries' export capability by lowering/increasing their production costs, depending on their use of fossil fuels as production inputs. Similarly, taxes on carbon emissions affect industries' export capability through increasing their production costs, depending on the emission intensity of their production. The relationship that we explore in our econometric analysis is therefore that between industry-country's export capability $\gamma_{o,t}^i$ and the country's carbon pricing policies interacted with the industry's carbon intensity.

Measures of carbon intensity

In our baseline specification we use two indicators of carbon intensity. The measure of carbon intensity that we use in the interaction with carbon prices is the amount of carbon dioxide equivalent emissions as a share of output. To measure this intensity, we use

Figure 6: Comparative advantage in “Computer, electronic and optical equipment” over time, for the economies with comparative advantage in the industry in 2010 or 2018



Note: Comparative advantage is the twice normalised estimated export capability. An economy has comparative advantage in an industry if the value is equal or larger than 1. Figure A.9 in Section A.4 visualises both the top 5 and the bottom 5 economies in 2010. Please see Table A2 for economy codes.

production CO₂ emissions factors from the OECD Trade in Embodied CO₂ (TECO2) database, which covers 66 economies at the same industry aggregation as the ICIO tables. The measure of carbon intensity that we use to interact with fossil fuel subsidies is the dependency of an industry on fossil fuel inputs. Given the lack of industry-level data on fossil fuel intensities for economies at different levels of economic development and with different fossil fuel policies, we use an ICIO tables-based proxy. It is computed as the value of inputs sourced from energy mining and extraction industries and from the industry manufacturing coke and refined petroleum, as a share of output in each country-industry.¹² The measure indicates the degree to which production in each country-industry directly depends on the output of energy mining and producing industries.

In each industry, there may be a range of technologies with different carbon intensities and the prevalent technology may vary across economies depending on their carbon prices. Higher carbon prices can lead firms to adopt new technologies that are less dependent on fossil fuels and/or less emission intensive. At the industry level, carbon intensity may decline if dirtier firms move production abroad. This endogenous choice of technology

¹²Energy mining and extraction industries are the mining of coal and lignite industry and the extraction of crude petroleum and natural gas industry.

whereby carbon pricing not only affects comparative advantage conditional on carbon intensity but also carbon intensity itself, could bias our estimation towards finding a larger policy effect on export capability. Hence, rather than using the actual carbon intensity of industries in each economy, we opt in our baseline analysis for the global average carbon intensity in each industry in 2010.¹³

Industries vary considerably in their reliance on fossil fuels as an input into production. Table A1 in the Appendix shows both the fossil fuel intensity and the carbon emissions intensity of each industry. We normalise all average intensities to be in the range from 0 to 1. The manufacturing sector is very heterogeneous with electronics and transport equipment ranking at the lower end of carbon intensity while basic metals and chemicals are ranking high.

Econometric specifications

In the econometric model, we include country-year and industry-year fixed effects that control for cost differences that are common within each industry across all countries (such as the global fossil fuel price) and costs that are common across all industries within each country (such as the average wage level). Moreover, we estimate the empirical model in first differences to alleviate any identification issues that could stem from time-invariant factors that affect both export capability and carbon prices. We also include lags of the dependent variable to account for potential reverse causality. This could be the case for instance, when industries with declining export capability attract government support in the form of lower carbon taxes/higher fossil fuel subsidies.

Our analysis is based on data for 45 economies and 16 industries in the period 2010-2018. The list of industries and economies can be found in the Appendix Table A1 and Table A2, respectively.

a) Baseline Estimation

Formally, we estimate the following empirical model:

$$\begin{aligned}\Delta \hat{\gamma}_{o,t}^i &= \alpha_{o,t} + \beta_t^i + \delta I^i \Delta \ln(P_{o,t}) \\ &+ \phi_1 \Delta \hat{\gamma}_{o,t-1}^i + \phi_2 \Delta \hat{\gamma}_{o,t-2}^i + \phi_3 \Delta \hat{\gamma}_{o,t-3}^i + \epsilon_{o,t}^i, \\ &\text{with } P_{o,t} \in \{C_{o,t}, F_{o,t}\},\end{aligned}$$

in which $P_{o,t}$ can either be the carbon price $C_{o,t}$ or be the fossil fuel support $F_{o,t}$, and Δ is the one-year difference operator. The terms $\alpha_{o,t}$ are country-year and β_t^i are industry-year

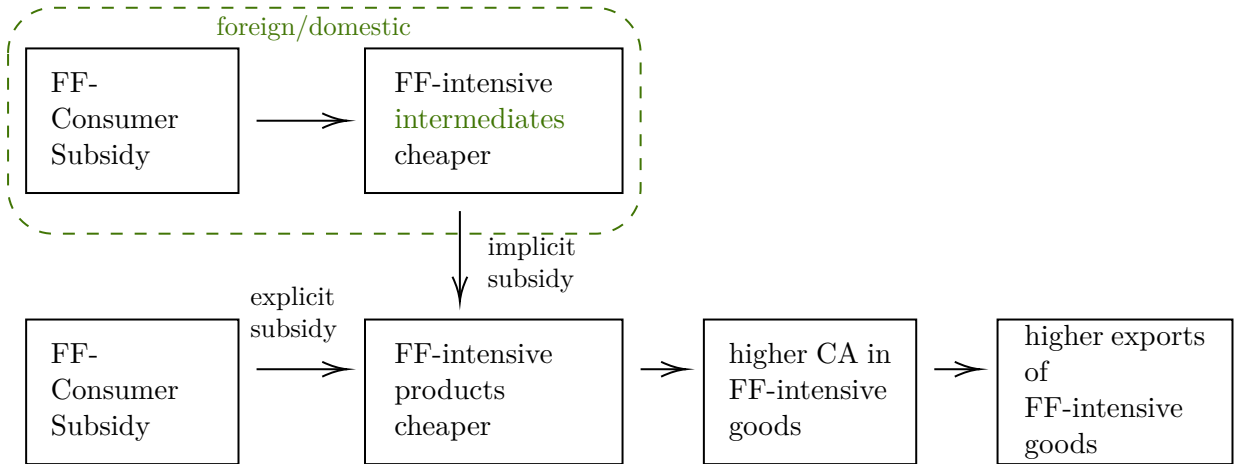
¹³Around 80% of the variance in the country-industry fossil fuel intensity in our sample is due to the differences across industries (industry fixed effects), supporting our assumption that despite cross-country variation, fossil fuel intensities are largely driven by industry-specific technological requirements that are common across countries.

fixed effects, and I^i is an industry's carbon intensity. The model also includes three lags of the dependent variable. A negative and statistically significant estimate of δ means that higher carbon pricing decreases export competitiveness, especially in carbon intensive industries. The elasticity can be also interpreted as the partial equilibrium impact on country-industry exports keeping demand and trade frictions constant (see Equation 1). Country-year and industry-year fixed effects ($\alpha_{o,t}$ and β_t^i) ensure that our estimate of δ is identified exclusively from the interaction between country-specific policies and industry-specific carbon intensities. We use two-way clustered standard errors over countries and industries.

b) Estimation of Spillovers along the Supply-Chain

Our empirical approach also allows us to identify potential policy spillovers across countries due to international supply chain linkages. A country's export capability in a product depends on the availability of specific production factors, such as capital, labour and intermediate inputs. When some of these production factors can be sourced internationally, domestic endowments and policies affect only a part of firms' total costs. The rest is determined by endowments and policies in countries from which they directly or indirectly source their inputs.

Figure 7: Illustration of how fossil fuel support has downstream effects



Note: FF stands for "fossil fuel" and CA stands for "comparative advantage".

In the context of our study, a foreign country's carbon pricing can affect a domestic industry's export capability to the extent that the industry sources inputs, directly or indirectly, from the foreign country. For instance, a change in carbon pricing policy that increases the cost of steel in one country may affect downstream industries in all countries that import steel from that country. As an example, assume that country A's

car production depends heavily on steel from country B. Country A's fossil fuel tax will not have a strong direct negative impact on the competitiveness of its car industry if the car industry has a relatively low fossil fuel use. However, country B's steel industry is highly dependent on fossil fuels: therefore, country B's fossil fuel tax has a large direct impact on its cost of steel production. If this higher cost of production translates into higher prices of country B's steel exports, country A's car sector may suffer from increased production costs.¹⁴ Hence, country B's fossil fuel tax may have a negative impact on the competitiveness of foreign industries that depend on country B's steel. An illustration of this implicit subsidy/tax is depicted in Figure 7.

We exploit the ICIO tables to calculate the total, both direct and indirect, exposure to carbon pricing policies. The exposure to foreign policies may be difficult to interpret which is why we split the analysis in exposure one-border-away and two-or-more-borders-away to reduce noise introduced by multiple interim stages of production. Similar to the decomposition of value chains in Wang et al. (2017), we decompose the dependence of industries on different streams of their value chain. We concentrate on three parts: (1) domestic production chains only, (2) production chains across one border, and (3) production chains across at least two borders.¹⁵

Analogous to the derivation of the inverse Leontief matrix B via $x = (I - A)^{-1}y = B y$, where x is the output and y the final demand vector,¹⁶ the production can be split in three parts and written as follows:

$$x = \underbrace{L}_C y + \underbrace{LA^F L}_D y + \underbrace{LA^F(B - L)}_E y.$$

The first component, C , captures all value chains in which all steps of downstream production happen domestically. The second one, D , contains value chains which cross only one border. The third component, E , are all value chains crossing at least two borders. A is a matrix of direct input dependencies between sectors and countries ($x = Ax + y$). A^F is the foreign part of A , hence has zeros for the domestic interdependencies. L is the domestic local inverse Leontieff matrix: similar to B , it contains all indirect and direct dependencies between sectors, but is now limited to purely domestic value chains – hence also has zeros for the cross-country dependencies. Details about the decomposition can

¹⁴There are reasons why input subsidies/taxes may not translate into lower export prices of the output. One of them being sufficient market power such that policy changes are not passed on to customers through lower/higher prices because they are absorbed by the producer's profit margins. Second, the carbon pricing policy effect might be mitigated by trade policy barriers. In the example above, the impact on car producers in country B may be counteracted by changes in import duties applied to steel by country B or export duties applied to steel by country A.

¹⁵Contrary to Wang et al. (2017), we do not distinguish whether the final demand is domestic or foreign, as we are not interested in effects influencing or resulting from final consumption.

¹⁶The element x_o^i is the output of sector i in country o and y_o^i is the final demand of sector i in country o . Then, the elements $b_{od}^{ij} \in B$ are the indirect dependencies of the production of sector i in country o on the final demand of sector j in country d .

be found in Appendix Section A.1.

To obtain weights for our spillover analysis, we can make use of the coefficients $c_{od}^{ij} \in C$, $d_{od}^{ij} \in D$, and $e_{od}^{ij} \in E$. As in our previous analyses, we need to weigh the policies with different carbon intensities across industries to account for heterogeneous exposure to carbon pricing policies. That is, for the embodied exposure to upstream foreign/domestic carbon pricing policies, we sum over policies weighted with the input exposure to the country and industry derived from ICIO tables (c_{od}^{ij} , d_{od}^{ij} , e_{od}^{ij}) and the respective industries' carbon intensities. We can split up the weighted sums for upstream (*us*) exposure of industry i in country o to policies of all countries in the three components:

$$cus_o^i(p) + dus_o^i(p) + eus_o^i(p) = \sum_d \sum_j I^j (c_{do}^{ji} + d_{do}^{ji} + e_{do}^{ji}) p_d,$$

where I is the carbon intensity of an industry and p is the change in a country's carbon pricing policy ($\Delta \ln(C)$ or $\Delta \ln(F)$). Details can be found in Appendix Section A.1.

To make sure that our results are not suffering from reverse causality bias, we are using an earlier structure of the supply chain in our regressions, in particular the one from 2010. The identification rests upon the assumption that switching suppliers is subject to transaction costs, and therefore the structure of supply chains adjusts slowly and only as a response to shocks that are large enough and perceived as permanent. Consequently, we assume that the production network structure in 2010 is still representative of the production structure in years from 2010 to 2018.

