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# From Free to Fee: How Emission Permit Allocation Affects Firms

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# From Free to Fee:
# How Emission Permit Allocation Affects Firms*

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**Abstract**

This study provides causal evidence on firm-level effects of free emission permits in emissions trading systems (ETS). We exploit an allocation reform, causing some firms to lose a substantial share of free permits. Fewer permits reduced emissions at announcement, with effects of about 14 percent after implementation. Economic activity declined likewise but only after implementation. We develop a multi-product general equilibrium model explaining this timing through a novel mechanism linking permit allocation to firms' product exit decisions. Firms receiving fewer free emission permits terminate their least productive products. Higher market shares for remaining products encourage earlier adoption of emission-reducing technology.

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# 1 Introduction

This paper examines how the allocation of free emission permits affects firm outcomes under emissions trading systems (ETS). This question has become increasingly important as emissions regulated by ETSs have expanded sharply in recent decades, and policymakers have relied heavily on free permits. The benefit of free permits is to reduce the regulatory burden and increase the international competitiveness of regulated firms (Martin et al., 2014). However, free permits may also distort firms' emission abatement decisions, thereby compromising the cost-effectiveness of ETS systems. This discussion has a long history and centers on the *independence property*, which states that, under well-defined market conditions, the initial allocation of permits does not affect firms' emission outcomes (Montgomery, 1972). Whether this property holds in practice determines the cost-effectiveness loss associated with free permit allocation (Hahn and Stavins, 2011). Yet, despite the central role of free permits in the practical design of ETS, empirical evidence on the independence of free permits is still scarce.

We provide new empirical evidence that fewer free emission permits decrease both firms' emissions and their economic activity level. We combine administrative data on emissions from manufacturing firms regulated under the EU ETS with balance-sheet information. For identification, we exploit a reform that shifted a discrete eligibility threshold for free allocation. Below this threshold, firms lost a substantial share of their free permits. This natural experiment allows us to estimate the causal effect of free permit allocation on firm outcomes using a difference-in-differences design. Existing theoretical work on the independence property cannot explain the empirical results that we document. Therefore, we develop a multi-product general equilibrium model based on the structure of Melitz (2003). Our framework suggests a novel mechanism that is consistent with our empirical findings.

We obtain three main findings. First, the reform-induced reduction in free emission permits leads to a substantial decline in emissions already at announcement. Second, economic activity decreases by a similar magnitude, but only after implementation. Third, we show that reducing free permit allocation can induce the exit of the least productive product lines within firms, thereby reducing firm size and emissions consistently with the empirical timing.

The emissions response of treated firms is substantial and economically meaningful. Emissions fall immediately upon the announcement of the reform, and the cumulative effect grows further at implementation as fewer free permits are allocated. Following the announcement, treated firms reduced verified emissions by about 9 percent relative to the control group. At the implementation, the effect increases to about 14 percent. The effect of the reform is in the same order of magnitude as the emissions response documented for the initial introduc-

tion of the EU ETS when comparing regulated to unregulated firms (Colmer et al., 2025; Dechezleprêtre et al., 2023). Our findings do not necessarily have implications for aggregate emissions, which are regulated by the emissions cap. Instead, they show that firms' emissions responses may be distorted by the allocation of free permits.

In addition to emissions, we examine firm-level balance-sheet outcomes that reflect the economic activity of firms. The pattern differs from the result on emissions. At the announcement of the reform, these measures remain broadly unchanged despite the decline in emissions. After the reform is implemented, firms' economic activity contracts sharply. This indicates that firms initially abate without shrinking and only reduce scale once the cut in free allocation is in place. Following implementation, revenue and total assets fall by about 16 and 9 percent, respectively, a magnitude comparable to the reduction in emissions. This shows that the independence of free permit allocation holds neither for emissions nor for economic activity levels.

Several mechanisms can explain why the independence property may fail in practice (Hahn and Stavins, 2011). One is output-based updating, under which free allocation can act as a production subsidy (Fischer, 2001). Although free allocation in the EU ETS is not directly linked to current firm output and is instead based on a historical reference period, firms receive allowances only as long as the installation continues to operate. Therefore, firm entry and exit can be distorted (Konishi and Tarui, 2015; Fowlie et al., 2016). We do not examine these extensive-margin responses. Instead, our empirical analysis shows that firms adjust on the intensive margin. We therefore combine the logic of output-based updating with the growing evidence on multi-product firms (Eckel and Neary, 2010; Mayer et al., 2014; Bernard et al., 2011) coming from the trade literature.

We develop a multi-product general equilibrium model based on the structure of Melitz (2003) in which firms operate a continuum of product lines that differ in productivity. At the product-line level, free permits do not directly affect a line's pricing rule, which depends only on its productivity and common input costs. This mirrors the benchmark logic behind the independence property. Free permit allocation matters at the firm level because products are aggregated. A reduction in free permits raises the fixed cost of operating a given product line and induces the least productive lines to exit. Adjustment occurs along the extensive margin of product lines, which reduces firm-level revenue and input demand. This gives an explanation of the empirical observation at the implementation of the reform, where the emissions response is accompanied by a contraction in firm economic activity.

In a second step, we extend the model to allow product lines to purchase a technology that reduces the carbon intensity of energy use. Adoption entails a fixed cost, making it optimal only for sufficiently productive product lines. When the reform is announced, treated firms

anticipate that the least productive product lines will become unprofitable and exit once the reduction in free allocation is implemented. At the same time, they anticipate that the remaining product lines will gain market share. This change in the expected profit of continuing product lines raises the return to investing in the efficiency-improving technology, making adoption optimal for a larger set of product lines already at the announcement. As a consequence, the model predicts a decline in emission intensity, measured as emissions per unit of revenue, upon announcement, consistent with the empirical pattern in which emissions fall before firm scale adjusts.

**Related literature and contribution** We primarily contribute to the literature on the causal effect of free emission permits on firm-level emissions. This relationship is closely related to whether the independence property holds in practice. Empirical evidence remains limited, despite being central for understanding whether free permit allocation distorts firms' emission responses and reduces the cost-effectiveness of ETSs. Fowlie and Perloff (2013) find no evidence that free allocation affects emissions. Their setting, however, is a much smaller, sub-national ETS that does not focus on carbon emissions. Zaklan (2023) finds that the independence property holds for larger power producers in the EU ETS. Despite providing compelling evidence on a large ETS, this evidence remains limited to the electricity sector, whose characteristics may limit the generalizability of the findings. Electricity is a homogeneous product, hardly tradable over large distances, and difficult to differentiate in quality.

Additionally, Ellerman and Reguant (2008) provide evidence from the ETS trial phase, suggesting that the initial grandfathered allocation did not affect production decisions of Spanish coal-fired electricity. More recently, Marchioro (2026), Pacelli (2026) and Köveker and Sogalla (2026) provide evidence using variation from switching from grandfathering to benchmarking following the 2013 reform. In this setting, firms that are less carbon-efficient within a product category lose more free permits, since allocation now depends on their distance to the emission-intensity frontier. In contrast, the variation in our setting comes from a sector-level eligibility cutoff, avoiding the concern that distance to the frontier is systematically correlated with firms' emission outcomes.

We contribute to this literature by testing the causal relationship between free permits and emissions in a large ETS covering the whole European manufacturing industry using a unique natural experiment. In contrast to previous work, this paper is not restricted to a single sector or country. These differences in settings matter for the results. We find evidence that free permits have a substantial effect on firm-level emissions. Since our mechanism is based on differentiated products, it is consistent with the absence of similar effects in the

electricity sector, as shown by Zaklan (2023).

We also contribute to the literature on why the independence property may fail in practice. Existing studies identify several mechanisms, including transaction costs (Stavins, 1995; Baudry et al., 2021), market power (Hahn, 1984; Malueg and Yates, 2009; Liski and Montero, 2011), uncertainty (Baldursson and von der Fehr, 2004), non-cost-minimizing behavior (Kahneman et al., 1990; Hortaçsu et al., 2019), and allocation rules that make permit transfers contingent on firms' production or operating decisions (Fischer, 2001).[1] Our paper relates to this last strand.

Under output-based updating, current production affects the number of free permits firms receive, thereby directly distorting output decisions. During our study period, however, free allocation in the EU ETS was based primarily on historical activity and therefore did not generate this direct output distortion. Instead, the relevant mechanism arises because firms generally have to remain active to continue receiving free allowances.

Ellerman (2008) first conceptualized this idea, arguing that continued eligibility for free allocation effectively turns free permits into an operating subsidy and, when entrants are also eligible for free allocation, can additionally subsidize entry. Building on this intuition, Konishi and Tarui (2015) develop a heterogeneous-firm general equilibrium model showing that free allocation can allow less productive firms to remain active.[2] Fowlie et al. (2016) show that grandfathering can be neutral for current output choices but non-neutral for dynamic industry structure, since free permits raise the continuation value of remaining active and thereby discourage exit and disinvestment.

This literature shows that free permit allocation with entry and closure provisions is not a neutral transfer. Once free permits are tied to entering or operating, they distort firm survival. However, these studies do not explain how firms adjust along the intensive margin. We fill this gap by combining the literature on activity-contingent free allocation with multi-product firm models originally developed in the international trade literature (Eckel and Neary, 2010; Bernard et al., 2011; Mayer et al., 2014). Bernard et al. (2011) provides the closest benchmark for our model because it features multi-product firms, CES demand, fixed markups, and product selection within firms. We introduce activity-contingent free permit allocation into a similar framework to study how firms adjust their product mix in response to the transfer. Unlike Eckel and Neary (2010) and Mayer et al. (2014), we abstract from core-competence structures and variable markups. Our mechanism only requires heterogeneous product lines whose survival depends on fixed operating costs.

[1] See Hahn and Stavins (2011) for a comprehensive overview.

[2] Anouliès (2017) extends the structure to a more realistic benchmark-based free-allocation rule and provides closed-form comparative statics using a Pareto productivity distribution. Dardati and Saygili (2020) add to this discussion by moving to a dynamic model and calibrating it to US data.

Finally, we are contributing to the extensive literature on the effects of ETS on firm emissions and performance. The central question in this literature is how firms respond to being regulated under an ETS relative to remaining outside the system. Aggregate evidence suggests that the scheme lowered EU-wide emissions despite initially low allowance prices (Bayer and Aklin, 2020), and micro-level studies find reductions among regulated firms or installations in Germany, France, Norway, and broader European samples (Petrick and Wagner, 2014; Dechezleprêtre et al., 2023; Colmer et al., 2025; Klemetsen et al., 2020).

Despite these emissions reductions, the literature finds limited evidence that EU ETS regulation substantially harmed regulated firms' economic performance. Across different settings, studies generally find no large negative effects on employment, output, exports, fixed assets, profits, or productivity (Petrick and Wagner, 2014; Marin et al., 2018; Löschel et al., 2019; Dechezleprêtre et al., 2023; Colmer et al., 2025; Hintermann et al., 2020), suggesting that regulated firms partly adjusted through investment and re-optimization rather than pure contraction. Additionally, Janser et al. (2025) suggest that firm exits may be a relevant adjustment margin, even if wages and employment are mostly unaffected.

Papers in this literature typically estimate the effect of being regulated by the EU ETS relative to remaining outside the system. This margin differs from the variation studied in our paper. We hold the ETS regulation fixed and instead examine a change in free permit allocation among already-regulated firms. Our findings still contribute to this literature, as they affect the interpretation of some of their findings. Existing estimates capture the effect of ETS regulation under the allocation rules in place during the sample period, when manufacturing firms received a substantial share of allowances for free (Colmer et al., 2025; Dechezleprêtre et al., 2023). If free permit allocation is not neutral, existing estimates capture the effect of ETS regulation combined with the prevailing free-allocation regime, rather than the effect of the carbon price alone. Our results show that reducing free allocation lowers emissions, but also reduces firm activity. This suggests that free permit allocation shapes the tradeoff between environmental effectiveness and firm-level economic performance. Therefore, finding emission reductions without reductions in economic activity may not persist into an ETS environment with fewer free permits.

Additionally, emissions reductions are generally weaker in Phase I and stronger in later phases, consistent with rising stringency and more credible allowance scarcity (Martin et al., 2016; Petrick and Wagner, 2014; Bayer and Aklin, 2020; Dechezleprêtre et al., 2023). Our results suggest that declining free allocation is one channel through which rising ETS stringency translates into stronger firm-level emissions reductions.

Evidence on firms' adjustment mechanisms suggests that regulated firms reduced emissions primarily through lower emissions intensity rather than scale contraction. Existing

studies document adjustments through reduced fossil-fuel use, energy-efficiency improvements, cleaner production, investment, and low-carbon innovation (Petrick and Wagner, 2014; Dechezleprêtre et al., 2023; Colmer et al., 2025; Löschel et al., 2019; Calel and Dechezleprêtre, 2016; Calel, 2020). On top of that, Barrows and Ollivier (2018) provide evidence that stronger competition induces firms to shift production toward their core products. Whether this makes firms cleaner depends on whether these core products are less emission-intensive. This suggests that emission intensity can also change mechanically through product-mix adjustment. Mayr-Dorn (2025) studies this channel theoretically in the context of emissions pricing and shows that the product-mix response is ambiguous, depending on the carbon intensity of marginal products. We contribute to this discussion by showing that product-mix adjustments are also relevant for the effects of free permit allocation, which is a fundamentally different policy margin. In addition to scale contraction through product-mix adjustments, we show that anticipating product-mix changes can also increase investments in low-carbon technology.

**Roadmap** The remainder of this paper is structured as follows. Section 2 provides an overview of the EU ETS, with a particular emphasis on the allocation of free emission permits between the different phases of the EU ETS. Section 3 presents the data set we assemble, alongside descriptive insights. We detail the empirical strategy in section 4, and section 5 presents the results of the empirical analysis. Section 6 reports a set of robustness checks. Section 7 introduces the theoretical model and section 8 summarizes the findings and concludes.

# 2 Institutional Background and Policy Reform

## 2.1 Allowance Allocation in the EU ETS

The European Union Emissions Trading System (EU ETS) stands as the world's oldest emissions trading program, having been implemented in 2005. Today, it remains the largest carbon market in terms of value traded (International Carbon Action Partnership, 2025). The EU ETS applies in all EU member states as well as Iceland, Liechtenstein, and Norway, with Northern Ireland covered for electricity generation. It covers around 10,000 installations in the energy sector and manufacturing industry, as well as aviation and, since 2024, maritime transport (European Commission, 2024c). Regulation under the EU ETS takes place at the installation level. Coverage is defined through activity-specific capacity thresholds in the EU ETS Directive. For most regulated sectors, an installation falls under the EU ETS if

its combustion installation has a rated thermal input exceeding 20 MW. This combustion threshold is therefore the primary criterion for determining coverage. For a limited number of industrial activities, however, coverage is instead based on sector-specific production-capacity thresholds rather than thermal input (European Parliament and Council, 2003, 2009).

The EU ETS was introduced to serve as a market-based mechanism for achieving emission reductions at minimal cost. However, concerns about the international competitiveness of EU industries led policymakers to allocate a large share of emission allowances for free. This strategy aimed to mitigate the *risk of carbon leakage*, i.e., the risk that carbon costs shift production to countries without comparable climate policies (Marcantonini et al., 2017). Additionally, free permit allocation enhances the political feasibility of the policy (Grubb et al., 2022).

The EU ETS has evolved through four distinct phases. During Phase I (2005-2007) and Phase II (2008-2012), Member States were responsible for setting and distributing allowances through National Allocation Plans. Allowances were mostly allocated for free based on past emissions, with only a few Member States auctioning small quantities (Marcantonini et al., 2017).

Phase III (2013-2020) marked a significant turning point in the design and governance of the EU ETS. The reform harmonized the system and strengthened its effectiveness by replacing decentralised National Allocation Plans with a single EU-wide cap and a common set of allocation rules (De Clara and Mayr, 2018). Under the harmonized EU ETS rules, installations in sectors on the carbon leakage list receive more free permits than other installations (European Commission, 2024a). The next section explains this allocation rule in more detail.

Phase IV (2021-2030) of the EU ETS retains the core design features introduced in Phase III but incorporates several adjustments to strengthen the system. Most relevant to our analysis, the criteria for identifying sectors eligible for carbon leakage protection have been revised and are now significantly more stringent, resulting in a narrower set of sectors receiving free allocation (European Commission, 2019b). Firms operating in sectors that lost their eligibility experienced a significant reduction in free permit allocation as shown in figure S1.

## 2.2 Free Permit Allocation

In both Phase III and Phase IV of the EU ETS, free permits are allocated at the installation level using a harmonized formula that links allocation to historical activity, emissions efficiency, and carbon leakage exposure (European Commission, 2024b):

$$x_{ist} = B_s \cdot HAL_{i\bar{t}} \cdot R_t \cdot CLEF_{st} \tag{1}$$

Here, $x_{ist}$ denotes the number of allowances allocated to installation $i$ in sector $s$ in year $t$. It is determined by four components: a sector-specific emissions benchmark $B_s$, the installation's historical activity level $HAL_{i\bar{t}}$, a time-varying reduction factor $R_t$ that adjusts for the declining cap, and a carbon leakage exposure factor $CLEF_{st}$.

The benchmark $B_s$ reflects the average emissions per unit of output of the top 10% most efficient EU installations in each product category. These benchmarks are expressed in tons of $CO_2$ per unit of product and provide a uniform standard across the EU[3]. Therefore, an installation that exactly meets its sector's benchmark would receive free permits equal to its expected emissions.

The term $HAL_{i\bar{t}}$ refers to the historical activity level of installation $i$, defined as the median annual output during a designated reference period[4]. This component anchors the allocation to the installation's past production, thereby decoupling it from current output choices and incentives for overproduction. Phase IV introduced a dynamic allocation mechanism to account for significant changes in production over time. If the output deviates by more than $\pm 15\%$ from the historical baseline, future free allocations are adjusted proportionally.

