When to go Green? Firm Dynamics during the Green Transition under the EU ETS *†

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Abstract

This project investigates the impact of carbon policy on firms' decisions to adopt clean technologies and its role in driving aggregate technological change, leveraging data from the EU Emissions Trading System (ETS) spanning from 2005 to 2019. By constructing a novel indicator, I find that mainly productive and polluting firms adopt improved abatement technologies when carbon prices are high. Conditional on investment, these firms are also more likely to exit the domestic economy. I estimate the cost of either decision using a dynamic discrete choice model of heterogeneous firms that operate within a two-country framework. An adoption of improved technology that reduces 20% of emissions is almost 6 times cheaper than relocating abroad. Calibrating the model on the transition of the EU ETS shows that, so far, emission output has been reduced by approximately 25%, but at an output cost of 3%. The reduction is mostly driven by output losses from highly polluting firms, though the share of clean technology adoption is steadily increasing. Lastly, I compute the optimal unilateral carbon policy to minimize domestic output losses along this transition towards the *fit-for-55* benchmark in 2030 and demonstrate that an excessively rapid increase in carbon prices would push too many firms out of the market.

Keywords: trade and environment, technology adoption, firm decisions, climate policy, carbon leakage.

JEL Codes: F18, F64, L1, Q56.

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1. Introduction

This study analyzes the mechanisms behind emission reductions and explores how governments can design optimal policies to foster emissions reductions and promote unilateral green technological change. . By examining firm-level data from 2005 to 2019, the paper assesses how firms respond to the European Emission Trading System (EU ETS), the most advanced emission reduction policy to date and how these impacted the decline in aggregate emissions (Figure 1a). Although policymakers view the decline in emission intensity as a success of the EU ETS, critics argue that the policy disproportionately affects firms without the capacity to transition to cleaner practices, as seen in the decreasing dispersion of emission intensity and the increasing variation in value added (Figure 1b). Even worse, concerns about carbon leakage persist, with emission-intensive activities potentially shifting to regions with weaker regulations, undermining the global effectiveness of the policy. This paper aims to answer this debate by quantifying the impact of each of these 3 mechanisms, while also examining the granular impact of the policy.

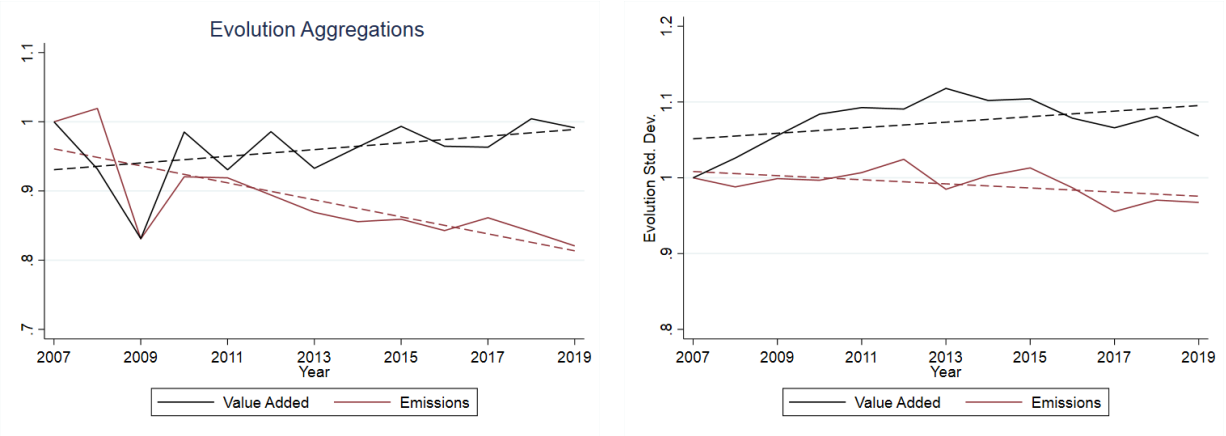
I start by empirically documenting that the reduction in emission output at the aggregate is driven by a small subset of large, polluting firms for whom the price of carbon bites more in their marginal cost. To capture structural changes in emission intensity, I develop a novel indicator that identifies persistent reductions in this outcome variable. These reductions are accompanied by increased capital investment and are more pronounced when carbon prices are high, suggesting that the EU ETS plays a crucial role in shaping abatement decisions. Finally, I find that polluting multinational subsidiaries are more likely to exit relative to their non-polluting counterparts.

Building upon these insights, this paper constructs and estimates a dynamic discrete choice model, where heterogeneous forward-looking firms have the option to invest and adopt a new level of clean technology or relocate abroad indefinitely, when faced with a carbon policy along the transition path towards a decarbonized economy. The firms are embedded into a two-country framework where the home country sets the carbon policies unilaterally. The model is used to estimate the shadow costs of adoption and relocation for the firms in the EU ETS, as well as the annual evolution of the shadow cost of adoption given the actual yearly price of carbon certificates.

The findings indicate that the observed reduction in emissions is largely driven by a mechanism in which more productive, high-emission firms allocate greater resources toward carbon abatement technologies. The model estimates that the cost of such investments is approximately six times lower than the cost of relocation. A decomposition of aggregate emissions reveals that while the primary driver of emission reductions is output contraction due to rising marginal costs, the significance of technology adoption is increasing. In addition, this study provides an initial assessment of whether the extensive allocation of free emissions certificates has contributed to mitigating carbon leakage. Furthermore, it examines the implications of implementing a carbon border adjustment mechanism (CBAM) on firm-level decision-making.

Finally, utilizing the previously estimated shadow costs, I compute the optimal unilateral carbon policy

Figure 1: Aggregate evolution manufacturing firms in EU ETS



(a) Evolution of emissions

(b) Evolution of s.d.

Note: Figure 1a documents the changes in total value added and emission intensity (emissions over value added) of all manufacturing firms present in the EU ETS since 2008. Firms for whom the number of plants covered by policy have shifted throughout this period are omitted. Figure 1b shows the progression of inequality, measured by the standard deviation of the logarithm of both value added and emission intensity for the same sample of firms.

and compare these optimal policies to those proposed by the European Union. In designing an optimal unilateral policy, the government faces a trade-off: while higher carbon prices incentivize the adoption of clean technologies, excessively high prices increase the risk of firm relocation abroad, exacerbating carbon leakage. To minimize aggregate domestic output losses, this trade-off results in a hump-shaped price of carbon, where it begins at a relatively low level and gradually increases before reaching a critical point around 2035 - 2040. The model would have predicted a sharp rise in the price of carbon in 2021 even without the presence of the COVID-19 / energy crisis.

The main contribution of this paper is the development and estimation of a novel tractable microeconomic model that tracks heterogeneous firms throughout the green transition, analyzing how their discrete choices shape aggregate outcomes. The model is easily estimated using the results in the empirical framework and it can explain the aggregate results in Figure 1a and Figure 1b well. A breakdown of aggregate emission reduction reveals that approximately 20% of the aggregate reduction is due to the adoption of new clean technologies. The rest can be seen as reduced emissions through output loss between firms - of which 90% directly and 10% due to relocation of firms. It demonstrates the prevalence of a catch-up effect where polluting firms find it best to adopt new levels of clean technology and become greener. Moreover, the model reveals an output loss of approximately 3% of domestically produced output. The model also reveals a distributional effect: while firms generally become greener under the policy, larger firms are better positioned to leverage the benefits of carbon pricing, enabling them to grow even larger. This dynamic,

while reducing emissions overall, exacerbates inequalities in firm size.

The model is particularly suited for counterfactual analysis. First, I explore the role of grandfathering free allocated certificates (Martin et al., 2014) and find that they have limited impact on the relocation decision. Secondly, the model reveals that the openness of a region significantly influences idiosyncratic abatement decisions - both relocation and adoption. In the short run, policies designed to support unilateral mitigation efforts, such as the Carbon Border Adjustment Mechanism (CBAM), may initially increase domestic CO2 emissions (4% rise), because such policies make the relocation decision less efficient, but this also reduces output loss (1% decrease). In the long run, by reducing competition from foreign firms, these policies encourage greater adoption of abatement technologies in both countries.

A third key finding of this paper arises from applying the calibrated quantitative model to analyze optimal unilateral carbon policy in the context of the idiosyncratic decisions. I find that a gradual increase in policy stringency keeps most firms engaged, leading to significant improvements in aggregate emission reductions. In analyzing counterfactual policies, I compare a loss function that targets aggregate emission reductions with one focused solely on domestic emissions. I also conduct several variations and robustness checks to identify the key components driving the main quantitative results. These variations include the extensive margin of firm entry and exit and employing an alternative functional form of the demand aggregator to assess the inequality implications.

This paper contributes to the existing literature in three key aspects. Firstly, this paper explicitly models the adoption decisions of firms when confronted with carbon policies building upon the literature on emission abatement within the structure of a trade model with heterogeneous firms (Copeland and Taylor, 2004; Shapiro and Walker, 2018; Forslid et al., 2018; Cherniwchan and Najjar, 2022).[1] These papers highlight the role large firms play in aggregate emissions and model it in a static model of firm dynamics based on Melitz (2003). This paper stacks these models, but deviates in one major aspect, by modeling investment as a sunk cost decision, I focus on the growth of emissions. [2] Intuitively, more polluting firms have higher incentive to increase abatement efforts, conditional on productivity. This paper extends this literature by demonstrating that the future level of clean technology does not only depend on firm size, but also on the current level of clean technology. In doing so, I highlight the implications of sunk costs in models of firm dynamics and trade following Alessandria et al. (2021). Additionally, introducing a sunk cost of relocation encourages firms to delay relocation in anticipation of better future conditions.

Secondly, this paper provides further evidence on the implications of the EU ETS policy for firm competition and dynamism (DechezleprÃªtre and Sato (2017), Martin et al. (2016), among others, see Verde (2020) for a comprehensive overview). Using a structural estimation approach, my findings confirm and

[1] From a methodological perspective, the estimation strategy of the structural model builds on the literature on dynamic discrete decisions methods (Rust, 1987; Arcidiacono and Ellickson, 2011) and it is extended to fit in a transition framework and capture general equilibrium effects.

[2] The construction of a dynamic model nest multiple other smaller factors as well. Among others, to track abatement quality, the model introduces a second form of firm heterogeneity that captures abatement quality, and further, the dynamic output elasticities of emissions in the production function are now implicit due to the presence of the sunk cost.

generalize the findings of Colmer et al. (2020) to the whole sample of EU ETS firms. Stricter abatement costs drive firms to reduce emissions, primarily through capital deepening. The model reveals that larger firms are better equipped to absorb the sunk costs of clean technology adoption. Related, this paper also speaks to the literature that searches for potential adverse affects of carbon leakage of the EU ETS. There is a small empirical literature on the effect of carbon leakage (Verde, 2020) on the extensive margin (Borghesi et al., 2020; DechezleprÃªtre et al., 2019) and the intensive margin (Martin et al., 2016), yet the answer to this question is mixed or insignificant. I document that exit is more likely for polluting subsidiaries of foreign multinationals, but that the cost is 6 times higher than adopting a 20% cleaner technology and the price has not been sufficiently high to see much relocation yet. By analyzing the impact of grandfathering carbon certificates and its implications on firm dynamics, I also relate to Martin et al. (2014).

Finally, by defining an optimal unilateral carbon policy, this study bridges the literature on optimal carbon policy to achieve the green transition and carbon policy and unilateral policy in terms of trade. More specifically, it builds on previous research (Golosov et al., 2014; Acemoglu et al., 2012; Hassler et al., 2021, ...) that examines how carbon policy is required to guide firms toward a decarbonized state of the economy. This paper considers the adoption rate of new technology as endogenous rather than the development of technology itself. Furthermore, it also supports studies on optimal unilateral carbon policy (Fowlie and Reguant (2022) Kortum and Weisbach (2021) among others, see FontagnÃ© and Schubert (2023) for an overview), which explore how countries can design effective mitigation strategies. This paper focuses on how unilateral carbon policies could best support the dynamic adoption decisions.

This paper is structured as follows. Section 2 describes the institutional setting of the EU ETS system and examines how carbon policy shapes the adoption decision for firms. Section 3 presents the associated dataset used in this analysis and explores the characteristics of firms that adopt clean technology or exit and how this decision depends on the price of carbon emissions. Section 4 characterizes the structural model of firm dynamics and estimates the dynamic discrete choice functions for the firms that participate in the EU ETS. **??** uses the estimated results from the earlier section and aims to compute the optimal carbon policy. [3] Finally, Section 7 concludes.

2. Institutional setting

2.1 The EU Emission Transaction System

To regulate greenhouse gas emissions, the European Union has set up the worlds largest cap-and-trade systems. The EU ETS, or the European Union Emissions Trading System, is a key policy tool used by the EU to address climate change and reduce carbon emissions. The following paragraphs provide a short overview of the trading system. An extensive summary on the EU ETS can be found on the website of the

[3] **??** is currently under construction and only parts have been completed in time

European Union on Climate Action. [4]

The EU ETS sets a limit (cap) on the total (industry) emissions permitted each year. As time goes on; this cap gets more stringent such that it would reduce emissions to 55 of its 2005 level by 2030. Through the market clearing of carbon certificates, where aggregate demand can not excess the cap of certificates, it creates a price of carbon which acts as a Pegouvian tax and harms firms in their marginal cost.

The government aims to encourage firms themselves to find cost-effective ways to reduce emissions through the adoption of cleaner technologies, energy efficiency measures, and other strategies to mitigate climate change. This way, the governmental body leaves it to the individual firm to find the most effective way to become less polluting. It does not decide for any specific measure for firms to be implemented to become cleaner, but leaves it up to firm to decide how to take this decision.

To address concerns about the competitiveness and economic impact of carbon pricing and prevent potential negative economic impacts, firms are allocated free emissions allowances. The aim is to disincentives firms from relocating their polluting production to regions with less environmental regulation. This threat is taken extremely seriously by the national governments.[5] To not disincentive firms that want to invest, the allocation of free certificates is based on the ex-ante profile of the firm (prior to phase III, from phase III onwards, certificates are benchmarked on the industry level), often termed grandfathering (Martin et al., 2014).

The policy has progressed through four distinct phases: Phase 1 (2005-2007) marked its inception, but it faced challenges due to over-allocation of allowances, resulting in incomplete markets with low carbon prices. It has often been described as a phase of learning, both for the governmental agency as for the participating firms (Cantillon and Slechten, 2023). Later, phase 2 (2008-2012) was the first true carbon reduction phase. It saw the expansions of the market and reductions in free allowances, and it was accompanied by an increase in price of carbon emissions and a fully grown secondary emission market where agents could trade without the participation of the government. It has experienced a decrease of approximately 6.5% in aggregate emissions relative to phase 1. The cap on the total emissions was tightened in phase 3 (2013-2020) with 1,74% yearly, and the supply of free allocated emission allowances reduced. This supply shifted from an ex-ante benchmark (grandfathering) to an industry-level benchmark, (Martin et al., 2014). The final phase prior to reaching *fit for 55*, Phase 4 (2021-2030) is even more ambitious and reduced the cap with 2.2% in the first 3 years, 4.3% from 2023-27 and 4.4% from 2028 onward to 2030. Each phase increased the scope of the policy and extended its role and its stringency.

[4] EU Emissions Trading System (EU ETS)

[5] For many countries, the allocation of free emissions allowances was a necessary step to approve the agreement. Additionally, some countries such as Belgium, The Netherlands and France even have additional subsidies in place to make it even more improbable that firms decide to move abroad.

2.2 Stylized model

To illustrate the conceptual trade-offs that forward-looking firms have to make when faced with the EU Emission policy, I introduce a simplified partial equilibrium dynamic model of heterogeneous firms that adopt increased levels of abatement technologies or decide to relocate abroad. This framework also presents notation that will be used throughout the paper.

The governments problem The government has at its disposal two policy instruments that it can utilize to encourage firms to adopt higher levels of clean technology while mitigating the risk of them relocating abroad. First, it can increase the price of carbon emissions either directly or by setting a limit on the 'supply of emissions' which then results into a price due to the laws of supply and demand.[6] The yearly carbon price can be written as a sequence $\zeta = \{\zeta_t, \zeta_{t+1}, ..., \zeta_T\}$. Second, to discourage firms from relocating to pollution heavens when prices are too high, the government can offer firms a number of free certificates - that can be used to omit emissions - to firms based on the initial conditions of the firm. As the allocation of free certificates is ex-ante, it does not depend on the marginal cost of the firm and can be seen as a fixed subsidy: $\kappa = \{\kappa_t, \kappa_{t+1}, ..., \kappa_T\}$. For notation, both polices are included in the matrix $R_t = (\kappa, \zeta)$.

The firm's problem The firms are heterogeneous in their level of marginal cost z abatement technology a_t. The latter encompasses both the input composition and the capacity of the firm to omit less.[7] A higher level of $a \in \mathbb{R}_0^+$ makes the firm less subjected to a carbon taxation.