Our OLS regression in first differences now makes use of the full exposure to own-industry and upstream policies, again with industry and country-clustered standard errors:

$$\begin{aligned} \Delta \hat{\gamma}_{o,t}^i = & \alpha_{o,t} + \beta_t^i + \delta_1 \underbrace{cus_{o,t}^i(p)}_{\text{domestic}} + \delta_2 \underbrace{dus_{o,t}^i(p)}_{\text{1 border}} + \delta_3 \underbrace{eus_{o,t}^i(p)}_{\geq 2 \text{ borders}} \\ & + \phi_1 \Delta \hat{\gamma}_{o,t-1}^i + \phi_2 \Delta \hat{\gamma}_{o,t-2}^i + \phi_3 \Delta \hat{\gamma}_{o,t-3}^i + \epsilon_{o,t}^i, \end{aligned}$$

for $p = \{\Delta \ln(C), \Delta \ln(F)\}$.

4 Results

4.1 The impact of carbon pricing policies on export capability

Table 1 presents our baseline estimates of the impact of carbon prices as measured in the WCPD and the ECR database. The coefficients associated with carbon prices have the expected signs; a higher carbon price is associated with a lower export capability. Column

(1) shows that a 10% increase in a carbon tax is associated with around 0.3% decrease in export capability in the most carbon intensive industry. On the other hand, industries with low carbon intensity are barely affected: a 10% higher carbon tax reduces export capability by 0.008 % in the least carbon intensive industry. Column (2) shows that we obtain an almost identical result using the ECR as a measure of policy, and column (3) suggests that the magnitude of this coefficient is driven by the explicit carbon price component of the ECR (i.e. carbon taxes and prices of emission allowances). Finally, column (4) shows that a 10% higher fuel excise tax (implicit carbon price) is associated with a 0.73% (0.018 %) lower export capability in the most (least) carbon intensive sector.¹⁷

Table 1: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Carbon Prices (C_o) from the WCPD and the OECD, for 2010-2018 in manufacturing sectors, in first differences.

| | (1) | (2) | (3) | (4) |
|----------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \Delta \ln(C_o)$ | -0.032** (0.0127) | -0.033*** (0.0093) | -0.033*** (0.0132) | -0.073*** (0.0104) |
| Constant | 0.005*** (0.0013) | 0.059*** (0.0033) | 0.063*** (0.0035) | 0.054*** (0.0028) |
| Policy C_o | WCPD-tax | ECR-tot | ECR-CP | ECR-FE |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ | CO ₂ |
| Frequency | yearly | triennial | triennial | triennial |
| Lags of $\Delta\hat{\gamma}_o^i$ | 3 | 3 | 3 | 3 |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes |
| N | 5,370 | 1,198 | 1,198 | 1,198 |
| R^2 | 0.453 | 0.417 | 0.418 | 0.420 |

Robust standard errors in parentheses, clustered over industries and countries.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the one-year or three-year difference operator (see row “Frequency”).

Table 2 presents the same regressions for measures of fossil fuel support. As expected, higher fossil fuel support is associated with higher export capability. An increase of fossil fuel support by 10% results in 0.6% higher export capability in the most fossil fuel intensive industry (column (1)).¹⁸ As before, the effect on the least fossil fuel intensive industry is much smaller, with a mere 0.06% reduction in export capability. Columns

¹⁷These results suggest that the trade effects do not depend on whether governments tax carbon in its input form (fossil fuels) or in its output form (emissions) – both increase companies’ costs. The adjustment responses, not captured in our analysis, may differ (e.g. reducing reliance on fossil fuels in production in the former case or investing into carbon capture technologies in the latter case) but both types of policies increase costs in the short run.

¹⁸Interestingly, the result for the basic metals (i.e., the most fossil fuel intensive) industry is very similar to the one obtained in [Garsous, Smith and Bourny \(2023\)](#) using firm-level data on total subsidies (not just those related to fossil fuel consumption) to 38 large global producers of steel and aluminium. The authors estimated that a 10% increase in government grants or tax concessions to steel and aluminium firms increases their production by 0.39% and 0.66%, respectively.

(2) and (3) of Table 2 compare the effects of the two underlying instruments of support to fossil fuel consuming industries – direct transfers and tax exemptions, respectively. While the effect of direct transfers is not well identified, which could be due to their relatively limited use in our sample, the coefficient on expenditures from fuel excise taxes is highly statistically significant.¹⁹ The latter coefficient is close in magnitude to that on fuel excise taxes in column (4) of Table 1, reassuring our findings: increasing tax breaks has the inverse effect of increasing effective tax rates.

Table 2: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Fossil Fuel Support (F_o), for 2010-2018 in manufacturing sectors.

| | (1) | (2) | (3) |
|-----------------------------------|---------------------------|---------------------------|---------------------------|
| | $\Delta \hat{\gamma}_o^i$ | $\Delta \hat{\gamma}_o^i$ | $\Delta \hat{\gamma}_o^i$ |
| $I^i \Delta \ln(F_o)$ | 0.061*** (0.0023) | 0.036 (0.0554) | 0.059*** (0.0073) |
| Constant | 0.003** (0.0011) | 0.003** (0.0013) | 0.003** (0.0011) |
| Policy F_o | FFS-tot | FFS-tra | FFS-tax |
| Intensity I^i | ICIO | ICIO | ICIO |
| Frequency | yearly | yearly | yearly |
| Lags of $\Delta \hat{\gamma}_o^i$ | 3 | 3 | 3 |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes |
| N | 5,393 | 5,393 | 5,393 |
| R^2 | 0.455 | 0.455 | 0.455 |

Robust standard errors in parentheses, clustered over industries and countries.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the one-year difference operator.

Tables A3, A4, and A5, columns (1)-(3), in the Appendix show that we obtain results similar to our baseline estimation when, instead of first differences, we estimate our model in levels with industry-country fixed effects. Furthermore, we present the baseline regressions in more detail in those tables, including the coefficients of the lagged dependent variable.

The results are robust to the exclusion of different industries, except for the most fossil-fuel intensive one, the manufacturing of basic metals. The only coefficient robust to the exclusion of this sector is that on fuel excise taxes from the ECR database. Our analysis is robust to the exclusion of different economies, to changing the measures of intensities, and to weighting the observations with the inverse standard errors of the first-stage estimated export capabilities.²⁰ Our baseline results for carbon prices are also

¹⁹As shown in Figure A.3, the measure of direct transfers per unit of fossil fuel consumed in Costa Rica reaches extremely high levels after 2015. This seems to be driven by data issues rather than underlying policy changes and therefore we exclude Costa Rica from the baseline estimation.

²⁰See Online Appendix Tables B1, B2, B3 and B4.

robust when export capabilities are estimated with a simpler gravity model as in [Hanson et al. \(2015\)](#).²¹

4.2 Quantification

To gauge the economic significance of our results we first use an R-squared decomposition to calculate the share of variation in export capability over time that can be attributed to changes in carbon pricing policies. As our policy indicators are likely to be correlated, partly by their construction because they include overlapping measures, we use an Owen-Shapley decomposition that takes into account correlation between explanatory variables and allows consistently estimating the contribution of a group of variables to the model’s explanatory power ([Huettner and Sunder, 2012](#)). Based on a regression that includes all of the indicators, we estimate that changes in carbon pricing policies can explain up to 1.2% of changes in country-industry export capabilities, in the periods 2012-2015 and 2015-2018, most of which can be attributed to changes in taxes or their exemptions.²²

Second, we use our regression results from column (1) in Table 2 to predict the decline in export capability in scenarios where economies eliminate fossil fuel subsidies, either unilaterally or all at once. To better understand the significance of the predicted reductions in export capability for the pattern of specialisation in global trade, we then calculate the implied changes in comparative advantage (see Section 3.1).²³ In a scenario where only one economy removes fossil fuel subsidies, the average predicted reduction in that economy’s comparative advantage in the manufacturing of basic metals (the most negatively affected industry) would be nine percent. This negative impact on international competitiveness would be mitigated if all economies were to remove their subsidies at the same time. In such a scenario, one-fifth of the economies in our sample that had the lowest fossil fuel subsidies (or none) would see their comparative advantage in basic metals increase by six percent on average. The remaining economies would see their comparative advantage fall by four percent on average.²⁴

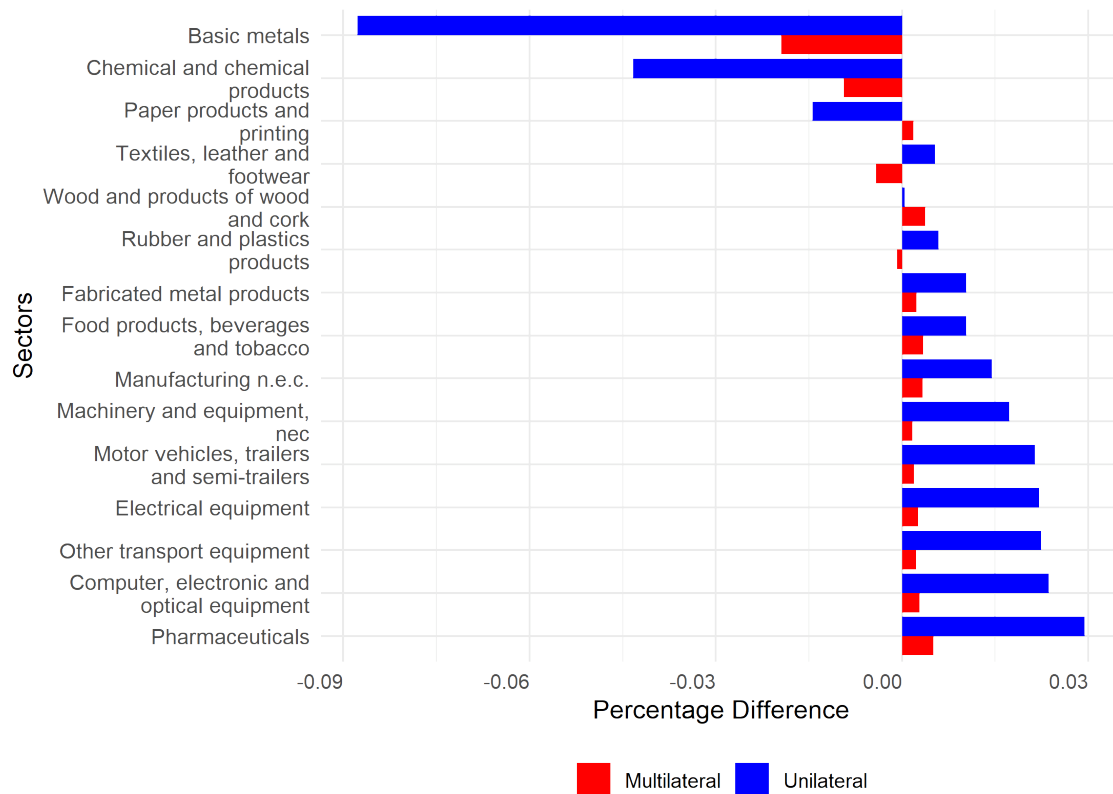
²¹However, the coefficients on all the policy instruments are less precisely estimated, and for fossil fuel support, specifically, the coefficients are not statistically significantly different from zero (see Online Appendix Tables B5 and B6).

²²After partialling out changes that were common to all industries in a country and to all countries in an industry in each period.

²³A change in a country’s carbon pricing policy has a direct impact on the production costs of its industries and thus on their export capability. However, changes in the international competitiveness of domestic industries also depend on policy changes in other economies. For instance, the international competitiveness of a domestic industry may increase despite an increase in the carbon price if the foreign carbon price increases more. In addition, a change in carbon pricing policy will also change the export capability of each industry relative to other domestic industries. For example, an increase in the carbon price will affect the capability of the basic metals industry (carbon intensive) more than that of the electronics industry (not carbon intensive). Therefore, an increase in the carbon price may increase the comparative advantage of the domestic economy in the production of electronics.