The component $R_t$ is a uniform cross-sectoral correction factor, also referred to as the cap-compliance factor. It ensures that the total volume of free permits allocated to industrial installations remains within the maximum amount permitted under the overall emissions cap. After calculating the preliminary allocation for each installation, based on the product benchmark, historical activity, and carbon leakage status, the European Commission verifies whether the sum of free permits exceeds the cap reserved per industry. If it does, a proportional adjustment is applied to all eligible installations by setting $R_t < 1$, thereby scaling down free allocations uniformly across sectors and Member States.

The final component, $CLEF_{st}$, is the carbon leakage exposure factor. It adjusts the level of free allocation based on whether a sector is deemed to be at significant risk of carbon leakage. During our sample period, sectors included on the carbon leakage list received their full allocation based on the benchmark and historical activity ($CLEF_{st} = 1$), while other sectors were subject to reduced allocation levels. In Phase III, sectors excluded from the carbon leakage list initially received 80% of their benchmarked allocation in 2013, with this share declining linearly to 30% by 2020. In Phase IV, this share was maintained at 30%

[3]Most benchmarks are product-based, but fallback values exist for heat and fuel consumption where product-level data are unavailable.

[4]The reference period was typically 2005–2008 for Phase III, and 2014–2018 for Phase IV.

from 2021 through 2026 and then gradually phased out from 2027, reaching zero in 2030.

In both Phase III and Phase IV, inclusion on the carbon leakage list and thus eligibility for full free allocation is based primarily on a quantitative assessment along two dimensions: emission intensity and trade intensity.[5] Together, these indicators are designed to identify sectors that are both exposed to international competition and for which carbon pricing represents a significant cost relative to value added. Both measures are computed by the European Commission using sector-level data. Sectors that exceed predefined thresholds in one or both dimensions are included in the carbon leakage list. These thresholds were substantially revised with the implementation of Phase IV of the EU ETS, referred to as *the reform* in this paper, and are described in more detail in the following section.

## 2.3 The Reform

In Phase III, the inclusion of a sector on the carbon leakage list was determined by a set of quantitative thresholds based on emission intensity and trade intensity. A sector qualified for full free allocation if it exhibited both an emission intensity of at least 5% and a trade intensity above 10%, or if it met either an emission intensity threshold of 30% or a trade intensity threshold of 30%.

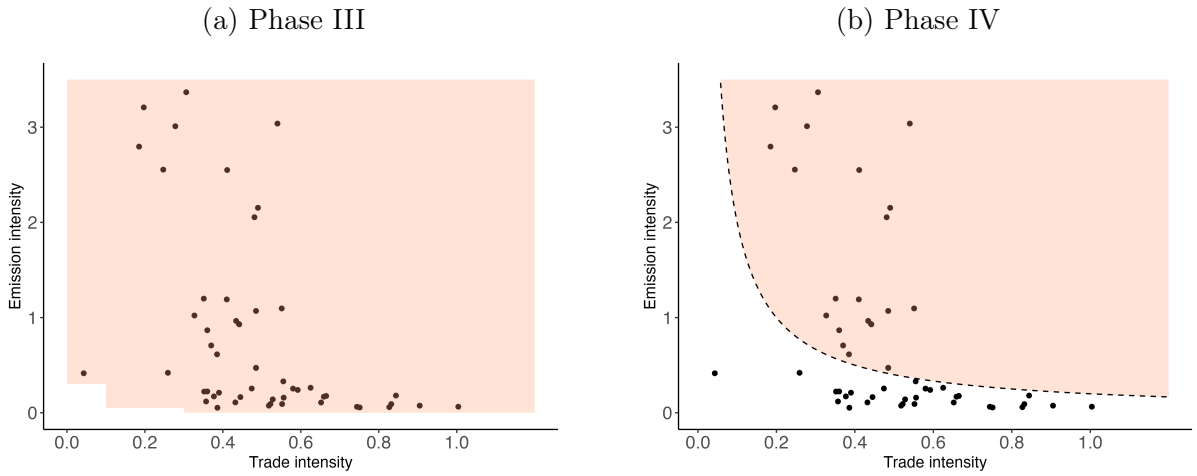
The resulting set of eligible sectors is illustrated in Figure 1, panel (a). The shaded area reflects the combined application of the thresholds described above. Sectors falling within this area were included on the carbon leakage list and had a carbon leakage exposure factor of 100%. While the Phase III criteria succeeded in capturing sectors with significant exposure to international competition, they also resulted in a broad and inclusive carbon leakage list. Many sectors qualified for full free allocation despite exhibiting only a modest emission intensity. This generous approach diluted the targeting effectiveness of the policy and extended carbon leakage protection to sectors with relatively low vulnerability.

Phase IV of the EU ETS introduced a more stringent definition of the carbon leakage risk[6]. Most notably, the three separate criteria used in Phase III were replaced by a single composite indicator. Sectors are considered at risk if the product of their trade intensity

[5]Emission intensity is defined as $\frac{\text{Direct emissions}+(\text{Electricity consumption}\times\text{Electricity emission factor})}{\text{Gross value added}}$, while trade intensity is defined as $\frac{\text{Imports}+\text{Exports}}{\text{Imports}+\text{Production}}$. Both measures are calculated and published by the European Commission (European Commission, 2018). Throughout the paper, we use these published sector-level measures rather than reconstructing them from the underlying data.

[6]Additionally, the EU ETS legislation mandates that the European Commission periodically establishes a carbon leakage list, subject to approval by Member States and scrutiny by the European Parliament. The first list covered 2013–2014, the second extended until 2020 (based on updated industry data from 2009–2011, but with the same quantitative criteria), and the third list was drawn up in 2018 using the new composite indicator methodology for the entirety of the 2021–2030 period (Marcantonini et al., 2017; European Commission, 2019a).

Figure 1: Quantitative Allocation Rule in Phase III and Phase IV




*Notes:* This figure shows the quantitative eligibility criteria for carbon leakage protection in Phase III (left) and Phase IV (right) of the EU ETS. Each dot represents a sector, defined at the four-digit NACE level, plotted by its trade intensity (horizontal axis) and emission intensity (vertical axis). Both measures are calculated by the European Commission and published in European Commission (2018). Emission intensity is expressed in kg $CO_2$ per euro of gross value added and includes indirect emissions from electricity consumption. In Phase III, sectors qualified if they met both a carbon-cost intensity of 5% and a trade intensity of 10%, or either a carbon-cost intensity of 30% or a trade intensity of 30%, resulting in a large shaded area of eligibility. Carbon-cost intensity values direct and indirect emissions at an assumed allowance price and expresses them as a share of gross value added; panel (a) plots emission intensity instead, so that both panels are shown on the axes underlying the Phase IV rule. Since treatment status is determined by the Phase IV criterion, this affects only the illustration of the pre-reform regime. In Phase IV, eligibility was restricted to sectors with a composite indicator (trade intensity $\times$ emission intensity) greater than 0.2, represented by the area above the dotted curve.

and emission intensity exceeds 0.2. This change significantly reduced the number of eligible sectors, from around 175 under the previous list to 63. Panel (b) of Figure 1 shows the new combined factor: all sectors above the dotted line are on the carbon leakage list, while sectors below the line are no longer included on the carbon leakage list.

The revised list was published in May 2018 (European Commission, 2018). At this point, firms and sectors could anticipate whether they would retain carbon leakage protection under the new regime.[7] This timing plays a key role in our identification strategy, as discussed in Section 4.

Alongside the revision of the carbon leakage criteria, Phase IV introduced two additional changes to the free allocation rules. First, the product benchmark values used to calculate

[7]Two consultation steps occurred the year preceding the publication of the revised list: a feedback period on the Inception Impact Assessment, ending on 13 November 2017, and a public consultation on methodological choices, launched on 20 November 2017. While these consultations may have informed firms about the broad direction of the reform, they did not reveal the final official sector-level classification. Moreover, our empirical design focuses on firms close to the eligibility cutoff, limiting concerns that the results are driven by firms whose loss of carbon leakage status may have been easier to anticipate.

free allocation were revised for a subset of sectors, including adjustments to account for the declining emission intensity of electricity generation. Second, a two-tier eligibility mechanism was introduced, allowing sectors with a composite indicator between 0.15 and 0.20 to apply for inclusion on the carbon leakage list through a qualitative assessment under Article 10b(2) of the ETS Directive (European Parliament and Council, 2018). To ensure a clean identification of the effects of the revised carbon leakage definition, we exclude all sectors affected by either of these additional changes. Our analysis therefore focuses exclusively on sectors whose treatment status changed solely as a result of the revised quantitative carbon leakage criterion.

# 3 Data and Summary Statistics

**Emissions and Allowances** We rely on publicly available data from the European Union Transaction Log (EUTL), which serves as the reporting and monitoring tool of the EU ETS. Specifically, we use a relational database constructed by Jan Abrell, which is based on the data from the EUTL.[8]

For emissions in each calendar year, ETS operators are required to monitor their emissions and prepare an emissions report. This report must be verified by an accredited verifier and submitted to the authority by 31 March of the following year. Then, by 30 September of the same year, operators must surrender the corresponding emission allowances in the Union Registry. The number of surrendered allowances must be at least equal to the verified emissions; otherwise, firms are subject to a monetary penalty.

The EUTL is the system that records the transfer of allowances between different actors. It provides detailed information on the compliance of installations, including verified emissions, as well as allocated and surrendered allowances for each year. We observe how many allowances were granted for free. Additional information includes the registry in which each installation is registered. For stationary installations[9], the registry corresponds to the country of location.

Jan Abrell provides a relational database that harmonizes the EUTL data and makes them more accessible for research. In addition to incorporating consistent NACE sector classifications, the database includes ORBIS firm identifiers based on the matching developed by the Joint Research Centre (European Commission, Joint Research Centre, 2026). These identifiers enable the linkage between installation-level EU ETS data and firm-level

[8]The data can be accessed at `https://www.euets.info/`.

[9]The EU ETS regulates greenhouse gas emissions from both stationary installations and aircraft operators, but we focus exclusively on stationary installations.

information from ORBIS, which is central to our empirical analysis.

The database provides annual observations for regulated installations from 2005 to 2022. We restrict the sample to installations for which the holding operator can be unambiguously identified.[10]

**Carbon Leakage Classification** The determination of a sector's carbon leakage status is pivotal for our analysis.[11] We obtain the carbon leakage lists from the European Commission and digitize them (European Commission, 2014, 2019a). We also use trade and emission intensity metrics, together with the carbon leakage factor, to restrict the sample and improve comparability (European Commission, 2018).

**Firm-Level Data** To analyze the impact of the reform on firm-level economic outcomes, we draw on data from the ORBIS database, which provides harmonized financial and operational information on firms across Europe. Specifically, we extract annual data on revenue, employment and total assets.[12] Our analysis focuses on manufacturing firms located in EU member states.

To minimize the impact of reporting issues on our results, we restrict our sample to firms with non-missing and positive revenue, total assets and number of employees. Following Abrell et al. (2022), we exclude observations where allocations exceed verified emissions by a factor of ten. We also remove observations in which both verified emissions and allocations are zero, ensuring that installations which have ceased operations but are still listed in the EUTL are excluded. The sample is balanced based on the availability of emission data.

**Descriptive Statistics** The final dataset is an annual firm-level panel constructed for the period 2014–2022. We aggregate installation-level data from the EUTL to the firm level using ORBIS identifiers. Table 1 presents descriptive statistics for the control and treatment groups. On average, firms in the treatment group exhibit higher revenue and employ more workers, but have lower emissions. This is expected given the way we select our treatment and control group. We provide a detailed discussion on this in section 4. Prior to the reform, both groups received more free permits than their verified emissions. After the reform, this ratio declined for both groups, but more significantly for treated firms. In the year before the

[10]Following a reform of the EUTL in 2012–2013, operator holding accounts of type 120-0 were required to close and reopen as type 100-7. As a result, some installations are associated with two accounts over time in the EUTL. To ensure an unambiguous link, we first exclude accounts that were already closed before 2014 and then retain only operator holding accounts of type 100-7.

[11]If a firm comprises installations associated with different NACE codes, we assign the NACE code corresponding to the installation with the highest cumulative emissions over the period.

[12]These variables ensure sufficient coverage of the firms of interest in ORBIS.

implementation of the reform, treated firms received, on average, slightly more free permits compared to their verified emissions.[13] At the time of the reform's implementation, treated firms received on average only 50% of their verified emissions in the form of free permits.

Table 1: Summary Statistics

| | Control | | | | | Treatment | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Min | Max | SD | N | Mean | Min | Max | SD |
| ***Financial Variables*** | | | | | | | | | | |
| **Revenue** | 2 246 | 580 901 | 389.68 | 18 750 395 | 1 230 604 | 884 | 2 495 986 | 3 548 | 92 654 000 | 9 031 196 |
| **Employees** | 2 246 | 944 | 1 | 104 023 | 3 676 | 884 | 8 097 | 4 | 413 811 | 38 656 |
| **Assets** | 2 246 | 502 534 | 290 | 11 383 277 | 1 100 323 | 884 | 3 434 308 | 5 716 | 126 285 000 | 13 641 825 |
| ***Emissions*** | | | | | | | | | | |
| **Emissions** | 2 763 | 125 456 | 434 | 3 911 793 | 317 161 | 1 053 | 32 546 | 249 | 412 137 | 42 010 |
| **Free / Emissions (%, 2020)** | 307 | 121 | 0 | 664 | 98 | 116 | 106 | 0 | 760 | 85 |
| **Free / Emissions (%, 2021)** | 307 | 99 | 1 | 595 | 82 | 116 | 50 | 0 | 403 | 55 |

*Notes:* This table reports summary statistics for financial variables and emissions by treatment status. The control group includes firms in sectors that remained on the carbon leakage list after the reform; the treatment group includes firms in sectors that lost eligibility. Financial outcomes include firm-level revenue, number of employees and total assets. Emissions refer to verified $CO_2$ emissions. The last two rows show the average share of emissions covered by free permits in 2020 and 2021, respectively, highlighting the shift in allocation resulting from the reform.

# 4 Empirical Strategy

## 4.1 Research Design

In this paper, we aim to estimate the effect of free permit allocation on firm outcomes. A key challenge is that the allocation of free permits is typically not exogenous. As highlighted by Fowlie and Perloff (2013), free permits are often allocated based on historical emissions, sectoral characteristics, and other factors that are themselves correlated with firms' current or future outcomes. Therefore, firms receiving more free permits may differ systematically from those receiving fewer, in ways that are not fully observable to the researcher. Consequently, regressing emissions or revenue on the level of free allocation would likely yield biased estimates of the true causal effect.

To credibly identify this causal effect, one would ideally observe a setting in which free permits are randomly assigned across otherwise comparable firms. In our setting, we exploit exogenous variation induced by the policy reform to the EU ETS, as described in detail in Section 2. As part of the 2018 revision, the European Commission introduced a new quantitative rule to determine which sectors are eligible to receive all of the benchmark

[13]Ratios above 100% can arise because free allocation was based on historical activity levels, while verified emissions reflect current production and may therefore be lower.

emissions allowances free of charge ($CLEF_{st} = 1$). This reform led to a substantial tightening of the criteria, resulting in a sharp reduction in the number of sectors classified as *at risk of carbon leakage*.

Our identification strategy compares firms in sectors that lost carbon leakage status following the reform with firms in sectors that retained their status and continued to receive most of their allowances for free. This comparison has important advantages. Since treatment is induced by a change in the allocation rule, all sectors in the estimation sample were on the carbon leakage list before the reform. This improves comparability relative to a comparison with sectors that never qualified for carbon leakage protection.

However, potential concerns about the comparability of the treatment and control groups remain. In particular, firms operating in sectors with large differences in emission intensity may not be a valid control group, since they are likely to differ systematically in unobserved characteristics that also shape outcome trajectories. To mitigate this concern, we restrict the sample to sectors close to the cutoff of the new quantitative rule, as shown in panel (a) of Figure 2.[14] Panel (b) shows the remaining sectors that we use for our estimation.[15]

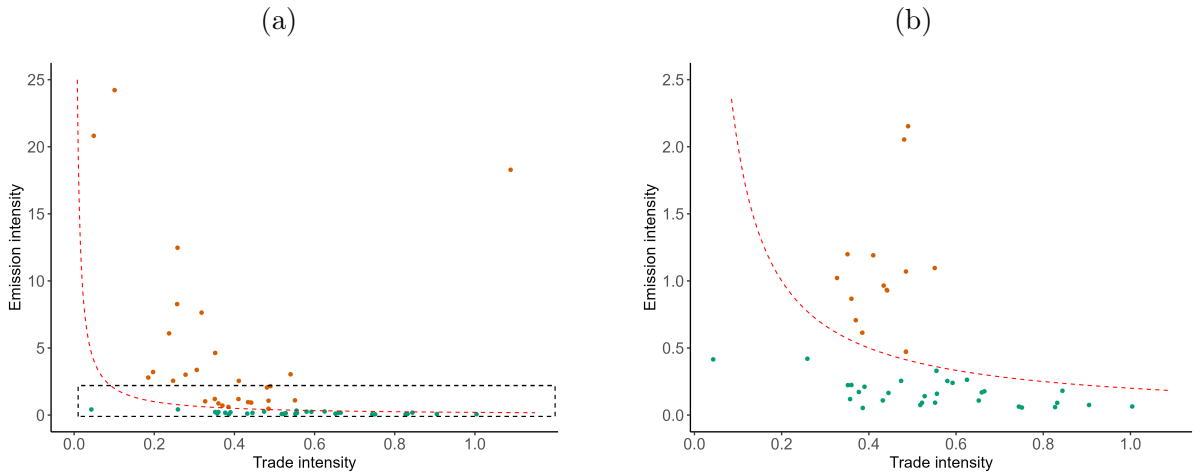
All sectors depicted in the figure received predominantly free permits in Phase III of the EU ETS. The red-colored sectors constitute the control group. They remain on the carbon leakage list and continue to benefit from near-full free allocation under Phase IV. The blue-colored sectors represent the treatment group. These sectors were removed from the carbon leakage list and received substantially fewer free permits after the reform. This restriction ensures that the sample contains only sectors that are similar in the characteristics directly determining treatment assignment. In this setting, variation in free permits stems from marginal differences in the sector's emission and trade intensity.