Given the governmental instrument, firms face three discrete decisions: They can comply with the policy, which gives them the option (i) to do nothing, (ii) to pay a sunk cost and adopt an improved carbon technology which reduces the impact of the policies on their marginal cost. Finally, (iii) they can opt to cease compliance and relocate abroad where such policies are absent, a phenomenon referred to as carbon leakage. This problem can be seen as an optimal stopping problem where the government is faced with the task to ensure that the highest share of firms invest and become cleaner.

The value of a firm is represented by the Bellman equation:

$$V_t(a_t, z; R_t) = \max_{d_t \in \{0,1,2\}} \{\pi(a_{t+1}, z, d_t; R_{t+1}) + \beta \mathbb{E}[V_{t+1}(a_{t+1}, z; R_{t+1} | a_t, d_t)]\}, \tag{1}$$

with static profits $\pi(a_{t+1}, z, d_t; R_{t+1})$ and discount factor $\beta \in (0,1)$. Profits are characterized by $\partial\pi/\partial a_t > 0$, and $\partial^2\pi/\partial^2 a_t < 0$ conditional on $\zeta > 0$ and $\partial\pi/\partial z > 0$.[8] Firms are price-takers on the carbon market and

[6] The Cap-and-Trade system differs from a carbon taxation in several ways. The latter imposes a tax on emissions directly, providing cost predictability but at a cost of flexibility (Metcalf, 2023). The former leaves it to the market clearing of the carbon market to set a price. Within the structure of the baseline model used throughout the text, these two systems coincide as the model abstracts from any uncertainty. Appendix A shows the relationship between the cap and the aggregate price in a setting like this with functional forms

[7] I adhere to one of the key aspects of the EU ETS, whereby firms are entrusted with the autonomy to determine the most effective measures to reduce their emission output.

[8] If the taxation $\zeta = 0$, then $\pi(a; \zeta, \kappa = 0) = \pi$ for all a_t. Hence, they do not internalize other indirect effects of climate emissions in their adoption decision - i.e. negative externalities, either through lower consumer value or increased aggregate risks - and will only invest if they are forced to do so.

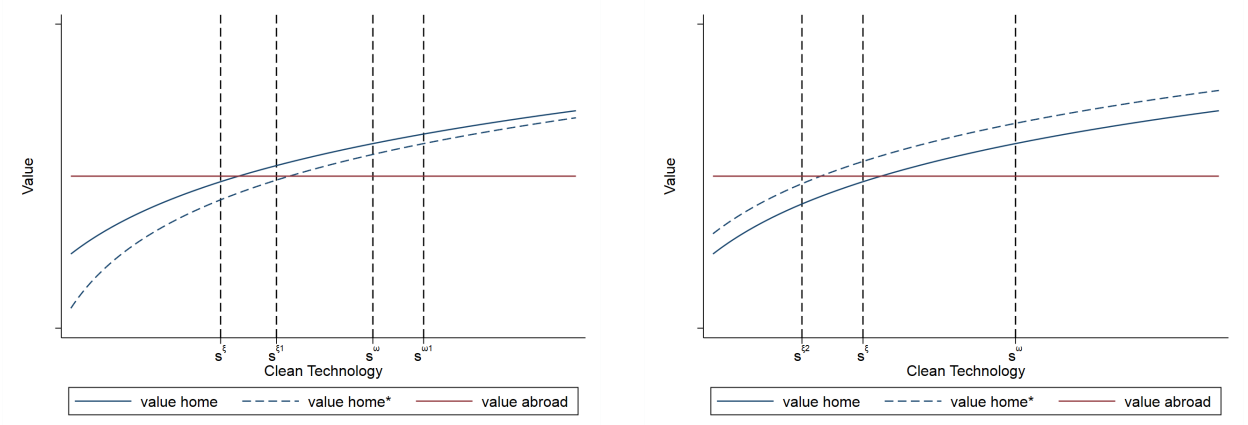
cannot endogenously affect the aggregate policies R_t. In this stylized setting, I further assume that the current levels of a_t are a sufficient condition in determining the discrete decision.

The profit values are normalized to the case where the firm chooses to do nothing ($d_t = 0$) and can be stated as follows:

$$\pi(a_{t+1}, z, d_t; R_{t+1}) = \begin{cases} \pi(a_t, z, 0; R_{t+1}) & \text{if } d_t = 0 \\ \pi(a_t \chi, z, 0; R_{t+1}) - k_{1,t} & \text{if } d_t = 1 \\ \pi(a_t, z, 0, 0) - k_2 & \text{if } d_t = 2 \end{cases} \tag{2}$$

Deciding to increase abatement levels ($d_t = 1$) yields a cost k_1 at the gain of $a_{t+1} = a_t \chi$ with a step-size increase $\chi > 1$. The DRS assumption of profit w.r.t. a_t makes that there is a cutoff for which $k_{1,t} = \pi(a_t \chi, z, 0; R_{t+1}) - \pi(a_t, z, 0; R_{t+1})$. Note that the cost of investment is time-dependent - intuitively a windmill with the same technology will become cheaper as time goes on. At the choice $d_t = 2$, the firm reaches a terminal state. The value function at this point states $V_t(|d_t = 2) \equiv V^f = \pi^f/(1-\beta)$.[9], where foreign profits π^f denote profits absent of any carbon policy (i,e. $\pi^f(a_t) \equiv \pi(a_t, z, 0, 0) = \pi^f$ for all levels of a_t).

Figure 2: Government policy tools



(a) Increase cost of carbon ζ

(b) Increase carbon subsidy κ

Graphical depiction of the policy tools employed by the home government for a firm with certain marginal cost $\bar{z}$. The red line shows the expected value of the home firm if it were to relocate abroad, independent of clean technology. The blue line gives the value of the firm in the presence of a carbon taxation $\pi(a_t, \bar{z}; R_t)$ and an increase in either $\zeta \to \zeta^*$ in Figure 2a or $\kappa \to \kappa^*$ in Figure 2b. The vertical line a^2 depicts the cutoff value at which firms become indifferent between investing and moving abroad. This line is k_2 away from the intersection of π^f and π. The thresholds line a^1 shows the moment at which firms are indifferent between abatement or not. All firms that are on the left of the thresholds a^2 move abroad. Firms between the two threshold values ($a^2 \leq a \leq a^1$) adopt a new level of clean technology. An increase in taxation ζ in Figure 2a shifts the value of the firm from $\pi \to \pi^*$ in (dashed line) and subsequently pushes the decision thresholds to the right: $a^2, a^1 \to a^{2,1}, a^{1,1}$. Increasing the fixed subsidy κ only affects $a^2 \to a^{2,2}$ in Figure 2a

[9] This infinite profit property ($V^f = \pi^f/(1-\beta)$) only holds when firms are in partial equilibrium. In the estimated model in Section 4, firms in the foreign country will be affected by the aggregate market price through the relocation decision and the trade channel.

The effect of an increase in ζ_t can be summarized as follows: $\partial \pi_t / \partial \zeta_t < 0$ and $\partial^2 \pi_t / \partial^2 \zeta_t > 0$ as shown in Figure 2a. Adjusting the value of ζ_t would raise the threshold at which firms become indifferent between adopting clean technology or not (from a^1 to $a^{1,1}$). However, such an increase in ζ_t would also mean that the threshold for firms to exit the domestic market and move towards a pollution heaven increases as well (from a^2 to $a^{2,1}$).

To combat carbon leakage, the government can increase the number of freely allocated certificates (Figure 2b) where $\partial \pi / \partial \kappa < 0$ and $\partial^2 \pi / \partial^2 \kappa = 0$. Since it does not affect the marginal value of the firm, it does not influence the adoption decision of the firm directly. It does, however affect the decision to move abroad (from a^1 to $a^{1,2}$). The optimal carbon policy to ensure that firms do not relocate abroad involves setting the emissions cap such that the value of clean technology of the firm, a, lies within two threshold values, $a^1 \leq a \leq a^2$.

2.2.1 Considerations and optimal policy

The framework generates a convergence in the distribution of emissions, where the most polluting firms exit the market or, conditional on not exiting would invest in clean technology. Other sources of heterogeneity z that solely affects the marginal cost of the firm. More productive firms can better absorb sunk costs, making it easier for them to invest and reduce emissions, potentially pushing less productive firms out. As a result, where a catch-up mechanism is visible in level of abatement, there could be a divergent pattern in size measures like value added, since larger firms find it easier to adopt new clean technologies.

Finally, the mechanism gives rise to the computation of an optimal policy. As firms upgrade to cleaner technologies over time, their risk of market exit falls, allowing the government to gradually tighten the emissions cap or raise carbon prices. Optimal unilateral emissions policy starts with a low carbon price (a lenient cap) and then gradually increases, thus progressively encouraging technology adoption while not overextending the price and causing firms to leave - maintaining production at home. While the degree to which this holds in the context of heterogeneous forward-looking firms has to be computed numerically, Appendix A provides stylized mathematical solutions for a unique case when the discount factor $\beta = 0$.

3. Data and reduced form evidence

3.1 Data gathering and sources

The analysis makes use of the European Union Transaction Log (EUTL) as its primary data source, encompassing annual emissions data for each installation owned by firms participating in the ETS from 2005 to 2022. This dataset is then combined with firm-level financial information from the ORBIS database, maintained by Bureau Van Dijk. In doing so, I account for the considerations posed by Kalemli-Ozcan et al. (2015).

The integration of these two datasets follows the matching procedure detailed in Letout (2022), and I

manually correct. The analysis is limited to the manufacturing sector only to ensure comparability between firms. As firms outside the manufacturing sector are structurally different, comparing them could lead to biased results.[10] Prices are deflated at the sector-country level using EUROSTAT data.

Throughout this analysis, several additional data sources are touched upon, such as the expected price of carbon certificates, oil and gas prices, and aggregate trade statistics. Data concerning the price of carbon certificates are obtained from THOMPSON REUTERS. Trade data from WIOD tables are used for aggregate statistics. A more elaborate explanation on the data gathering process and the sources used can be found in Appendix B.

3.2 Reduced form evidence

The aggregate results in Figure 1b in Section 1 and subsequently Appendix C point towards large, polluting firms which are responsible for the decrease in emissions.[11] To assess whether the observed effects align with the mechanism explained in Section 2 rather than a shift-share dynamic where greener firms have become larger, I employ a local projections approach to track the emissions trajectory of ex-ante polluting incumbents. The analysis reveals that the most polluting firms reduce their emissions more significantly on average, while changes in their value added align closely with Gibrat's law. The latter demonstrates that relocation towards small green firm has therefore been limited. Second, one could think of green entrants as representing an extreme case of potential shift-share evolution. I find that they tend to be smaller and less impactful overall, yet display higher emission intensity. Notably, their emission intensity does not converge to lower levels over time relative to incumbents, which weakens the argument for a green-driven compositional effect.

Finally, to address the possibility of relocation effects beyond the covered ETS firms, towards the non-covered manufacturing sector, I compare aggregate value-added growth between the ETS-covered firms and broader manufacturing firms using EUROSTAT data. The results indicate that ETS firms have experienced faster growth, suggesting that large-scale relocation into the non-ETS sector is unlikely to be driving the observed dynamics. All the results can be found in more detail in Appendix C. Note that these findings are not conclusive but rather serve as suggestive evidence to inform the development of a structural analytical framework.

The model captures the transition dynamics from an initial state in which the external costs of carbon emissions are not structurally internalized (i.e., no Pigouvian tax is in place) to a future state where net-zero emissions have been achieved (Golosov et al., 2014). It is used to estimate the trajectory of the economy along this path toward a zero-carbon future and to infer counterfactual analyses that explore how different

[10] For instance, the full list of firms that abide to the carbon policies contains electric and waste management companies among others, these are firms that do not trade abroad and have no risk of relocating. They are considered different for the government as well and have received less carbon certificates. The aforementioned mechanism is therefore not applicable for these firms.

[11] Figure 1b only shows the results for the cross-sectional distribution of the standard deviation emission intensity relative to value added as a measure of value added. Appendix C also shows the results for the evolution of skewness, Herfindahl index and market share as additional measures of inequality. They confirm the decrease in inequality for emission intensity and demonstrate a degree of stability for value added.

policy interventions could accelerate the transition.

4. Structural Estimation

The reduced-form analysis shows that the primary effects are driven by polluting incumbents. This raises the central question of the paper: to what extent can the observed decline in aggregate emissions be attributed to these firms, and how do policies shape this reduction? To answer this, I revisit the discrete choice model from Section 2 and embed it within a general equilibrium asymmetric two-country trade model, where firms are heterogeneous in both their level of clean technology and productivity. I first lay out the building blocks of the model, and then turn to the estimation, both outside the model and within its framework.

4.1 Model

The firms decision function is modeled within a firm dynamics model with heterogeneous firms that trade (Atkeson and Burstein, 2010). Firms operate across two countries $(\{h, f\}$, which are ex-ante symmetric in their firm distributions. Asymmetry arises solely through unilateral environmental policy differences implemented by the home country. The economy includes two sectors: a homogeneous goods sector that stabilizes aggregate costs, and a differentiated, polluting sector responsible for emissions. All equations are conditioned on the presence of the homogeneous sector.[12]

The model differs from the stylized model in Section 2 in 3 major ways. First, I add an additional state variable to govern productivity. It now has a fixed and variable component. This generates additional idiosyncratic firm-level uncertainty (Alessandria et al., 2021) and also proves to be a more flexible way to map to the data and more closely aligned with the data (Bartelsman et al., 2013; Sterk et al., 2021).

Secondly, the stylized model treats the clean technology investment as a purely discrete decision, I generalize this by introducing multiple discrete investment types, varying from minor to substantial (i.e., $\chi \in 1.05, 1.10, 1.20, 1.30$). For tractability, I maintain the discrete nature of the decision, allowing it to remain estimable within the context of a discrete choice model.

Finally, I explicitly model the general equilibrium conditions the firm is subject to within the ETS policy. More specifically, the firms are affected by the aggregate price and foreign trade on the output-side to generate an *indirect carbon-leakage* and on the input-side the carbon cap through the budget clearing.

I start by characterizing the function forms of the equations underlying the firms" idiosyncratic decision function. I then show the aggregate distributions and the market clearing conditions. Finally I outline the estimation strategy. All equations are described for the firms in the home country unless otherwise specified.

[12] In the EU, the polluting sector accounts for around 40% of emissions but only 12% of value added and 6% of employment, justifying the inclusion of a non-polluting sector.

4.1.1 Firms

Production Firms are heterogeneous in their productivity z_t, and their level of clean technology a_t. Productivity consists out of a fixed z^F and a transitory component z^T such that $z = z^F + z_t^T$ following Bartelsman et al. (2013) and Sterk et al. (2021) among others. The transitory component z_t^T follows an AR(1) process:

$$z_{t+1}^T = \rho z_t^T + \sigma_\xi \xi_{t+1} \tag{3}$$

Where σ_ξ denotes the standard deviation of idiosyncratic productivity shocks and $\xi \sim N(0,1)$ is an independent and identically distributed (i.i.d.) standard normal random variable. The parameter ρ denotes the persistence of the productivity process. The conditional distribution of z_{t+1}^T is independently distributed of the other state variables and denotes $G(z_{t+1}^T | z_t^T)$. Since the firms' profit maximization is static, I drop the time index t to increase readability.

The firms operate given a constant-returns-to-scale production function $q = zl$ with technology z and the only input labor l. As a byproduct, emissions are modeled as the production of an additional good proportional to output, $e = \frac{q}{a}$. Consequently, emissions can also seen as an input of production (Copeland and Taylor, 2004; Shapiro and Walker, 2018). The abatement factor stands orthogonal to the production factor. It could be restated as a Leontief production function where $q = \min[zl, ae]$ in the short term, where a acts as the share of e in the production function.[13] A major benefit of considering it orthogonal to productivity sits its interpretation where the taxation is a deviation from the steady state and the only way to return to the steady state at the firm level is for the abatement technology $a \to \infty$, considering it a backstop technology (Golosov et al., 2014). [14]

Preferences and demand Demand in the home country for the domestically produced goods is a downward sloping function of the charging price:

$$q_{hd} = p_{hd}^{-\eta} P_h^{\eta} Q_h \tag{4}$$

Where Q_h and P_h denote the composite aggregate demand for the home country and the associated price index respectively. The demand for the exported good depends on the aggregate foreign price $q_{hx} = p_{hx}^{-\eta} P_f^{\eta} Q_f$, with $p_{hx} = \tau p_{hd}$ with iceberg cost $\tau > 1$.

Profit maximization Demand in the home and foreign country are separable. Given the demand for each variety in the home country, combined with the production function and externality gives the domestic

[13] By adding emissions in the production function this way, I deviate from the literature that considers a Cobb-Douglas production function Copeland and Taylor (2004); Shapiro and Walker (2018). The dynamic nature of this model - implied by the sunk abatement decision - creates an implicit, dynamic, elasticity of substitution between the two factors of production.