²⁴To obtain the average predicted change in the unilateral scenario we first predict the reduction in export capabilities of each economy if the economy removed its fossil fuel subsidies in 2018. Then we

Figure 8: Average predicted change in comparative advantage if fossil fuel subsidies were removed



Note: Comparative advantage is the twice normalised predicted export capability (see Section 3.1). In the unilateral scenario, we calculate the predicted change in comparative advantage for each economy if the economy alone removed fossil fuel subsidies, and then calculate the average change across all economies. In the multilateral scenario, we calculate the average predicted changes in comparative advantage when all economies remove their subsidies at once.

Figure 8 shows the average predicted changes for all industries. The manufacturing of chemicals and chemical products has the second highest fossil fuel intensity and therefore would be also negatively affected by reductions in subsidies. However, the figure also illustrates that most other industries would see an increase in comparative advantage. This stems from our econometric estimates that suggest very minor impact of carbon pricing policies on export capability of industries where fossil fuels have relatively low importance in the production input mix.

4.3 Spillovers along the supply chain

The results in Tables 3 and 4 show that taking into account the overall carbon intensity of the domestic upstream value chain leads to similar estimates compared to our previous estimation (see Table 1). Exposure to carbon taxes, as measured by the WCPD, has a significant negative effect on the competitiveness of an industry (Table 3, column (1)), while exposure to fossil fuel support measures has a significant positive effect, driven by the tax breaks component (Table 4, column (3)). The coefficients on the domestic exposure to ECR, on the other hand, become smaller and lose their statistical significance.

The results suggest that even industries that have relatively low carbon intensity can be negatively/positively impacted by an increase in carbon taxes/subsidies if they rely on carbon intensive domestic inputs. For example, a 10 percent increase in a domestic carbon tax would have a minor direct impact on export capability of fabricated metal producers (0.033 percent). However, the industry relies heavily on inputs from the basic metals industry and therefore the domestic policy change can reduce its export capability indirectly. This indirect effect varies across economies depending on how much their domestic fabricated metal producers rely on domestic suppliers when sourcing carbon intensive inputs. Our estimates range from 0.59 percent in economies with a large domestic basic metals industry to mere 0.03 percent in economies that rely almost entirely on foreign suppliers.²⁵ The average indirect effect across economies is 0.17 percent in the fabricated metals industry, which is more than five times larger than the direct effect.

When it comes to spillovers of foreign policies along the supply chain, our results suggest that a domestic industry may see a decline in export competitiveness if it imports

calculate the predicted changes in its comparative advantage, keeping fossil fuel subsidies of all other economies constant. The average predicted change in the multilateral scenario, on the other hand, is calculated using the predicted changes in export capabilities when all economies remove their subsidies.

²⁵The domestic component $cus_{o,t}^i(p)$ can be expressed as a sum of the direct domestic policy effect and the indirect (upstream) domestic policy effect as follows: $cus_{o,t}^i(p) = \Delta \ln(C_o) \sum_j I^j c_{oo}^{ji} = \Delta \ln(C_o) I^i + \Delta \ln(C_o) \sum_{j \neq i} I^j c_{oo}^{ji}$. Hence in our example the direct effect of a 10 percent increase in domestic carbon tax is calculated as $10 * (-0.092) * 0.036 = 0.033$ and the indirect domestic effect is calculated in a similar manner but the direct carbon intensity (0.036) is replaced with a sum of carbon intensities of all industries weighted by their Leontieff coefficient associated with the domestic fabricated metals industry (where we deduct 1 from the own industry coefficient).

Table 3: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on upstream value chain exposure to Carbon Prices (C_d), for manufacturing industries in 2010-2018 in first differences. Exposure is based only on manufacturing sectors.

| | (1) | (2) | (3) |
|---|---------------------------|---------------------------|---------------------------|
| | $\Delta \hat{\gamma}_o^i$ | $\Delta \hat{\gamma}_o^i$ | $\Delta \hat{\gamma}_o^i$ |
| for $\Delta \ln(C_d)$ | | | |
| Domestic | -0.092*** (0.0294) | -0.046 (0.0439) | -0.180* (0.0853) |
| 1 border | 2.301 (2.6117) | -3.275* (1.7095) | -7.101*** (2.0918) |
| ≥ 2 borders | 0.176 (3.8010) | 2.412 (1.4973) | 13.842 (7.9772) |
| Constant | 0.006** (0.0024) | 0.000 (0.0174) | 0.051* (0.0263) |
| Policy C_d | WCPD-tax | ECR-CP | ECR-FE |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ |
| Lags of $\Delta \hat{\gamma}_o^i$ | 3 | 3 | 3 |
| Frequency | yearly | triennial | triennial |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes |
| N | 5,706 | 1,936 | 1,936 |
| R^2 | 0.452 | 0.440 | 0.442 |

Robust standard errors in parentheses, clustered over industries and countries.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the one-year difference operator.

carbon intensive intermediate inputs²⁶ from an economy that raises its effective carbon rate, especially from fuel excise taxes (columns (2) and (3) in Table 3). On the other hand, there are consistently no supply chain policy spillovers from foreign upstream stages that are more than one border away, i.e. when there is at least one additional production stage in another economy before the intermediate inputs reach the domestic industry.

In our baseline empirical strategy we use the trade network of 2010 as an exogenous representation of the supply chain structure, which may introduce some noise if there is a significant change in the structure within the decade of our study. However, changing the exposure structure to the one-year lagged input-output matrix does not alter our findings.

²⁶Including intermediate inputs whose production itself relies on carbon intensive inputs from the same economy.

Table 4: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on upstream value chain exposure to Fossil Fuel Support (F_d), for manufacturing industries in 2010-2018 in first differences. Exposure is based only on manufacturing sectors.

| | (1) | (2) | (3) |
|---|--------------------------|--------------------------|--------------------------|
| | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| for $\Delta \ln(F_o)$ | | | |
| Domestic | 0.345* | -0.479 | 0.594*** |
| | (0.1682) | (0.3400) | (0.0352) |
| 1 border | 11.440 | -4.087 | 13.617 |
| | (10.3417) | (16.4943) | (10.2578) |
| ≥ 2 borders | -20.071 | 5.263 | -26.231* |
| | (14.1574) | (18.6550) | (14.5707) |
| Constant | 0.011** | 0.007*** | 0.015** |
| | (0.0039) | (0.0014) | (0.0058) |
| Policy F_o | FFS-tot | FFS-tra | FFS-tax |
| Intensity I^i | ICIO | ICIO | ICIO |
| Lags of $\Delta\hat{\gamma}_o^i$ | 3 | 3 | 3 |
| Frequency | yearly | yearly | yearly |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes |
| N | 6,266 | 6,266 | 6,266 |
| R^2 | 0.434 | 0.433 | 0.435 |

Robust standard errors in parentheses, clustered over industries and countries.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the one-year difference operator.

When determining the exposure to carbon pricing policies, the presented results only use the exposure through inputs from other manufacturing industries. In a robustness check, we include also the electricity and transport sectors in the measure of exposure to policies affecting upstream stages of production. While most of the results remain similar, the explanatory power of the regressions is somewhat reduced which leads us to conclude that the addition of the two sectors in the policy exposure variable increases its noisiness rather than improves identification.

5 Conclusion and discussion

We use three different sources of data on carbon pricing policies to show that, irrespective of the exact measure and policy coverage, less stringent carbon pricing policies lead to an increase in comparative advantage in carbon intensive industries. In the first step, we estimate country-industry export capabilities using a fixed-effects gravity model. In the second step, we regress the change in a country-industry export capability on the country's change in carbon pricing interacted with the industry's carbon intensity, controlling for country- and industry-specific changes. Our results suggest that a 10% increase in a country's carbon tax (10% decrease of fossil fuel subsidies) leads to a 0.3% (0.6%) decline

in export capability in the most carbon intensive industry. On the other hand, industries with low carbon intensity are barely affected: a 10% higher carbon tax reduces export capability by 0.008% (0.06%) in the least carbon intensive industry.

We show that changes in all the policy instruments combined can explain up to 1.2% of the changes in export capabilities in the periods 2012-2015 and 2015-2018. Moreover, we use our econometric estimates to illustrate the potential impact of removing fossil fuel subsidies on the pattern of comparative advantage. Our estimates suggest that such changes could significantly reduce an economy's comparative advantage in two most fossil fuel intensive industries – basic metals and chemicals – if the economy eliminated subsidies alone. However, we also show that most other industries, where fossil fuels have relatively low importance in the production input mix, would see an increase in comparative advantage. If, on the other hand, all economies removed subsidies simultaneously the impact on the pattern of comparative advantage would be much less pronounced.

We further extend our analysis to account for potential policy spillovers along the supply chain. The results suggest that carbon pricing policies compound along the domestic supply chain so that an industry's export competitiveness increases when its carbon intensive domestic suppliers face lower carbon prices or higher fossil fuel subsidies. We also find some limited empirical support for supply chain spillovers of foreign carbon and fossil fuel taxes.

Our analysis is the first to estimate the trade-distorting impact of carbon prices and fossil fuel support in a large sample of economies and to show that the impact is similar across a range of policy instruments. By showing that a stricter carbon pricing in one economy can reduce its competitiveness in emission-intensive production, our analysis also relates to studies that focus on carbon leakage. However, our results do not imply that the resulting shift in production would lead to increased global emissions as this would depend on the relative emission intensity of the economies that become relatively more competitive.

Our results highlight that competitiveness in carbon-intensive industries is related to a whole range of policy instruments that include not only direct carbon taxes and carbon pricing schemes, but also fossil fuel excise taxes and support for fossil fuel use in certain industries. More broadly, our analysis suggests that it is important to consider the full spectrum of policies that impact the cost of using fossil fuels in production when assessing the stringency of a country's carbon pricing. It also shows that, despite their limitations, existing measures of these policies provide useful information that can be combined to assess their economic impact.

Since our empirical strategy exploits the variation in export capability and carbon pricing policies over time, our estimates represent short-run effects that may be mitigated in longer run through technology adjustment or changes in input sourcing patterns. Furthermore, while economically meaningful, our results are largely driven by the most

carbon intensive industry – basic metals production. Finally, the analysis would benefit from information on the value of renewable energy subsidies, which may interact with carbon pricing policies and mitigate the negative impact of higher carbon prices or lower fossil fuel subsidies on the competitiveness of energy intensive industries.

References

- Abowd, John, Robert H. Creecy, and Francis Kramarz.** 2002. “Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data.” Center for Economic Studies, U.S. Census Bureau Longitudinal Employer-Household Dynamics Technical Paper.
- Aichele, Rahel, and Gabriel Felbermayr.** 2015. “Kyoto and Carbon Leakage: An Empirical Analysis of the Carbon Content of Bilateral Trade.” *The Review of Economics and Statistics*, 97(1): 104–115.
- Aldy, Joseph E., and William A. Pizer.** 2015. “The Competitiveness Impacts of Climate Change Mitigation Policies.” *Journal of the Association of Environmental and Resource Economists*, 2(4): 565–595. Publisher: The University of Chicago Press.
- Arezki, Rabah, Thiemo Fetzer, and Frank Pisch.** 2017. “On the comparative advantage of U.S. manufacturing: Evidence from the shale gas revolution.” *Journal of International Economics*, 107: 34–59.
- Balassa, Bela.** 1965. “Trade Liberalisation and “Revealed” Comparative Advantage.” *The Manchester School*, 33(2): 99–123. eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-9957.1965.tb00050.x>.
- Branger, Frédéric, Philippe Quirion, and Julien Chevallier.** 2016. “Carbon Leakage and Competitiveness of Cement and Steel Industries Under the EU ETS: Much Ado About Nothing.” *The Energy Journal*, 37(3): 109–135. Publisher: International Association for Energy Economics.
- Burniaux, Jean-Marc, Jean Château, and Jehan Sauvage.** 2011. “The Trade Effects of Phasing Out Fossil-Fuel Consumption Subsidies.” OECD, Paris.
- Colmer, Jonathan, Ralf Martin, Mirabelle Muûls, and Ulrich J Wagner.** 2024. “Does Pricing Carbon Mitigate Climate Change? Firm-Level Evidence from the European Union Emissions Trading System.” *The Review of Economic Studies*, rdae055.
- Costinot, Arnaud, Dave Donaldson, and Ivana Komunjer.** 2012. “What Goods Do Countries Trade? A Quantitative Exploration of Ricardo’s Ideas.” *The Review of Economic Studies*, 79(2): 581–608.
- Dechezleprêtre, Antoine, Caterina Gennaioli, Ralf Martin, Mirabelle Muûls, and Thomas Stoerk.** 2022. “Searching for carbon leaks in multinational companies.” *Journal of Environmental Economics and Management*, 112: 102601.
- Dolphin, Geoffroy, and Qinrui Xiahou.** 2022. “World carbon pricing database: sources and methods.” *Scientific Data*, 9(1): 573. Number: 1 Publisher: Nature Publishing Group.
- Eaton, Jonathan, and Samuel Kortum.** 2002. “Technology, Geography, and Trade.” *Econometrica*, 70(5): 1741–1779.
- Egger, Peter, Mario Larch, Sergey Nigai, and Yoto Yotov.** 2021. “Trade costs in the global economy: Measurement, aggregation and decomposition.” WTO Staff Working Paper Working Paper ERSD-2021-2.