Our main analysis is based on a balanced panel of firms observed continuously throughout the study period. This sample choice ensures that we capture effects within firms only, as firms that enter or exit the sample are excluded from the estimation. In our data set, firm entry and exit often involve inconsistent or incomplete reporting, and it is frequently unclear when a firm has truly ceased operations, introducing potential measurement error. Receiving fewer free permits increases the total cost of firms. Therefore, firms may be more

[14] We choose a cutoff of an emission intensity of 2.52. We argue that the most problematic sectors to include have a very high emission intensity (max = 24.22). Our choice is close to the median of the potential control group (median = 2.35) balancing between the inclusion of enough control firms and the exclusion of firms far from the cutoff. We provide the results with alternative sample choices in Section 6.

[15] Since carbon-leakage status is a deterministic function of the composite indicator, a regression discontinuity (RD) design in the indicator would be the natural benchmark. However, the indicator varies only at the sector level, leaving too few observations near the threshold for local estimation as required for continuity-based RD inference (Lee and Card, 2008). Moreover, a cross-sectional RD in outcome levels would forfeit the panel variation around the announcement and implementation dates that is central to our analysis. In Section 6, we show that our results are not sensitive to our choice of the threshold.

Figure 2: Selected Sample of Treatment and Control Units




*Notes:* This figure shows the selected sample of treated and control sectors based on their position relative to the Phase IV carbon leakage eligibility threshold. Each dot represents a sector, plotted by its trade intensity and emission intensity. The red dots indicate control sectors that remained eligible for near-full free allocation; the blue dots indicate treated sectors that lost eligibility under the reform. The dashed curve represents the threshold defined by the composite rule (trade intensity $\times$ emission intensity $> 0.2$). The sample is restricted to sectors near the cut-off to ensure comparability.

likely to exit and less likely to enter the market and the coefficient of our main specification can be interpreted as the lower bound of the total effect. By restricting our sample to a balanced panel, the interpretation of the dynamic difference-in-differences estimates is more transparent, given that it ensures that our estimation is not affected by potential measurement error and reflects changes in outcomes for a consistent set of firms over time.

## 4.2 Regression Analysis

We use a difference-in-differences (DiD) specification to estimate the average treatment effect of a reduction of free emission allowances on firms. The baseline regression takes the form:

$$\ln(y_{i,s,t}) = \alpha_i + \gamma_t + \rho_A \left(\text{Treat}_s \times \text{Post2018}_t\right) + \rho_I \left(\text{Treat}_s \times \text{Post2021}_t\right) + \varepsilon_{i,s,t}, \qquad (2)$$

where $\ln(y_{i,s,t})$ denotes the logarithm of the outcome variable for firm $i$ in sector $s$ at time $t$. The specification includes firm fixed effects $\alpha_i$ to control for time-invariant differences across firms and year fixed effects $\gamma_t$ to capture common shocks affecting all firms in a given year. $\text{Treat}_s$ equals one for firms in treated sectors. $\text{Post2018}_t$ equals one from 2018 onward, while $\text{Post2021}_t$ equals one from 2021 onward. The coefficient $\rho_A$ therefore captures the effect following the announcement of the reform, while $\rho_I$ captures the additional effect following

its implementation. The total post-implementation effect is given by $\rho_A + \rho_I$. Standard errors are clustered at the sector level, which is the treatment level.

While the classical DiD provides a single average effect of the reform, it does not allow us to examine the timing and dynamics of the treatment. To address this, we also estimate a dynamic difference-in-differences model, which traces the evolution of treatment effects over time:

$$\ln(y_{i,s,t}) = \alpha_i + \gamma_t + \sum_k \beta_k \left(Treat_s \times \mathbb{1}[t - c_i = k]\right) + \varepsilon_{i,s,t}. \tag{3}$$

Here, $\mathbb{1}[t - c_i = k]$ is an event-time indicator equal to one if year $t$ is $k$ years relative to the treatment year $c_i$ of firm $i$, with the last pre-treatment year serving as the omitted baseline. The coefficients $\beta_k$ measure the ATT in each relative year. Our implementation includes three pre-treatment years (2014–2016) and five post-treatment years (2018–2022). The parallel trends assumption requires that $\beta_k$ for $k < 0$ are statistically indistinguishable from zero. Standard errors are again clustered at the sector level.

## 4.3 Identification

The identification of our difference-in-differences (DiD) framework relies on two key assumptions: the no anticipation and the parallel trends assumption (Roth et al., 2023). The no anticipation assumption requires that units do not adjust their behavior prior to treatment in response to future policy changes. We define the first post-treatment year as 2018. That is the year in which the revised carbon leakage list was announced. As detailed in Section 2, this announcement marked the earliest moment at which firms could have plausibly learned about their treatment status. We therefore use 2017 as our reference period.

The parallel trends assumption implies that in the absence of treatment, the treated and control groups would have followed similar trajectories in the outcome variables. Despite the fact that the parallel trend assumption cannot be directly tested, our research design nevertheless speaks to the plausibility of this assumption.

Firms operating in sectors with very different emission intensities are likely to differ systematically in unobserved characteristics that may independently shape outcome trajectories. To mitigate this concern, we restrict the sample to sectors very close to the eligibility cutoff. By construction, sectors in this near-threshold window must be similar in the variables that determine treatment assignment. With this restriction, our identifying assumption is that, within this set of sectors close to the cutoff, treated and control firms would have exhibited parallel trends in the outcomes in the absence of the reform. Table S2 shows statistics of emission and trade intensity by treatment status before and after our sample restriction.

Still, several concerns remain. First, firms may have attempted to influence their treatment status. Direct manipulation of the underlying eligibility metrics is, however, unlikely in our setting. The relevant emissions and trade intensity values were constructed from historical data that predate the announcement of the Phase IV rule. This makes it impossible for firms to manipulate their emissions according to the rule. More broadly, the cutoff itself emerged from a policy process that, in principle, could be subject to lobbying. The simplicity and transparency of the rule nevertheless speak against substantial scope for strategic manipulation along the quantitative margin. Rather, any plausible influence would have operated through efforts to obtain a qualitative assessment or exception, which constituted a potentially viable lobbying strategy in the policy debate. Such qualitative adjustments applied only to a very small number of sectors, which we exclude from our estimation sample.

Second, broader macroeconomic shocks, such as the COVID-19 pandemic or the war in Ukraine, might affect treated and control sectors differently. We provide evidence on the robustness of our results to such shocks in Section 6.

Third, treated and control firms may differ systematically in their ability to pass through cost shocks. Pass-through has been studied extensively in electricity markets, where it is generally found to be high (Fabra and Reguant, 2014). For manufacturing firms, pass-through is less well measured and likely to be more heterogeneous across sectors (Hintermann et al., 2020). In particular, the ability to pass through costs is closely related to trade exposure (Grubb et al., 2022). Firms that are more exposed to international competition may be less able to pass through a cost shock to consumers and may therefore be more vulnerable to such a shock. This could affect the scale response we estimate.

In contrast to emission intensity, however, there is considerable overlap in trade intensity between treated and control sectors. This reduces the concern that our results are mechanically driven by differences in pass-through ability. To address remaining concerns, we also include trade intensity in the matching procedure discussed in Section 6.

Another concern is that EUA prices increased substantially during our study period, as shown in Figure S2. Variation in permit prices can matter for our estimates through two channels. First, it can scale the treatment intensity. The monetary value of free permits, and thus the implicit transfer generated by free allocation, is proportional to the contemporaneous EUA price. Therefore, the effect of the reform we measure includes both the quantity of free permit allocation, as well as its value induced by the EUA price. Second, EUA prices may have an effect on firms' emissions independent of the value of their free permits. For our identification, this becomes a threat if our treatment and control groups are affected differently.

Changes in EUA prices during the sample period may affect treated and control firms

differently for two reasons. First, exposure to the carbon price varies with baseline emissions intensity, so a given increase in the permit price represents a larger cost shock for firms that emit more per unit of activity. Second, treated and control firms operate in different sectors. Because sectors rely on different production technologies and input mixes, they may differ in their abatement elasticity. Thus, the same price change can induce different adjustments in emissions and production across groups.

Despite our sample restrictions, Figure 2 indicates that the sectors in the control group are more emission-intensive and therefore more exposed to EUA prices than the sectors in the treatment group. If higher baseline exposure implies a stronger emissions response to rising EUA prices, emissions in the control group would fall more than emissions in the treatment group, even absent the reform. In that case, our difference-in-differences estimates would be biased toward zero, implying that the estimated treatment effect should be interpreted as a conservative estimate of the reform's total impact on emissions.

A final concern is that treated and control firms may differ in their abatement elasticities. High-emission manufacturing activities are often characterized as 'hard-to-abate', reflecting limited technological scope for deep emissions reductions in the short to medium run. Importantly, this characterization applies most strongly to the very high-intensity process industries that are far from the regulatory cutoffs, such as steel, cement, and primary aluminum (Intergovernmental Panel on Climate Change, 2022). These sectors are not represented in our analysis sample, as shown in Table S1. The industries included in our estimation sample exhibit substantially lower emission intensity than the canonical hard-to-abate sectors, reducing concerns that differences in technological abatement constraints mechanically drive the differential emissions responses we estimate.

# 5 Results

Table 2 reports our main results from estimating Equation 2. The first column shows that emissions decline substantially among treated firms relative to untreated firms following treatment. We estimate statistically significant reductions both at the announcement of the reform in 2018 and at its implementation in 2021. Taken together, the two coefficients imply a total reduction in emissions of about 14 percent.

The dynamic estimates from Equation 3 are shown in Figure 3. The effect on emissions emerges immediately after the announcement and increases over time. The estimates are statistically significant from 2018 onward. While the parallel trends assumption cannot be tested directly, the pre-announcement coefficients show no evidence of a differential pre-trend.

Our results provide direct evidence against the view that the *independence property* ap-

Table 2: Baseline Estimation

| Dependent Variables: | Verified Emissions (logs) | Revenue (logs) | Employees (logs) | Assets (logs) |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Treatment Effect 2018 | -0.0897*** | -0.0118 | -0.0655* | -0.0120 |
| | (0.0260) | (0.0379) | (0.0382) | (0.0294) |
| Treatment Effect 2021 | -0.0528** | -0.1608*** | -0.0510** | -0.0907*** |
| | (0.0246) | (0.0322) | (0.0217) | (0.0224) |
| *Fixed-effects* | | | | |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 3,816 | 3,130 | 3,130 | 3,130 |
| $R^2$ | 0.97649 | 0.97555 | 0.97424 | 0.98313 |
| Within $R^2$ | 0.01487 | 0.01468 | 0.00644 | 0.00733 |

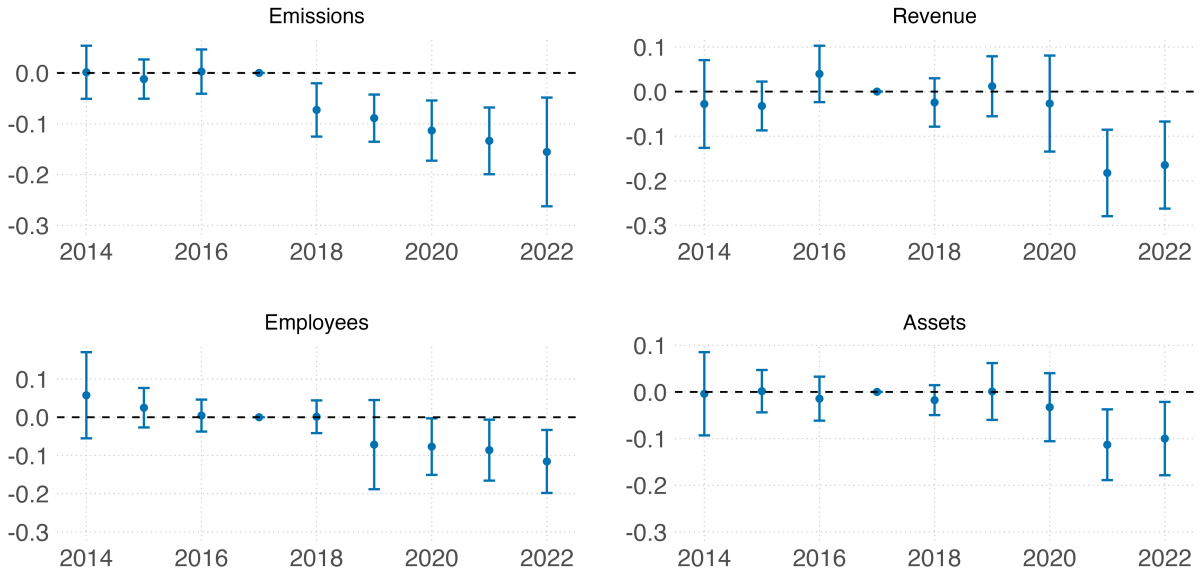
*Notes:* This table presents difference-in-differences estimates of the effect of the reform on firm-level outcomes. The coefficients correspond to the average effect of the policy reform on treated firms when the reform is announced (2018) and implemented (2021). All variables are log-transformed and standard errors clustered at the sector level. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

proximately holds in practice, especially in the EU ETS (Zaklan, 2023; Fowlie and Perloff, 2013). Our findings complement Zaklan (2023), who studies similar variation in the electricity sector of the EU ETS and finds that the independence property holds overall in that setting. We show that this conclusion may not extend to the broader manufacturing industry and therefore may not hold in general.

In Section 7, we provide a model that is consistent with our emissions results, including the timing of the observed reductions. The model also helps reconcile our findings with those of Zaklan (2023), who studies the electricity sector. In our model, the mechanism operates through adjustments within multi-product firms, a margin that is largely absent in electricity generation, where firms produce a relatively homogeneous good.

The magnitude of the estimated emissions response is economically meaningful. The reduction is similar to the estimated effect of being regulated by the EU ETS in Phases I and II (Colmer et al., 2025). Importantly, these firm-level responses do not necessarily translate into changes in aggregate emissions, which are determined by the emissions cap. Instead, our estimates indicate that free permit allocation shifts abatement effort across firms, in contrast to the equalization of marginal abatement costs implied by the independence property. The size of the response suggests that this reallocation is quantitatively important and therefore highly relevant for the cost-effectiveness of the system.

Figure 3: Dynamic Difference-in-Differences Results




*Notes:* This figure shows dynamic treatment effects on firm-level economic outcomes using event-time indicators. Each panel reports coefficients from separate regressions with firm and year fixed effects. The outcomes are verified emissions, revenue, the number of employees, and total assets. All variables are log-transformed. The vertical bars represent 95% confidence intervals, with standard errors clustered at the sector level. Significant declines are observed after the policy announcement and particularly following the implementation year (2021), suggesting that the loss of free permit allocation negatively affected firm performance across multiple dimensions.

We next examine the effect of free permit allocation on firms' economic activity. Columns (2) to (4) of Table 2 report the results for revenue, employment, and total assets. For revenue and total assets, we estimate substantial and statistically significant reductions of 16 and 9 percent, respectively, at the implementation of the reform, while the announcement has no effect. The dynamic estimates in Figure 3 confirm this pattern. The coefficients remain close to zero in all years before the implementation and show a strong and persistent decline thereafter.

For employment, the baseline estimates point to a decline of similar magnitude, with the reduction already visible one to two years before the implementation. These estimates are less robust than those for revenue and assets. They attenuate to zero once sector-specific trends are included and in the matched sample, as we show in Section 6. Therefore, we interpret the baseline employment response as suggestive rather than conclusive. A weak and gradual adjustment is in line with extensive evidence that employment adjusts only gradually because firms face substantial hiring and firing frictions (Hamermesh and Pfann,

1996; Pfann and Palm, 1993; Cederlöf et al., 2025). Our theoretical model abstracts from labor adjustment costs and characterizes the long-run relationship between firm activity and labor demand. Given this abstraction, we do not expect the model's predictions for employment to hold as sharply in the data as those for revenue and emissions.

Taken together with the results on emissions, our findings suggest that the independence of free permit allocation and firm level outcomes does not hold in the EU ETS. The reform affected firms in two phases. At the announcement, treated firms reduce their emissions while their economic activity remains unchanged. At the implementation, emissions decline further, but this time together with firms' economic activity. The contraction in economic activity is of a similar order of magnitude to the reduction in emissions. In Section 7, we show that this pattern, including its timing, is consistent with our model.

Showing that the independence property may fail in practice has important implications for the interpretation of existing evidence on the effects of emissions trading systems in general, and the EU ETS in particular. A large literature estimates the effect of the EU ETS on firms' emissions and economic performance (Colmer et al., 2025; Dechezleprêtre et al., 2023; Petrick and Wagner, 2014; Klemetsen et al., 2020). These papers typically estimate the effect of being regulated by the EU ETS relative to remaining outside the system. They show that emissions are reduced significantly while economic activity remains mostly unchanged. This margin differs from the variation studied in our paper. We hold ETS regulation status fixed and instead examine a change in the compensation embedded in free permit allocation among already-regulated firms.

Our findings suggest that existing estimates capture the effect of ETS regulation under the free permit allocation in place during the sample period, rather than a general effect that would prevail under a different amount of free permit allocation. Since manufacturing firms often received a substantial share of their allowances for free during the studied period (Colmer et al., 2025; Dechezleprêtre et al., 2023), the estimated effects need not coincide with the effects of the same system under substantially lower free allocation. In particular, our results suggest that the absence of a trade-off between emission reductions and firms' economic performance need not persist as free allocation is phased out in the coming years.