[14] This way of writing would be also in line with the literature on the misallocation of resources (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008) where the cost of emissions can be seen as the firm-specific output lost relative to the optimal output.

profit function:

$$\pi_{hd} = p_{hd} q_{hd}(p_{hd}) - W l_{hd} - W \zeta e_{hd} \tag{5}$$

Given the demand for both input factors, the profit maximization w.r.t. price yields the following price setting:

$$p_{hd} = \frac{\eta}{\eta - 1} \frac{W c_h}{z} \tag{6}$$

With marginal cost $c_h \equiv (1 + z\zeta/a)$. Quick comparative statics indicate that as $a \to \infty$ then $c \to 1$. Intuitively, the policy has no direct effect for extremely clean firms. One can interpret this limit-case as the implementation of a firm-specific backstop technology (Golosov et al., 2014) where its individual emissions are zero. Likewise, the degree of misallocation in a pure economic sense is non-existent $(c = 1)$ when the price of carbon is zero $(\zeta \to 0)$. Firms do not internalize this externality outside of the Pegouvian tax.

Profits generated from exports π_{hx} are derived in a similar manner as the price of the exported equals $p_{hx} = \tau p_{hd}$. I do not include a fixed cost of exporting because firms in the EU ETS are typically large and active in internationally traded sectors, making them likely to export.

Total profits are $\pi_h = \pi_{hd} + \pi_{hx} + \kappa \tilde{z}$. Here κ represents the lump-sum subsidies provided by the home government to domestic firms to mitigate carbon leakage. These subsidies are allocated based on productivity shares $\tilde{z}$, resembling the grandfathering approach used by the EU for distributing emission certificates to larger firms (Martin et al., 2014).[15]

Firms in the foreign country have the same profit function π_f, absent of the two policies $(\kappa, \zeta = 0)$.

Dynamic investment and Bellman equation To better reflect realistic decision-making, I relax the discrete nature of the clean technology decision to one with various ranges of the size of the investment decision: $\chi = \{1.05, 1.10, 1.20, 1.30\}$. One can interpret this differential as ranging from incremental to disruptive. Formally, the cost of the investment decision:

$$k_1 = k_1^F d_t + k_1^C \chi^2 \tag{7}$$

where $k_1^F, k_1^C > 0$. The investment cost k_1 is unscaled and it is composed of a fixed cost of investing k_1^F and a convex adjustment cost k_1^C expressed as a function of the percent investment rate χ (Cooper and Haltiwanger, 2006). Intuitively, the first one governs the discrete decision and the latter governs the range of the investment decision.

Finally, the Bellman equation in Equation 1 remains the same with the exception that productivity z_t now becomes time-dependent through the inclusion of a transitory component z_t^T as in Hopenhayn (1992).

[15] In the data, the correlation between the log-values of the number of certificates and value added is approximately 0.43, while the correlation with the persistent component of productivity equals 0.37.

4.1.2 Aggregate distribution and Market clearing

Number and distribution of firms The measure of firms active in the economy is normalized and can be stated as the sum over the firms in the two countries $N_t = N_{h,t} + N_{f,t} = 1$. The number of firms active in the home country is $N_{h,t} = \int \mu_h(z_t, a_t) = 0.5$ and the foreign country $N_{f,t} = \int \mu_f(z_t, a_t)$. The distribution of firms in the home country exhibits the following motion:

$$\mu_h(z_{t+1}, a_{t+1}) = \int_{z*a} Pr(d_t|a_t, z_t, \Upsilon_t) F(a_{t+1}, z_{t+1}|z_t, a_t, d_t) d\mu_h(z, a_t) \tag{8}$$

where the transition operator $F(a_{t+1}, z_{t+1}|z_t, a_t, d_t)$ describes the transition law for the firms conditional on remaining at home. It encompasses both the endogenous effect of the discrete choice to d_t as well as the AR(1) motion of the transitory productivity component z^T. The probability function $Pr(d_t|a_t, z_t, \Upsilon_t)$ denotes the probability of each decision. Note that since the model is in a state of transition, the decision operator d_t depends on time t as does the number and the distribution of firms. If $d_t = 2$, the firm exits the home economy, consequently $N_{h,t} \leq N_{h,t=0}$ for all t.

The evolution of the distribution of firms in the foreign country is characterized by an influx of firms from the home country seeking to avoid the carbon policy:

$$\mu_f(z, a_{t+1}) = \mu_f(z_t, a_t) - \int_{z*a} Pr(d_t = 2|a_t, z_t, \Upsilon_t) F(a_{t+1}, z_{t+1}|z_t, a_t, d_t = 2) d\mu_h(z_t, a_t)] \tag{9}$$

The first part of the equation entails the current distribution of firms currently present in the foreign country. The second part includes the new firms that evade the home country($d_t = 2$) multiplied by the probability of relocating, $Pr(d_t = 2|a_t, z_t, \Upsilon_t)$, i.e. minus the number of domestic firms. Firms that relocate keep their current level of clean technology a_t and productivity z_t (Ramondo et al., 2015).

Output market clearing The clearing conditions in this model are twofold: the budget constraint of the home government and the clearing of the output market. Since these conditions are considered within a single period, the time index t is omitted for clarity and readability. Aggregate demand allocated to the differentiated good in both countries is stable and normalized to $I_h = Q_h P_h = 1$ and $I_f = Q_f P_f = 1$. The home demand satisfies:

$$Q_h = \left[\int_{z*a} q_{hd}(z, a)^{\frac{\eta-1}{\eta}} d\mu_h(z, a) + \int_{z*a} q_{fx}(z)^{\frac{\eta-1}{\eta}} d\mu_f(z, a) \right]^{\frac{\eta}{\eta-1}} \tag{10}$$

The associated price index for the home country can be summarized as:

$$P_h = \left[\int_{z*a} p_{hd}(z, a)^{1-\eta} d\mu_d(z, a) + \int_{z*a} p_{fx}(z)^{1-\eta} d\mu_f(z, a) \right]^{\frac{1}{1-\eta}} \tag{11}$$

The aggregate demand as the price index for the foreign market are set equally.

Government budget clearing Finally, the budget clearing of the home government entails:

$$\int_{z*a} \zeta e(z,a) d\mu_h(z,a) = \int_{z*a} \tilde{z}\kappa d\mu_h(z,a) \tag{12}$$

Where the left hand side denotes the government revenue through the taxation of the emission output. The right hand side reallocates this as lump sum to all home firms subsidy κ based on an allocation share determined by the ratio of the persistent productivity component of each firm ($\tilde{z} = (z^F)^\eta / \int_j (z_j^F)^\eta dj$). The budget condition determines the value of κ.

4.1.3 Green transition

The economy transitions from an initial steady state ($t = 0$), where firms do not internalize emissions, to a second state at time T, characterized by zero emissions across all firm types due to Pigouvian taxation and universal adoption of a backstop technology. The initial phase corresponds with Phase I of the ETS, which was used as a trial period with monitored but untaxed emissions (Cantillon and Slechten, 2023). This phase is used to estimate the trade cost $\tau = 1.44$ using the estimation procedure coined by Head and Ries (2001), and augmented by AntrÃ s and Chor (2018). The second phase results from a transition framework where technological progress makes clean technologies widely accessible. To encourage firms to adopt these technologies, the government sets a cap on aggregate emission output, thus increasing the firms marginal cost.

Technological progress In the baseline version of the model, the price of technology diminishes at an exogenous rate. I assume that the cost of the clean technology investment evolves at a constant rate γ_1. There is a sector that makes the cost of an investment cheaper over time:

$$k^x_{1,t} = \gamma_1 k^x_{1,t} \qquad s.t.\ \gamma_1 < 1 \qquad for\ \ x = \{Q, F\} \tag{13}$$

The progress rate covers both the convex (k_1^Q), as the fixed cost (k_1^F) of investment at the same rate. The only constraint in the estimation is the fact that the evolution of the technology parameter has to be lower than 1. Aside from being consistent with general economic progress (Calel and DechezleprÃªtre, 2016), it is a necessary requirement for the convergence towards a decarbonized economy in T years.

Carbon market One major difference between the a *Cap-and-trade* program relative to *direct taxation*, is that the government sets the cap and leaves it up to market forces to determine the price of carbon. Firms are price-takers in the input market for carbon certificates. The carbon price ζ_t is endogenously determined given the market clearing function of the exogenously set carbon cap E_t^S for each time t. The cap of carbon is set ex-ante (during phase I) and known to all firms. The optimal price of carbon at time t is determined

by:

$$\zeta_t^* = \arg\min_{\zeta_t} \left| E_{h,t}^S - E_{h,t}^D(\zeta_t) \right| \tag{14}$$

Where the aggregation of emissions follows: $E_{h,t}^D = \int_{z*a} e(z_t, a_t) d\mu(z,a)$. The price of carbon is set for the whole sequence $t = 1, 2, \ldots, T$. The idiosyncratic demand for carbon at time t depends on the price of carbon as well as the level of the state variables (z_t, a_t). This process also sets the supply of free carbon certificates κ through the government budget clearing.

4.2 Estimation strategy

The estimation procedure stacks the estimation of the state variables outside the model as well as the trade cost and the initial distribution, as well as their yearly idiosyncratic decisions. The model is then used to estimate the cost of each decision as well as the technological progress parameter of the investment decision. Finally, $\beta = 0.92$ and $\eta = 6$ are set a priori.

4.2.1 Outside the framework of the model

I begin by estimating firm-level productivity, which I decompose into persistent and transitory components. Subsequently, I construct a firm-level measure of clean technology adoption and characterize its joint non-parametric distribution with productivity. Given these state variables, I derive indicators for clean technology investment and multinational market exit. Finally, to validate the consistency of these indicators with the theoretical framework of the paper.

Firm Productivity To estimate firm productivity, I assume firms operate under a value-added production function that is Leontief in emissions $e_{i,t}$ and materials $m_{i,t}$: $q_{i,t} = min\{e^{z_{i,t}} f(k_{i,t}, l_{i,t}), m_{i,t}, a_{i,t} e_{i,t}\}$. The productivity term $z_{i,t}$ is estimated using the methodology outlined in Ackerberg et al. (2015). I divide output by a markup of 1.2 following Asker et al. (2014). Full details of the estimation procedure are provided in Appendix D. The structural model in the paper remains agnostic about the exact composition of inputs within $f(.)$. To maintain focus and tractability, I treat these as a single composite input: labor.

To decompose idiosyncratic productivity $z_{i,t}$ in a persistent z_i^F and a transitory component $z_{i,t}^T$. I set $z_{i,t} = z_i^F + z_{i,t}^T$ and consider the evolution of the transitory component: $z_{i,t}^T = \rho z_{i,t-1}^T + \xi_{i,t}$. The innovation to the transitory component is i.i.d. and behaves as $\xi_{it} \sim N(0, \sigma_\xi^2)$. Combining both expressions leads to the following equation:

$$z_{i,t} = \alpha_i + \rho z_{i,t-1} + \xi_{i,t} \tag{15}$$

where the persistence parameter $|\rho| < 1$ and α_i constitutes firm fixed effects. The fixed component can be backed out as $z_i^F = \alpha_i / (1 - \rho)$. Here, the distribution of the transitory component $z_{i,t}^T$ is parametrically identified - the estimation procedure does not require me to make an assumptions on the parametric distribution of the fixed component.

Clean technology The level of clean technology can be backed out through the Leontief assumption on the production function as well: $q_{i,t} = a_{i,t}e_{i,t}$. Akin to the literature on revenue

Quick correlations show that, indeed, more productive firms have higher levels of clean technology independent of the sector they are in (Copeland et al., 2022; Shapiro and Walker, 2018).

Investment decision ($d_t = 1$) The investment decision is not observed in the data, however, I do observe changes in clean technology $a_{i,t}$. Consequently, I can back out structural changes in this state variable $a_{i,t}$ as the adoption of new, improved technology . Since investment are often lumpy and infrequent (Cooper and Haltiwanger, 2006), I propose a method, inspired by Bessen et al. (2019), to back out this decision:

$$d_{1,t}(\chi) = \mathbb{1}\underbrace{\{\chi\tilde{a}_{i,t+1} \geq \tilde{a}_{i,t}\}}_{\text{Transitory state}}\underbrace{\left\{\chi\frac{1}{B}\sum_{b=1}^{B=2}\tilde{a}_{i,t+b} \geq \frac{1}{W+1}\sum_{w=0}^{W=2}\tilde{a}_{i,t-w}\right\}}_{\text{structural state}} \tag{16}$$

where $d_{1,t}(\chi)$ indicates the decision to invest for various cutoff-factors $\chi \in \{1.05, 1.10, 1.20\}$. The transitory state governs the lumpiness of the increase and the structural state the long-term implications. Following the literature (Cooper and Haltiwanger, 2006), I consider the decision to invest to occur one year prior to the actual outcome change.

To ensure this is truly a factor of investment, I conduct various comprehensive before speaking of this as an indicator of technology adoption. First, to truly check whether it is an indicator of investment I apply a falsification exercise where I test the comovement of capital and labor in an event-study design (Sun and Abraham, 2021), relative to that of a bootstrapped sample of firms that do not invest.

Second, to ensure that the firms that invest in technology are also those whose emissions are reduced more as discussed in the Section 3, I regress whether they invest at least once during a phase on their ex-ante characteristics. Third, to ensure that the ETS is at least partially pushing these firms to invest and it's not only driven by other factors such as oil prices, or shifts in aggregate demand, I regress the investment indicator on the price of carbon interacted by their level of clean technology to generate a novel firm-level impact of the price. Detailed regressions equations and Appendix D. All results point towards this being an investment decision - driven by the same subset of firms. They are also more common when the price is high.[16]

This outcome-based approach offers distinct advantages relative to using input-based approaches: it avoids the need to classify specific firm actions as abatement and sidesteps the difficulty of estimating the output additionality of such efforts. This aligns with the EU ETS, allowing firms autonomy in choosing how to achieve reductions in emission intensity. Additionally, this way it fits directly within the model.

[16]The results for phase III are all statistically significant. The results for phase II are suggestive but not all of this is statistically significant. I attribute the lack of statistical significance to both the financial crises and subsequent debt crises in the European Union at this time as well as the fact that phase II was on average less stringent that phase III.

Firm relocation decision ($d_t = 2$) A second decision the firm can take is the decision to exit the economy and relocate abroad. I consider only firms that are a subsidiary of multinational firms to be able to afford the sunk cost associated with this decision.[17]

To examine whether more polluting firms are more likely to exit, I estimate the relationship between the firms decision to exit during a phase of the ETS on their ex-ante characteristics. An important caveat relates to the allocation of free emissions certificates (κ), which may distort this relationship. An ample supply of κ can reduce exit incentives, irrespective of their level of clean technology. Furthermore, if κ is allocated to likely exiters, not controlling for κ might distort the link between clean technology adoption and exit behavior. Additionally, the position of productivity is ambiguous in this relationship. Productive firms might be better positioned to adopt improved clean technology and will therefore not exit, but firms do have to pay the sunk cost to exit. Empirically, this relationship is highly nonlinear. Controlling for size and the allocation of certificates, there is indeed a negative statistical significant between clean technology and the decision to exit.

Foreign trade To measure the cross-border trade costs τ_{gj} I use the Head and Ries (2001) index, extended by AntrÃ s and Chor (2018) to the industry level. The index uses the observed values of bilateral trade flows relative to the domestic absorption to infer the cross-border costs. I compute the following:

$$\tau_t = \left(\frac{X_{gjt} X_{jgt}}{X_{ggt} X_{jjt}} \right)^{-\frac{1}{2\gamma}} \tag{17}$$

with time index $2007 \geq t > 2005$. The variables X_{gg} and X_{jj} denote the domestic absorption and $\gamma > 1$ is the trade elasticity with respect to the iceberg trade cost. In this setting, I follow AntrÃ s and Chor (2018) and adopt a value of $\gamma = 5$. Note that this implies that international trade costs are equal to 1 and that trade costs are symmetric *i.e.*$\tau_{gj} = \tau_{jg} = \tau$. The time index is capped to be between 2005 and 2007 in order not to get deluded with the taxation from the home government t and s. I assume that the distribution of productivity is orthogonal to the country and all variation in the output by country is captured through differences in marginal cost. This also means that $\tau_{gj} > 1$ for $g \neq j$.

4.2.2 Within the model

I initiate the estimation strategy by revising the discrete choice function Equation 1 in Section 2 as a function of the idiosyncratic agents. The payoff of agents in period t depends on their observed state variables a_t and z_t, the exogenous aggregate economic conditions Υ_t, and an agent-specific variable $\varepsilon(d_t)$, not observed by the econometrician. The general equilibrium version of the ex ante value function from Equation 1 can be

[17] Firm exit is relatively infrequent in the dataset, which is consistent with the empirical finding that larger firms have a significantly lower probability of exit (Sterk et al., 2021). Although exit rates are higher among non-multinational firms, their overall contribution to aggregate output and emissions is comparatively minor. Accordingly, in the baseline version of the model, I do not distinguish between types of exits and exclude non-multinational firms from the analysis. Appendix D proved the comparative analysis between multinationals

written as $V_t(a_t, z_t; \Upsilon_t)$, where Υ_t is a vector that encapsulates government policies R_t and the general equilibrium price indices. This value function can then be expressed as an average over all potential unobserved values ε_t.

$$V_t(a_t, z; \Upsilon_t) \equiv \int \tilde{V}_t(a_t, z, \varepsilon_t; \Upsilon_t) g(\varepsilon_t) d\varepsilon_t \tag{18}$$

While the econometric framework is based on the infinite horizon contraction mapping in Rust (1987), It deviates from their framework as instead of a stationary setting, I examine a non-stationary transition version of the model. Consequently, rather than relying on a contraction mapping framework, the solution method is based on backward induction.