- Garsous, Grégoire, Donal Smith, and Dylan Bourny.** 2023. “The climate implications of government support in aluminium smelting and steelmaking: An Empirical Analysis.” OECD, Paris.
- Hanson, Gordon, Nelson Lind, and Marc-Andreas Muendler.** 2015. “The Dynamics of Comparative Advantage.” National Bureau of Economic Research w21753, Cambridge, MA.
- Head, Keith, and Thierry Mayer.** 2014. “Gravity Equations: Workhorse, Toolkit, and Cookbook.” Elsevier Handbook of International Economics.
- Huettnner, Frank, and Marco Sunder.** 2012. “Axiomatic Arguments for Decomposing Goodness of Fit According to Shapley and Owen Values.” *Electronic Journal of Statistics*, 6.
- Jia, Zhijie.** 2023. “The hidden benefit: Emission trading scheme and business performance of downstream enterprises.” *Energy Economics*, 117: 106488.
- Khastar, Mojtaba, Alireza Aslani, and Mehdi Nejati.** 2020. “How does carbon tax affect social welfare and emission reduction in Finland?” *Energy Reports*, 6: 736–744.
- Lane, Nathan.** 2024. “Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea.” CESifo Working Paper 11388.
- Levinson, Arik.** 2009. “Technology, International Trade, and Pollution from US Manufacturing.” *American Economic Review*, 99(5): 2177–2192.
- Misch, Florian, and Philippe Wingender.** 2024. “Revisiting carbon leakage.” *Energy Economics*, 107786.
- Naegele, Helene, and Aleksandar Zaklan.** 2019. “Does the EU ETS cause carbon leakage in European manufacturing?” *Journal of Environmental Economics and Management*, 93: 125–147.
- OECD.** 2015. *OECD Companion to the Inventory of Support Measures for Fossil Fuels 2015*. OECD Publishing, Paris.
- OECD.** 2019. “Measuring distortions in international markets: The aluminium value chain.” OECD, Paris.
- Sato, Misato, and Antoine Dechezleprêtre.** 2015. “Asymmetric industrial energy prices and international trade.” *Energy Economics*, 52: S130–S141.
- Wang, Zhi, Shang-Jin Wei, Xinding Yu, and Kunfu Zhu.** 2017. “Characterizing Global Value Chains: Production Length and Upstreamness.” National Bureau of Economic Research w23261, Cambridge, MA.

A Appendix

The appendix contains supplementary tables and details about methodology and data. Additional materials are available in the Online Appendix.

A.1 Decomposition of the Value Chain

Production x_o^i in sector i country o can be decomposed as follows:

$$\begin{aligned}
 x_o^i &= \sum_j l_{oo}^{ij} y_o^j + \sum_{d \neq o} \sum_m \sum_k \sum_j l_{oo}^{im} a_{od}^{mk} l_{dd}^{kj} y_d^j + \sum_{d \neq o} \sum_m \sum_k \sum_j l_{oo}^{im} a_{od}^{mk} \left[\sum_e b_{de}^{kj} y_e^j - l_{dd}^{kj} y_d^j \right], \\
 x &= \underbrace{L}_C y + \underbrace{L A^F L}_D y + \underbrace{L A^F (B - L)}_E y, \\
 x_o^i &= \sum_d \sum_j (c_{od}^{ij} + d_{od}^{ij} + e_{od}^{ij}) y_d^j,
 \end{aligned} \tag{A.1}$$

with $a_{od}^{ij} \in A$, $x_o^i \in x$, $y_o^i \in y$, $b_{od}^{ij} \in B$, $c_{od}^{ij} \in C$, $d_{od}^{ij} \in D$, $e_{od}^{ij} \in E$ and $l_{od}^{ij} \in L$. A^F is the foreign part of A , hence has zeros for the domestic interdependencies. L is the local inverse Leontieff matrix: Similar to B , it contains all indirect and direct dependencies between sectors, but is now limited to purely domestic value chains – hence also has zeros for the cross-country dependencies.

With L , A^F , and B , we can decompose the value chain downstream of sector i in country o into three parts, and split it into different dependencies on final demand for goods from sector j in d , namely c_{od}^{ij} , d_{od}^{ij} , and e_{od}^{ij} . The first component, C , captures all value chains in which all steps of downstream production happen domestically. The second one, D , contains value chains which cross only one border; that is, the good might get processed domestically (l_{oo}^{im}), then crosses one border (a_{od}^{mk}), and lastly, gets processed abroad again (l_{dd}^{kj}). The third component, E , are all value chains crossing at least two borders: Similar to D , goods cross one border for sure, and then might cross multiple other borders (b_{de}^{kj}) before reaching demand – for completeness, the value chains crossing exactly one border (D) need to be deducted.

To analyse downstream policy spillovers, we rewrite (A.1) such that we obtain final demand as a weighted average of upstream production:

$$y_d^j = \sum_o \sum_i \frac{(c_{od}^{ij} + d_{od}^{ij} + e_{od}^{ij}) y_d^j}{x_o^i} x_o^i + \underbrace{\left(1 - \sum_o \sum_i (c_{od}^{ij} + d_{od}^{ij} + e_{od}^{ij}) \right)}_{v_d^j} y_d^j,$$

in which the last term represents the value added of j - d 's own production, $v_d^j y_d^j$.

The impact of o 's policy upstream on production of good j - d downstream depends on the upstream share $us_o^{jd} = \sum_i (c_{od}^{ij} + d_{od}^{ij} + e_{od}^{ij})$.

The combined exposure to carbon pricing policies coming from upstream for j - d is hence the weighted sum of upstream policies p_o with intensity I^i :

$$\sum_o \sum_i (c_{od}^{ij} + d_{od}^{ij} + e_{od}^{ij}) I^i p_o = cus_d^j(p) + dus_d^j(p) + eus_d^j(p).$$

This approach coincides with the one in [Levinson \(2009\)](#) for calculating embodied (upstream) emissions.

A.2 Fossil Fuel Intensities across Industries

Table A1: CO₂ Emission and Fossil Fuel Intensities

| Industry | CO ₂ | FF - ICIO | FF - EA |
|---|-----------------|-----------|---------|
| Basic metals | 1.00 | 1.00 | 0.69 |
| Other non-metallic mineral products ^a | 0.95 | 0.89 | 1.00 |
| Rubber and plastics products | 0.48 | 0.48 | 0.14 |
| Manufacturing nec; repair and installation of machinery and equipment | 0.39 | 0.21 | 0.09 |
| Chemical and chemical products | 0.28 | . | 0.42 |
| Mining and quarrying, non-energy producing products | 0.24 | 0.84 | . |
| Pharmaceuticals, medicinal chemical and botanical products | 0.24 | 0.31 | 0.01 |
| Paper products and printing | 0.18 | 0.30 | 0.25 |
| Wood and products of wood and cork | 0.09 | 0.23 | 0.17 |
| Food products, beverages and tobacco | 0.08 | 0.16 | 0.11 |
| Textiles, textile products, leather and footwear | 0.08 | 0.21 | 0.14 |
| Fabricated metal products | 0.04 | 0.19 | 0.11 |
| Machinery and equipment, nec | 0.03 | 0.18 | 0.08 |
| Motor vehicles, trailers and semi-trailers | 0.03 | 0.19 | 0.05 |
| Electrical equipment | 0.03 | 0.17 | 0.05 |
| Other transport equipment | 0.03 | 0.32 | 0.05 |
| Computer, electronic and optical equipment | 0.02 | 0.10 | 0.04 |

Note: The displayed intensities are normalised industry averages for 2010. For CO₂, they are the CO₂ emissions factors in tonnes per USD of output from the OECD's TECO2 database. ICIO-based fossil fuel (FF) intensities are based on the input coefficients on sectors 05T06 and 19 in the OECD inter-country inter-industry input-output tables. The EA-based fossil fuel intensities are the fuel consumption in kJ per USD of output from the WIOD Environmental Accounts.

^aExcluded from the main analysis as the very high carbon- and fossil-fuel intensity of the industry is driven by the production of cement. The extent of international trade in cement is limited by its high transportation costs relative to its value and while international trade exists, it is typically limited to neighbouring regions. Including the sector biases our results downwards.

A.3 Visualisation of Policy Instruments

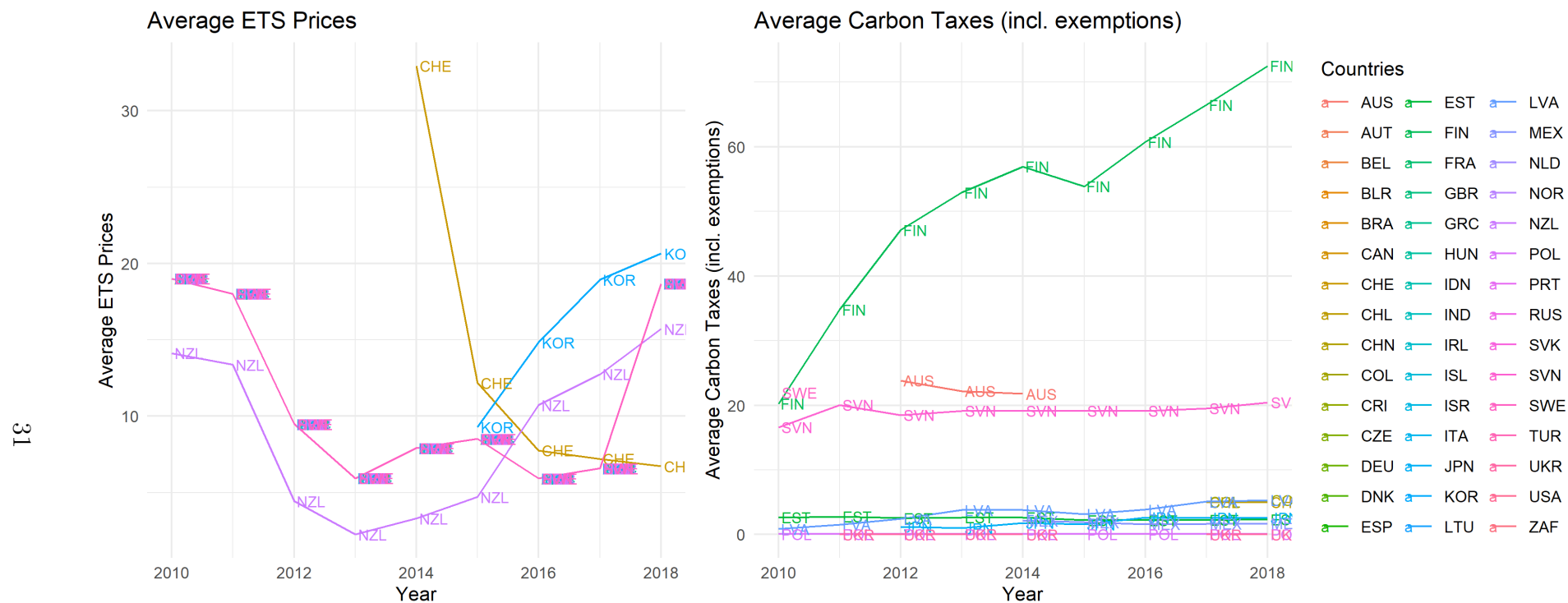


Figure A.1: Prices from ETS and carbon taxes per ton of CO₂ for Manufacturing, 2010-2018