A central motivation for allocating free permits is to shield regulated firms from international competitive pressures. Accordingly, the implications of free allocation for trade flows have been extensively studied in the empirical literature (Grubb et al., 2022). Our setting is well suited to test whether the reduction in free allocation affected external adjustment margins. As shown in Appendix S4, we use sector level data and find no statistically significant effect of the reform on either imports or exports in treated sectors. However, the point estimates are in line with our firm level results and the scale effect we outline in our model,

rather than carbon leakage. Given the limited power of the sector-level trade analysis, the insignificant estimates should be interpreted cautiously.

# 6 Robustness

**Matching Procedure** We employ a matched difference-in-differences approach to validate our main results, following a methodology commonly used in related work (Colmer et al., 2025; Zaklan, 2023). Matching variables are measured in 2017, the year preceding the announcement of the policy reform. Firms are matched with replacement based on firm-level emission intensity[16], total assets, verified emissions, and sector-level non-EU imports. These variables improve comparability between firms in terms of environmental performance, firm size, emissions levels, and exposure to international trade. Similar to Colmer et al. (2025), we implement a nearest-neighbor matching approach using the Mahalanobis distance. Under this approach, we use the full sample without imposing any restrictions on sector-specific emission intensity. Appendix S3 details the matched difference-in-differences methodology and shows that our results are robust to this alternative estimation strategy and to different matching specifications. All results, except for employment, remain qualitatively unchanged and highly significant. Estimates remain in the same order of magnitude, with slightly larger estimates for emissions and slightly smaller ones for economic activity.

**Industry Trends** Another potential concern of our empirical strategy is that sector-specific trends can be correlated with our treatment timing. To address this, we augment our baseline specification with sector-specific linear time trends, which relax the standard parallel-trends assumption by allowing outcomes within two-digit sectors to follow their own linear trajectories over time. In this specification, the treated–control comparison is identified from deviations from those sector trends after the reform. This directly addresses the concern that the effect we measure is driven by pre-existing, slow-moving sector dynamics that are correlated with treatment status. Examples include differential technological progress and background decarbonization trends, long-run demand shifts, gradual changes in global competition, or slow-moving differences in relative input-price sensitivity stemming from energy mix and factor substitutability. Table S4 reports results using both two- and four-digit sector-specific trends. We view the two-digit specification as the more natural robustness check, since it allows for differential trends across broad industries without controlling at the level of treatment assignment. We additionally report four-digit trends as a more demanding specification, although these may partly absorb the post-reform adjust-

[16]Measured as the ratio of total verified emissions to revenue.

ment. Across both specifications, the effects on revenue and assets remain robust, while the employment effect becomes insignificant. The emission results are even more precise using two digit trends compared to the baseline, but lose precision controlling for four digit sector trends.

More broadly, because treatment varies at the sector-year level, sector-year shocks cannot be absorbed by fixed effects and are fundamentally inseparable from the treatment effect within a sector. Identification therefore rests on the assumption that such shocks are not systematically correlated with treatment status, even after controlling for sector trends. For confounding shocks to explain our results, however, they would need to generate differential changes closely aligned with the reform timing and reproduce the distinct pattern of an early emissions response followed by a contraction in economic activity, which remains similar across our main robustness exercises.

**Country-Time Fixed Effects** Further, we include country-time fixed effects to absorb confounders that vary at the country-year level. These fixed effects flexibly control for aggregate macroeconomic conditions such as GDP growth, unemployment, and inflation, as well as nationwide policy changes, including tax reforms, energy policies, and environmental regulation. They also account for country-level input price dynamics such as average electricity and gas prices and wage growth, and other country-level shocks, including exchange rate movements in non-euro countries. Table S5 shows that our results remain robust.

**Major Economic Shocks** Two major macroeconomic shocks during our sample period were the COVID-19 pandemic and Russia's invasion of Ukraine. Common shocks affecting all firms are absorbed by the year fixed effects. To the extent that these events interacted with slow-moving sectoral dynamics, our inclusion of sector-specific time trends further mitigates this concern. In addition, the country-time fixed effects capture differential national exposure to these shocks, for example, differences in reliance on Russian gas, heterogeneity in labor market institutions, and the availability and generosity of short-time work schemes. A residual concern is the presence of sector-specific shocks within country-years that are not well approximated by linear sector trends or fully absorbed by country-year effects. Reassuringly, Figure 3 shows no discrete changes in the first pandemic year (2020) or at the onset of the war (2022), suggesting that our estimates are not driven by these events. We also exclude sectors that are most plausibly affected by these shocks, and Figure S3 shows that our results remain robust.

**Common Support and Cutoff Sensitivity** In our main analysis, we restrict the sample to sectors close to the eligibility threshold to improve comparability between treatment and control firms. Two concerns remain. Differences in observable firm characteristics may persist within this sample, and the particular cutoff used to select control sectors is essentially arbitrary. For the differences in observable firm characteristics, we trim firms based on their pretreatment averages of emissions, revenue, employment, and assets. Specifically, for each variable, we identify the group with the lower maximum value and exclude firms in the other group whose pretreatment average exceeds this maximum. This procedure enhances common support by eliminating observations that could never be observed in both groups, thereby ensuring that results are not driven by extreme values. Figure S4 illustrates the distributions before and after trimming, and Figure S5 the estimated treatment effects. The results remain largely unchanged, confirming that our findings are not sensitive to the lack of overlap in observables. For the particular cutoff, we vary the emission-intensity cutoff used to define the control group. Table S3 re-estimates the baseline specification for both narrower and wider windows around the eligibility threshold and shows that the estimated effects remain stable across all outcomes.

# 7 Model

Our empirical results show a significant and non-trivial effect of a reduction in free permits on firms' activity level. We observe a clear distinction between the announcement and implementation phases of the reform. At the announcement, verified emissions decline while the economic indicators remain stable, consistent with firms using emissions more efficiently. At implementation, we observe an additional and economically meaningful adjustment margin. Relative to control firms, treated firms shrink, leading to lower employment, fewer total assets, reduced revenues, and further declines in emissions. These findings directly imply that firm-level outcomes are not independent of the initial allocation of emission allowances. Our findings, therefore, provide direct empirical evidence against the independence property.

Our model builds on the idea of conditional allocation (Fischer, 2001). Free permits are only a neutral transfer if their allocation does not depend on firms remaining active (Ellerman and Reguant, 2008; Konishi and Tarui, 2015). If firms must continue to operate to receive allowances, free allocation acts as an operating subsidy and distorts entry and exit decisions. We apply this argument to a multi-product firm environment commonly used in the trade literature (Eckel and Neary, 2010; Bernard et al., 2011; Mayer et al., 2014). In this framework, the same logic operates at the level of product lines rather than firms. This allows us to explain the intensive margin adjustments of firms that we observe in our

empirical analysis.

The model is based on the framework of Melitz (2003). In our model, each firm consists of a continuum of product lines. We first show that free permits do not directly affect the pricing rule of a product line, which reflects the benchmark logic of the independence property. Line-level quantities and revenues respond only indirectly, through the firm-level price index. However, at the aggregate firm level, the allocation design can have an effect. Specifically, fewer free permits increase the fixed costs of a given product line, causing the least productive lines to exit the market. Firms therefore adjust along the extensive margin, leading to a reduction in firm-level revenue and input factor demand.

Second, in an extended version of the model, we allow firms to purchase a cleaner technology that reduces emissions per unit of energy. Firms anticipate the exit of the least productive product lines, resulting in higher revenues for the remaining lines after implementation. This strengthens incentives to invest in the high-efficiency technology already at the announcement stage, thereby reducing emissions at that time.

**Households**

The representative household supplies labor inelastically at $\bar{L}$, owns the firms, and allocates nominal expenditure $R$ across the goods of the modeled economy. The household does not save and spends its entire expenditure each period. Utility is derived from a composite consumption good that aggregates a continuum of differentiated varieties supplied by a large number of firms ($N$). Preferences over these goods are represented by a C.E.S. aggregator:

$$U = \left( \sum_{j=1}^{N} Q_j^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \quad \text{where} \quad Q_j = \left( \int_{\Omega_j} q_j(\varphi)^{\frac{\sigma-1}{\sigma}} \, d\varphi \right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma > \varepsilon > 1$$

where $Q_j$ is the total quantity of a firm $j$, and each firm produces a continuum of goods or product lines[17]. $\varphi$ represents the productivity level and $\Omega_j$ the mass of goods from firm $j$. These goods are substitutes, with an elasticity of substitution of $\sigma > 1$. Products from other firms are also substitutes with an elasticity of substitution of $\varepsilon > 1$. We assume that $\sigma > \varepsilon > 1$ to reflect the fact that purchasing a good from another firm may involve additional switching costs for consumers. For example, buying a personal computer is often tied to a specific operating system. Switching to a computer produced by another firm may require adapting to a different operating system, which lowers the effective elasticity of substitution relative to that between products offered by the same firm.

[17]In this model, each product line produces one good.

Dixit and Stiglitz (1977) showed that the set of varieties can be understood as an aggregate good $Q \equiv U$, which is associated with an aggregate price index:

$$P = \left( \sum_j P_j^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}} \quad \text{where} \quad P_j = \left( \int_{\Omega_j} p_j(\varphi)^{1-\sigma} d\varphi \right)^{\frac{1}{1-\sigma}} \tag{4}$$

where $P_j$ is the firm level aggregate price index. Equation 4 allows us to derive the optimal consumption and expenditure decision on the firm level: $Q_j = Q \left( \frac{P_j}{P} \right)^{-\varepsilon}$ and $R_j = R \left( \frac{P_j}{P} \right)^{1-\varepsilon}$, where $Q_j$ and $R_j$ are the firm-level quantity and revenue, respectively. $Q$ and $R$ denote the corresponding aggregates for the modeled economy, with $R = PQ$. Similarly, within a firm $j$, the quantity and revenue of any given product line is $q_j(\varphi) = Q_j \left( \frac{p_j(\varphi)}{P_j} \right)^{-\sigma}$ and $r_j(\varphi) = R_j \left( \frac{p_j(\varphi)}{P_j} \right)^{1-\sigma}$.

**Production**

All firms and all product lines have the same production function which requires two factors, labor and energy. For a product line to operate, a fixed cost $F_j(\tau) = f_{\text{fix}} - x_j \tau$ has to be paid every period. $f_{\text{fix}}$ represents general costs that are independent of the ETS, while $x_j$ and $\tau$ are the number of free permits allocated to a product line and the carbon price, respectively. Firms participate in a broader emissions trading system and take the permit price $\tau$ as given. We assume $F_j > 0$, i.e. the value of free permits does not exceed the non-ETS fixed cost of operating a product line; this is required for the zero-profit condition and for every comparative static below.[18] Taken together, $x_j$ and $\tau$ determine the value of the transfer. The technology which is used for production has constant returns to scale. The cost minimization problem of a product line is:

$$\min_{\ell_j, e_j} \; w\ell_j + (P_e + \tau) e_j \quad \text{s.t.} \quad \varphi_j \, \ell_j^{\alpha} e_j^{1-\alpha} = 1$$

where $\ell_j$ is labor hired by a specific product line of a firm $j$ and $e_j$ is energy. The price of labor is given by the wage $w$ and the price of energy by $P_e$. The wage $w$ is taken as numéraire with fixed labor supply. The price of energy is the exogenous world price. For the carbon emissions associated with the energy used, $\tau$ has to be paid additionally. For simplicity, the conversion of energy units and carbon emissions is normalized to one. Product lines differ in

[18] $F_j > 0$ requires only that the value of free permits, $x_j \tau$, falls short of the non-ETS fixed cost $f_{\text{fix}}$. It does not require free permits to fall short of verified emissions. The ratios above one in Table 1 therefore do not conflict with $F_j > 0$: they reflect that the transfer is large relative to the *variable* carbon bill, which arises because free allocation is based on historical activity levels while verified emissions reflect current production.

their productivity level $\varphi$, but they all face the same production structure, input prices, and fixed costs $F_j$. A firm is a monopolist for each of its product lines and therefore maximizes profits, setting the price. Equivalently, minimizing costs on the product level allows us to calculate the unit cost of a given product line in firm $j$ and to obtain the pricing rule:

$$c_u(\varphi) = \frac{1}{\varphi} \underbrace{\left(\frac{w}{\alpha}\right)^{\alpha} \left(\frac{P_e + \tau}{1-\alpha}\right)^{1-\alpha}}_{\equiv \Psi}, \qquad p_j(\varphi) = \underbrace{\frac{\sigma}{\sigma - 1}}_{\text{constant markup}} \frac{\Psi}{\varphi}$$

The expression $c_u(\varphi)$ shows again that the only difference between these product lines is the productivity $\varphi$. The term $\Psi$ is the same for all products. Note that the optimal price of a product line is independent of the fixed cost $F_j$. This is in line with the independence property, since the intensive margin is not *directly* affected by free permits: a line's price, and hence its quantity conditional on the firm-level aggregates $Q_j$ and $P_j$, does not respond to its own fixed cost. Quantities and revenues nonetheless adjust when $F_j$ alters the mass of active lines and thereby the firm index, which is the channel underlying the reallocation studied below. Similar to atomistic firms in Melitz (2003), the ratios of any two product lines' quantity and revenue only depend on their relative productivity levels:

$$\frac{q_j(\varphi)}{q_j(\varphi')} = \left(\frac{\varphi}{\varphi'}\right)^{\sigma} \quad \frac{r_j(\varphi)}{r_j(\varphi')} = \left(\frac{\varphi}{\varphi'}\right)^{\sigma-1} \tag{5}$$

**Aggregation**

In our model, we distinguish between two types of aggregate variables. For firm $j$, the firm-level aggregates for price, revenue, quantity, and profit are denoted $P_j$, $R_j$, $Q_j$, and $\Pi_j$, respectively. The firm-level inputs are the labor $L_j$ and energy $E_j$. The aggregates for the economy are defined as the sum of the same variables over all firms.

An equilibrium is characterized by a finite set of firms $N$. Each firm $j \in \{1, ..., N\}$ operates a mass $M_j$ of product lines which differ in their productivity $\varphi$. $\mu(\varphi)$ is a distribution of productivity levels over the subset $(0, \infty)$, such that $\int_0^\infty \mu(\varphi) d\varphi = 1$. The distribution is the same for all firms. Similarly to Melitz (2003), we define $\tilde{\varphi}_j$ as a weighted average of the product line productivity levels $\varphi$: $\tilde{\varphi}_j \equiv \left[\int_0^\infty \varphi^{\sigma-1} \mu(\varphi)\, d\varphi\right]^{\frac{1}{\sigma-1}}$. $\tilde{\varphi}_j$ is independent of the number of product lines $M_j$ in a firm. If each product line operated at productivity $\tilde{\varphi}_j$, the firm's price index would be unchanged relative to that implied by its actual within-firm distribution of productivities. Accordingly, $\tilde{\varphi}_j$ summarizes the within-firm productivity distribution in $P_j$ as a single sufficient statistic, conditional on $M_j$ and common cost shifters. Under CES and constant markups, all firm-level aggregates decompose into the mass of

active lines $M_j$ and a single statistic of within-firm heterogeneity $\tilde{\varphi}_j$. As shown in Appendix S5.1, firm-level aggregate quantity, revenue and profits are then given by:

$$P_j = M_j^{\frac{1}{1-\sigma}} p_j(\tilde{\varphi}_j) \qquad Q_j = M_j^{\frac{\sigma}{\sigma-1}} q_j(\tilde{\varphi}_j) \qquad R_j = M_j r_j(\tilde{\varphi}_j) \qquad \Pi_j = M_j \pi(\tilde{\varphi}_j) \tag{6}$$

By combining Equation 6 with the optimal expenditure decision, the ratios between the firm level aggregates and the economy aggregates can be calculated:

$$\frac{P_j}{P} = \frac{M_j^{-\frac{1}{\sigma-1}} \tilde{\varphi}_j^{-1}}{\left(\sum_{m=1}^{N} M_m^{\frac{\varepsilon-1}{\sigma-1}} \tilde{\varphi}_m^{\varepsilon-1}\right)^{-\frac{1}{\varepsilon-1}}} \qquad \frac{R_j}{R} = \left(\frac{P_j}{P}\right)^{1-\varepsilon} = \frac{M_j^{\frac{\varepsilon-1}{\sigma-1}} \tilde{\varphi}_j^{\varepsilon-1}}{\sum_{m=1}^{N} M_m^{\frac{\varepsilon-1}{\sigma-1}} \tilde{\varphi}_m^{\varepsilon-1}} \tag{7}$$

The firm level energy input for production $E_j^p$, and respectively for labor $L_j^p$ can be derived by combining the pricing rule and the definition for revenue, $r(\varphi) = p(\varphi)q(\varphi)$, and making use of the fact that the expenditure for each input is constant. Taking the sum over all firms gives the economy-wide inputs used in production. The ratios of inputs of firm $j$ relative to all inputs equal the ratio of revenue:

$$L_j^p = \frac{\alpha(\sigma-1)}{\sigma w} R_j \quad \text{and} \quad E_j^p = \frac{(1-\alpha)(\sigma-1)}{\sigma(P_e+\tau)} R_j \quad \Rightarrow \quad \frac{R_j}{R} = \frac{L_j^p}{L^p} = \frac{E_j^p}{E^p} \tag{8}$$

For the comparison with our empirical results, the relative price level $\frac{P_j}{P}$ of a treated firm $j$ is crucial, since it determines the relative revenue $\frac{R_j}{R}$ as well as the relative energy demand and thus emissions $\frac{E_j}{E}$. An increase in the firm level price relative to the economy-wide price index will decrease revenue and emissions, as implied by Equations 7 and 8.