The horizon of the dynamic model is infinite and non-stationary. Since the parameter of technological progress $\gamma > 1$ ensures that the model transitions towards a balanced growth environment where none of the firms finds it optimal to deviate as they all have a level of $a \to \infty$. In practice, I follow Acemoglu et al. (2016) and consider that full decarbonization is reached in at least 1000 years from now.[18] Consequently, the optimal decision at time $T \leq 1000$ will be not to deviate from the current situation:

$$\arg\max_{d_T} [v_T(z_T, a_T, d_T; \Upsilon_T) + \varepsilon_T] = 0 \qquad \forall z_T, a_T \tag{19}$$

From T, backwards recursion will be applied to solve the model. The ex ante value at time $T-1$ is a function of all potential probabilities as well as the error term ε_T. The latter I assume to be additively separable. The distribution of the error term $g(\varepsilon)$ is assumed to be a general extreme value distribution in order to obtain closed form solutions.

$$V_{T-1}(z_{T-1}, a_{T-1}; \Upsilon_{T-1}) = \int \sum_{d_{T-1}} [v_T(z_{T-1}, a_{T-1}, d_{T-1}; \Upsilon_{T-1}) + \varepsilon_T] g(\varepsilon_{T-1}) d\varepsilon_{T-1} \tag{20}$$

I estimate the model over the full state space due to the need of also including the aggregate equilibrium effects by which the firm let their decisions depend on. The probability of an an arbitrary choice d_t given the conditional value function v_t yields:

$$Pr_t(d_t | a_t, z_t, \Upsilon_t) = \frac{exp(v_t(a_t, z_t, d_t; \Upsilon_t))}{\sum_{d_{jt}} exp(v_t(a_t, z_t, d_{jt}; \Upsilon_t))} \tag{21}$$

where j governs the 4 discrete choices - do nothing, invest and relocate. The probability of all options j yields $\sum_{d_{j,t}} p_t(d_{j,t} | a_t, z, \Upsilon_t) = 1$ and $Pr_t(d_{j,t} | a_t, z, \Upsilon_t) \geq 0 \; \forall \; j$. Forming these probabilities for each individual i at each time period t yields the components necessary to set up a likelihood function to obtain the parameter vector $\hat{\theta} = \{k^F_{1,0}, k^C_{1,0}, k_2, \gamma_1\}$ which is a function of the four unknown variables: the cost of both choices and the evolution of the cost investment cost $k_{1,t}$.

While backwards recursion is done until time T is reached, the data is only available until the year 2018

[18] After 1000 years, the cost of investment is $k_{1,1000} = \gamma_1^{1000} k_{1,1} \approx 0$. The actual time it takes to reach full de-carbonization depends on the specification and the exact parameter values in the model. Foreign firms do not have an incentive to invest thus their emission production will not be affected outside of shifts in output through the general equilibrium conditions.

- stated as 10 years from the steady state in phase I when phase II starts (2008, where $t = 0$). With N_h firms, the estimated parameters are obtained by:

$$L(\theta) = \sum_{t=1}^{10} \sum_{i=1}^{N_h} ln[Pr_t(d_{i,t}|a_{i,t}, z_{i,t}, \Upsilon_t, \theta)] + ln[F(a_{i,t+1}, z_{i,t+1}|a_{i,t}, z_{i,t}, \Upsilon_t)] \tag{22}$$

where $F(a_{i,t+1}, z_{i,t+1}|a_{i,t}, z_{i,t}, \Upsilon_t)$ is the transition operator associated with the probabilities of the discrete choices. Note that these are the same as those in the aggregate distribution evolution. From here one can obtain the estimates $\hat{\theta}$ that minimize the likelihood function.

5. Results

5.1 Estimation Results

This section first documents that the model can generate satisfying outcomes that resemble those observed in the data, where the regression results are compared in Section 3 with those from the model. Next, I delve deeper in the firm heterogeneity and explore the unequal product of the carbon taxation on firm-level outcomes. I then explore the impact of each decisions on aggregate emissions and output. Finally, I conduct various robustness tests to evaluate the validity of the results.

Table 1: Parameter estimates

Variable:		Value:	s.e.:
Fixed abatement adoption cost	k_1^F	3.2399	(0.0547)
Convex Abatement adoption cost	k_1^O	1.72	(0.1243)
Relocation cost	k_2	17.992	(0.3131)
Evolution abatement cost	γ_1	0.993	(0.0033)

The table presents the estimated results for the parameters in the log likelihood function in Equation 22. Standard errors are documented in parenthesis in the second column.

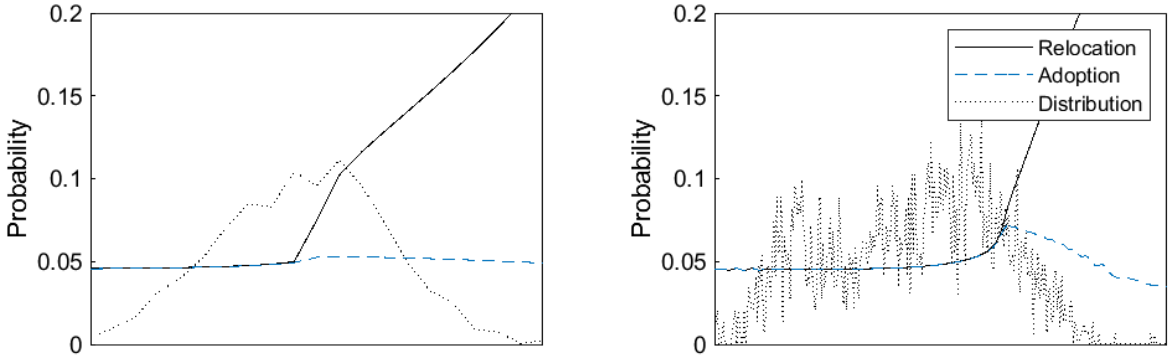
The parameter estimates are given in Table 1. The cost of relocation is approximately six times more expensive than the adoption of an abatement technology of 20%. An evolution parameter of $\gamma_1 < 1$ indicates that investment costs decrease over time. However, since γ_1 is only slightly below one, the decrease in costs is minimal.

5.2 Baseline results

5.2.1 Firm Inequality

Probabilities - invest exit The model provides outcomes that highlight the role of large polluting firms in reducing aggregate emissions. Figure 3 shows the average annual probability of adopting new clean technology or relocate abroad along the productivity and the clean technology dimension for firms operating in the home country (note that the decision to do nothing is one minus the other). The figure demonstrates that the probability of engaging in either decision is increasing in both margins.

Figure 3: Decision probability by dimension



(a) Productivity margin

(b) Clean technology margin

Note: Figure 3a shows the unweighted annual average probability of adoption and relocation (given cumulatively) along the productivity dimension for the years 2008 to 2019. The probability density for the productivity margin is shown in dotted lines. Figure 3b documents the annual average unweighted probability for either decision along the clean technology dimension for the years 2008 to 2019. The underlying non-parametric clean technology distribution is given by the dotted line.

Emission decomposition The individual emission output can be decomposed into two channels conditional on the firm remaining active in the home country. There is the direct channel where carbon taxation reduces output, and the indirect abatement adoption channel. The evolution of emissions is a function of the current emissions minus the counterfactual 'optimal' emission output if the taxation would have been zero: $\Delta e(a_t, z_{t+1}) = e_{t+1}(a_{t+1}, z_{t+1}) - e^*_{t+1}(a_t, z_{t+1})$. Decomposing the individual growth of emissions further leads to two specific components:

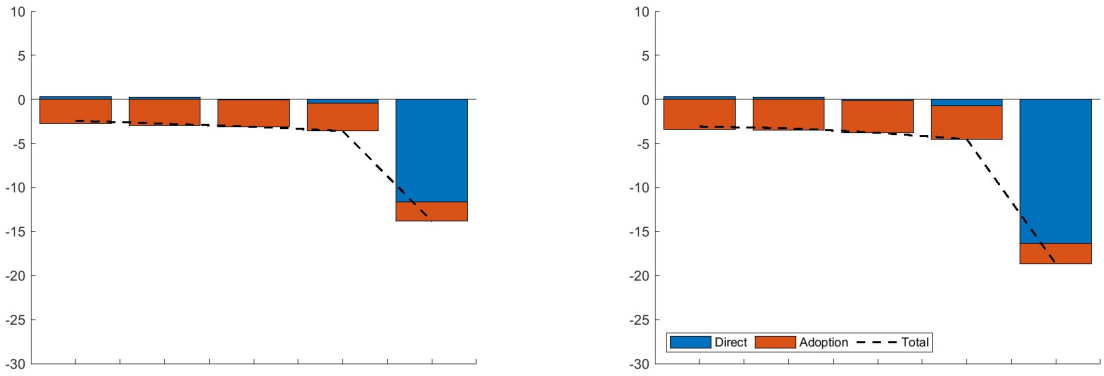
$$\Delta e(a_t, z_{t+1}) = \underbrace{[e_{t+1}(a_{t+1}, z_{t+1}) - e_{t+1}(a_t, z_{t+1})]}_{\text{adoption}} + \underbrace{[e_{t+1}(a_t, z_{t+1}) - e^*_{t+1}(a_t, z_{t+1})]}_{\text{direct effect}} \tag{23}$$

Where a_{t+1} denotes the potential future level of abatement technology. The first component captures

the effect of an investment relative to not doing so, while the second term captures the effect of the taxation relative to what would happen if the firm did not invest. If the firm does not invest, the first component cancels out and only the direct effect remains.[19] The evolution of the total price index is captured in the direct effect.

Figure 4 shows the heterogeneous decomposition of the reduction in aggregate emissions for the less polluting (Figure 4a) and polluting firms (Figure 4b) for the period 2008- 2018, decomposed into 5 evenly spaced quintiles. It is clear in both graphs that the main reduction in emissions is driven by more productive firms for whom the direct effect prevails. In addition, the reduction is also larger for the more polluting firms.

Figure 4: Reduction in CO2 emission output



(a) Low emission intensity firms

(b) High emission intensity firms

Note:Figure 4a shows the changes in emission output for 5 quintiles of productivity for firms which are below median emission intensity, for the period from 2008 to 2018. The more right on the x-axis the higher average productivity of the quintile. The decomposition is conducted given Equation 23. The blue part of the bar shows the implication of the direct effect of the taxation while in red, the effect of the investment is given. The dashed line shows the total reduction. Figure 4b shows the same decomposition but for the emission-intense firms.

Figure 4 shows the heterogeneous decomposition of the reduction in aggregate emissions for the less polluting (Figure 4a) and polluting firms (Figure 4b) for the period 2008- 2018, decomposed into 5 evenly spaced quintiles. It is clear in both graphs that the main reduction in emissions is driven by more productive firms for whom the direct effect prevails. In addition, the reduction is also larger for the more polluting firms.

[19]Due to the CES assumption for the individual demand, conditional on their level of clean technology, all firms of different productivity levels reduce their emissions at a constant rate (i.e. the degree to which firms reduce their emissions is equal across firms). Only because of the increased investment rate for more polluting firms, these firms reduce their emissions more.

While the results highlight that inequality in the size dimension is indeed increasing, this does not signify any implications on welfare due to CES structure of demand which yields an efficient market, conditional on the firms remaining in the market. Stepping away from CES to any non-homethetic demand system makes inequality inefficient and therefore causes any welfare loss. **This will be a robustness test but is still under construction**

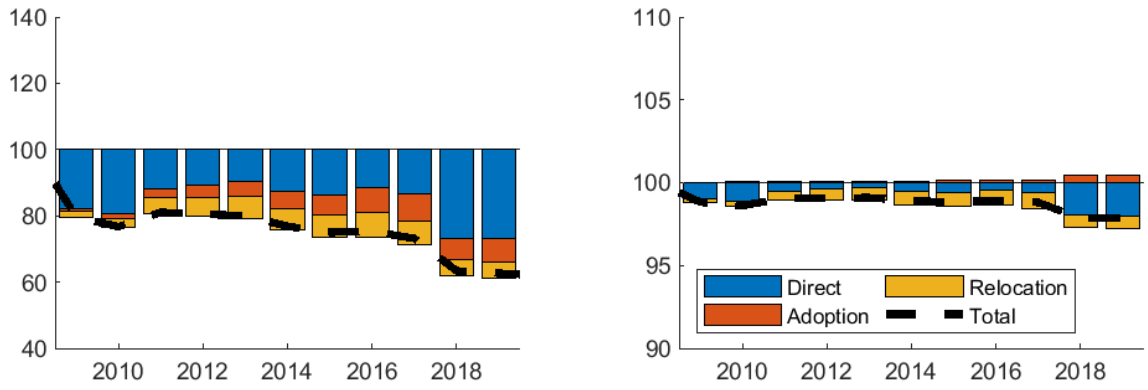
5.2.2 Aggregate outcomes

To see to what extent the decision on the adoption of abatement can explain the aggregate evolution of domestic emissions, I decompose its evolution into a direct effect - where decisions are zero - and an indirect effect which can be further decomposed up to a first order approximation into an investment and relocation decision (Equation 23). The direct margin yields the effect of the carbon policies ζ_t, absent of all idiosyncratic decisions. The two other components capture the contribution of their respective individual decisions d_t:

$$\begin{aligned} \Delta E_{h,t} &= E_{h,t} - E^*_{h,t} \\ \Delta E_{h,t} &= \underbrace{[E_{h,t}|_{d_t=0} - E^*_{h,t}]}_{\text{direct margin}} + \underbrace{[E_{h,t}|_{d_t=1} - E_{h,t}|_{d_t=0}]}_{\text{Investment}} + \underbrace{[E_{h,t}|_{d_t=2} - E_{h,t}|_{d_t=0}]}_{\text{Relocation}} \end{aligned} \tag{24}$$

where $E^*_{h,t}$ denotes the counterfactual domestic emissions, independent of any carbon policies. The partial derivative of all three margins is lower or equal to 0 (as discussed **??**). The decomposition of aggregate output $\Delta Q_{h,t}$ is equal, yet in this case, the contribution of the investment decision will be positive rather than negative.[20]

Figure 5: Decomposition aggregate variables



(a) Aggregate domestic Emissions

(b) Aggregate domestic Output

Note: Figure 5a documents the evolution of the total domestic emissions $E_{h,t}$ from 2008 to 2019. They are normalized w.r.t. the optimal scenario (i.e. those where there are no policies set by the government). To a first-order approximation of the aggregate price index, the relative deviation from the optimal scenario can be decomposed into a 'direct' effect, denoting the output reduction effect, and a 'relocation' and 'adoption' effect that highlight the aggregate impact of the idiosyncratic decisions up to a first-order approximation. Note that the total effect in dashed lines does not suffer from this approximation. Figure 5b shows the evolution of aggregate domestically produced output $\int (q_{hx} + q_{hd}) d\mu_h$ as a deviation from the optimal output where there was no taxation. The decomposition is done similarly to the aggregate emission variable.

[20] One could read the differences in aggregate outcome as the de degree of misallocation present in the economy. As denoted earlier, this is solely a function of the carbon price ζ and the average abatement a_t. Since the average level of a_t is increasing, the degree to which misallocation harms the economy is decreasing as well ($\Delta Q_{h,t} = Q_{h,t} - Q^*_{h,t}$). The extent to which this difference between output remains even after all domestic firms have $a \to \infty$ depends on the rate of relocation towards the foreign country. The decomposition of aggregate outcomes will be discussed more extensively in the next section.

The decomposition results in Figure 5 indicate that aggregate emission intensity has reduced significantly already, relative to the situation in phase I of the economy. Most of this reduction is driven by the direct effect of the taxation - the reduced output due to an increase in marginal cost. The impact of the other 2 is not to be underestimated either. The direct effect is predominant in the output reduction as well (Figure 5b). The share of adoption becomes increasingly important as time goes on.

5.3 Counterfactual analysis

This model is highly suited for counterfactual analysis. Given the estimated parameters, I analyze the extent to which domestic measures, such as the free allocation of carbon certificates, and changes in trade policy, influence firm-level decisions and subsequently aggregate economic and environmental outcomes.