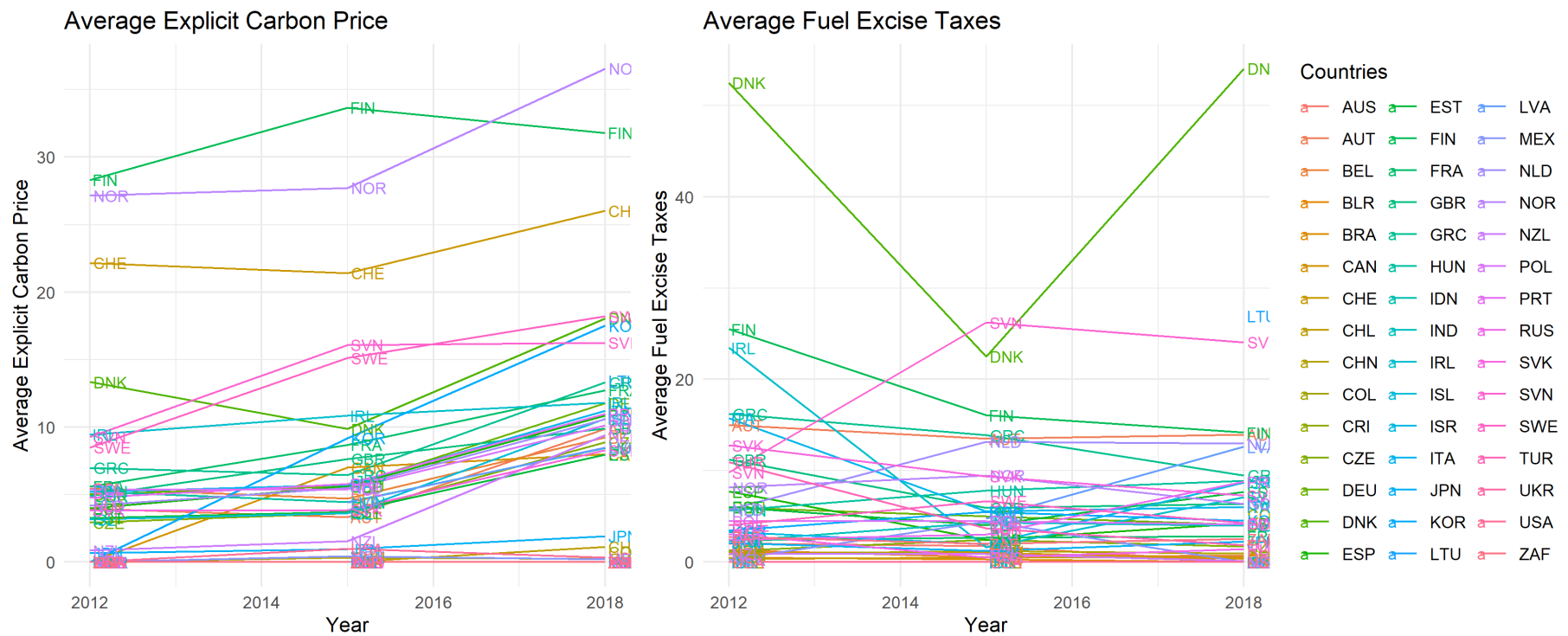


Figure A.2: OECD's Effective Carbon Rate components: explicit carbon prices and fuel excise taxes per ton of CO₂ for the Industrial Sector, 2012-2018, in EUR

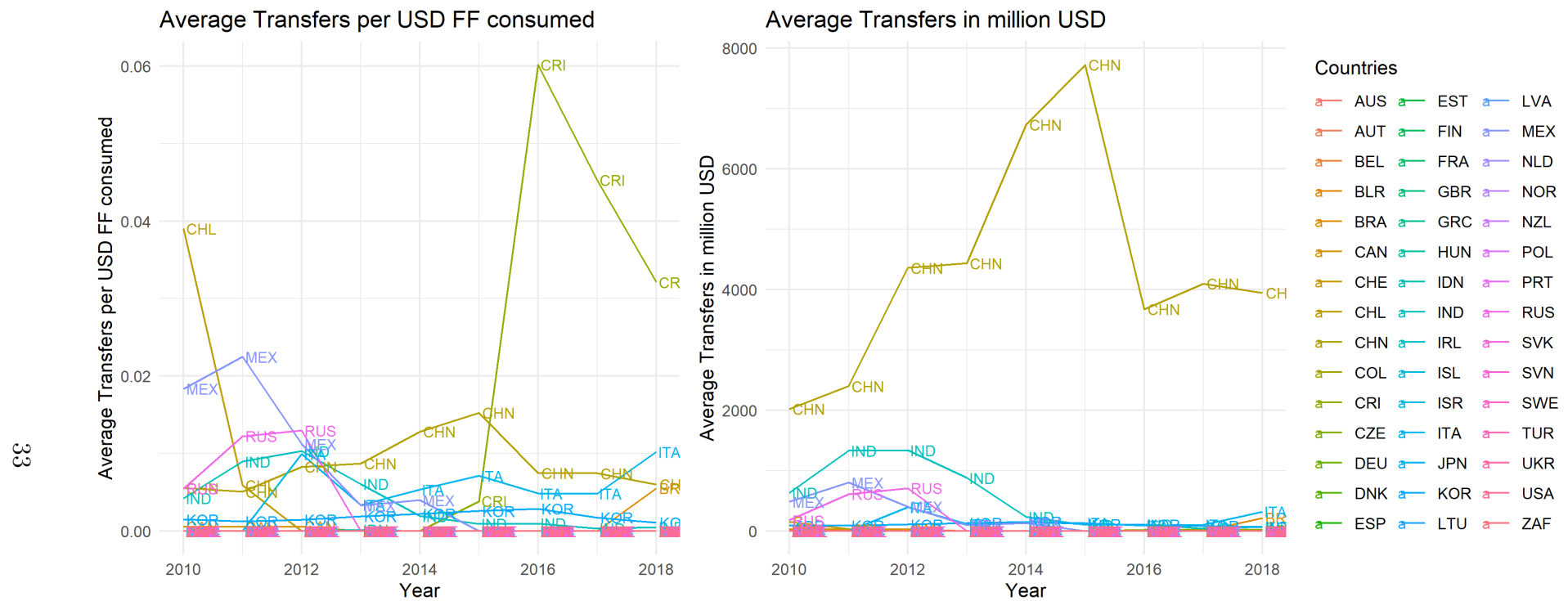


Figure A.3: Budgetary Transfers to Fossil Fuel Consumption for Manufacturing, 2010-2018, in USD, either in transfers over fossil fuel consumed (both in USD) (left) or in total value in USD (right)

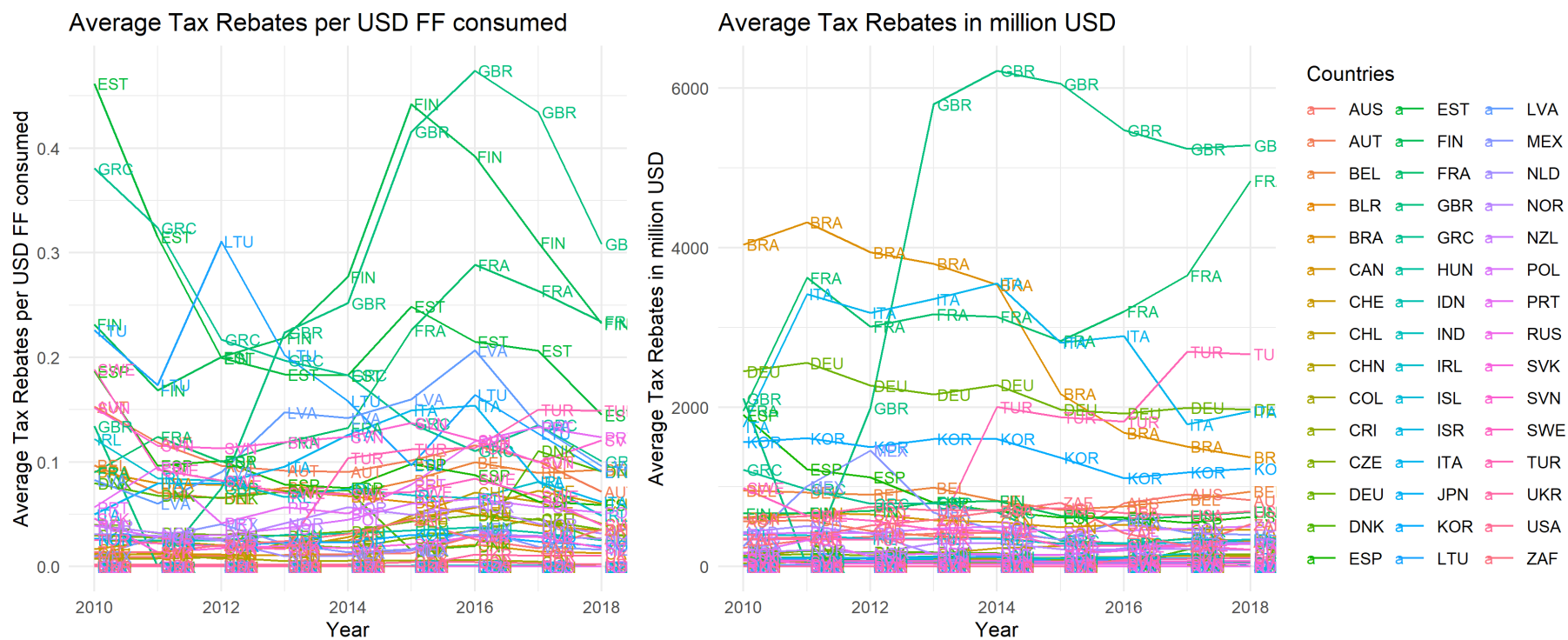


Figure A.4: Tax Rebates to Fossil Fuel Consumption for Manufacturing, 2010-2018, in USD, either in rebates over fossil fuel consumed (both in USD) (left) or in total value in USD (right)