In the following, we elaborate on the intuition underlying Equation 7 and highlight its form, which comprises two components in the numerator and two in the denominator. First, $M_j^{-\frac{1}{\sigma-1}}$ indicates that a larger mass of product lines within firm $j$ decreases the relative price index. Since $P_j$ represents the minimized costs of one unit of firm $j$'s CES bundle, more varieties expand consumer options and make it cheaper to achieve the same utility. Second, $\tilde{\varphi}_j$ represents the weighted average productivity within firm $j$. The higher the average productivity $\tilde{\varphi}_j$, the lower the firm-level price index given the pricing rule.

The denominator can be interpreted as the top nest normalizer. It is the market-wide benchmark against which all firms compete. When any firm adds more product lines, this benchmark rises, which lowers the aggregate price index and slightly squeezes everyone else's shares. The same dynamic occurs if a firm improves the average productivity of its active lines. If all firms improve by the same margin, the benchmark rises proportionally, so relative shares are unchanged. More product lines within a firm ($M_j$ larger) or higher average

productivity ($\tilde{\varphi}$) decrease $P_j$ and therefore $P$ through its share. The exponent $\frac{\varepsilon-1}{\sigma-1}$ shows that within-firm substitutability ($\sigma$) dampens the benefit of adding varieties, while across-firm substitutability ($\varepsilon$) amplifies how those within-firm gains translate into market share.

**Entry and Exit**

There is an unbounded pool of prospective entrants of product lines into any given firm $j$. Prior to entry, those lines are identical and must pay a fixed cost $f_{e,j} > 0$. Note that the entry cost is the same for all product lines. After entry, product lines draw their initial productivity parameter $\varphi_j$ from a distribution $g(\varphi)$ which has support over $(0, \infty)$ with a continuous cumulative distribution $G(\varphi)$. The distribution $g(\varphi)$ is common across firms.

After entry, a product line may immediately exit and not produce. If a product line produces, it faces a constant probability $\delta$ to receive a bad shock and exit. The value of the product line can then be expressed as $v_j(\varphi) = \max\left\{0, \frac{\pi_j(\varphi)}{\delta}\right\}$. Active product lines must have a positive profit. Thus, the lowest possible productivity level of active variants (hereafter cutoff level) yields a profit of zero: $v_j(\varphi_j^*) = 0 \iff \pi_j(\varphi_j^*) = 0$. Any product line that draws a productivity level $\varphi_j < \varphi_j^*$ will exit immediately. Similar to Melitz (2003), $\mu(\varphi_j)$ is the conditional distribution of $g(\varphi_j)$ on $[\varphi_j^*, \infty)$ and allows us to express the firm level average productivity level $\tilde{\varphi}_j$ as a function of the cutoff level: $\tilde{\varphi}_j(\varphi_j^*) = \left[\frac{1}{1-G(\varphi_j^*)} \int_{\varphi_j^*}^{\infty} \varphi_j^{\sigma-1} g(\varphi_j)\, d\varphi_j\right]^{\frac{1}{\sigma-1}}$. Since the average productivity level $\tilde{\varphi}_j$ is completely determined by the cutoff productivity level $\varphi_j^*$, the average profit and revenue levels are as well. Using Equation 5 and the definition of average revenue $\bar{r}_j \equiv \int r_j(\varphi)\mu_j(\varphi)\, d\varphi$ and profits $\bar{\pi}_j \equiv \int_0^{\infty} \pi_j(\varphi)\mu_j(\varphi)\, d\varphi$, the zero profit cutoff condition (ZPC) is:

$$\pi(\varphi_j^*) = 0 \iff \frac{r(\varphi_j^*)}{\sigma} = F_j \iff \bar{\pi}_j = F_j \left[\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-1} - 1\right] \tag{9}$$

where the ZPC is used to pin down the average product line profit $\bar{\pi}_j$. The expression $\bar{v}_j \equiv \int_{\varphi_j^*}^{\infty} v_j(\varphi)\, \mu_j(\varphi)\, d\varphi = \frac{1}{\delta}\, \bar{\pi}_j$ captures the present value of firm $j$'s average profit flows and thus the average value of its product line. The expected stream of future profits must compensate for the entry cost $f_{e,j}$. Hence, the net value of entry is given by the value of the product line conditional on successful entry, weighted by the probability of entry, minus the fixed cost: $\frac{1-G(\varphi_j^*)}{\delta}\, \bar{\pi}_j - f_{e,j}$. If this value were negative, no product line would enter. In an equilibrium where entry is unrestricted, this value cannot be positive as well. Therefore,

$v_{e,j} = 0$, which allows us to derive the free entry (FE) condition:

$$\bar{\pi}_j = \frac{\delta f_{e,j}}{1 - G(\varphi_j^*)} \tag{10}$$

The ZPC and FE retain the properties established in Melitz (2003), ensuring the existence and uniqueness of the equilibrium values $\varphi_j^*$ and $\bar{\pi}_j$. For this equilibrium to be in a steady state, let $n_j$ be the flow of new draws each period and $\delta$ the death probability. In steady state, inflows of successful entrants equal outflows of incumbents that die. The period-to-period change is: $M_{j,t+1} - M_{j,t} = n_{j,t}\left[1 - G(\varphi_j^*)\right] - \delta M_{j,t}$, where stationarity requires this change to be zero. Therefore, $M_j = \frac{n_j}{\delta}\left[1 - G(\varphi_j^*)\right]$. We use this expression together with Equations 10 and 6 to show that $\Pi_j = n_j\, f_{e,j}$. Thus, each period, firm $j$ spends $n_j\, f_{e,j}$ on entry attempts, which equals in a stationary equilibrium the profits generated by the incumbent product lines $\Pi_j$. Due to the Cobb-Douglas production function, we know that the entry wage bill will be: $wL_j^e = \alpha\Pi_j$ and $E_j^e = \frac{1-\alpha}{P_e+\tau}\Pi_j$. The total inputs can then be expressed as:

$$L_j^{\text{tot}} = L_j^p + L_j^e = \frac{\alpha}{w}\left(\frac{\sigma - 1}{\sigma}R_j + \Pi_j\right) \qquad E_j^{\text{tot}} = \frac{1-\alpha}{P_e + \tau}\left(\frac{\sigma - 1}{\sigma}R_j + \Pi_j\right)$$

In the following two sections, we analyze the policy reform using this framework, beginning with a brief discussion on how the model maps to the institutional and empirical settings. The first section examines the effect of reducing free permits for a subset of firms. The second one extends the model to allow firms to invest in emission-reducing technology, which enables us to assess the impact of the announcement of a reduction in free permits.

**Policy Implementation**

In the EU ETS, the amount of free permits is calculated at the installation level. Installations or sub-installations are closely related to our concept of product lines. The free permits are allocated based on four different components, as shown in Equation 1. The benchmark $B_s$ is sector-based and therefore identical across all product lines, under the assumption that each firm operates in only one sector. This assumption is well supported by our data.[19]

In our model, we abstract from the historical activity level $HAL_{i\bar{t}}$. As outlined in section 2, firms cannot manipulate their treatment status by decisions on their production or input demand. Consequently, firm size and past emissions do not play a strategic role in this

[19]In our sample, 95% of firms operate installations in a single sector. Only a small share of firms (less than 2% of the sample) have more than one treatment status. In these cases, we assign firms to the sector corresponding to the installation (or group of installations) with the highest emissions. Our results are robust to excluding these firms.

context. We therefore abstract from this factor in the model and focus exclusively on identifying the effect of the reform. The time-varying reduction factor $R_t$ affects all installations uniformly. Lastly, the carbon leakage factor, $CLEF_{st}$, is the key component of the allocation rule, as it constitutes our treatment. Under the data-consistent assumption that each firm operates within a single sector, all of a firm's product lines are exposed to the treatment in the same way. Hence, a firm is either treated or not.

In our empirical analysis, we compare firms that experience a reduction in free permits in a difference-in-difference setting. Our main outcome variables are emissions, revenue, and other inputs in treated firms relative to control firms. The equivalent variables in the model are therefore the aggregated firm-level outcomes relative to the rest of the economy: $\frac{R_j}{R_{-j}}$, $\frac{E_j}{E_{-j}}$ and $\frac{L_j}{L_{-j}}$. Although the model abstracts from capital, firms operating fewer product lines require less productive capacity. We therefore read the decline in total assets, a broad measure of firm scale, as consistent with the contraction the model predicts through revenue and input demand. As discussed above, those ratios depend on the relative price index of firm $j$: $\frac{P_j}{P_{-j}}$. In our model, free permits decrease the fixed cost of every product line $F_j = f_{\text{fix}} - x_j\tau$. We assume that each product line in firm $j$ receives the same amount of free permits $x_j$. Therefore, to understand the effect of the implementation of the reform, we take the derivative of the price index of firm $j$ relative to all other firms $m \neq j$ with respect to the fixed cost:

$$\frac{\partial}{\partial F_j} \ln\left(\frac{P_j}{P_{-j}}\right) = \Bigg[\underbrace{-\frac{1}{\sigma-1}\frac{1}{M_j}\frac{\partial M_j}{\partial F_j}}_{\text{selection and entry}(+)} \quad \underbrace{-\frac{1}{\tilde{\varphi}_j}\frac{\partial \tilde{\varphi}_j}{\partial F_j}}_{\text{composition }(-)}\Bigg] \; (+\,\text{GE spillovers}) \tag{11}$$

where the GE spillovers are given by $-\sum_{m\neq j}\frac{R_m}{R_{-j}}\left[-\frac{1}{\sigma-1}\frac{1}{M_m}\frac{\partial M_m}{\partial F_j} - \frac{1}{\tilde{\varphi}_m}\frac{\partial \tilde{\varphi}_m}{\partial F_j}\right]$. For the detailed steps of the derivation of the policy impact, see Appendix S5.2. Overall, the fixed cost affects the relative price of firm $j$ by jointly shaping the total mass of product lines, $M_j$, and the weighted average productivity of its operating lines, $\tilde{\varphi}_j$. It does so through three distinct channels - the selection channel, the entry-flow channel, and the composition channel.
$M_j$ is affected through the entry-flow and the selection channel:

$$\frac{\partial M_j}{\partial F_j} = \underbrace{\frac{\partial n_j}{\partial F_j}\frac{1-G(\varphi_j^*)}{\delta}}_{\text{entry-flow}} - \underbrace{\frac{n_j}{\delta}\, g(\varphi_j^*)\frac{d\varphi_j^*}{dF_j}}_{\text{selection}} \tag{12}$$

The entry-flow channel captures the fact that higher fixed costs discourage the entry of new product lines. Fewer attempts decrease the overall mass of product lines within firm $j$.

In Equation 12, the channel is captured by a change in the entry-flow as a result of a change in fixed cost $\frac{\partial n_j}{\partial F_j} < 0$, multiplied by the probability that an entry is successful $1 - G(\varphi_j^*)$ and discounted by the death probability $\delta$.

The selection channel arises because higher fixed costs raise the survival cutoff, $\frac{\partial \varphi_j^*}{\partial F_j} > 0$. Given density $g(\varphi_j^*)$ near this threshold, an increase in the cutoff reduces the survival rate and thus shrinks the mass of product lines $M_j$ of firm $j$. Hence, both the entry-flow channel and the selection channel have a negative effect on $M_j$.

Finally, the composition channel describes the effect of fixed cost on the weighted average productivity $\tilde{\varphi}_j$:

$$\frac{\partial \tilde{\varphi}_j}{\partial F_j} = \underbrace{\frac{\partial \tilde{\varphi}_j}{\partial \varphi_j^*}}_{\text{truncation raises mean}} \underbrace{\frac{\partial \varphi_j^*}{\partial F_j}}_{\text{tougher cutoff}} > 0 \tag{13}$$

Here, a tighter survival cutoff for product lines $\left(\frac{\partial \varphi_j^*}{\partial F_j} > 0\right)$ increases the average productivity, since the least productive product lines leave the market. The term $\frac{\partial \tilde{\varphi}_j}{\partial \varphi_j^*} > 0$ captures the fact that the truncation of the distribution increases the weighted average productivity.

Appendix S5.2 establishes these comparative statics under a Pareto productivity distribution. Higher fixed costs reduce entry and raise the survival cutoff, while selection increases the average productivity of the remaining product lines. Under the maintained assumption $\theta > \sigma - 1$, which is required for average productivity to be well defined, the reduction in product variety dominates this composition effect. General-equilibrium spillovers further reinforce the increase in the relative price index.

Combining these results, we conclude that a reduction in free permits increases the relative price index $\frac{P_j}{P_{-j}}$ and therefore reduces relative revenue $\frac{R_j}{R_{-j}}$ and production input demand $\frac{L_j^p}{L_{-j}^p}$ and $\frac{E_j^p}{E_{-j}^p}$.[20] Thus, the model predicts qualitatively exactly the response we observe in our empirical analyses at the implementation of the reform. The comparative statics scale with the inverse of the net fixed cost $F_j$. The model therefore predicts stronger responses for product lines whose free allocation covers a larger share of their fixed operating costs, since the same reduction in free permits is proportionally larger for them. In the next part, we discuss the announcement effect we observe only for emissions.

[20] Under the Pareto distribution, aggregate operating profits satisfy $\Pi_j = \frac{\sigma-1}{\sigma\theta} R_j$. Hence, the expressions above imply that total labor and energy demand are proportional to $R_j$ and therefore have the same response to the reform.

**Announcement of Policy Change**

In this section, we extend the model by allowing for an investment that lowers the emission factor of the energy used by product lines. Product lines can decide to pay a fixed cost $K$ that grants them access to a cleaner technology characterized by an emission factor $\kappa > 0$. All derivations supplementary to this section are in Appendix S5.3. With the high emission efficiency technology $\kappa_h < \kappa_\ell$, each unit of energy generates fewer emissions and the cost minimization problem of product lines becomes:

$$\min_{\ell_j,\, e_j} \; w\ell_j + (P_e + \tau\kappa)\, e_j \quad \text{s.t.} \quad \varphi_j\, \ell_j^{\alpha} e_j^{1-\alpha} = 1$$

Then, the pricing rule becomes:

$$p(\kappa;\varphi) = \frac{\sigma}{\sigma-1}\frac{\Psi(\kappa)}{\varphi} \quad \text{and} \quad m \equiv \frac{\Psi(\kappa_h)}{\Psi(\kappa_\ell)} = \left(\frac{P_e + \tau\kappa_h}{P_e + \tau\kappa_\ell}\right)^{1-\alpha} < 1$$

where $\Psi(\kappa) = \left(\frac{w}{\alpha}\right)^{\alpha}\left(\frac{P_e+\tau\kappa}{1-\alpha}\right)^{1-\alpha}$. Emissions of a product line are $\kappa\, e_j$. Since energy expenditure is a constant share $1-\alpha$ of variable cost, the emission–revenue mapping of a line follows immediately:

$$\kappa\, e(\varphi) = \frac{\kappa}{P_e + \tau\kappa}\,\frac{(1-\alpha)(\sigma-1)}{\sigma}\, r(\varphi) \tag{14}$$

The factor $\frac{\kappa}{P_e+\tau\kappa}$ is strictly increasing in $\kappa$, so adoption lowers a line's emissions per unit of revenue. At the same time, the cleaner technology lowers marginal costs and prices, which increases demand for the adopting product line and partly offsets the reduction in emission intensity. In the Appendix we show that total emissions nevertheless decline when the emission-intensity effect dominates this rebound effect. This holds when $P_e > (\sigma-1)(1-\alpha)\tau\kappa_\ell$, and is therefore more likely when the carbon-cost component of energy costs is small relative to the energy price.

Now, each product line has two potential prices, $p_h$ is the unit price when the high efficiency technology is adopted and $p_l$ is the low efficiency equivalent. Using $m$, $p_h$ can be expressed as a function of $p_l$: $p_h(\varphi) = m\, p_\ell(\varphi)$. Similarly, the revenue of a product line adopting the technology can be expressed as $r_h(\varphi) = m^{1-\sigma} r_\ell(\varphi)$. This allows us to calculate the increase in value of a product line that results from adopting the high efficiency technology:

$$\Delta v(\varphi) = \frac{\Delta\pi(\varphi)}{\delta} \qquad \text{where} \qquad \Delta\pi(\varphi) = \frac{1}{\sigma}(m^{1-\sigma}-1) r_\ell(\varphi) \tag{15}$$

A product line will adopt the high efficiency technology when the gain from adoption exceeds the cost: $\frac{\Delta\pi(\varphi)}{\delta} \geq K \iff \Delta\pi(\varphi) \geq \delta K$. Taking the firm-level aggregates $R_j$ and $P_j$ as given, we obtain a unique productivity cutoff, above which a product line will adopt:

$$\varphi_j^A = \varphi_j^* \left[ \frac{\sigma \delta K}{r_\ell(\varphi_j^*)(m^{1-\sigma} - 1)} \right]^{1/(\sigma-1)} \tag{16}$$

Product lines with a productivity level $\varphi_j > \varphi_j^A$ will invest in the high-efficiency technology. The productivity threshold increases in the adoption cost $\delta K$, given that a higher present value of extra operating profits is needed to make the investment worthwhile, which requires a higher productivity. Larger $r(\varphi_j^*)$ increases every line's incremental profits due to the technology, decreasing the threshold. If the technology is weak ($m \to 1$), the threshold converges towards infinity, given that the gain of the technology adoption goes towards zero. As we show in the Appendix, the adoption threshold depends negatively on $F_j$, with $\frac{\partial \ln \varphi_j^A}{\partial \ln F_j} = \frac{1}{\theta} - \frac{1}{\sigma-1} < 0$ under $\theta > \sigma - 1$. A higher fixed operating cost raises the survival cutoff and induces the least productive product lines to exit. The resulting reallocation of demand raises the revenue of the remaining product lines and, since the gain from adoption is proportional to revenue, strengthens their incentive to adopt the cleaner technology. This comparative static compares equilibria with different permanent levels of the fixed cost. It therefore captures the total effect of the reform on adoption, as it would arise without an announcement period.