5.3.1 Government budget

First, a counterfactual analysis is set up to address the debate over whether the fixed free allocation of emissions has influenced the firms relocation decision or merely resulted in windfall profits (Martin et al., 2014). To explore this, I compare the baseline results with a scenario where the supply of free certificates is to zero ($\kappa = 0$) for all domestic firms. Thus government budget in Equation 12 does not clear. To allow for budget clearing again, I set up a second counterfactual model where the government now rebates their income as a static subsidy towards new clean technology adoption, modifying Equation 12 to:

$$s_{1,t} \int_{z*a} \int_{\chi} pr(d_{1,t}(\chi) = 1 | z_t, a_t) d\mu_h(z,a) = \zeta_t \int e(z_t, a_t) d\mu_h(z,a) \tag{25}$$

where $s_{1,t}$ denotes the subsidy for the investment good $k^F_{1,t}$, such that $k^F_{1,t} = k^{F*}_{1,t} - s_{1,t}$ where $k^{F*}_{1,t}$ is the fixed part of the sunk cost of adoption, determined in the baseline model. The subsidies are multiplied by the share of firms that will invest in clean technology.[21,22]

Table 2 depicts the result of two counterfactual domestic policy models relative to the baseline model. Setting the number of rebated certificates to zero would decrease the share of domestic firms with 1%, subsequently reducing the amount of revenue and emissions produced in the home country to 80.70% and 98,3% from counterfactual levels as if there had not been a carbon policy. Terminating the supply freely allocated certificates reduces the domestic emissions further, but at an aggregated cost in terms of domestic sales. Rebating the costs as subsidy to the investment good diminishes this reduction and increases the adoption rate with 5%.

[21] Only applying the fixed cost on the fixed component of the adoption decision makes that I do not differentiate between either type of adoption χ and each recieves equal subsidies.

[22] Note that this simplified subsidy schema is assumed to be static (i.e. the decreasing process of the cost ($k^{F*}_{1,t} = \gamma k^{F*}_{1,t-1}$) does not depend on the subsidy scheme.) and that the clean technology sellers behave in perfect competition and do not reap any of the benefits of the subsidy.

Table 2: Relative change for counterfactual policies from 2008 in 2019

	Baseline	**Domestic policy**				**Trade policy**			
		Nothing		*Rebatement* k_1		*CBAM*		τ^H	
			(%)		(%)		(%)		(%)
Domestic adoption rate	7.40	7.39	(99.7)	7.81	(105.3)	7.48	(100.3)	7.37	(99.5)
Foreign adoption rate						3.31			
Domestic firms (N_h)	99.73	99.60	(99.5)	99.69	(99.7)	100.00	(100.3)	99.80	(100.1)
Domestic emissions (E_h)	81.78	80.70	(98.6)	80.3	(98.4)	83.06	(102.4)	83.4	(102.8)
Domestic sales (I_h^S)	98.98	98.3	(99.1)	98.6	(99.98)	99.2	(100.6)	99.4	(101)
Share of imports	25.43	25.43	(100)	25.43	(100)	25.32	(99)	12.06	(47)

Aggregate implications of various counterfactual models relative the baseline model, following the transition from 2008 ($t = 0$) to 2018 ($t = 10$). The aggregate levels for the domestic number of firms N_h, emissions omitted E_h, and income generated I_h^S are normalized by $L_x = (x^{2018} - x^{2008})/x^{2008} * 100$. The adoption ratios ($Pr_h(d_t = 1)$ and $Pr_f(d_t = 1)$) and import ratio denote the average during the period: $100/T \sum_{t=0}^{T=10} x_t$. Percentages, denoted in brackets, for the counterfactual models are given as $(L_x^C - L_x^B)/L_x^B * 100$ where L_x^B denotes its respective level of the variable in the baseline model and L_x^C of the counterfactual model. The import ratio presents the ratio of goods imported from the foreign country in the total demand. The domestic policy counterfactual consist out of two versions, one where the supply of free carbon certificates is set to zero (column 1) and one where the governments rebates them as investment subsidy (column 2). The trade policy block examines the adoption of a pollution taxation for foreign firms akin to domestic firms during the period - a Carbon Border Adjustment Mechanism - and an increase in tariffs $\tau^H > \tau$, constant across all goods.

5.3.2 Trade channel

A second channel explored in more depth is the trade channel. To address potential leakage effects, at the beginning of 2024, EU has implemented a carbon border adjustment mechanism where imported foreign goods are subjected to the same carbon policy. The counterfactual model will examine what would have happened if the policy had been widespread and implemented at the beginning of the transition in 2008. This policy is then compared with a direct tariff increase of 20% ($\tau^H = 1.2\tau$). This tariff differential acts not only as more representative of the current economic situation, but is also considered a second-best policy to reduce emissions (Farrokhi and Lashkaripour, 2022).

The rationale for both trade policies within the scope of the model is the same: a decrease in competition from foreign firms alleviates the downward pressure on domestic prices, leaving more room for domestic firms to adopt new technologies, and reducing the threat of exit. In addition, a targeted policy, like CBAM, highlights the clean technology margin and provides foreign firms with a mechanism to invest.

To set up the counterfactual model and allow for investment in the foreign country, I assume that the investment cost for the adoption of green technology $k_{1,t}$ evolves identically in both countries. This makes the distribution of foreign firms more alike the evolution of the home distribution.

The last 2 columns of Table 2 show the results for the 2 counterfactual models relative to the baseline model. Implementing a CBAM during the period 2008 to 2018 would have reduced the share of companies moving abroad to essentially zero. This would in turn have led to an increased adoption rate and increased revenue share of the home country in the total budget. However, due to the decreased competition from foreign and increased number of firms, domestic emissions would have gone up. Finally, in more autarkic situations, a carbon policy of the same magnitude would have lesser effect in its reduction. Openness damages the sales of the domestic firms more, but it also leads them to reduce their emissions more rapidly.

6. Achieving fit-for-55

The preceding section examines the baseline scenario in which the carbon trajectory is set by the European Union and develops counterfactual analysis accordingly. This section seeks to challenge this trajectory and develop an optimal transition policy framework to achieve the objectives of the Fit for 55 initiative, while minimizing the loss in aggregate domestic output. Given the potential trade-off whereby elevated carbon prices may result in firm exits, it is of great importance to ensure the retention of as many firms as possible for domestic production.

- **THE RESULTS ARE STILL UNDER CONSTRUCTION**

6.1 Optimal policy

The evolution of the cap is exogenously determined and known by all agents. It evolves depending on the initial stock of emissions E^S_{h,t_0} and a discount function $\theta(t)$:

$$E^S_{h,t} = \theta(t) E^S_{h,t_0} \tag{26}$$

where the discount function is specified as a second-order polynomial, $\theta(t) = b_1 t^2 + b_2 t + b_3$. Here the constant term is fixed at $b_3 = 1$. Since at $t = 0$ and $t = 22$ the values are known, the system can be expressed in terms of a single unknown parameter, b_1. The specification depends solely on the time variable t and the single free parameter b_1. This formulation enables the function to exhibit both concave ($b_1 > 0$) and convex ($b_1 < 0$) trajectories for the carbon reduction path, aimed at reaching a targeted level of emissions of 55% of the 2008 levels at t_{22}. To determine an optimal carbon policy, the parameters b_1 and the derived parameter $b_2(b_1)$ are solved simultaneously. The cap is constrained to be strictly decreasing over time, i.e. $\partial\theta(t)/\partial t < 0$ for all $t \in 0, \ldots, 22$.

The home government aims to minimize a sequence of aggregate home emissions $\{E^h_t\}^{t_{25}}_{t_0}$ conditional on the loss of demanded output for the period 2005 to 2030. It uses a higher discount factor $\beta_G = 0.98\%$ than the firms to discount future deviations from the optimal output given commonly assumed in Integrated assessment models (Golosov et al., 2014). The optimization procedure can be determined by:

$$\min_{\{E^S_{h,t}\}_{t_0}^{t_{22}}} \sum_t \beta_G^t \left\{ \left[Q^*_{h,t} - Q_{h,t}(E^S_{h,t}) \right]^2 \right\} \qquad s.t.$$

$$\begin{aligned} E^S_{h,t} &= \theta(t) E^S_{h,t_0} \\ E^S_{h,T_{22}} &= 0.55 E_{h,t_0} \\ \theta(t) &= b_1 t^2 + b_2 t + b_3, \quad for\ t \leq t_{22} \\ \partial\theta(t)/\partial(t) &< 0, \quad for\ t \leq t_{22} \\ E^S_{h,t} &= (1 - 0.044) E^S_{h,t-1} \quad for\ t > t_{22} \end{aligned} \tag{27}$$

where Equation 27, determines the optimal value of b_1 for which the deviation from the optimal aggregated domestic demanded output is smallest.

6.1.1 Results

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6.2 Carbon damages

Finally, I compute the optimal reduction in CO2 from a unilateral welfare point of view where optimal demand is subjected to the a damage function. So far, the paper has abstracted from utilizing a damage function in the model. The intuition being that the agents in this economy did not internalize the implications of carbon damages in their idiosyncratic demand, an assumption that as time progresses further, seems to become less and less likely following the literature on green technology investment and awareness of climate damages (Costa et al., 2024).

Consequently, I extend the model by adding a damage function in the presence of a non-exhaustible carbon-generating resource, following Golosov et al. (2014), Uzawa (2003), among others. The damage function enters linearly in the aggregate demand.[23] Total spendable income at time t equals:

$$I_{h,t} = exp\left(-\xi \frac{S_t - \bar{S}}{\bar{S}} \right) I^*_{h,t} \tag{28}$$

Where actual income spend ($I_{h,t}$) is a function of the total income $I^*_{h,t}$, multiplied with a damage function. This function depends on a damage parameter ξ, the atmospheric concentration of carbon at time t S_t and $\bar{S}$ is its preindustrial stock. The values are normalized w.r.t. the preindustrial concentration of carbon. In the baseline model earlier without damages, actual and total income would coincide ($I_{h,t} = I^*_{h,t} = 1$). Income in the foreign country gets affected the same way with a damage function of equal size.

Due to the demand function and the linear damage function, all firms will be affected the same way. The design of this section is not to give new insights in the heterogeneity of firms and their relation to carbon

[23] I assume that the damage affects the non-polluting homogeneous sector as much as the polluting heterogeneous one such that the share of income spent to each sector remains constant. The assumption of non-exhaustible resources can be interpreted as the abundance of coal (Golosov et al., 2014)

damages, but only to define the optimal path of carbon taxes in relation to the literature on the social cost of carbon and to examine how the idiosyncratic decisions generate different outcomes. The stock of atmospheric emissions is linear and depends on the year emissions omitted and a depreciation factor:

$$S_t - \bar{S} = \sum_{t}^{s} [\varphi_L + (1-\varphi_L)\varphi_0(\varphi)^s] E_{t-s} \tag{29}$$

where the depreciation structure and its parameter values come directly from Golosov et al. (2014). I differentiate from them in the time dimension with $t = 1$. $\varphi_L = 0.2$ defines the share of emissions which will remain in the atmosphere forever. A share $(1-\varphi_0) = 0.607$ exits the atmosphere immediately. A remainder decays at a geometric rate $\varphi = 0.9976$. The yearly total of omitted carbon emissions are $E_t = E_{h,t} + E_{f,t}$. I set the damage parameter ξ such that $\xi \bar{S} = 2.379 * 10^{-5}$. The initial stock of emissions and the preindustrial stock are $S_0 = 802$ and $\bar{S} = 581$, respectively.

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7. Conclusion

This study presents a comprehensive examination of carbon taxation on the firms decisions to invest in clean technology and its influence on aggregate technical change. The paper finds that more productive and polluting firms demonstrate a greater inclination to invest in clean technology when anticipating a high carbon price. This highlights the effectiveness of carbon taxation as a tool for reducing climate emissions. Albeit the policy yields substantial heterogeneous effects as only large firms are capable of investing in clean technology, the shift in aggregate clean technology is mostly driven by large firms becoming greener and capturing an increased market share, while smaller firms are left behind. This research cannot differentiate between changes in input composition and changes in a firm's capacity to produce cleaner goods in their investment decision. Subsequent research could distinguish between the two to ascertain whether it represents the true capacity enhancement or merely a shift towards cleaner inputs.

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A. Analytical Results

A.1 A 2-period without forward looking agents

Suppose there are 2 periods and the discount factor is infinitely small. Recall $\partial\pi\ \partial a > 0$ and $\partial\pi/\partial e < 0$ Suppose the government has set a determined trajectory for the aggregate cap $\bar{e} = \{\bar{e}_1, \bar{e}_2\}$. This trajectory is known to the firm.

The cap $\bar{e}$ is set exogenously and the firm has the option to endogenously change $a \in \{a_0, a_1, a_2\}$ by investing 0 times, 1 time or twice. As in the text, the investment is sunk with costs k and has a determined increase of $\chi > 1$ with $a' = \chi a$. The relocation decision is given as a constant π^f, independent of a.

Each period $t \in \{1,2\}$; the firm can choose between three decisions,doing nothing, invest, or relocating abroad $d^* = \{d_1, d_2, d_3\}$. The profits are normalized relative to the profit of doing nothing. Conditional on the firm remaining in the market at time $t = 1$, the payoffs between year 1 and year 2 are the following:

A.2 A 2-period without forward looking agents

A.2.1 Static setting

Let there be 1 firm. producing a good q given 1 input labor l. Additionally, they produce emissions $e = l/a^\alpha$. They set the price as a markup over marginal cost and have a downwards sloping demand curve $q = p^{-\eta}$. η signifies the elasticity of demand and α generates the increasing concave relation between profits and clean technology as in the text.

$$q = l = a^\alpha e, \qquad p = \frac{\eta}{\eta-1}\left(\frac{t}{a^\alpha}\right), \qquad q(p) = \left(\frac{\eta}{\eta-1}\right)^{-\eta}\left(\frac{t}{a^\alpha}\right)^{-\eta}, \qquad e = \frac{l}{a^\alpha} = \left(\frac{\eta}{\eta-1}\right)^{-\eta} t^{-\eta} a^{\alpha(\eta-1)} \tag{A.1}$$

Let the government set a cap $\bar{e}$ on emissions omitted by the representative producer. The optimal carbon price t given the cap $\bar{e}$ equals:

$$\begin{aligned} \bar{e} &= \left(\frac{\eta}{\eta-1}\right)^{-\eta} t^{-\eta} a^{\alpha(\eta-1)} \\ t &= \left[e^{-1}\left(\frac{\eta}{\eta-1}\right)^{-\eta} a^{\alpha(\eta-1)}\right]^{\frac{1}{\eta}} \\ t^* &= \bar{e}^{\frac{-1}{\eta}} \frac{\eta-1}{\eta} a^{\alpha\frac{\eta-1}{\eta}} \end{aligned} \tag{A.2}$$

Writing the price and quantity of the produced good as a function of the cap $\bar{e}$:

$$p = \bar{e}^{\frac{-1}{\eta}} a^{\frac{-\alpha}{\eta}}, \qquad q = a^\alpha \bar{e} \tag{A.3}$$

profits can be similarly written as:

$$\begin{aligned}\pi &= pq - te = p^{1-\eta} - t\frac{p^{-\eta}}{a^{\alpha}} \\ \pi &= \frac{(\eta-1)^{\eta-1}}{\eta^{\eta}}(t)^{1-\eta}a^{\alpha(\eta-1)} \\ \pi &= \frac{1}{\eta}\bar{e}^{\frac{\eta-1}{\eta}}a^{\alpha\frac{\eta-1}{\eta}}\end{aligned} \tag{A.4}$$

A.2.2 Dynamic setting

Suppose the government has set a determined trajectory for the aggregate cap $\bar{e} = \{\bar{e}_1, \bar{e}_2\}$. This trajectory is known to the firm.

The cap $\bar{e}$ is set exogenously and the firm has the option to endogenously change $a \in \{a_0, a_1, a_2\}$ by investing 0 times, 1 time or twice. As in the text, the investment is sunk with costs k and has a determined increase of $\chi > 1$ with $a' = \chi a$. The relocation decision is given as a constant π^f, independent of a.

at time t=2 Each period $t \in \{1,2\}$; the firm can choose between three decisions, invest, doing nothing, or relocating abroad $d^* = \{d_1, d_2, d_3\}$. Conditional on the firm remaining in the market at time $t = 1$, the payoffs between year 1 and year 2 are the following:

$$\pi(a_2, z, d_t; e_2) = \begin{cases} \pi(a_1, z, 0; \bar{e}_2) & \text{if } d_t = 0 \\ \pi(a_1\chi, z, 0; \bar{e}_2) - k_1 & \text{if } d_t = 1 \\ \pi^f - k_2 & \text{if } d_t = 2 \end{cases} \tag{A.5}$$

Given the functional forms. Firms invest if their profits are

For firms that have invested in period 1: Firms choose to invest rather than exit

$$\pi^f - k_2 < \pi(a_1, z, 0; \bar{e}_2)\chi^{\alpha\frac{\eta-1}{\eta}} - k_1 = \pi(a_0, z, 0; e_2)\chi^{2\alpha\frac{\eta-1}{\eta}} - k_1 \tag{A.6}$$

For firms that did not invest in period 1: Firms choose to invest rather than exit

$$\pi^f - k_2 < \pi(a_0, z, 0; \bar{e}_2)\chi^{\alpha\frac{\eta-1}{\eta}} - k_1 \tag{A.7}$$

From here, it is easy to see that firms with

B. Data gathering and analysis

B.1 Data gathering process

This section shows the construction of the dataset. It also documents some facts on the relative importance of these firms to the total economy in the EU. The main dataset is formed by the combination of two sources:

emission data for all firms in the ETS, obtained from the European Transaction Log (EUTL), and their annual financial data from ORBIS, provided by Bureau van Dijk.