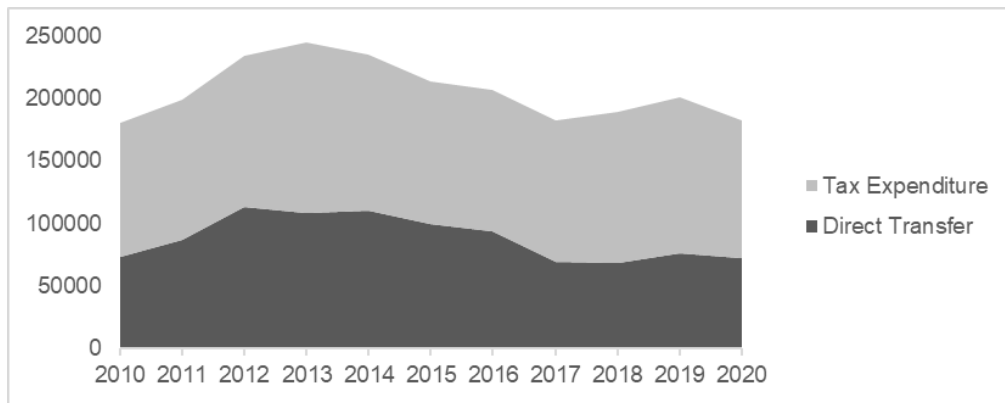


Figure A.5: Total Fossil Fuel Support by Instrument, in million USD

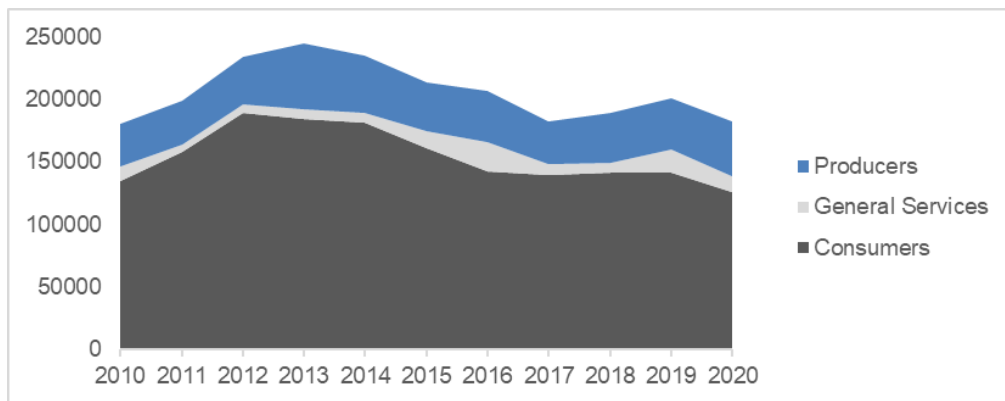


Figure A.6: Total Fossil Fuel Support by Beneficiary, in million USD

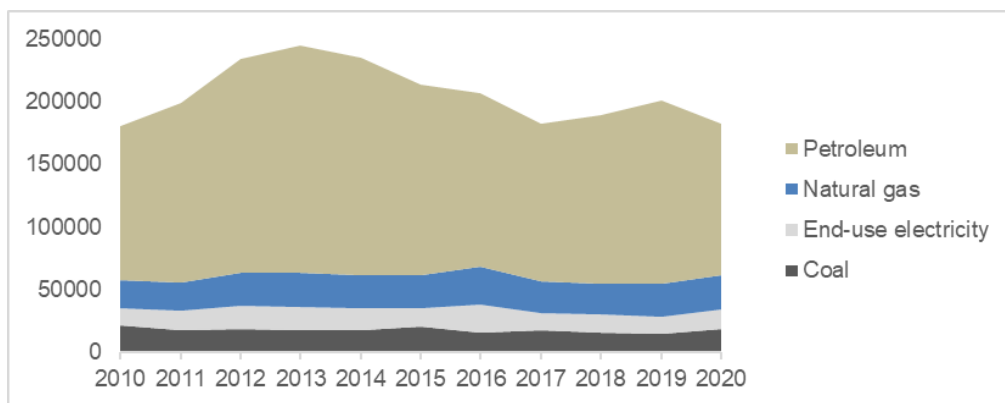


Figure A.7: Total Fossil Fuel Support by Fuel Type, in million USD

A.4 Visualisation of Comparative Advantage in Selected Industries

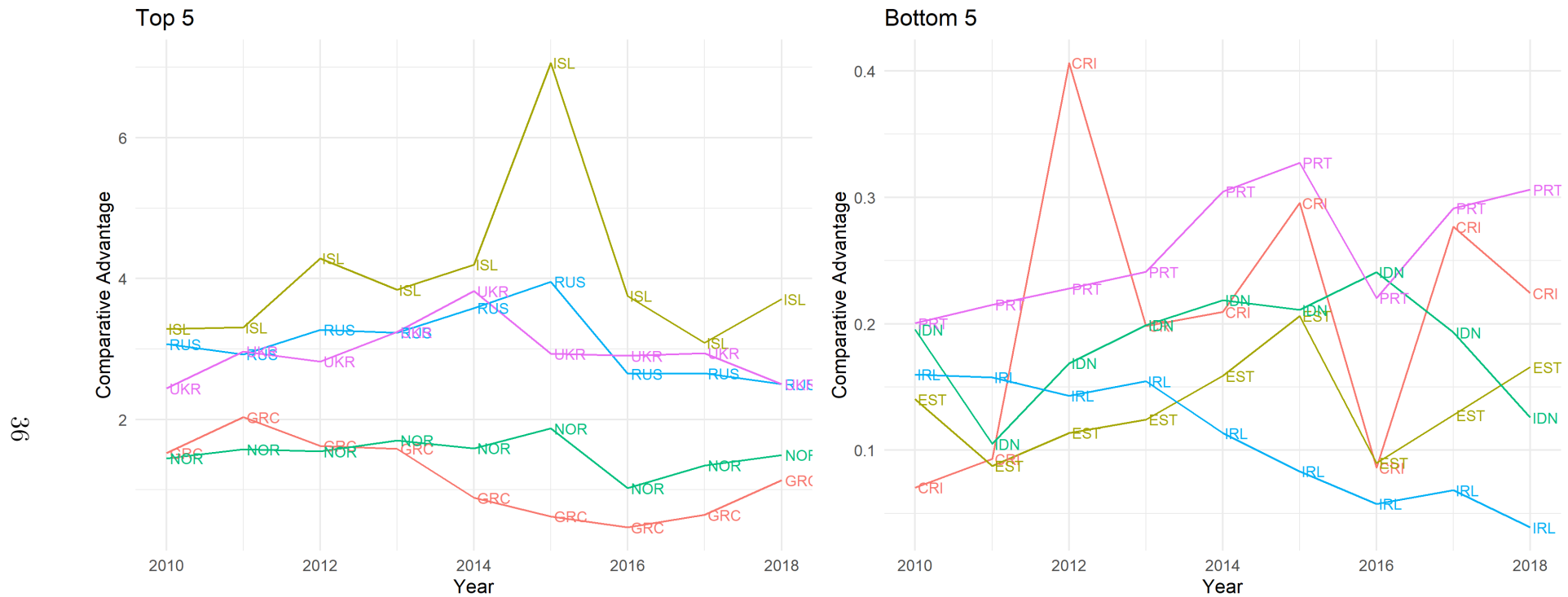


Figure A.8: Comparative advantage in "Basic Metals" for the top 5 (left) and the bottom 5 countries in 2010 (right)

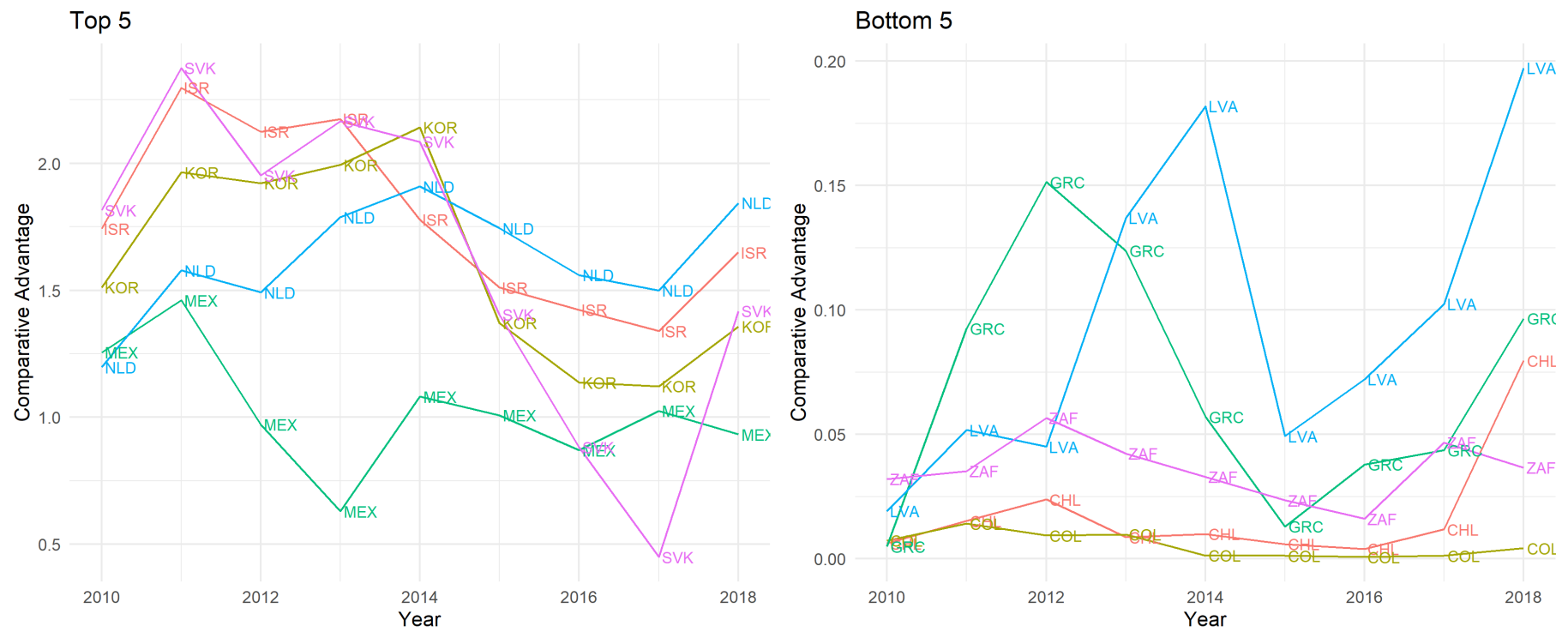


Figure A.9: Comparative advantage in “Computer, electronic and optical equipment” for the top 5 (left) and the bottom 5 countries in 2010 (right)

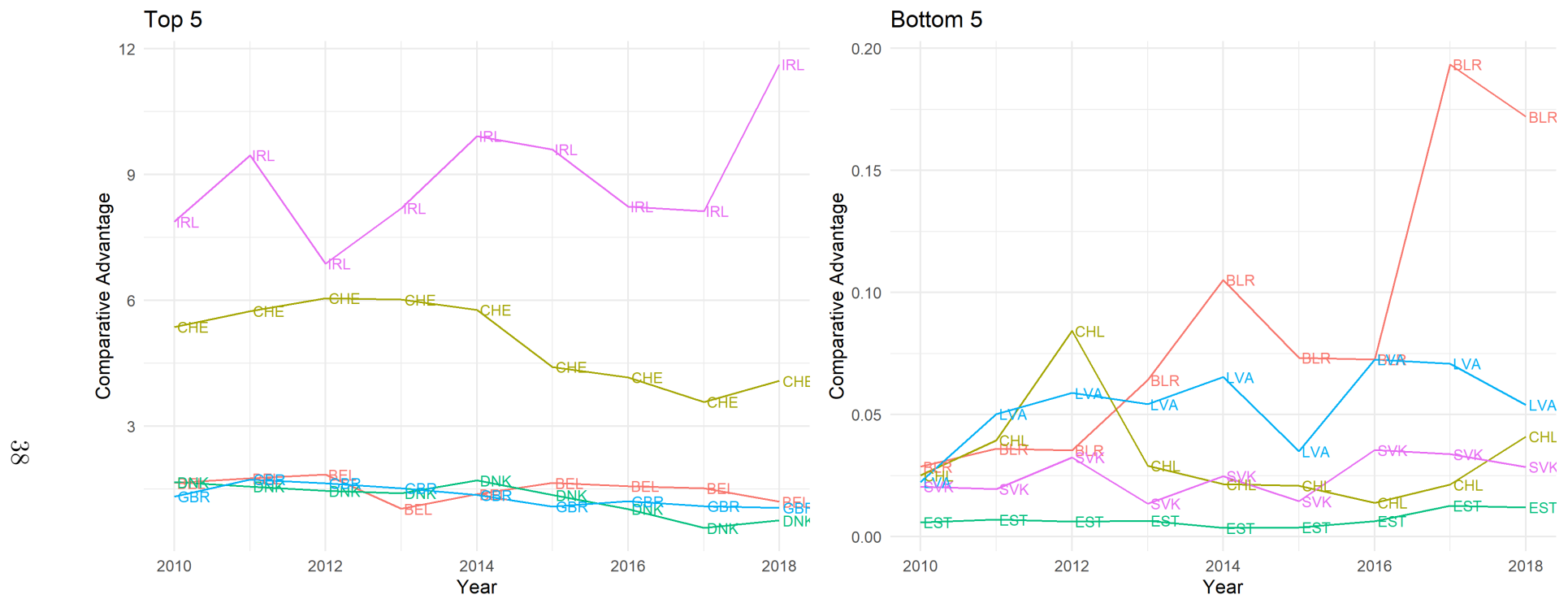


Figure A.10: Comparative advantage in “Pharmaceuticals, medicinal chemical and botanical products” for the top 5 (left) and the bottom 5 countries in 2010 (right)