Equation 16 takes the firm-level aggregates as given, while in equilibrium a positive mass of adopters lowers the firm-level price index and with it the gain from adoption. As we show in the Appendix, this feedback raises the equilibrium adoption cutoff but attenuates rather than reverses its responses to the policy, since adoption decisions are strategic substitutes within the firm.

We model technology adoption as a one-time, irreversible investment decision made when the policy change is announced. Product lines choose whether to incur the adoption cost $K$ based on the current and expected future profit gains from the technology. Anticipating higher future returns does not by itself imply that firms invest immediately rather than waiting until implementation. For tractability, we abstract from the underlying investment-timing problem and from subsequent opportunities to revise this technology choice.[21] To understand how the announcement of the reform affects treated firms, note first that the gain from adopting the high-efficiency technology depends on the revenue of the respective

[21] In practice, uncertainty about completion (Jeon, 2024), learning before implementation (Pérez and Ponce, 2015), or expected equipment shortages or price increases (Goolsbee, 1998) can make delay costly and thereby induce investment following an announcement.

product line, as shown in Equation 16. The value of a technology is determined by the discounted stream of profit gains generated by lower production costs associated with the high-efficiency technology. This stream extends over an infinite horizon and is discounted using the constant death probability $\delta$. The intuition behind the announcement effect is that the remaining product lines of the treated firm $j$ anticipate higher future revenue. Their revenue is going to be higher, because they receive some share of the demand of those product lines exiting the market due to the higher fixed cost. The fact that the elasticity of substitution within firms is larger than between firms ($\sigma > \varepsilon > 1$) ensures that product lines of treated firm $j$ are more affected than all other firms $m \neq j$. Allowing for the revenue to change in the future, the value of a product line is based on $\Delta\pi_0$ in the current period and $\Delta\pi_1$ in all periods after:

$$\Delta v_0(\varphi) = \Delta\pi_0(\varphi) + (1-\delta)\Delta\pi_1(\varphi) + (1-\delta)^2\Delta\pi_1(\varphi) + \cdots = \Delta\pi_0(\varphi) + \frac{1-\delta}{\delta}\Delta\pi_1(\varphi)$$

This allows us to express the productivity cutoff, including the announcement effect, where $\frac{r_\ell^1(\varphi)}{r_\ell^0(\varphi)} \equiv \Phi_j$:

$$\varphi_{0,j}^A = \varphi_{0,j}^* \left[ \frac{\sigma K}{r_\ell^0(\varphi^*)(m^{1-\sigma}-1)} \frac{1}{1+\frac{1-\delta}{\delta}\Phi_j} \right]^{\frac{1}{\sigma-1}} \tag{17}$$

Note that if the revenue remains the same for a given product line ($r_\ell^1(\varphi) = r_\ell^0(\varphi)$ and $\Phi_j = 1$), Equation 17 simplifies to 16. In the Appendix, we provide a detailed discussion on the components that affect $\Phi_j$. When $M_j$, the number of product lines of firm $j$, decreases in $t = 1$, households substitute those with other products in firm $j$. Then, the productivity cutoff above which a product line chooses to invest in the high efficiency technology decreases ($\frac{\partial \varphi_{0,j}^A}{\partial \Phi_j} < 0$). To determine whether this effect is stronger for treated firm j than for other firms $m \neq j$, consider their relative change in future product-line revenue. Using product-line demand and the firm-level demand system gives:

$$\frac{\Phi_j}{\Phi_m} = \left( \frac{P_j^1/P_j^0}{P_m^1/P_m^0} \right)^{\sigma-\varepsilon} \tag{18}$$

Aggregate expenditure and the economy-wide price index cancel in this comparison. From the implementation analysis, an increase in $F_j^1$ raises $P_j^1$ relative to $P_m^1$. Hence, because $\sigma > \varepsilon$, it raises the expected future revenue of product lines in treated firm $j$ relative to those in other firms. We show in the Appendix that the relative change in the productivity

cutoff can be expressed as:

$$\frac{\partial}{\partial F_j^1} \ln\left(\frac{\varphi_{A,j}^0}{\varphi_{A,m}^0}\right)\Bigg|_{\Phi=1} = -\frac{1-\delta}{\sigma-1}(\sigma-\varepsilon)\left(\underbrace{\frac{1}{P_j^1}\frac{\partial P_j^1}{\partial F_j^1}}_{+} \underbrace{-\frac{1}{P_m^1}\frac{\partial P_m^1}{\partial F_j^1}}_{+}\right) \tag{19}$$

Thus, the announcement lowers the technology-adoption cutoff more strongly in the treated firm. The mechanism reflects two opposing forces. The exit of product lines shifts demand toward the remaining products within firm $j$, with strength $\sigma-1$, while the higher firm-level price index shifts demand toward other firms, with strength $1-\varepsilon$. Since $\sigma > \varepsilon$ the within-firm reallocation dominates, increasing the expected future revenue and technology-adoption incentives of the surviving product lines.

**Conclusion**

Taken together, this model rationalizes our empirical findings at the announcement as well as at the implementation of the reform. At the implementation of the reform, higher fixed costs decrease the mass of product lines of treated firms. This increases the price index of those firms compared to all other firms. Therefore, revenue and input demand fall. Due to the anticipation of a higher demand, the remaining product lines in the treated firm have a stronger incentive to invest in a cleaner technology than all other firms. Adoption lowers the emission intensity of these lines. Therefore, treated firms may decrease their emissions relative to non-treated firms immediately upon announcement, which we also observe in our empirical analysis.

# 8 Conclusion

This paper provides new evidence on the role of free emission permits in emissions trading systems. First, we exploit a major reform in the EU ETS with a sharp eligibility cutoff. By using a difference-in-differences design, we isolate the causal effect of losing access to free permit allocation on firm emissions and economic activity levels. Second, we develop a multi-product general equilibrium model, analyzing the relationship between free emission permits and firm outcomes in ETS.

We obtain three major results. First, emissions among treated firms substantially declined at the announcement and declined further at the implementation of the reform. Second, the drop in emissions is accompanied by a decline in the economic activity of firms

only at the implementation. Third, our multi-product general equilibrium model shows that extensive margin adjustments on the product level can explain the patterns we observe.

A caveat of the empirical design is that identification is obtained from firms in sectors close to the eligibility cutoff. This strengthens our identification, but it also implies that the estimates are most informative for firms with relatively low emissions intensity. Despite having a large share of the manufacturing industry in our sample, firms operating in sectors far from the cutoff are plausibly different along dimensions that matter for adjustment. Therefore, external validity beyond the near-threshold set of sectors cannot be assumed.

These findings have direct implications for policy makers and for the design of emissions trading systems. They indicate that free permit allocation is not neutral, but affects both emissions and firms' economic activity. Free allocation can sustain product lines that would otherwise not operate, thereby increasing activity while lowering average productivity because less productive product lines remain in the market. This extensive-margin response also matters for environmental performance beyond the direct scale effect. By keeping marginal product lines active, free allocation can dampen the expansion of more productive product lines. It also weakens incentives for those lines to adopt cleaner technologies, which may reduce abatement and slow down technological upgrading.

Policymakers should be aware that the role of free allocation is broader than preserving international competitiveness. As free permits are phased down in the coming years and the EU transitions toward a carbon border adjustment mechanism, the firm responses we show in this paper become part of the policy trade-offs. Accounting for the effects of free allocation on firms' scale and technology adoption is therefore important for designing and managing the transition.

These findings also point to two directions for future research. First, it is important to study the implications of free allocation for firms in highly emissions-intensive sectors. Our empirical setting is less informative about these sectors and additional evidence is needed to understand their response. At the same time, they account for a large share of regulated emissions, and free allocation is most prevalent in these activities. Given that this paper shows that free permits affect emissions, reductions in free allocation could be especially consequential in these industries.

Second, the adjustment mechanism suggested by the model should be tested in empirical settings that allow the predicted patterns to be observed more directly, for example, with data that observe the products firms produce, and technology adoption. Such evidence would help assess the external relevance of the mechanism and its ability to account for the magnitude of the effects.

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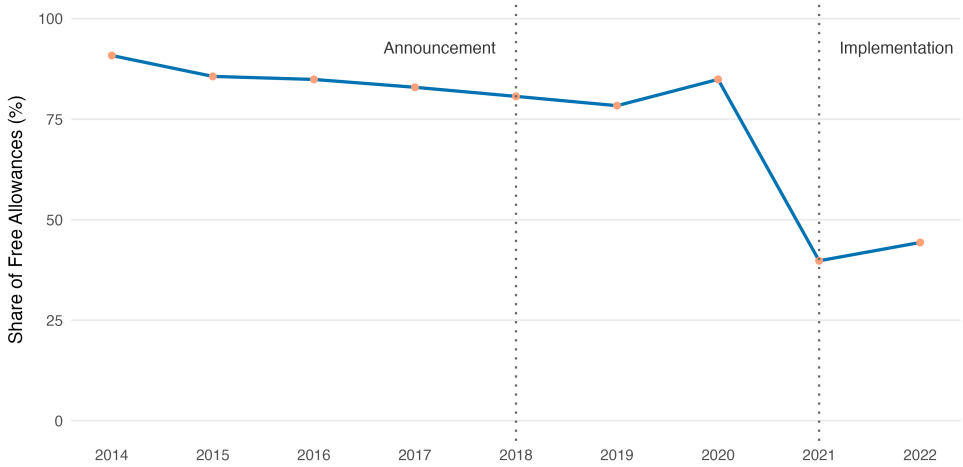
# Appendix

## From Free to Fee: How Emission Permit Allocation Affects Firms

Marie Alder, Eva Franzmeyer, and Benjamin Hattemer

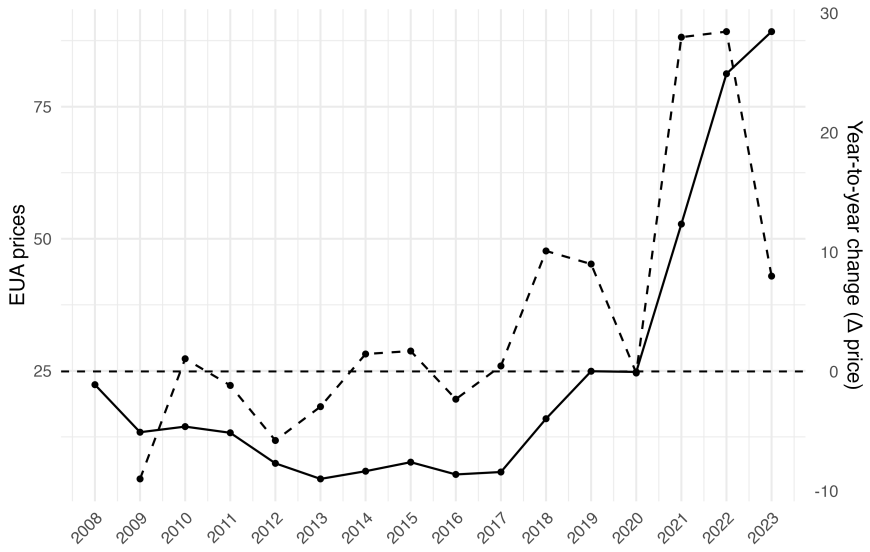
# S1 Additional Figures

Figure S1: Share of free permits for Affected Firms

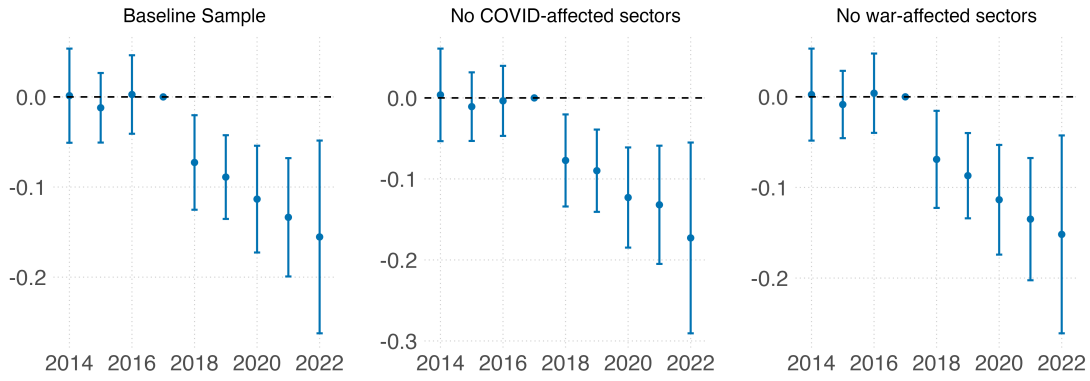



*Notes:* This figure shows the average share of free permits for firms affected by the change in the criteria for free permits. The dotted lines indicate the announcement of the policy reform in May 2018 and its implementation in 2021. *Sources:* Authors' calculations based on EUTL data, Orbis data, and data from the European Commission (see Section 3 for more details on the data used).

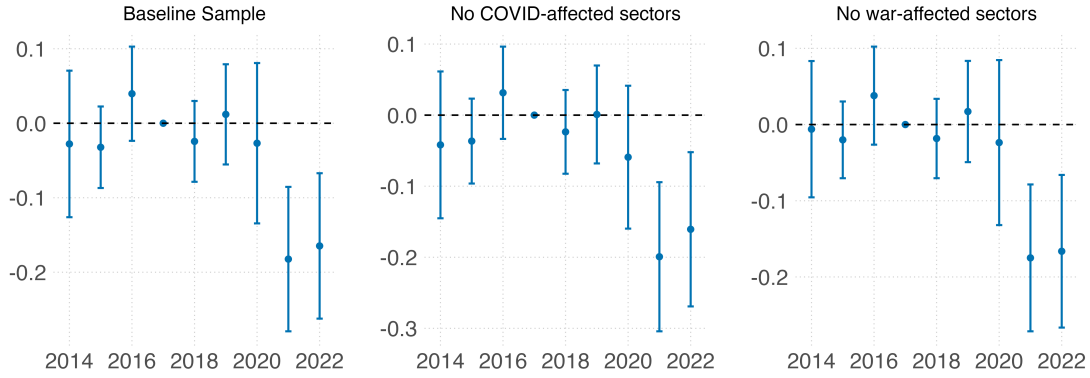
Figure S2: Evolution of EUA Prices




*Notes:* This figure plots the evolution of EUA prices. The dashed line shows year-to-year changes in prices. EUA prices increased substantially during the study period. *Source:* European Energy Exchange.




(a) Firm-level emissions

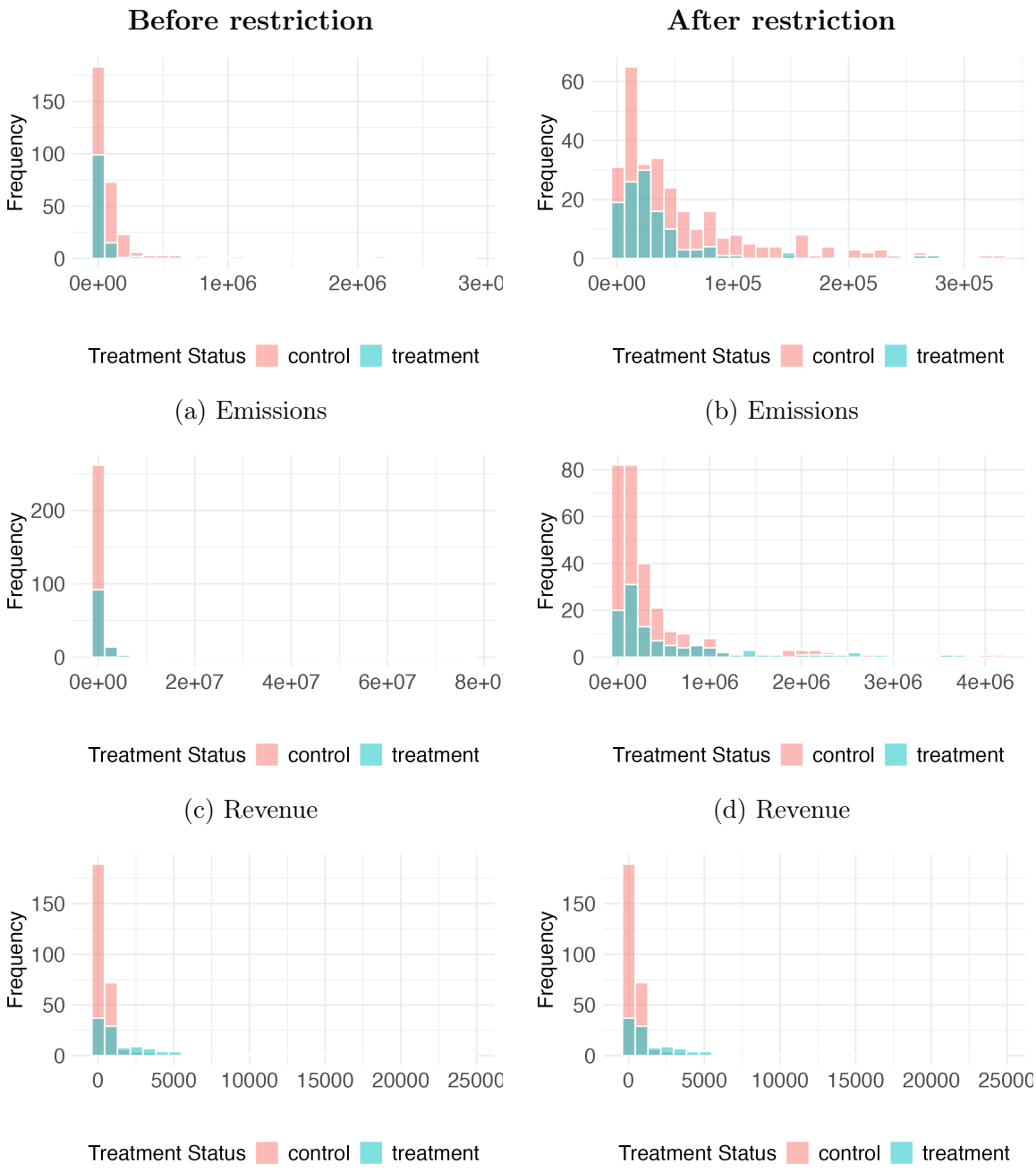



(b) Firm-level revenue

Figure S3: Robustness to Major Economic Shocks

*Notes:* This figure shows dynamic treatment effects under different sample restrictions. Panel A presents results for firm-level emissions, while Panel B presents results for firm-level revenue. In each panel, the left graph reports estimates for the baseline restricted sample, the middle graph excludes sectors strongly affected by COVID-19 (e.g., pharmaceutical manufacturing), and the right graph excludes sectors likely affected by the war in Ukraine (e.g., arms and shipbuilding). The estimated reductions in emissions and revenue remain consistent across the alternative samples, suggesting that the main results are not driven by sector-specific shocks associated with the pandemic or the war in Ukraine.