This section begins with an explanation of how the emission data is collected, followed by the gathering of the financial data. The methodology for combining these two datasets is then outlined. Finally, the other data sources used in the study are discussed, along with the construction of several key variables.

B.1.1 Emission data

The data gathering process starts with the gathering of the data on the European Transaction log data (EUTL) from 2005 to 2022. The preparation closely follows the methodology by JaraitÄ et al. (2016). Emission data - both the amount of used as well as received emission certificates - is documented at the installation level for all European firms. The data also holds information on the yearly ownership of these installations.

Table B.1: Data processing EUTL

Method	id	Count	Percentage (%)
Source data	Installations	19624	100%
Omittance empty company registration numbers and airlines	Installations	17176	90.9%
Collapse to company registration number	Firm	10682	100%
Matching procedure Letout (2022)	Firm	8615	90.5%
Manual corrections	Firm	8863	90.5%
Limit to manufacturing sector	Firm	5186	90.5%

NOTE: test

In the baseline dataset, all installations are aggregated up to the firm level. Airline companies and entities having an account, but lacking an installation identifier with the EU EUTL are excluded. Such accounts are typically utilized solely for the purpose of trading carbon certificates. In cases where a firm possesses multiple accounts but at least one of these accounts is linked to an installation that omits emissions, the emission certificates used will be aggregated up to the firm level. The number of installations per firm - year will be used in this analysis as a measure of carbon leakage. Installations that belong to more than 1 firm are assigned to the firm that does not exit the EU. This amount to less than 0.5% of the installations. During this consolidation,

A subsequent dataset is developed at the installation level that tracks the evolution of entry and exit at the installation over time. Note that entry in the dataset is involuntary and depends on the regulations set forward by the European Union. At the year 2013, a regulatory change saw an increase in the type of sectors and firms covered by the policy. Firms that were not in the EUTL prior to 2013 are omitted from the analysis. Firms that saw an increase in the number of their installations exposed to the policy change are flagged and omitted in some part of the analysis.

The emission data is combined with the yearly non-consolidated financial accounts of each firm found

in ORBIS for the year 2005 to 2020. The data includes among others the added value, number of employees, materials, and (fixed) tangible assets. It also has data on the exit-decision by the firm as well as the date of incorporation. The analysis is limited to the manufacturing sector due to the better documentation of the financial variables in ORBIS as well as the relative ease of comparability between firms. Firms are considered to be manufacturing firms if they have at least one installation that is active in the manufacturing sector (Nace rev.2 2d >9 & $\leq$ 33)

B.1.2 Financial data

The emission data is combined with the yearly non-consolidated financial accounts of each firm found in ORBIS for the year 2005 to 2022. The data includes, among others, the added value, number of employees, materials, and (fixed) tangible assets. The analysis is limited to the manufacturing sector due to the better documentation of the financial variables in ORBIS as well as the relative ease of comparability between firms. Firms are considered to be manufacturing firms if they have at least one installation that is active in the manufacturing sector (Nace rev.2 2d >9 & $\leq$ 33)

The matching procedure for the Emissions data (EUTL) and the financial data used (RBIS) in this study is a slight deviation of Letout (2022). Some manual adjustments are made based on the address of the installation and addresses found in the online version of ORBIS.

I rely on the procedures lined out by Kalemli-Ozcan et al. (2015) to ensure the data is suited for analysis. The issues discussed there are less critical in my analysis, as it primarily focuses on large firms, which are often better represented in national accounts. Table B.2 shows that almost 98% of the initial manufacturing firms of 5185 have been identified. Financial data for countries like Iceland, the Netherlands, Estonia, Croatia, Greece, Lithuania, and Malta is insufficiently reported. Firms based in those countries are therefore omitted from the analysis. I do not intend to examine cross-country differences. Finally, to address potential inconsistencies in reporting across countries, I rely on country and country-time fixed effects.

Table B.2: Data processing ORBIS global

Method	id	Count	Percentage (%)
Source data	Installations	19624	100%
Omittance empty company registration numbers and airlines	Installations	17176	87.5%
Collapse to company registration number	Firm	10682	100%
Matching procedure Letout (2022)	Firm	8615	80.6%
Manual corrections	Firm	8863	83.0%
Limit to manufacturing sector	Firm	5186	100%
Financial data available	Firm	4519	87.1%

NOTE: data processing from raw EUTL data towards financial data from ORBIS GLOBAL.

B.1.3 Deflating financial values

Financial values are deflated using sector-price data from eurostat. Various deflators are used. Material costs and operating revenue are deflated using xxx. (Tangible) capital is deflated by XXX. Value added is deflated by xxx and wages xxx.

B.1.4 Ownership structure

The ownership linkages are needed to construct an indicator of the multinational character of the firm (Ramondo et al., 2015). To evaluate the multinational nature of the firms in the dataset, I rely on the ownership linkages at the year 2019, as reported in ORBIS. A firm is considered to own another if it is the global ultimate owner with more than 50% of the ownership shares. I assume that ownership linkages remain constant over time.

I distinguish between firms that are subsidiaries of other entities and those that are owners of other entities. Additionally, I break down these ownership linkages further, into categories based on their scope, identifying whether they are national, European, or foreign ownership linkages. Shares of the linkages for each category can be found in Table B.3.

B.1.5 Documentation of data

The main dataset used in this analysis is based on the financial data from ORBIS and the emission data from the EUTL. Table B.3 provides summary statistics of the baseline data used throughout the text.

Table B.3: Summary statistics main dataset

Variable	average	p10	P90
Number of employees	857.80	23	1490
Emissions (tonne)	192462	3189	270776
Value added (million Euro)	633.72	0.67	337.18
Number of installations	1.65	1	3
Multinationals	Domestic	European	Foreign
Subsidiary	0.41	0.22	0.20
Ultimate owner	0.18	0.01	0.00
Extensive margin	Number of Firms	Entry rate	Exit rate
	4216	0.01	0.012

NOTE: average statistics over the period from 2005 to 2022. The CO2 emissions are documented per tone and Value added data in million euros. The multinational dimension is split in whether the firm is a subsidiary of either a domestic, European, or non-European entity - or whether they are the owner of such entities. Note that this does not have to add up to 0, firms without any subsdiary entities can also exist. Entry and Exit rate are computed by dividing all observations relative to the number of observed entry and exits respectively.

While this is a small subset of firms relative to the total economy in the European Union - there are

only 3623 firms in this dataset - the ETS captures mainly large firms, the average firm has more than 750 employees and adds a yearly value to the economy of more than 633 million euros. The economy is not dynamic, with a yearly entry and exit rate of around 1 percent.

B.2 Other data sources

Other data sources used in this analysis are

C. Reduced-form Evidence

C.1 Aggregate statistics

The aggregate figures presented in the main text employ the standard deviation as a metric of cross-sectional inequality to illustrate that the variation in emissions intensity is declining over time, whereas the evolution of value added is either increasing or, at best, remaining stable. While the standard deviation is a common measure of inequality, it represents only one dimension. To assess the robustness of this relationship and rule out spurious findings, I also examine alternative indicators of inequality, specifically the skewness of the distribution, and the Herfindahl-Hirschman Index (HHI) and market share of the 10 largest firms as two nonparametric measures of market concentration.

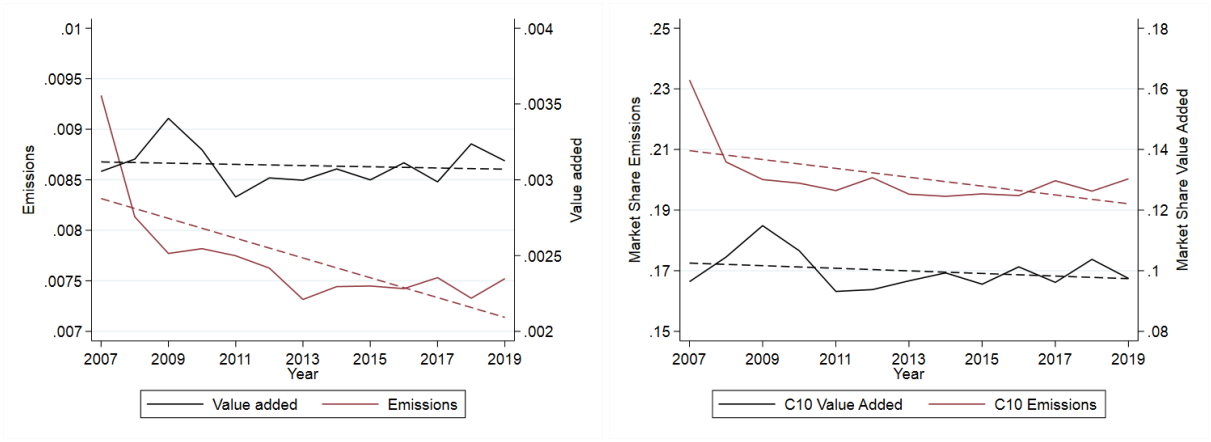
The aggregate results are found in Figure D.6. The left panel (Figure C.4a) displays the evolution of the Herfindahl-Hirschman Index (HHI) for emissions and value added between 2007 and 2019. The HHI for emissions shows a steady decline over time, indicating a decreasing concentration of emissions among firms, and thus a more even distribution of emissions across the firm population. In contrast, the HHI for value added remains relatively stable, suggesting that market concentration in terms of economic output has not substantially changed over the same period. The same relation holds for the market share of the 10 largest firms (Figure C.4b). Finally, Figure C.1c illustrates the skewness of emissions intensity and value added over time. Skewness in emissions intensity is increasing slightly, highlighting that the the share of extreme polluters is declining and that the distribution normalizes. Conversely, the skewness of value added declines, particularly in the early years, indicating an increase in asymmetry towards one where large firms have become more important.

In conclusion, these figures indicate that between 2007 and 2019, emissions became more evenly distributed across firms (decreasing HHI and slightly increasing skewness), while market concentration in value added remained stable (stable HHI) with a slight increase in the dominance of large firms (decreasing skewness).

C.2 Local projections

To test whether these results are truly indicating the growth of these incumbents and do not hide a potential shift-share mechanism where small green firms increase their market share. As a final measure of insurance, I examine the evolution of incumbents based on their ex-ante conditions. I generate a binary variable $D_{i,t}$

Figure C.1: Relative evolution inequality



(a) HHI

(b) Market share (C10)

(c) Skewness

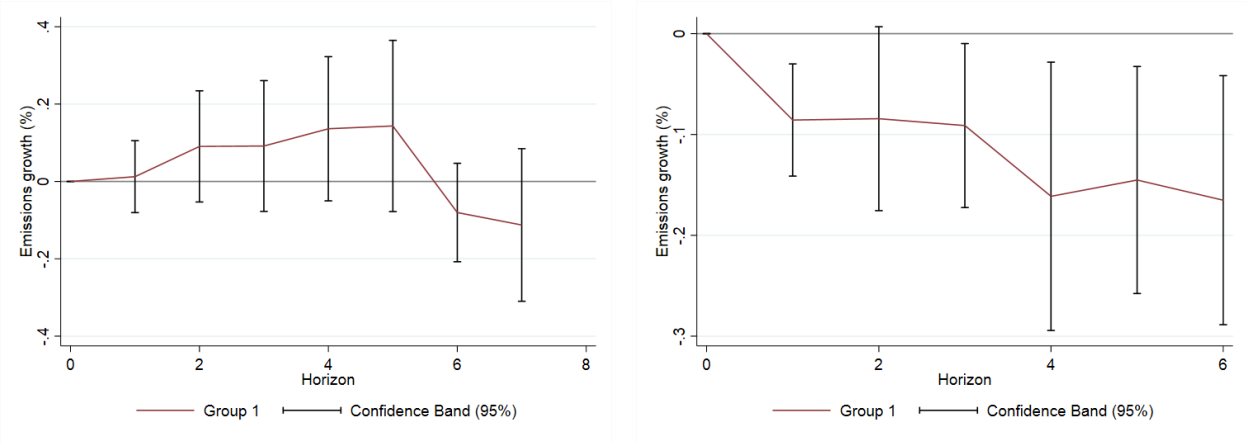
Note: Comparative analyses of the growth path of large emission-intensive firms relative to all other firms in the ETS in their evolution of emission output (upper 2 figures) and value added (lower 2 figures) for the year 2007 and 2012. The years are selected as the 2 years prior to the initialisation of a new phase of the ETS. Note that the start of phase III is considered to have been much more stringent that phase II. Confi

that indicates whether a firm is polluting more than the average firm and larger than the average firm (i.e. $D_{i,t} = 1\{\frac{e_{i,t}}{va_{i,t}} > \frac{\bar{e_{i,t}}}{va_{i,t}}, va_{i,t} > \bar{va_{i,t}}\}$. I then track the evolutions of emissions and size, proxied by value added, over time using a local-projections-type regression CITE DUBE 2023 AND JORDA 2005:

$$\Delta \ln(e_{i,t+h}) = \beta D_{i,t} + \xi_c + \iota_s + \varepsilon_{i,t} \tag{C.8}$$

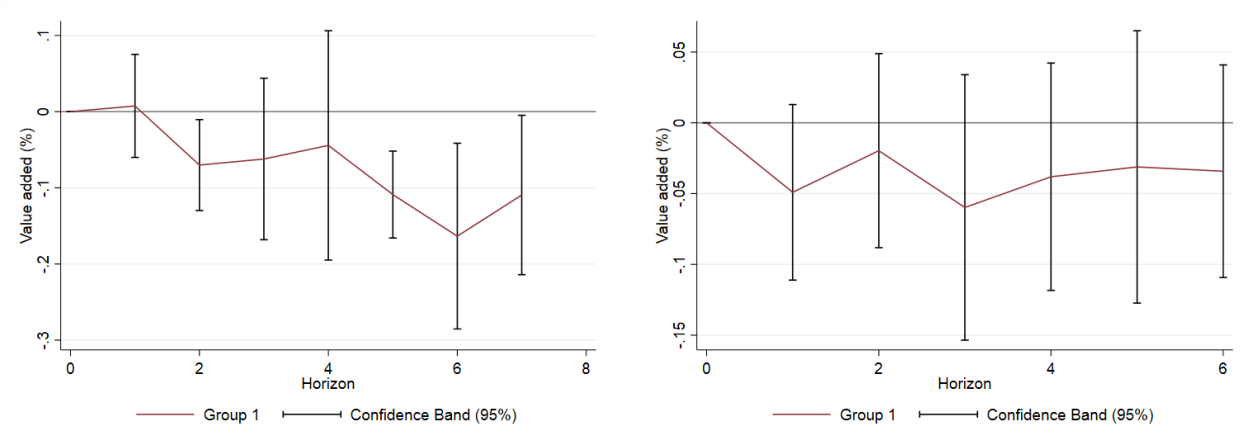
where $\Delta \ln(e_{i,t+h})$ is the differential in emissions. ξ_c and ι_s are country and sector fixed effects and $t \in \{2007, 2012\}$, either capturing the initial conditions at the start of phase II or phase III of the ETS. The results are shown in Figure C.2.

Figure C.2: Relative evolution large polluting firms



(a) Emissions (2007)

(b) Emissions (2012)



(c) Value added (2007)

(d) Value added (2012)

Note: Comparative analyses of the growth path of large emission-intensive firms relative to all other firms in the ETS in their evolution of emission output (upper 2 figures) and value added (lower 2 figures) for the year 2007 and 2012. The years are selected as the 2 years prior to the initialisation of a new phase of the ETS. Note that the start of phase III is considered to have been much more stringent that phase II. Confi

Figure C.2a and Figure C.2c show no significant divergence in emissions or value added between large polluting firms and other firms from the start of 2007. Their evolution coincides with the start of financial crisis and at the start of Phase II of the ETS, It likely reflects the broader economic slowdown, which seems to hint towards large emission-intensive firms being hit more than the average firm, reducing their capacity to invest in green technology. This provides suggestive evidence of the financial crises and the subsequent debt crises having had large impacts on the firms' capacity to invest in green technology.

In contrast, from 2012 onward, when aggregate economic conditions had been relatively stabilized, and ahead of the stricter Phase III, emissions among large polluters began to decline more visibly. Figure C.2b

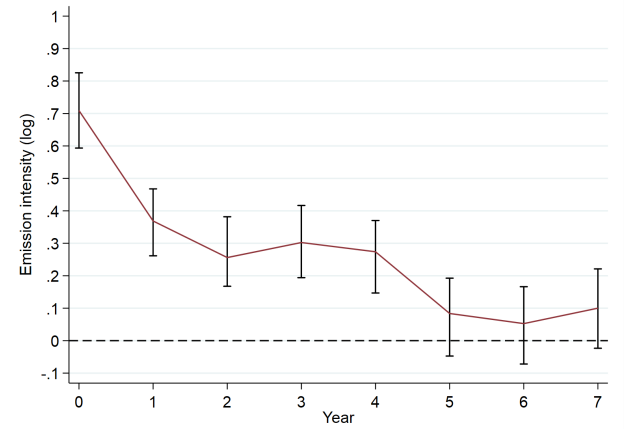
shows a downward trend in emissions growth, especially in the first few years after 2012. The point estimate at Horizon 0 is about -10%, and the decline continues gradually to about -15% by 4 years. Note that these point-estimates have large confidence intervals.