A.5 Economies

Table A2: Economies with ISO3 Code and Name

| ISO3 | Name | ISO3 | Name | ISO3 | Name |
|------|----------------|------|--------------------|------|--------------------|
| ARG | Argentina | EST | Estonia | LVA | Latvia |
| AUS | Australia | FIN | Finland | MEX | Mexico |
| AUT | Austria | FRA | France | NLD | Netherlands |
| BEL | Belgium | GBR | United Kingdom | NOR | Norway |
| BRA | Brazil | GRC | Greece | NZL | New Zealand |
| CAN | Canada | HUN | Hungary | POL | Poland |
| CHE | Switzerland | IDN | Indonesia | PRT | Portugal |
| CHL | Chile | IND | India | RUS | Russian Federation |
| CHN | China | IRL | Ireland | SVK | Slovak Republic |
| COL | Colombia | ISL | Iceland | SVN | Slovenia |
| CRI | Costa Rica | ISR | Israel | SWE | Sweden |
| CZE | Czech Republic | ITA | Italy | TUR | Türkiye |
| DEU | Germany | JPN | Japan | UKR | Ukraine |
| DNK | Denmark | KOR | Korea, Republic of | USA | United States |
| ESP | Spain | LTU | Lithuania | ZAF | South Africa |

A.6 Extensions and Robustness

Estimation in Levels

For robustness checks, we run panel regressions, with sector and country clustered standard errors:²⁷

$$\hat{\gamma}_{o,t}^i = \alpha_{o,t} + \beta_t^i + \zeta_o^i + \delta I^i \ln(P_{o,t}) + \phi \hat{\gamma}_{o,(t-1)}^i + \epsilon_{o,t}^i, \quad (\text{A.2})$$

with $P_{o,t} \in \{C_{o,t}, F_{o,t}\}$,

in which $P_{o,t}$ can be either the carbon price $C_{o,t}$ or the fossil fuel support $F_{o,t}$. The terms $\alpha_{o,t}$ are country-year, β_t^i are industry-year, and ζ_o^i are industry-country fixed effects, and I^i is the industry's carbon or fossil-fuel intensity. $\epsilon_{o,t}^i$ is an error term i.i.d. across countries and industries.

By using industry-country fixed effects ζ_o^i , we take away any variation across industries and countries that is constant over time and therefore identify our results only from changes (not levels) of our policy variables.²⁸ As we suspect that the error term $\epsilon_{o,t}^i$ may be correlated within industries and within countries, we cluster our standard errors in those two dimensions.²⁹

²⁷When we analyse the ETS prices separately, we cluster over ETS system instead of country as the EU ETS variation applies to multiple countries at the same time.

²⁸See the discussion on baseline level of tax breaks in the measurement of fossil fuel support.

²⁹When we analyse the ETS prices separately, we cluster over ETS system instead of country as the

Robustness Regression Results

Table A3: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Carbon Prices (C_o) from the WCPD, for 2010-2018 in manufacturing sectors.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------------|--------------------------|
| | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \ln(C_o)$ | 0.010 (0.0075) | -0.016 (0.0129) | 0.028*** (0.0011) | | | |
| $I^i \Delta \ln(C_o)$ | | | | -0.004 (0.0122) | -0.032** (0.0127) | 0.029*** (0.0031) |
| $L\hat{\gamma}_o^i$ | 0.317*** (0.0405) | 0.316*** (0.0406) | 0.317*** (0.0297) | | | |
| $L\Delta\hat{\gamma}_o^i$ | | | | -0.394*** (0.0387) | -0.394*** (0.0386) | -0.393*** (0.0220) |
| $L^2\Delta\hat{\gamma}_o^i$ | | | | -0.229*** (0.0331) | -0.229*** (0.0330) | -0.228*** (0.0200) |
| $L^3\Delta\hat{\gamma}_o^i$ | | | | -0.109*** (0.0315) | -0.109*** (0.0317) | -0.109*** (0.0280) |
| Constant | -0.575*** (0.0341) | -0.560*** (0.0338) | -0.595*** (0.0257) | 0.004*** (0.0013) | 0.005*** (0.0013) | 0.004*** (0.0011) |
| Policy C_o | CP-tot | CP-tax | CP-ETS | CP-tot | CP-tax | CP-ETS |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ |
| FE (ζ_o^i) | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes |
| N | 6,042 | 6,042 | 6,042 | 5,370 | 5,370 | 5,370 |
| R^2 | 0.979 | 0.979 | 0.979 | 0.453 | 0.453 | 0.453 |

Robust standard errors in parentheses, clustered over sectors and countries (for the analysis of ETS, the sectoral dimension is clustered).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: L denotes the one-year lag operator, Δ the one-year difference operator. Carbon prices are from the World Carbon Pricing Database (CP-tot) and contain prices from emission trading systems and carbon taxes, corrected for tax exemptions (CP-tax), in USD per tCO₂. The intensities I^i are CO₂ emissions factors in tonnes per USD of output from the OECD's TECO2 database.

Table A4: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Effective Carbon Rates (C_o), for 2012-2018 in manufacturing sectors.

| | (1) $\hat{\gamma}_o^i$ | (2) $\hat{\gamma}_o^i$ | (3) $\hat{\gamma}_o^i$ | (4) $\Delta\hat{\gamma}_o^i$ | (5) $\Delta\hat{\gamma}_o^i$ | (6) $\Delta\hat{\gamma}_o^i$ |
|----------------------------------|---------------------------|---------------------------|---------------------------|---------------------------------|---------------------------------|---------------------------------|
| $I^i \ln(C_o)$ | 0.005 (0.0147) | -0.010 (0.0066) | -0.043*** (0.0056) | | | |
| $I^i \Delta \ln(C_o)$ | | | | -0.030*** (0.0093) | -0.033** (0.0132) | -0.073*** (0.0104) |
| $L\hat{\gamma}_o^i$ | 0.429*** (0.0633) | 0.428*** (0.0645) | 0.429*** (0.0642) | | | |
| $L\Delta\hat{\gamma}_o^i$ | | | | -0.328*** (0.0711) | -0.328*** (0.0709) | -0.325*** (0.0710) |
| $L^2\Delta\hat{\gamma}_o^i$ | | | | -0.103* (0.0556) | -0.102* (0.0556) | -0.106* (0.0552) |
| $L^3\Delta\hat{\gamma}_o^i$ | | | | -0.025** (0.0103) | -0.024* (0.0125) | -0.026** (0.0107) |
| Constant | -0.415*** (0.0634) | -0.394*** (0.0505) | -0.343*** (0.0381) | 0.059*** (0.0033) | 0.063*** (0.0035) | 0.054*** (0.0028) |
| Policy C_o | ECR-tot | ECR-CP | ECR-FE | ECR-tot | ECR-CP | ECR-FE |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ |
| FE (ζ_o^i) | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes |
| N | 1,805 | 1,805 | 1,805 | 1,198 | 1,198 | 1,198 |
| R^2 | 0.984 | 0.984 | 0.984 | 0.417 | 0.418 | 0.420 |

Robust standard errors in parentheses, clustered over sectors and countries.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: L denotes the three-year lag operator, Δ denotes the three-year difference operator. Carbon prices are from the OECD's Effective Carbon Rate (ECR-tot) which consists of the explicit carbon price (ECR-CP) and the fuel excise tax (ECR-FE). The ECR has data for 2012, 2015, 2018 only. The intensities I^i are CO₂ emissions factors in tonnes per USD of output from the OECD's TECO2 database.

Table A5: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Fossil Fuel Support (F_o), for 2010-2018 in manufacturing sectors.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------------|--------------------------|
| | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \ln(F_o)$ | 0.068** (0.0278) | 0.009 (0.0715) | 0.076* (0.0382) | | | |
| $I^i \Delta \ln(F_o)$ | | | | 0.061*** (0.0023) | 0.036 (0.0554) | 0.059*** (0.0073) |
| $L\hat{\gamma}_o^i$ | 0.373*** (0.0265) | 0.373*** (0.0270) | 0.373*** (0.0263) | | | |
| $L\Delta\hat{\gamma}_o^i$ | | | | -0.363*** (0.0362) | -0.364*** (0.0365) | -0.363*** (0.0363) |
| $L^2\Delta\hat{\gamma}_o^i$ | | | | -0.185*** (0.0276) | -0.185*** (0.0277) | -0.185*** (0.0278) |
| $L^3\Delta\hat{\gamma}_o^i$ | | | | -0.090** (0.0405) | -0.089** (0.0403) | -0.090** (0.0405) |
| Constant | -0.485*** (0.0239) | -0.411*** (0.0207) | -0.491*** (0.0325) | 0.003** (0.0011) | 0.003** (0.0013) | 0.003** (0.0011) |
| Policy F_o | FFS-tot | FFS-tra | FFS-tax | FFS-tot | FFS-tra | FFS-tax |
| Intensity I^i | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO |
| FE (ζ_o^i) | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes |
| N | 5,993 | 5,993 | 5,993 | 5,393 | 5,393 | 5,393 |
| R^2 | 0.978 | 0.978 | 0.978 | 0.455 | 0.455 | 0.455 |

Robust standard errors in parentheses, clustered over sectors and countries.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: L denotes the one-year lag operator, Δ denotes the one-year difference operator. Fossil fuel support is in per unit of fossil fuel consumption (support in USD over consumption in USD), either the total value (FFS-tot), or split in budgetary transfers (FFS-tra) and tax exemptions (FFS-tax). The fossil fuel (FF) intensities I^i are based on the input coefficients on sectors 05T06 and 19 in the OECD inter-country inter-industry input-output tables.

B Online Appendix: Additional Robustness Regression Results

Table B1: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Carbon Prices or on Fossil Fuel Support (P_o), for 2010-2018 in manufacturing sectors, with different intensities I^i .

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|----------------------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------------|--------------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------------|--------------------------|
| | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \ln(P_o)$ | -0.006 (0.0171) | -0.035 (0.0214) | 0.021*** (0.0015) | | | | 0.109*** (0.0331) | -0.058 (0.0548) | 0.139*** (0.0369) | | | |
| $I^i \Delta \ln(P_o)$ | | | | -0.030 (0.0213) | -0.046*** (0.0141) | -0.005 (0.0302) | | | | 0.088*** (0.0208) | 0.013 (0.0113) | 0.095*** (0.0268) |
| Constant | -0.551*** (0.0439) | -0.550*** (0.0328) | -0.600*** (0.0169) | 0.004** (0.0014) | 0.003** (0.0013) | 0.002* (0.0010) | -0.435*** (0.0328) | -0.375*** (0.0216) | -0.449*** (0.0374) | -0.001*** (0.0003) | -0.001*** (0.0003) | -0.001*** (0.0003) |
| Policy P_o | CP-tot | CP-tax | CP-ETS | CP-tot | CP-tax | CP-ETS | FFS-tot | FFS-tra | FFS-tax | FFS-tot | FFS-tra | FFS-tax |
| Intensity I^i | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-EA | FF-EA | FF-EA | FF-EA | FF-EA | FF-EA |
| Lags of $\hat{\gamma}_o^i$ | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lags of $\Delta\hat{\gamma}_o^i$ | 0 | 0 | 0 | 3 | 3 | 3 | 0 | 0 | 0 | 3 | 3 | 3 |
| FE (ζ_o^i) | yes | yes | yes | no | no | no | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| N | 5,664 | 5,664 | 5,664 | 5,034 | 5,034 | 5,034 | 5,993 | 5,993 | 5,993 | 5,393 | 5,393 | 5,393 |
| R^2 | 0.979 | 0.979 | 0.979 | 0.460 | 0.460 | 0.459 | 0.982 | 0.982 | 0.982 | 0.438 | 0.437 | 0.438 |

Robust standard errors in parentheses, clustered over sectors and countries (for the analysis of ETS, the jurisdiction of the ETS is used instead).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the one-year difference operator. Carbon prices are from the World Carbon Pricing Database (Dolphin and Xiahou, 2022) (CP-tot) and contain prices from emission trading systems (CP-ETS) and carbon taxes, corrected for tax exemptions (CP-tax), in USD per tCO₂. Fossil fuel support is in per unit of fossil fuel consumption (support in USD over consumption in USD), either the total value (FFS-tot), or split in budgetary transfers (FFS-tra) and tax exemptions (FFS-tax). ICIO-based fossil fuel (FF) intensities are based on the input coefficients on sectors 05T06 and 19 in the OECD inter-country inter-industry input-output tables. The EA-based fossil fuel intensities are the fuel consumption in kJ per USD of output from the WIOD Environmental Accounts.