Figure S4: Descriptive Statistics on Common Support




(a) Emissions

(b) Emissions

(c) Revenue

(d) Revenue

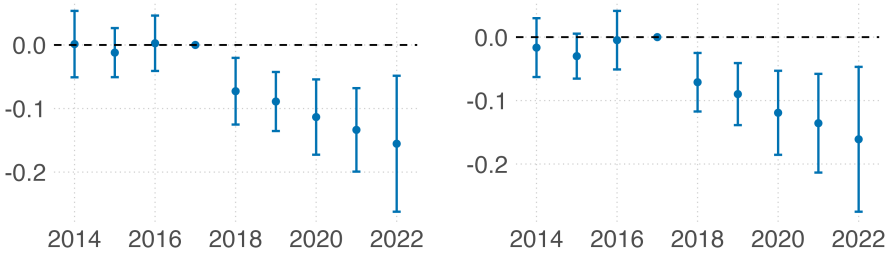
(e) Employment

(f) Employment

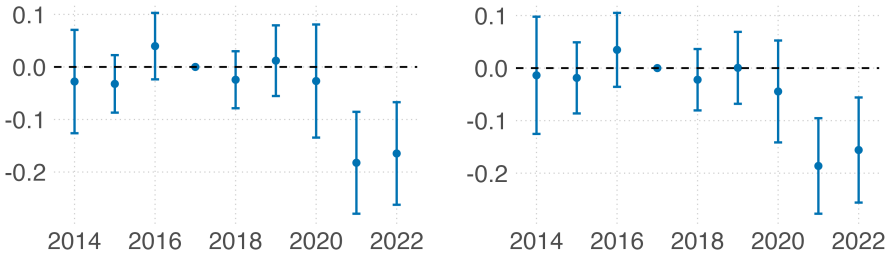
*Notes:* This figure shows the distributions of pretreatment average emissions, revenue, and employment by treatment status before and after common-support trimming. For each variable, we identify the group with the lower maximum and exclude firms in the other group whose pretreatment average exceeds this maximum. The resulting sample exhibits greater overlap between treated and control firms.

Figure S5: Baseline Results Before and After Restrictions on the Common Support

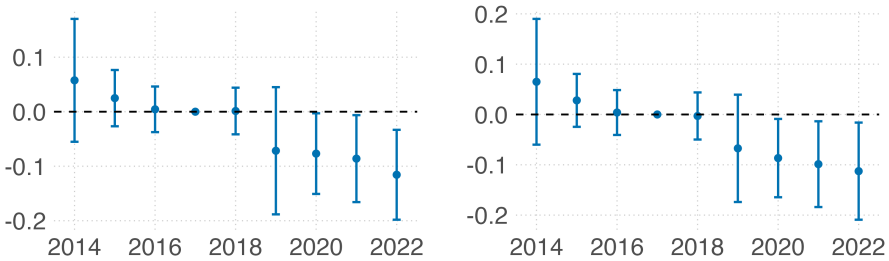
(a) Estimation on emissions, before (left panel) and after (right panel) restriction



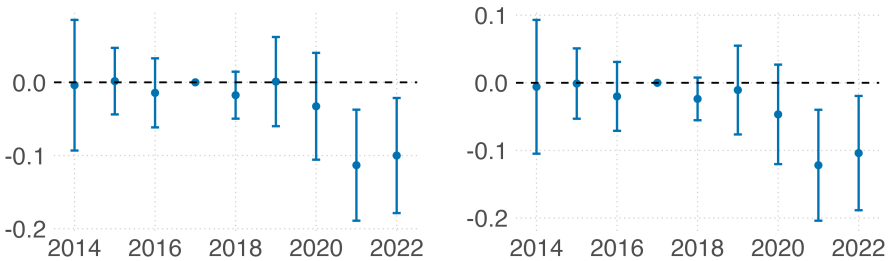

(b) Estimation on revenue, before (left panel) and after (right panel) restriction




(c) Estimation on employment, before (left panel) and after (right panel) restriction




(d) Estimation on assets, before (left panel) and after (right panel) restriction




*Notes:* This figure presents dynamic treatment effects on firm-level variables across different sample restrictions. The left panels show the results using the full sample, while the right panels use the restricted sample. Variables are log-transformed and standard errors are clustered at the sector level. The estimated results remain robust across specifications, suggesting that the main results are not driven by the restriction of the sample.

# S2 Additional Tables

Table S1: Classification of sectors according to their treatment status

| Status | NACE | Description | In restricted sample |
|---|---|---|---|
| Control | C10.41 | Manufacture of oils and fats | Yes |
| Control | C10.62 | Manufacture of starches and starch products | **No** |
| Control | C10.81 | Manufacture of sugar | **No** |
| Control | C11.06 | Manufacture of malt | Yes |
| Control | C13.95 | Manufacture of non-wovens and articles made from non-wovens, except apparel | Yes |
| Control | C17.11 | Manufacture of pulp | Yes |
| Control | C17.12 | Manufacture of paper and paperboard | **No** |
| Control | C19.10 | Manufacture of coke oven products | **No** |
| Control | C19.20 | Manufacture of refined petroleum products | **No** |
| Control | C20.12 | Manufacture of dyes and pigments | Yes |
| Control | C20.13 | Manufacture of other inorganic basic chemicals | **No** |
| Control | C20.14 | Manufacture of other organic basic chemicals | Yes |
| Control | C20.15 | Manufacture of fertilisers and nitrogen compounds | **No** |
| Control | C20.16 | Manufacture of plastics in primary forms | Yes |
| Control | C20.17 | Manufacture of synthetic rubber in primary forms | Yes |
| Control | C20.60 | Manufacture of man-made fibres | Yes |
| Control | C23.11 | Manufacture of flat glass | **No** |
| Control | C23.13 | Manufacture of hollow glass | **No** |
| Control | C23.19 | Manufacture and processing of other glass, including technical glassware | Yes |
| Control | C23.20 | Manufacture of refractory products | Yes |
| Control | C23.31 | Manufacture of ceramic tiles and flags | **No** |
| Control | C23.51 | Manufacture of cement | **No** |
| Control | C23.52 | Manufacture of lime and plaster | **No** |
| Control | C24.10 | Manufacture of basic iron and steel and of ferro-alloys | **No** |
| Control | C24.20 | Manufacture of tubes, pipes, hollow profiles and related fittings, of steel | Yes |
| Control | C24.31 | Cold drawing of bars | Yes |
| Control | C24.42 | Aluminium production | **No** |
| Control | C24.43 | Lead, zinc and tin production | **No** |
| Control | C24.44 | Copper production | Yes |
| Control | C24.51 | Casting of iron | Yes |
| Treatment | C10.20 | Processing and preserving of fish, crustaceans and molluscs | Yes |
| Treatment | C11.01 | Distilling, rectifying and blending of spirits | Yes |
| Treatment | C11.04 | Manufacture of other non-distilled fermented beverages | Yes |
| Treatment | C13.20 | Weaving of textiles | Yes |
| Treatment | C13.91 | Manufacture of knitted and crocheted fabrics | Yes |
| Treatment | C13.93 | Manufacture of carpets and rugs | Yes |
| Treatment | C13.99 | Manufacture of other textiles n.e.c. | Yes |
| Treatment | C16.29 | Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials | Yes |
| Treatment | C20.20 | Manufacture of pesticides and other agrochemical products | Yes |
| Treatment | C20.59 | Manufacture of other chemical products n.e.c. | Yes |
| Treatment | C21.20 | Manufacture of pharmaceutical preparations | Yes |
| Treatment | C22.11 | Manufacture of rubber tyres and tubes; retreading and rebuilding of rubber tyres | Yes |
| Treatment | C22.19 | Manufacture of other rubber products | Yes |
| Treatment | C23.43 | Manufacture of ceramic insulators and insulating fittings | Yes |
| Treatment | C23.44 | Manufacture of other technical ceramic products | Yes |
| Treatment | C24.53 | Casting of light metals | Yes |
| Treatment | C25.40 | Manufacture of weapons and ammunition | Yes |
| Treatment | C26.11 | Manufacture of electronic components | Yes |
| Treatment | C27.32 | Manufacture of other electronic and electric wires and cables | Yes |
| Treatment | C27.40 | Manufacture of electric lighting equipment | Yes |
| Treatment | C27.51 | Manufacture of electric domestic appliances | Yes |
| Treatment | C27.90 | Manufacture of other electrical equipment | Yes |
| Treatment | C28.11 | Manufacture of engines and turbines, except aircraft, vehicle and cycle engines | Yes |
| Treatment | C28.13 | Manufacture of other pumps and compressors | Yes |
| Treatment | C28.15 | Manufacture of bearings, gears, gearing and driving elements | Yes |
| Treatment | C28.30 | Manufacture of agricultural and forestry machinery | Yes |
| Treatment | C28.91 | Manufacture of machinery for metallurgy | Yes |
| Treatment | C28.94 | Manufacture of machinery for textile, apparel and leather production | Yes |
| Treatment | C30.11 | Building of ships and floating structures | Yes |
| Treatment | C30.30 | Manufacture of air and spacecraft and related machinery | Yes |

Table S2: Summary of Emission Intensity and Trade Intensity by Treatment Status

| Variable | Status | Mean | Median | Max | Min |
|---|---|---|---|---|---|
| **Panel A: Before Restriction** | | | | | |
| Emission Intensity | Control | 6.05 | 3.01 | 24.22 | 0.47 |
| | Treatment | 0.18 | 0.18 | 0.42 | 0.05 |
| Trade Intensity | Control | 0.31 | 0.28 | 1.09 | 0.05 |
| | Treatment | 0.61 | 0.58 | 1.00 | 0.04 |
| **Panel B: After Restriction** | | | | | |
| Emission Intensity | Control | 1.45 | 1.20 | 2.15 | 0.47 |
| | Treatment | 0.18 | 0.18 | 0.42 | 0.05 |
| Trade Intensity | Control | 0.45 | 0.48 | 0.55 | 0.33 |
| | Treatment | 0.61 | 0.58 | 1.00 | 0.04 |

*Notes:* This table reports summary statistics for emission intensity and trade intensity across treatment and control groups. Treated sectors—those that lost eligibility for free allocation—display substantially lower emission intensity and higher trade intensity than control sectors, consistent with the reform's objective of concentrating protection on sectors with both high emission cost exposure and high trade exposure. The limited overlap in emission intensity between the two groups motivates the sample restriction applied in the main analysis to improve comparability. Panel A presents statistics for the full sample prior to the restriction, while Panel B reports statistics for the restricted sample. The restriction markedly narrows differences in emission intensity between treatment and control sectors.

Table S3: Sensitivity to the Emission-Intensity Cutoff

| EI cutoff: | $\leq 1.0$ | $\leq 1.5$ | $\leq 2.52$ (baseline) | $\leq 4.0$ | $\leq 8.0$ |
|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Verified Emissions* | | | | | |
| Treatment × Post (2018) | -0.073** | -0.077** | -0.090*** | -0.093*** | -0.090*** |
| | (0.036) | (0.033) | (0.026) | (0.023) | (0.023) |
| Treatment × Post (2021) | -0.056* | -0.063** | -0.053** | -0.077*** | -0.072*** |
| | (0.029) | (0.027) | (0.025) | (0.025) | (0.026) |
| Observations | 2,133 | 2,574 | 3,816 | 8,316 | 9,045 |
| *Revenue* | | | | | |
| Treatment × Post (2018) | -0.011 | -0.018 | -0.012 | -0.020 | -0.015 |
| | (0.053) | (0.048) | (0.038) | (0.034) | (0.034) |
| Treatment × Post (2021) | -0.165*** | -0.147*** | -0.161*** | -0.140*** | -0.150*** |
| | (0.035) | (0.032) | (0.032) | (0.026) | (0.027) |
| Observations | 1,725 | 2,066 | 3,130 | 6,763 | 7,360 |
| *Employment* | | | | | |
| Treatment × Post (2018) | -0.067 | -0.055 | -0.065* | -0.058* | -0.054* |
| | (0.052) | (0.045) | (0.038) | (0.032) | (0.032) |
| Treatment × Post (2021) | -0.050 | -0.043 | -0.051** | -0.046** | -0.049*** |
| | (0.031) | (0.028) | (0.022) | (0.018) | (0.018) |
| Observations | 1,725 | 2,066 | 3,130 | 6,763 | 7,360 |
| *Total Assets* | | | | | |
| Treatment × Post (2018) | 0.017 | 0.004 | -0.012 | -0.037 | -0.035 |
| | (0.040) | (0.040) | (0.029) | (0.027) | (0.026) |
| Treatment × Post (2021) | -0.114*** | -0.101*** | -0.091*** | -0.073*** | -0.075*** |
| | (0.027) | (0.030) | (0.022) | (0.018) | (0.018) |
| Observations | 1,725 | 2,066 | 3,130 | 6,763 | 7,360 |
| *Sample* | | | | | |
| Control sectors | 8 | 13 | 15 | 22 | 25 |
| Control firms | 120 | 169 | 307 | 807 | 888 |

*Notes:* This table presents difference-in-differences estimates of the effect of the reform on firm-level outcomes for alternative values of the emission-intensity cutoff that defines the estimation sample. Each column retains control-group firms in sectors with an emission intensity below the stated cutoff; the treatment group (30 sectors, 117 firms) is unaffected by the restriction. Column (3) corresponds to the baseline sample used in the main analysis. The coefficients correspond to the average effect of the policy reform on treated firms when the reform is announced (2018) and implemented (2021). All variables are log-transformed, all specifications include firm and year fixed effects, and standard errors are clustered at the sector level. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

Table S4: Baseline Results with Industry Trends

| Sector trends: | No trends | 2-digit trends | 4-digit trends |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Verified Emissions* | | | |
| Treatment × Post (2018) | -0.090*** | -0.123*** | -0.068** |
| | (0.026) | (0.027) | (0.029) |
| Treatment × Post (2021) | -0.053** | -0.077*** | -0.037 |
| | (0.025) | (0.027) | (0.027) |
| Observations | 3,816 | 3,816 | 3,816 |
| *Revenue* | | | |
| Treatment × Post (2018) | -0.012 | 0.013 | -0.040 |
| | (0.038) | (0.047) | (0.035) |
| Treatment × Post (2021) | -0.161*** | -0.141*** | -0.186*** |
| | (0.032) | (0.039) | (0.045) |
| Observations | 3,130 | 3,130 | 3,130 |
| *Employment* | | | |
| Treatment × Post (2018) | -0.065* | -0.042 | 0.018 |
| | (0.038) | (0.048) | (0.040) |
| Treatment × Post (2021) | -0.051** | -0.033 | 0.010 |
| | (0.022) | (0.025) | (0.037) |
| Observations | 3,130 | 3,130 | 3,130 |
| *Total Assets* | | | |
| Treatment × Post (2018) | -0.012 | 0.003 | -0.002 |
| | (0.029) | (0.027) | (0.020) |
| Treatment × Post (2021) | -0.091*** | -0.080*** | -0.080*** |
| | (0.022) | (0.026) | (0.023) |
| Observations | 3,130 | 3,130 | 3,130 |

*Notes:* This table presents difference-in-differences estimates of the effect of the reform on firm-level outcomes under alternative sector-specific linear time trends. Column (1) reports the baseline specification; column (2) adds linear trends at the 2-digit NACE industry level; column (3) adds linear trends at the 4-digit NACE sector level, the level at which treatment is assigned. The coefficients correspond to the average effect of the policy reform on treated firms when the reform is announced (2018) and implemented (2021). All variables are log-transformed, all specifications include firm and year fixed effects, and standard errors are clustered at the sector level. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

Table S5: Baseline Results with Country-Time Fixed Effects

| Dependent Variables: | Verified Emissions | Revenue | Employees | Assets |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Treatment x Post (2018) | -0.0828*** | -0.0040 | -0.0498 | -0.0031 |
| | (0.0278) | (0.0430) | (0.0358) | (0.0295) |
| Treatment x Post (2021) | -0.0560** | -0.1825*** | -0.0486** | -0.0946*** |
| | (0.0240) | (0.0313) | (0.0211) | (0.0227) |
| *Fixed-effects* | | | | |
| Firm FE | Yes | Yes | Yes | Yes |
| Country x Time FE | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 3,789 | 3,094 | 3,094 | 3,094 |
| $R^2$ | 0.97770 | 0.97674 | 0.97666 | 0.98400 |
| Within $R^2$ | 0.01330 | 0.01681 | 0.00441 | 0.00675 |

*Notes:* This table presents difference-in-differences estimates of the effect of the reform on firm-level outcomes. The coefficients correspond to the average effect of the policy reform on treated firms when the reform is announced (2018) and implemented (2021). All variables are log-transformed and standard errors clustered at the sector level. We include firm fixed effects and country-time fixed effects. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

# S3 Matching Procedure

We employ a direct matching procedure to validate our main results. Matching variables are measured in 2017, the year preceding the announcement of the policy reform. Firms are matched with replacement based on firm-level emission intensity, total assets, non-EU imports, and verified emissions. Firm-level emission intensity is measured as the ratio of verified emissions to revenue. Assets, verified emissions, and emission intensity are log-transformed, while non-EU imports are measured as the log of sector-level non-EU imports. These variables are chosen to compare treatment and control firms that are similar in terms of environmental performance, firm size, emissions levels, and exposure to international trade. Similar to Colmer et al. (2025), we implement a nearest-neighbor matching approach using the Mahalanobis distance. Panel A of Table S6 reports differences between treatment and control firms in the unmatched sample in 2017. Panel B reports the corresponding differences after matching. The post-match differences are smaller than the pre-match differences for the main firm characteristics, indicating improved comparability between treatment and control firms.