Finally, the Figure C.2d shows stable value added, implying emissions reductions occurred without harming firm performance. These patterns suggest that Gibrat's Law holds, as firm size does not diverge. Despite being larger and more polluting, these firms did not grow faster economically. The regression results support that emissions reductions were due to mitigation at the firm level, rather than due to shifts in market share.

C.3 Entry dynamics

The local projections already tested whether the decline in emissions came from large, highly polluting incumbent firms. However, this analysis was only conducted from the perspective of incumbents relative to other incumbents who were already incorporated at the start of the policy. A more extreme form of the relocation of market share could be the evolution of entrants. A substantial body of literature on creative destruction emphasizes the role of new entrants in driving the development of novel innovative products Aghion and Howitt (1992); Klette and Kortum (2004); Acemoglu et al. (2018), which is often accompanied by a subsequent expansion in their market share Haltiwanger et al. (2013, 2016). To verify that the observed trends are not the result of shifts in market share among entrants affecting both all emission-intense firms under the ETS equally, I compare the trajectories of entrants relative to those of incumbent firms.

Figure C.3: Emission intensity of entrants



Note: Emission intensity of entrants compared to incumbents. A sample of placebo entrants is drawn from the pool of incumbents and tracked over the same seven-year period. This procedure is bootstrapped 100 times (Young, 2019). The vertical intervals represent the 5th and 95th percentiles of the bootstrapped coefficients.

I only classify firms newly appearing in the financial data as real entrants. I exclude cases where existing firms enter the ETS through the acquisition of a polluting facility or through expanded regulatory coverage

due to increased stringency of the policy.[24] The rate of entry is 1.03% - extremely small relative to the common entry rate in the economy Haltiwanger et al. (2013), suggesting that entry in itself plays a marginal role - however this number does not specify the quality (in terms of clean technology) of these respective entrants.

Entrants oftentimes start out more polluting than their incumbent counterpart. To see why they have a lower level of emission intensity relative to the incumbents and thus contribute positively to the aggregate reduction in emission intensity, I track them over time. More specifically, I track them for 7 years post entry. I do allow for attrition both at the level of incumbents and entrants. The regression is specified the following way:

$$ln(ei_{i,t}) = \sum_{\tau=-4}^{T=3} \alpha_\tau G_\tau D_i + \iota_{t,c} + \delta_{t,s} + \eta_{c,s} + \varepsilon_{i,t} \tag{C.9}$$

where $\ln(ei_{i,t})$ denotes the logarithm of emission intensity, G_τ measures years from the treatment event, and $\iota_{t,c}$ $\delta_{t,s}$, $\eta_{c,s}$ capture time-country, time-sector and country-sector fixed effects, respectively. Error terms $\varepsilon_{i,t}$ are clustered at the country-sector level.

The results in Figure C.3 show that entrants initially exhibit significantly higher emission intensity than the incumbent comparison group. It is only around year 5 post-entry that their emission intensity converges, eliminating any structural difference between the two groups. This suggests that entrants do not actively contribute to the decline in aggregate emission intensity; at best, they pollute at similar levels as incumbents.

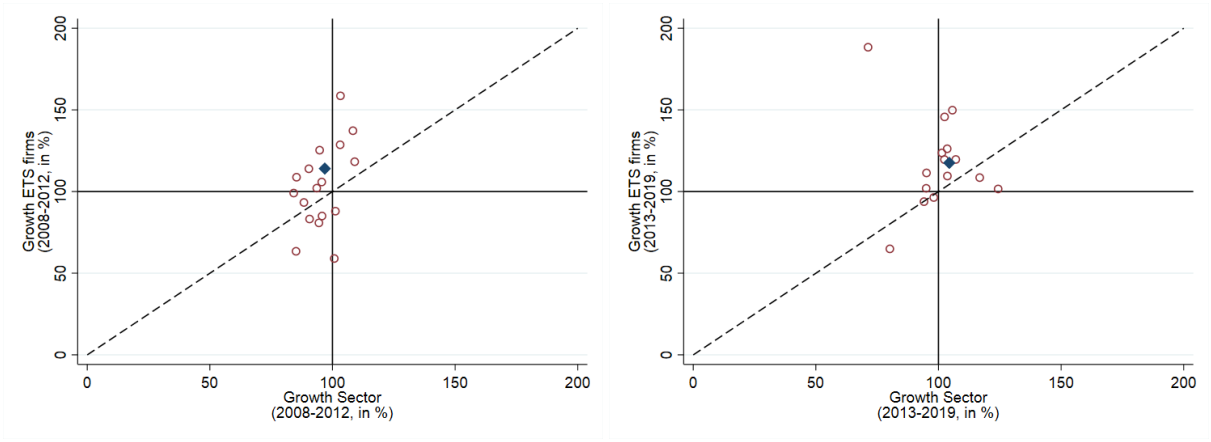
C.4 Relocation towards non-ETS

Finally, I investigate potential patterns of economic activity relocation between regulated (ETS-covered) and non-regulated firms within each nace 2-digit sector, I compare the growth rate of value added for the two groups. Potential divergent growth rates may indicate shifting activity away from regulated sectors. I distinguish across two Phase II and Phase III given their differing regulatory stringency and macroeconomic contexts.

Figure C.4 provides a comparative analysis of value-added growth (deflated) for ETS-covered firms relative to their respective sectors during Phase II (2008 - 2012) and Phase III (2013 - 2019) of the EU Emissions Trading System (ETS). The 45-degree line denotes parity in performance: points above this line indicate that ETS firms have outperformed their broader industry peers. In both subfigures, a majority of the observations lie above this parity line, suggesting that ETS firms consistently achieved higher growth in value added compared to their sectors. As a final check, the aggregate indicator for the entire manufacturing economy, represented by the blue diamond, also lies above the parity line in both phases. Overall, the figure suggests that participation in the ETS does not appear to have hindered firm-level growth, thus relocation towards the non-ETS sector has been minimal.

[24] The latter is captured in the following subsection - a direct comparison between the ETS-firms and the rest of the industry.

Figure C.4: Growth value added relative to the sector



(a) Growth Phase II

(b) Growth Phase III

Note: Comparative analyses of growth in value added (deflated) for the firms active in the ETS and the whole sector. the x-axes denotes the growth of the sector in percentages relative to their economic situation at the beginning of the phase - while the y-axis shows this for the aggregate of ETS-firms in the sector. The 45-degree line indicates an equal performance of the ETS-firms and the industry. If the observation is above this line, the ETS-firms have performed better than their industry. The blue dot indicates the aggregate manufacturing economy.

D. Structural Estimation

D.1 construction of indicators

The estimation strategy of the model requires the creation of various variables outside the scope of the model. This section dives a bit deeper in how these are created and conducts various robustness tests to check the validity of the creation of these indicators. I start by the estimation of a value-added production function based on Ackerberg et al. (2015). I then decompose this into a persistent and a transitory variable. Secondly, I compute an indicator that To truly speak of investment, I analyze whether (i) this indicator is associated with a capital increase rather than just a value added increase. I regress it on the price of carbon to test whether the ETS has had influence on the investment decision. And to see whether this investment is of a first-order magnitude I test whether the ex-ante characteristics of firms that engage in the investment decision are similar to those that have reduced their emissions the most following the local projection analysis in the descriptive statistics. Finally, I construct an exit-variable for multinational subsidiaries that exit. Also here, i check the ex-ante characteristics of firms that will exit in a few years.

D.1.1 Production function estimation

To start the productivity estimation, I restate the production function described in the paper:

$$q_{it} = \min\{e^{z_{it}} f(k_{it}, l_{it}), m_{it}, e_{it} a_{it}\} \tag{D.10}$$

The parameter of productivity z_{it} is measured as a residual of a production function $f(.)$ with value added q as an output and two inputs, labor l and capital k. I estimate revenue productivity. The chosen functional form of the production function $f(.)$ is Cobb-Douglas in its inputs and Leontief in materials m and emissions e where the latter also depends on the level of clean technology a. I exclude emissions in the production function estimation strategy, as they are needed to determine the clean technology parameter a. The production function can be described in logarithms as follows:

$$\ln q_{it} = \beta_0 + \beta_k \ln k_{it} + \beta_l \ln l_{it} + z_{it} + \varepsilon_{it} \tag{D.11}$$

Productivity is composed of two terms: z and ε. The error term ε reflects measurement error or unexpected production shocks unobservable to both the firm during input decisions and the econometrician. The term z represents shocks visible to the firm before input decisions but hidden from the econometrician. Since firms base input choices on z, endogeneity arises if ω is not accounted for.

To address endogeneity, I use a semi-parametric estimation method following Ackerberg et al. (2015). This approach employs a proxy variable to invert out z, for which I use intermediate inputs, (Levinsohn and Petrin, 2003): $\ln m_{it} = f_{it}(\ln z_{it}, \ln k_{it}, \ln l_{it})$. Inversion works solely based on the assumption that intermediate inputs are strictly monotonic in z. To prevent functional dependence issues, labor is included in the input function (Ackerberg et al., 2015). Observed productivity z is assumed to follow a dynamic process $z_{it} = g(z_{it-1}) + \xi_{it}$.

The production function estimation involves two steps. First, the inverted intermediate input function is substituted into the production function to remove the unobserved productivity term ε, without estimating labor or capital coefficients. In the second step, the labor and capital coefficients (β_l and β_k) are estimated by combining the inverted demand function and the productivity process. Productivity ($z + \varepsilon$) is then obtained as the residual of the equation $q_{it} - \beta_k * \ln k_{it} - \beta_l * \ln l_{it}$. All functions are approximated by third-order polynomials. The two steps can be summarized as follows:

$$\begin{aligned} \ln q_{it} &= \beta_0 + \beta_l * \ln l_{it} + \beta_k * \ln k_{it} + f^{-1}(\ln m_{it}, \ln k_{it}, \ln l_{it}) + \varepsilon_{it} \\ &= \theta(\ln m_{it}, \ln k_{it}, \ln l_{it}) + \varepsilon \end{aligned} \tag{D.12}$$

$$\ln q_{it} = \beta_l * \ln l_{it} + \beta_k * \ln k_{it} + g(\hat{\theta}_{it-1} - \beta_0 - \beta_l * \ln l_{it-1} - \beta_k * \ln k_{it-1}) + \xi_{it} + \varepsilon_{it} \tag{D.13}$$

The coefficients are estimated using a generalized method of moments (GMM). Following standard practice, labor is treated as a flexible input and capital as a fixed input, with capital adjustments taking one period to affect production. As a result, current capital and lagged labor are uncorrelated with the innovation and error terms. The GMM estimation uses the sample analogues of the following moments:

$$E\left\{ (\xi_{it} + \varepsilon_{it}) \begin{bmatrix} \ln k_{it} \\ \ln l_{it-1} \end{bmatrix} \right\} \tag{D.14}$$

The estimation results of the two output elasticities for the sample of ETS-firms are given in Table D.4.

D.1.2 Productivity decomposition

The only restriction set on the observed productivity z is the condition of it being a Markov process: $z_{it} = g(z_{it-1}) + \xi_{it}$. It can be further decomposed into a permanent and a transitory component, where all time variation is captured by the transitory component. I restrict the process for the transitory component further to an AR(1), such that:

$$z_{i,t} = z_i^F + z_{i,t}^T, \qquad \text{with} \quad z_{i,t}^T = \rho z_{i,t-1}^T + \xi_{i,t} \tag{D.15}$$

where $|\rho| < 1$ and the innovation to the transitory component is i.i.d. and behaves as $\xi_{i,t} \sim N(0, \sigma_\xi^2)$. Substituting the second part of the expression for $z_{i,t}^T$, I can rewrite productivity as:

$$z_{i,t} = z_i^F + \rho(z_{i,t-1} - z_i^F) + \xi_{it} = (1-\rho)z_i^F + \rho z_{i,t-1} + \xi_{i,t} \tag{D.16}$$

Note that this equation equals the earlier Markov process as the functional form can be written as $g(z_{i,t-1}) = (1-\rho)z_i^F + \rho z_{i,t-1}$.

Table D.4: Productivity estimation strategy

Estimation productivity	coefficient	s.e.
Log(capital)	0.834^{***}	(0.145)
Log(labor)	0.187^{***}	(0.025)
Observations	36941	
No. of firms	3493	
Persistence productivity	coefficient	s.e.
Lag(productivity)	0.35^{***}	0.005
Observations	37,854	
No. of firms	3493	

NOTE: the upper part of the table shows output elasticities of the production function estimation based on Ackerberg et al. (2015). The lower part demonstrates the outcome variable of ρ in Equation D.15. The standard deviation of the transitory component equals $\sigma(z_{it}^T) = 0.36$.

The regression in Equation D.15 makes no assumption on the parametric distribution of z_i^F. It does so for $z_{i,t}^T$ with ξ being normal and i.i.d.

D.1.3 Green investment

Clean technology Under the assumption that emissions are Leontief in the value-added production function, the abatement technology can be written as a ratio of the two.

$$a_{it} = \frac{q_{it}}{e_{it}} \approx \frac{va_{it}}{e_{it}} = \frac{a_{it} p_{it} q_{it}}{q_{it}} \tag{D.17}$$

where p_{it} are deflated at the country-sector level using Eurostat deflator data. Note that - akin to the production estimation due to the absence of firm-specific prices - this is a measure of revenue clean technology

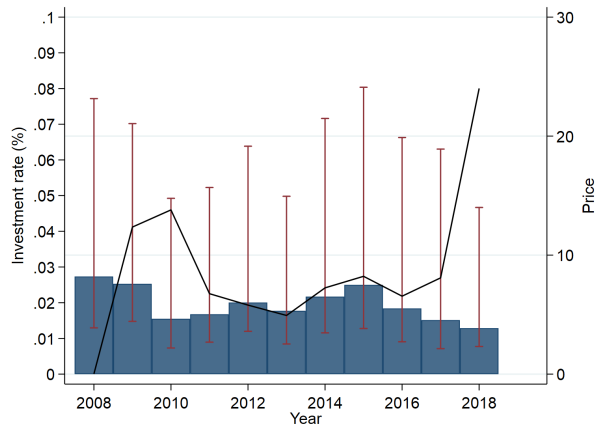
rather than clean technology. The inverse of this measure is oftentimes used as emission intensity - the degree of emissions used to produce one unit of output.

Clean technology investment The decision to undertake emission abatement is both costly and infrequent, often characterized by lumpiness and persistence. While direct costs of abatement are unobservable, changes in the level of clean technology $a_{i,t}$ provide a measurable outcome through which successful abatement can be inferred. To capture these changes, I construct a novel binary indicator $d_{1,t}(\chi) \in \{0,1\}$ inspired by Bessen et al. (2019), which signals whether firm i engaged in abatement activity, with magnitude χ, in year t.

$$d_{1,t}(\chi) = \mathbb{1}\underbrace{\{\chi \tilde{a}_{i,t+1} \geq \tilde{a}_{i,t}\}}_{\text{Transitory state}} \underbrace{\left\{\chi \frac{1}{B}\sum_{b=1}^{B=2} \tilde{a}_{i,t+b} \geq \frac{1}{W+1}\sum_{w=0}^{W=2} \tilde{a}_{i,t-w}\right\}}_{\text{structural state}} \tag{D.18}$$

where the indicator $d_{1,t}(\chi)$ equals 1 only if two conditions are met. The indicators yields two components: a *transitory state* which captures a shock to emission intensity at time t, exceeding a threshold $\chi \in \{1.05, 1.10, 1.20, 1.30\}$ reflecting the lumpiness of such reduction. The *structural state* ensures the absorption into a new state that is persistently lower than the initial state, with average emission intensity over the next two years at least $(\chi - 1)\%$ lower than the previous three-year average.

Figure D.5: Yearly aggregate investment rate



Note: Emission intensity of entrants compared to incumbents. A sample of placebo entrants is drawn from the pool of incumbents and tracked over the same seven-year period. This procedure is bootstrapped 100 times (Young, 2019). The vertical intervals represent the 5th and 95th percentiles of the bootstrapped coefficients.