Table B2: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Effective Carbon Rates (C_o), for 2012-2018 in manufacturing sectors, with different intensities I^i .

| | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------------------|---------------------|----------------------|-----------------------|--------------------------|--------------------------|--------------------------|
| | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \ln(C_o)$ | -0.036 (0.0471) | -0.050 (0.0381) | -0.038* (0.0178) | | | |
| $I^i \Delta \ln(C_o)$ | | | | -0.076 (0.0499) | -0.090 (0.0565) | -0.068*** (0.0207) |
| Constant | -0.312* (0.1521) | -0.302** (0.1067) | -0.318*** (0.0574) | 0.062*** (0.0049) | 0.079*** (0.0132) | 0.051*** (0.0027) |
| Policy C_o | ECR-tot | ECR-CP | ECR-FE | ECR-tot | ECR-CP | ECR-FE |
| Intensity I^i | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO |
| Lags of $\hat{\gamma}_o^i$ | 1 | 1 | 1 | 0 | 0 | 0 |
| Lags of $\Delta\hat{\gamma}_o^i$ | 0 | 0 | 0 | 3 | 3 | 3 |
| FE (ζ_o^i) | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes |
| N | 1,692 | 1,692 | 1,692 | 1,123 | 1,123 | 1,123 |
| R^2 | 0.984 | 0.984 | 0.984 | 0.432 | 0.437 | 0.431 |

Robust standard errors in parentheses, clustered over countries and sectors.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the three-year difference operator. Carbon prices are from the OECD's Effective Carbon Rate (ECR-tot) which consists of the explicit carbon price (ECR-CP) and the fuel excise tax (ECR-FE). The ECR has data for 2012, 2015, 2018 only. ICIO-based fossil fuel (FF) intensities are based on the input coefficients on sectors 05T06 and 19 in the OECD inter-country inter-industry input-output tables.

Table B3: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Carbon Prices or on Fossil Fuel Support (P_o), for 2010-2018 in manufacturing sectors, with weights for observations.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|----------------------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------------|--------------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------------|--------------------------|
| | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \ln(P_o)$ | 0.010 (0.0075) | -0.017 (0.0132) | 0.027*** (0.0001) | | | | 0.087** (0.0334) | 0.012 (0.0635) | 0.097** (0.0450) | | | |
| $I^i \Delta \ln(P_o)$ | | | | -0.001 (0.0091) | -0.030** (0.0132) | 0.028*** (0.0008) | | | | 0.042 (0.0279) | 0.026 (0.0498) | 0.039 (0.0401) |
| Constant | -0.484*** (0.0280) | -0.469*** (0.0266) | -0.502*** (0.0262) | 0.005*** (0.0013) | 0.006*** (0.0012) | 0.005*** (0.0013) | -0.448*** (0.0324) | -0.361*** (0.0187) | -0.455*** (0.0381) | 0.002** (0.0010) | 0.002* (0.0012) | 0.002* (0.0011) |
| Policy P_o | CP-tot | CP-tax | CP-ETS | CP-tot | CP-tax | CP-ETS | FFS-tot | FFS-tra | FFS-tax | FFS-tot | FFS-tra | FFS-tax |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO |
| Lags of $\hat{\gamma}_o^i$ | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lags of $\Delta\hat{\gamma}_o^i$ | 0 | 0 | 0 | 3 | 3 | 3 | 0 | 0 | 0 | 3 | 3 | 3 |
| FE (ζ_o^i) | yes | yes | yes | no | no | no | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| N | 5,898 | 5,898 | 5,898 | 5,258 | 5,258 | 5,258 | 5,843 | 5,843 | 5,843 | 5,393 | 5,393 | 5,393 |
| R^2 | 0.981 | 0.981 | 0.981 | 0.466 | 0.466 | 0.466 | 0.980 | 0.980 | 0.980 | 0.469 | 0.469 | 0.469 |

Robust standard errors in parentheses, clustered over sectors and countries (for the analysis of ETS, the jurisdiction of the ETS is used instead).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the one-year difference operator. Carbon prices are from the World Carbon Pricing Database ([Dolphin and Xiahou, 2022](#)) (CP-tot) and contain prices from emission trading systems (CP-ETS) and carbon taxes, corrected for tax exemptions (CP-tax), in USD per tCO₂. Fossil fuel support is in per unit of fossil fuel consumption (support in USD over consumption in USD), either the total value (FFS-tot), or split in budgetary transfers (FFS-tra) and tax exemptions (FFS-tax). The weights are the inverse standard errors of the first-stage estimations of $\hat{\gamma}_o^i$, namely $1/\text{se}(\hat{\gamma}_o^i)$.

Table B4: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Effective Carbon Rates (C_o), for 2012-2018 in manufacturing sectors, with different weights for observations.

| | (1) $\hat{\gamma}_o^i$ | (2) $\hat{\gamma}_o^i$ | (3) $\hat{\gamma}_o^i$ | (4) $\Delta\hat{\gamma}_o^i$ | (5) $\Delta\hat{\gamma}_o^i$ | (6) $\Delta\hat{\gamma}_o^i$ |
|----------------------------------|---------------------------|---------------------------|---------------------------|---------------------------------|---------------------------------|---------------------------------|
| $I^i \ln(C_o)$ | -0.011 (0.0099) | -0.020*** (0.0042) | -0.036* (0.0187) | | | |
| $I^i \Delta \ln(C_o)$ | | | | -0.039*** (0.0103) | -0.038** (0.0136) | -0.064*** (0.0110) |
| Constant | -0.331*** (0.0543) | -0.324*** (0.0426) | -0.298*** (0.0327) | 0.055*** (0.0031) | 0.059*** (0.0033) | 0.050*** (0.0026) |
| Policy C_o | ECR-tot | ECR-CP | ECR-FE | ECR-tot | ECR-CP | ECR-FE |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ |
| Lags of $\hat{\gamma}_o^i$ | 1 | 1 | 1 | 0 | 0 | 0 |
| Lags of $\Delta\hat{\gamma}_o^i$ | 0 | 0 | 0 | 3 | 3 | 3 |
| FE (ζ_o^i) | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes |
| N | 1,757 | 1,757 | 1,757 | 1,166 | 1,166 | 1,166 |
| R^2 | 0.986 | 0.986 | 0.986 | 0.441 | 0.441 | 0.442 |

Robust standard errors in parentheses, clustered over countries and sectors.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the three-year difference operator. Carbon prices are from the OECD's Effective Carbon Rate (ECR-tot) which consists of the explicit carbon price (ECR-CP) and the fuel excise tax (ECR-FE). The ECR has data for 2012, 2015, 2018 only. The intensities I^i are CO₂ emissions factors in tonnes per USD of output or are the ICIO input coefficient on sectors 05T06 and 19 in 2010. The weights are the inverse standard errors of the first-stage estimations of $\hat{\gamma}_o^i$, namely $1/\text{se}(\hat{\gamma}_o^i)$.

Table B5: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Carbon Prices (C_o) and on Fossil Fuel Support (F_o), for 2010-2018 in manufacturing sectors; $\hat{\gamma}_o^i$ estimated with [Hanson et al. \(2015\)](#).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|----------------------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------------|--------------------------|----------------------|----------------------|----------------------|--------------------------|--------------------------|--------------------------|
| | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \ln(P_o)$ | 0.006 (0.0060) | -0.013 (0.0109) | 0.018*** (0.0002) | | | | 0.006 (0.0500) | 0.047 (0.0653) | -0.009 (0.0358) | | | |
| $I^i \Delta \ln(P_o)$ | | | | -0.008 (0.0114) | -0.031* (0.0167) | 0.020*** (0.0055) | | | | -0.014 (0.0156) | 0.016 (0.0560) | -0.016 (0.0166) |
| Constant | 10.994*** (1.2599) | 11.004*** (1.2606) | 10.982*** (1.2595) | -0.185*** (0.0190) | -0.185*** (0.0190) | -0.185*** (0.0189) | 9.826*** (1.4159) | 9.839*** (1.4548) | 9.843*** (1.4260) | -0.165*** (0.0202) | -0.165*** (0.0202) | -0.165*** (0.0202) |
| Policy P_o | CP-tot | CP-tax | CP-ETS | CP-tot | CP-tax | CP-ETS | FFS-tot | FFS-tra | FFS-tax | FFS-tot | FFS-tra | FFS-tax |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO | FF-ICIO |
| Lags of $\hat{\gamma}_o^i$ | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lags of $\Delta\hat{\gamma}_o^i$ | 0 | 0 | 0 | 3 | 3 | 3 | 0 | 0 | 0 | 3 | 3 | 3 |
| FE (ζ_o^i) | yes | yes | yes | no | no | no | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| N | 6,042 | 6,042 | 6,042 | 5,370 | 5,370 | 5,370 | 5,993 | 5,993 | 5,993 | 5,393 | 5,393 | 5,393 |
| R^2 | 0.993 | 0.993 | 0.993 | 0.760 | 0.760 | 0.760 | 0.993 | 0.993 | 0.993 | 0.795 | 0.795 | 0.795 |

Robust standard errors in parentheses, clustered over sectors and countries (for the analysis of ETS, the jurisdiction of the ETS is used instead).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the one-year difference operator. Carbon prices are from the World Carbon Pricing Database ([Dolphin and Xiahou, 2022](#)) (CP-tot) and contain prices from emission trading systems (CP-ETS) and carbon taxes, corrected for tax exemptions (CP-tax), in USD per tCO₂. Fossil fuel support is in per unit of fossil fuel consumption (support in USD over consumption in USD), either the total value (FFS-tot), or split in budgetary transfers (FFS-tra) and tax exemptions (FFS-tax). The export capability $\hat{\gamma}_o^i$ is estimated according to [Hanson et al. \(2015\)](#) methodology.

Table B6: OLS Regression of Exporter Capability ($\hat{\gamma}_o^i$) on Effective Carbon Rates (C_o), for 2012-2018 in manufacturing sectors, with γ_o^i via [Hanson et al. \(2015\)](#).

| | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------------------|----------------------|----------------------|----------------------|--------------------------|--------------------------|--------------------------|
| | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ | $\Delta\hat{\gamma}_o^i$ |
| $I^i \ln(C_o)$ | -0.010 (0.0118) | -0.004 (0.0064) | -0.024 (0.0169) | | | |
| $I^i \Delta \ln(C_o)$ | | | | -0.053*** (0.0134) | -0.027** (0.0094) | -0.048** (0.0175) |
| Constant | 7.670*** (1.5685) | 7.644*** (1.5686) | 7.674*** (1.5722) | -0.335*** (0.0169) | -0.333*** (0.0177) | -0.340*** (0.0176) |
| Policy C_o | ECR-tot | ECR-CP | ECR-FE | ECR-tot | ECR-CP | ECR-FE |
| Intensity I^i | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ | CO ₂ |
| Lags of $\hat{\gamma}_o^i$ | 1 | 1 | 1 | 0 | 0 | 0 |
| Lags of $\Delta\hat{\gamma}_o^i$ | 0 | 0 | 0 | 3 | 3 | 3 |
| FE (ζ_o^i) | yes | yes | yes | no | no | no |
| FE ($\alpha_{o,t}, \beta_t^i$) | yes | yes | yes | yes | yes | yes |
| N | 1,805 | 1,805 | 1,805 | 1,198 | 1,198 | 1,198 |
| R^2 | 0.995 | 0.995 | 0.995 | 0.732 | 0.731 | 0.731 |

Robust standard errors in parentheses, clustered over countries and sectors.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Δ denotes the three-year difference operator. Carbon prices are from the OECD's Effective Carbon Rate (ECR-tot) which consists of the explicit carbon price (ECR-CP) and the fuel excise tax (ECR-FE). The intensities I^i are CO₂ emissions factors in tonnes per USD of output from the OECD's TECO2 database. The export capability $\hat{\gamma}_o^i$ is estimated according to [Hanson et al. \(2015\)](#) methodology.