To test whether this is truly a variable of invest I conduct 2 counterfactual analysis. I first Second, I test whether the degree to which the price of carbon changes has any implications for fir

Finally, to see whether I capture the reductions of the firms assigned in the first analyis, i

Co-movement of other financial variables I set up a first event-study type regression to assess the relationship between key variables and the indicator of structural reductions. While this regression analysis does not aim to look at the causal effect of the reduction of emissions, I exploit the literature on difference-in-difference regressions for their notation (Callaway et al., 2021). The reductions occur at staggered intervals as firms choose their timing. Firms engage in the decision to reduce at time $\tau = -1$ with the outcomes at $\tau = 0$. I compare the firms that reduced their emission once $D_i = 1$ with those that never did so $D_i = 0$, excluding firms with multiple reductions to maintain clarity. The regressions specification can be written as:

$$ln(x_{i,t}) = \sum_{\tau=-4}^{T=3} \alpha_\tau G_\tau D_i + \iota_t + \delta_i + \varepsilon_{i,t} \tag{D.19}$$

Where $x_{i,t}$ is the variable of interest - Material cost, capital and emission output. The variable G_τ denotes the distance - in years - from the actual treatment decision. ι_t and δ_i denote time- and firm fixed effects. The strictest specification even has time-sector-country fixed effects and capture all variation unique to the growth of a sector or country. Error terms $\varepsilon_{i,t}$ are clustered at the firm level. I approach the selection of the control group in similar spirit to Young (2019). I select a random sample of firms out of all firms that never reduce their emission intensity: $\sum_t^T \omega_{i,t} = 0$. They obtain a placebo treatment $G_\tau = 1$ at a certain time τ. This procedure is bootstrapped 100 times. The point-estimate in the graphs in **??** show the median value and the confidence intervals the $10-90$ percentile. The length of S is chose to be exact 1 year longer in both dimensions than the structural reduction to capture potential returns to the mean.

?? shows the co-movement of capital, material cost, and emissions with the emission-reduction indicator. What stands out is that capital has had an increase with approximately 10% relative to those that do not reduce their emissions. In contrast, the evolution of the cost of materials - as either substitute or complement to emission output - seems to be statistically insignificantly different from the evolutions of the control group. The reduction is thus not associated with an increase in 'more expensive' or reduction in total emission intensive input factors. Secondly, the emission output had not experienced any upward movement after the 2nd year post reduction - the year the constraints by the structural state of the reduction indicator had ended (i.e. W in Equation D.18). This indicates that there is no return to the mean afterwards for the reduction in emissions.

The signaling function of price To see whether firms internalize the imposed taxation in their decision to reduce their emissions rather than other reasons such as structural change and other trade shocks, I conduct a second regression analysis that examines the influence of the carbon price ζ_t on the decision to reduce for more emission-intensive firms.

$$d_{1,i,t} = \beta \ln(a_{i,t}) + \phi \ln(a_{i,t}) \ln(\zeta_t) + \iota_{c,t} + \tau_{s,t} + \delta_i + \varepsilon_{i,t} \tag{D.20}$$

where the yearly reduction decision $d_{1,i,t}$ depends on emission intensity $\ln(a_{i,t})$ interacted with the carbon price ζ_t. Emission intensity is normalized to facilitate readability. To account for additional variation, I

include sector-year $\tau_{s,t}$, country-year $\iota_{c,t}$, and firm fixed effects δ_i. The findings in **??** suggest that firms primarily consider the price of carbon certificates in their emission reduction decision, revealing the importance of ETS as a driving mechanism. While other factors like structural changes might also play a role, the ETS does affect it. The elasticity of a reduction should be interpreted as conditional to emission intensity $\varepsilon = \phi * \ln(a_{i,t})$.

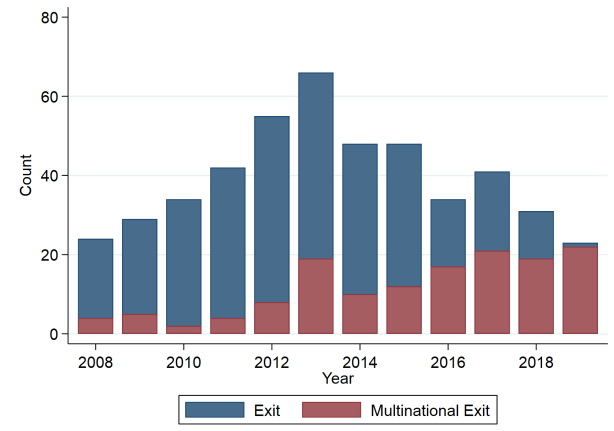
Ex-ante firm characteristics The mechanism in Section 2 in the main body of the paper presumes that firms that reduce their emissions are typically larger and more polluting. Reduced form evidence all hinted towards this being true. I assess whether this relation is also true for their decision to invest. I compare their ex-ante firm characteristics akin to the local projection regression in Figure C.2: one linking reductions in Phase II to their ex-ante conditions in Phase I 2007, and another for Phase III based on their 2012 characteristics, using a linear probability model:

$$d_{1,t} = \beta \ln va_{i,0} + \eta \ln a_{i,0} + \iota_s + \delta_c + \varepsilon_{i,0} \tag{D.21}$$

where $d_{1,t} \in \{0,1\}$ indicates if a firm invests at least once in years $t \in \{2008\text{-}2012, 2013\text{-}2018\}$. $va_{i,0}$ and $a_{i,0}$ represent the initial value-added and emission intensity, with β and η capturing their effects. Errors are clustered by sector-country, with fixed effects δ_c and ι_s accounting for cross-country policy and cross-sectoral differences.[25]

D.1.4 Firm exit

Figure D.6: (multinational) Exit rate



Note:

The second decision that firms can take other than adopting novel levels of clean technology is the

[25]Country fixed effects are crucial due to variation in carbon policies—for example, Sweden complements the ETS with national measures, while Belgium offsets relocation risks with subsidies.

Table D.5: Signaling function of price (t >2012)

χ	10%	10%	10%	20%	30%
	(1)	(2)	(3)	(4)	(5)
$\ln(a_{i,t})\ln(\zeta_t)$	-0.242***	-0.198***	-0.250***	-0.050*	-0.029
	(0.042)	(0.043)	(0.044)	(0.042)	(0.022)
$\ln(a_{i,t})$	-0.828***	-1.293***	-0.822***	-0.695***	-0.521***
	(0.119)	(0.339)	(0.122)	(0.087)	(0.071)
$\ln(a_{i,t})\ln(p^{oil})$		0.106			
		(0.071)			
$\ln(\kappa_{i,t}/e_{i,t})\ln(\zeta_t)$			0.007		
			(0.004)		
Observations	13,950	13,950	13,781	13,950	13,950
Adjusted R-squared	0.093	0.093	0.098	0.070	0.059
Year-Country fe	✓	✓	✓	✓	✓
Year-Sector fe	✓	✓	✓	✓	✓
Firm fe	✓	✓	✓	✓	✓
Clustered S.E.	firm	firm	firm	firm	firm

Robust standard errors in parentheses

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

Note: yearly number of entrants, among which some are multin

decision to relocate production abroad - i.e. carbon leakage.

As a measure of carbon leakage on the extensive margin i

To construct a measure of carbon leakage, I only consider subsidiaries of multinational as (i) they are more likely to have the financial capital to back it up, but more importantly, (ii) they are typically less anchored by local economic conditions and relations.

I start by empirically documenting (in Figure D.6) that most firms that exit are non-multinationals, but a small share of them are multinational firms

ne linking the likelihood to exit in Phase II to their ex-ante conditions in Phase I 2007, and another for Phase III based on their 2012 characteristics, using a linear probability model akin to **??** To test wether

$$d_{2,t} = \alpha_s + \delta_c + X_0'\gamma + \varepsilon_{i,0} \tag{D.22}$$

where $d_{2,t} \in \{0,1\}$ and the time variable $t \in \{2008-2012, 2013-2019\}$ $t \in \{$2008-2012, 2013-2018$\}$. The ex-ante matrix X_0 encompasses the firms' level of fixed productivity z_i^F, their level of clean technology $a_{i,0}$ and their level of allocated aggregate emission certificates. Errors are clustered by sectoral level , with fixed effects δ_c and ι_s accounting for cross-country policy and cross-sectoral differences.

Table D.6: Firm exit

	Phase II			Phase III		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(fixed productivity)	0.004	0.013	0.052	-0.216***	-0.219***	-0.211***
	(0.068)	(0.063)	(0.080)	(0.023)	(0.030)	(0.025)
ln(allocated certificates)	-0.020***		-0.025***	-0.008*		-0.013**
	(0.005)		(0.007)	(0.004)		(0.005)
ln(clean technology)		-0.022	-0.144**		-0.010	-0.091***
		(0.033)	(0.065)		(0.029)	(0.027)
Observations	1,600	1,628	1,543	1,715	1,690	1,647
Adjusted R-squared	0.044	0.031	0.048	0.053	0.049	0.054
Country fe	✓	✓	✓	✓	✓	✓
Sector fe	✓	✓	✓	✓	✓	✓
Clustered S.E.	Sector	Sector	Sector	Sector	Sector	Sector

Robust standard errors in parentheses

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

Note: yearly number of entrants, among which some are multin

D.2 Mapping data to the model

the logarithms of the variables are normalized so using a min-max-scaling to preserve its non-parametric structure. To combat outliers in the model, the data is winsorized at the 1% level to reduce the impact of outliers. The scaling is the following:

$$x^{norm} = \frac{x - x^{min}}{x^{max} - x^{min}} \tag{D.23}$$

Where x is the logarithm of the value if the value is not yet expressed as logarithm. x^{norm} is therefore the normalized variable. Except for the innovation of the transitory component ξ_{it} which is i.i.d. and has a normal distribution $N(0, \sigma^2_\xi)$, the distributions for the underlying state variables are non-parametric, as is their joint distribution.

The data for the 3 underlying state variables is binned into categories where the size of the grid for the 3 values $a^{grid} = 306; z^{F,grid} = 5$ and $z^{T,grid} = 11$. The grids are spaced in equal distances of the logarithm of the variable (note that z^T and z^F are already expressed in logs).

Each firm is assigned a grid value based on the minimal distance between the bin and the value . This ensures the non-parametric nature of the joint distribution between a and z^F, which naturally arises.

- FIGURE ON JOINT DISTRIBUTION

The relation between the state variables and other variables - either reduced form or within the context of the model - is discussed in other parts of the paper.

Table D.7: Multinational exit

	Phase II			Phase III		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(fixed productivity)	0.024	0.030	0.026	-0.156***	-0.195***	-0.195***
	(0.051)	(0.047)	(0.056)	(0.052)	(0.056)	(0.052)
ln(allocated certificates)	-0.003		-0.002	-0.012**		-0.011***
	(0.002)		(0.003)	(0.004)		(0.003)
ln(clean technology)		0.017	0.021		0.078	0.017
		(0.026)	(0.034)		(0.051)	(0.049)
Observations	876	921	851	1,061	1,072	1,029
Adjusted R-squared	0.003	0.002	0.003	0.014	0.008	0.012
Country fe	✓	✓	✓	✓	✓	✓
Sector fe	✓	✓	✓	✓	✓	✓
Clustered S.E.	Sector	Sector	Sector	Sector	Sector	Sector

Robust standard errors in parentheses

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

Note:

E. Model results

E.1 Solving the model

The model is solved using a nested numerical methods approach. To solve After the model is solved, it is estimated using a MLE strategy.

More specifically:

First steady state 1 is solved for the aggregate price. This is a simple analytical procedure with the distributions of the 2 productivity state variables known. Since the carbon policies are set to zero, making firms unable to deviate from their current state. I set the value of the ex-post value function to be equal to the one of the ex-ante distribution - however $a = a^{max}$ for all firms.

Here onward, I start with an iterative procedure to minimize the maximum likelihood (EQUATION XXX IN THE PAPER). The model consists of a nested iterative loop with 2 loops. I start from the inner loop and diverge.

1. Inner loop: A random path of carbon prices is drawn for the whole period. Given (i) this path of carbon prices, (ii) the exogenously set carbon cap and (iii) the ex-ante determined aggregate distribution from the first steady state, I search for the yearly aggregate price indices. in the domestic market P_h. As the distribution of firms is set and aggregate demand is stable, the market in the foreign market clears automatically given P_h - which in turn gives the foreign aggregate price index too.

2. Outer loop: given the aggregate prices and carbon price, the sum of carbon emissions is computed. This loop minimizes the differential between the demanded sum of carbon emissions and the exogenously determined cap. The price of carbon is updated.

3. Herein, the distribution at the ex-post steady-state gets updated with the share of firms that exit the domestic economy - this differential gives the only long-lasting effect on the economy.

After the model is solved, I estimate it using a simple maximum likelihood estimator with a Nelder-Mead simplex algorithm. The maximum likelihood procedure aims to find the values of $\{k_1^F, k_1^Q, \gamma_1, k_2\}$

The model consists of 3 state variables: There are 11 grid values for the transitory component of productivity, 5 for the and 191 values of clean technology. The criteria to solve the model for each iteration can be summarized as the maximum relative error between the new and old values over the time steps:

$$\text{crit} = \max_{1 \leq t \leq T} \left| \frac{x^{new}(t) - x^{old}(t)}{x^{old}(t)} \right| \tag{E.24}$$

where x equals the aggregate price index in the first iteration (P_h) and the aggregate domestic demand for emissions in the second iterative procedure (E_h^D). To update the carbon price - aggregate prices, I apply a simple binary search method per-time-step t.

E.2 Decompositions

E.2.1 Decomposing aggregate price index

To decompose the shifts of the aggregate price index in the home country ΔP_h, I start by defining 2 new indices: P_h^A and $P*_h$ denote actual price index and the optimal price index where there are no carbon policies in place respectively. P^0, P^1, P^2 denote the aggregate price indices given each decision (none, adoption, relocation).

$$\begin{aligned}
\Delta P_h &= P^A - P^* \\
&= \underbrace{P_h^A - P_h^0}_{\text{Decisions}} + \underbrace{P_h^0 - P_h^*}_{\text{taxation}} \\
&= \underbrace{P_h^A - P_h^0}_{\text{Decisions}} + \underbrace{P_h^0 - P_h^*}_{\text{taxation}} + P_h^1 - P_h^1 + P_h^2 - P_h^2 + P_h^0 - P_h^0 \\
&= \underbrace{P_h^0 - P_h^*}_{\text{taxation}} + \underbrace{P_h^1 - P_h^0}_{\text{adoption}} + \underbrace{P_h^2 - P_h^0}_{\text{relocation}} + P_h^A + \underbrace{P_h^0 - P_h^1 - P_h^2}_{-\tilde{P_h^A}} \\
&= \underbrace{P_h^0 - P_h^*}_{\text{taxation}} + \underbrace{P_h^1 - P_h^0}_{\text{adoption}} + \underbrace{P_h^2 - P_h^0}_{\text{relocation}}
\end{aligned} \tag{E.25}$$

This decomposition is correct up to a first order approximation of $\tilde{P_h^A}$. When the impact of either decision on its respective price index is sufficiently small (i.e. $P_h^X \approx P_h^0$ for $X = \{1,2\}$), the decomposition remains relatively unbiased.

The decomposition is similar for the price index in the foreign country.

E.2.2 Decomposing aggregate emissions

Rewrite where E^A and $E*$ denote actual emissions and optimal emissions without the carbon policies in place. E^0, E^1, E^2 denote the emissions given each decision. Note that the aggregate prices remain the same as if E^A was reached.

$$\begin{aligned}
\Delta E_h &= E^A - E^* \\
&= \underbrace{E^A - E^0}_{\text{Decisions}} + \underbrace{E^0 - E^*}_{\text{taxation}} \\
&= \underbrace{E^A - E^0}_{\text{Decisions}} + \underbrace{E^0 - E^*}_{\text{taxation}} + E^1 - E^1 + E^2 - E^2 \\
&= \underbrace{E^A - E^0}_{\text{Decisions}} + \underbrace{E^0 - E^*}_{\text{taxation}} + \underbrace{E^1 - E^0}_{\text{adoption}} + \underbrace{E^2 - E^0}_{\text{relocation}} + E^0 - \underbrace{E^1 - E^2 + E^0}_{E^A} \\
&= \underbrace{E^0 - E^*}_{\text{taxation}} + \underbrace{E^1 - E^0}_{\text{adoption}} + \underbrace{E^2 - E^0}_{\text{relocation}}
\end{aligned} \tag{E.26}$$

E.3 Evolution of the carbon cap

The carbon cap evolves at a second order function: $y = ax^2 + bx + c$. The evolution has to satisfy 2 constraints. It has to pass two points on the grid $(0, 100)$ and $(22, 55)$ and the equation can never be increasing in x within this domain $x = [0, 22]$. The first point $(0, 100)$ determines $c = 100$. The second point determines $b(a)$.

Solving for b, at the end point, we obtain

$$\begin{aligned}
55 &= a(22)^2 + b(22) + 100 \\
-45 &= 484a + 22b \\
b &= -\frac{45}{22} - 22a
\end{aligned} \tag{E.27}$$

Thus $y = ax^2 + (-45/22 - 22a)x + 100$.

For the second constraint to hold, which ensures that the emission cap is always decreasing, the slope ($dy/dx = 2ax + b$) must always be negative:

$$\begin{aligned}
0 &< 2ax + b \\
\frac{45}{22} &< 2ax - 22a \\
x &> \frac{22a + 45/22}{2a}
\end{aligned} \tag{E.28}$$

Due to its second-order nature, it is a sufficient condition to test whether it is positive at the end- and starting point. For $x = \{0, 22\}$, the equation remains negative as long as $a \in (-45/484, 45/484)$.