Table S6: Pre- and Post-Match Differences

**Panel A: Pre-Match difference**

| | Emissions | Revenue | Employees | Assets | Emission Intensity |
|---|---|---|---|---|---|
| | -1.232*** | 0.955*** | 1.250*** | 0.983*** | -2.253*** |
| | (0.103) | (0.181) | (0.176) | (0.187) | (0.189) |
| Observations | 1346 | 1143 | 1143 | 1143 | 1143 |
| Adjusted $R^2$ | 0.043 | 0.030 | 0.066 | 0.033 | 0.147 |

**Panel B: Post-Match difference**

| | Emissions | Revenue | Employees | Assets | Emission Intensity |
|---|---|---|---|---|---|
| | -0.0762 | 0.347** | 0.955*** | 0.412** | -0.423** |
| | (0.0930) | (0.172) | (0.190) | (0.179) | (0.178) |
| Observations | 1030 | 1030 | 1030 | 1030 | 1030 |
| Adjusted $R^2$ | 0.000 | 0.010 | 0.087 | 0.014 | 0.014 |

*Notes:* This table presents differences in firm characteristics between treated and control firms in 2017. Panel A uses the unmatched sample, while Panel B uses the matched sample based on Mahalanobis nearest-neighbor matching. Emission intensity is measured at the firm level as verified emissions divided by revenue. All variables are log-transformed. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

Table S7 presents estimates from OLS regressions estimated on the matched sample. Standard errors are clustered two ways, at the firm level and at the matching-group level.

Each estimate captures the difference between treatment and matched control firms relative to 2017. The results indicate a decline in verified emissions after the announcement and implementation of the reform. This replicates the findings of our baseline specification closely. The magnitude of the effect is slightly larger and more precisely estimated than in our baseline estimation. Revenue and assets also decline significantly by 2021, while the estimates for employment are not statistically significant. The magnitude of the reduction in revenue and assets is lower compared to the observed reductions in our baseline specification. Overall, the results show that our qualitative results remain robust to this alternative empirical strategy. The effect sizes increase for the emission response and decrease for the economic activity, but remain closely related and highly statistically significant. Table S8 shows that the estimated

Table S7: The Effect on the Environmental and Economic Performance of Firms

| | Verified Emissions | Revenue | Employees | Assets |
|---|---|---|---|---|
| Treatment 2018 | -0.100*** | 0.005 | -0.012 | 0.015 |
| | (0.027) | (0.027) | (0.030) | (0.024) |
| Treatment 2021 | -0.080** | -0.117*** | -0.012 | -0.069** |
| | (0.037) | (0.035) | (0.031) | (0.029) |
| Observations | 2875 | 2732 | 2732 | 2732 |
| Adjusted $R^2$ | 0.021 | 0.016 | -0.000 | 0.007 |

*Notes:* This table presents estimates from OLS regressions estimated on the matched sample. Standard errors are clustered in two ways, at the firm level and at the matching-group level. Each estimate reflects the difference between treated firms and matched control firms relative to 2017. All outcome variables are log-transformed. We present estimates for two time periods: when the reform is announced in 2018 and when the reform is implemented in 2021. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

effects on verified emissions are robust to alternative matching procedures, including Euclidean distance, matching without replacement, and using fewer nearest neighbours. Table S9 further shows that the results remain robust when imposing alternative restrictions on matching distance, retaining only observations whose pairwise distance lies below the 99th, 95th, or 90th percentile of the distance distribution.

Table S8: Alternative Matching Specifications

| | Euclidean | No replacement | 4NN | 3NN | 2NN |
|---|---|---|---|---|---|
| Treatment 2018 | -0.111*** | -0.085*** | -0.113*** | -0.091*** | -0.091*** |
| | (0.029) | (0.026) | (0.028) | (0.026) | (0.028) |
| Treatment 2021 | -0.095** | -0.066* | -0.084** | -0.092** | -0.087** |
| | (0.039) | (0.033) | (0.037) | (0.038) | (0.043) |
| Observations | 2875 | 2875 | 2300 | 1725 | 1150 |
| Adjusted $R^2$ | 0.029 | 0.015 | 0.026 | 0.026 | 0.023 |

*Notes:* This table presents estimates from OLS regressions estimated on matched samples using alternative matching procedures. Standard errors are clustered in two ways, at the firm level and at the matching-group level. Each estimate reflects the difference between treated firms and matched control firms relative to 2017. All outcome variables are log-transformed. We present estimates for two time periods: when the reform is announced in 2018 and when the reform is implemented in 2021. Different matching specifications are presented in each column. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

Table S9: Alternative Distance Restrictions

| | 99th Percentile | 95th Percentile | 90th Percentile |
|---|---|---|---|
| Treatment 2018 | -0.098*** | -0.097*** | -0.087*** |
| | (0.027) | (0.027) | (0.027) |
| Treatment 2021 | -0.079** | -0.077** | -0.072** |
| | (0.037) | (0.036) | (0.035) |
| Observations | 2845 | 2741 | 2602 |
| Adjusted $R^2$ | 0.020 | 0.020 | 0.017 |

*Notes:* This table presents estimates from OLS regressions estimated on matched samples under alternative restrictions on matching distance. Standard errors are clustered in two ways, at the firm level and at the matching-group level. Each estimate reflects the difference between treated firms and matched control firms relative to 2017. All outcome variables are log-transformed. We present estimates for two time periods: when the reform is announced in 2018 and when the reform is implemented in 2021. Each column restricts the matched sample to observations below the stated percentile of the matching-distance distribution. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

# S4 Analysis on Trade

## S4.1 Data

To analyze trade patterns, we rely on the ComExt Intra- and Extra-European trade database, published by Eurostat. The data are available at the annual level and include information on the declarant country, partner country, trade value in euros, trade type (import or export) and the 4-digit CPA code for the sector. Using a common key, we translate the CPA sector codes to the 4-digit NACE classification. We apply the same classification of treated and control sectors as described in Table S1, consistent with the firm-level analysis.

In addition, we draw on tariff data from UNCTAD's TRAINS database, accessed through the World Integrated Trade Solution (WITS). These data are harmonized across countries at the 6-digit level of the Harmonized System and are available annually at the declarant–partner country level. We translate the 6-digit HS codes to the 4-digit NACE sector classification using a mapping from Eurostat. For tariffs, we rely on preferential rates, which we obtain through the bulk download option on the WITS website.

## S4.2 Empirical Strategy

Relying on the same identification assumption as in our firm-level analysis, we estimate the effect of losing free allocation on trade flows using a difference-in-differences design, estimating the specification:

$$\begin{aligned} \ln y_{ij,s,t} = \tau_{ij,t} + \tau_{ij,s} + \rho_A \left(\text{Treat}_s \times \text{Post2018}_t\right) \\ + \rho_I \left(\text{Treat}_s \times \text{Post2021}_t\right) + \beta \, \text{T}_{ij,s,t} + u_{ij,s,t} \end{aligned} \tag{S1}$$

The term $\ln y_{ij,s,t}$ is the value of imports or exports in sector $s$ between declarant country $i$ and partner country $j$ during the year $t$. The specification includes country-pair-sector fixed effects $\tau_{ij,s}$, which control for time-invariant sectoral characteristics that may differ across each country pair. We further include country-pair–year fixed effects $\tau_{ij,t}$ to absorb common shocks affecting all sectors in a given bilateral relationship at time $t$. As an additional control, we account for bilateral tariffs $T_{ij,s,t}$ that may vary over time and across sectors. The treatment indicator $Treat_s$ is defined analogously to the main analysis. $\text{Post2018}_t$ equals one from 2018 onward, while $\text{Post2021}_t$ equals one from 2021 onward. The coefficient $\rho_A$ therefore captures the effect following the announcement of the reform, while $\rho_I$ captures the additional effect following its implementation. We restrict our sample to the same sectors as in our firm-level estimation.

## S4.3 Results

Columns 1 and 2 in Table S10 report the results using the restricted sample of sectors close to the allocation cutoff. None of the estimated coefficients is statistically significant at conventional levels.[22] We therefore interpret the trade results cautiously. For transparency, we report the corresponding p-values in the table. The firm-level results show that treated firms decrease their activity at the time of implementation. We would therefore expect a decline in exports and imports at this point.

This prediction differs from a carbon-leakage channel. Under carbon leakage, fewer free permits would lead EU consumers and downstream firms to replace contracting domestic production with foreign supply of the same products. Imports should therefore increase in treated sectors. Instead, at implementation we estimate declines of similar magnitude for both exports and imports, of about 5 percent, although neither coefficient is statistically significant. The announcement coefficients are small and of opposite sign. This symmetry speaks against leakage as a relevant margin, consistent with the existing literature (Naegele and Zaklan, 2019; Grubb et al., 2022).

The magnitude of the trade effects is smaller than the decline in revenue observed in the firm-level analysis. This is plausible even if the mechanism is fully present. ComExt measures total sector-level trade, while treated ETS firms account for only a subset of exporters within each sector.[23] In addition, non-ETS firms in the same sectors may absorb part of the lost demand, pushing the aggregate trade response below this simple dilution benchmark.

Overall, we do not interpret the trade results as direct evidence in support of the firm-level findings or the mechanism we propose, given the lack of power. The coefficients' size and sign, however, are consistent with those findings.

[22] This absence of statistically significant effects is not surprising given the structure of the trade data. With standard errors of 0.033 for exports and 0.050 for imports, the minimum detectable effects at conventional size and power are roughly 9.5 and 14 log points, respectively. Effects of the size implied by the firm-level contraction are therefore below what the trade specification can reliably detect.

[23] If treated ETS firms account for one third to one half of sector-level exports, a firm-level contraction of 16 percent implies a sector-level export effect of roughly 5 to 8 percent. This is close to our point estimates of 4.6 to 6.4 percent. Marin et al. (2018) report the shares of firms regulated by the EU ETS 2-digit manufacturing sector in the first two phases of the EU ETS: Paper and paper products: 19.4%, coke and refined petroleum: 20.9%, other non-metallic mineral products: 16.6%. Therefore, the coefficients are in a plausible range.

Table S10: Baseline Estimation

| Dependent Variables: | Exports (logs) | Imports (logs) |
|---|---|---|
| Model: | (1) | (2) |
| *Variables* | | |
| Treatment × Post (2018) | -0.0176 | 0.0247 |
| | (0.0254) | (0.0284) |
| Treatment × Post (2021) | -0.0461 | -0.0529 |
| | (0.0330) | (0.0495) |
| p-value (2018) | 0.492 | 0.390 |
| p-value (2021) | 0.170 | 0.291 |
| *Fixed-effects* | | |
| Sector-i-j | Yes | Yes |
| Time-i-j | Yes | Yes |
| *Fit statistics* | | |
| Observations | 879,909 | 571,286 |
| $R^2$ | 0.89008 | 0.90659 |
| Within $R^2$ | $7.41 \times 10^{-5}$ | $4.44 \times 10^{-5}$ |

*Notes:* This table presents estimates from the difference-in-differences specification. All outcome variables are log-transformed. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01.

# S5 Model Derivations

## S5.1 Aggregation

### Prices

By starting from Equation 4, the firm-level price $P_j$ can be expressed as:

$$P_j = \left( \int_{\Omega_j} p_j(\varphi)^{1-\sigma} d\varphi \right)^{\frac{1}{1-\sigma}} = \left[ \int_0^{\infty} p_j(\varphi)^{1-\sigma} \underbrace{M_j}_{\text{Total mass}} \underbrace{\mu(\varphi)\, d\varphi}_{\text{Probability of landing near } \varphi} \right]^{\frac{1}{1-\sigma}}$$

Using the pricing rule, we can get an expression for $P_j$:

$$\begin{aligned}
P_j^{1-\sigma} &= \int_0^{\infty} p_j(\varphi)^{1-\sigma} M_j \, \mu(\varphi)\, d\varphi \\
&= \int_0^{\infty} \left( \frac{\sigma}{\sigma - 1} \frac{\Psi}{\varphi} \right)^{1-\sigma} M_j \, \mu(\varphi)\, d\varphi \\
&= M_j \left( \frac{\sigma}{\sigma - 1} \Psi \right)^{1-\sigma} \underbrace{\int_0^{\infty} \varphi^{\sigma-1} \, \mu(\varphi)\, d\varphi}_{\equiv \tilde{\varphi}^{\sigma-1}} \\
&= M_j \underbrace{\left( \frac{\sigma}{\sigma - 1} \frac{\Psi}{\tilde{\varphi}} \right)^{1-\sigma}}_{p_j(\tilde{\varphi})^{1-\sigma}}
\end{aligned}$$

where $\tilde{\varphi} \equiv \left[ \int_0^{\infty} \varphi^{\sigma-1} \, \mu(\varphi)\, d\varphi \right]^{\frac{1}{\sigma-1}}$. Aggregating to the top nest gives:

$$\begin{aligned}
P^{1-\varepsilon} &= \sum_j \left( M_j^{\frac{1}{1-\sigma}} p_j(\tilde{\varphi}_j) \right)^{1-\varepsilon} \\
&= \sum_j \left( M_j^{\frac{1}{1-\sigma}} \frac{\sigma}{\sigma - 1} \frac{\Psi}{\tilde{\varphi}_j} \right)^{1-\varepsilon} \\
&= \left( \frac{\sigma}{\sigma - 1} \Psi \right)^{1-\varepsilon} \sum_j M_j^{\frac{1-\varepsilon}{1-\sigma}} \tilde{\varphi}_j^{\varepsilon-1} \\
\Rightarrow P &= \left( \frac{\sigma}{\sigma - 1} \Psi \right) \left[ \sum_j M_j^{\frac{1-\varepsilon}{1-\sigma}} \tilde{\varphi}_j^{\varepsilon-1} \right]^{\frac{1}{1-\varepsilon}}
\end{aligned}$$

We can then derive the firm-level aggregate price relative to the economy-wide aggregate price, which gives Equation 7:

$$\begin{aligned}\frac{P_j}{P} &= \frac{\frac{\sigma}{\sigma-1}\Psi\, M_j^{-\frac{1}{\sigma-1}}\tilde{\varphi}_j^{-1}}{\frac{\sigma}{\sigma-1}\Psi\left(\sum_m M_m^{\frac{\varepsilon-1}{\sigma-1}}\tilde{\varphi}_m^{\varepsilon-1}\right)^{-\frac{1}{\varepsilon-1}}} \\ &= \frac{M_j^{-\frac{1}{\sigma-1}}\tilde{\varphi}_j^{-1}}{\left(\sum_m^N M_m^{\frac{\varepsilon-1}{\sigma-1}}\tilde{\varphi}_m^{\varepsilon-1}\right)^{-\frac{1}{\varepsilon-1}}}\end{aligned}$$

**Quantity, Revenue and Profits**

From Equation 5, we know that:

$$q_j(\varphi) = q_j(\tilde{\varphi})\left(\frac{\varphi}{\tilde{\varphi}}\right)^{\sigma}$$

Combining this expression with the utility function gives:

$$\begin{aligned}Q_j &= \left(\int_{\Omega_j} q_j(\varphi)^{\frac{\sigma-1}{\sigma}}\, d\varphi\right)^{\frac{\sigma}{\sigma-1}} \\ &= \left(\int_0^{\infty} q_j(\varphi_j)^{\frac{\sigma-1}{\sigma}}\, M_j\mu(\varphi_j)d\varphi_j\right)^{\frac{\sigma}{\sigma-1}} \\ &= \left(\int_0^{\infty}\left(q_j(\tilde{\varphi})\left(\frac{\varphi}{\tilde{\varphi}}\right)^{\sigma}\right)^{\frac{\sigma-1}{\sigma}} M_j\mu(\varphi_j)d\varphi_j\right)^{\frac{\sigma}{\sigma-1}} \\ &= q_j(\tilde{\varphi})\tilde{\varphi}^{-\sigma}M_j^{\frac{\sigma}{\sigma-1}}\left(\int_0^{\infty}\varphi^{\sigma-1}\mu(\varphi_j)d\varphi_j\right)^{\frac{\sigma}{\sigma-1}} \\ &= q_j(\tilde{\varphi})\tilde{\varphi}^{-\sigma}M_j^{\frac{\sigma}{\sigma-1}}\tilde{\varphi}^{\sigma} = q_j(\tilde{\varphi})M_j^{\frac{\sigma}{\sigma-1}}\end{aligned}$$

Similarly, we can calculate $R_j$:

$$\begin{aligned}
R_j &= \int_0^\infty r_j(\varphi_j)\, M_j \mu(\varphi_j) d\varphi_j \\
&= \int_0^\infty r_j(\tilde{\varphi}) \left(\frac{\varphi_j}{\tilde{\varphi}}\right)^{\sigma-1} M_j \mu(\varphi_j) d\varphi_j \\
&= M_j r_j(\tilde{\varphi}) \tilde{\varphi}^{1-\sigma} \underbrace{\int_0^\infty \varphi_j^{\sigma-1} \mu(\varphi_j) d\varphi_j}_{\equiv \tilde{\varphi}^{\sigma-1}} \\
&= M_j r_j(\tilde{\varphi})
\end{aligned}$$

Finally, firm-level profits $\Pi_j$ can be found by:

$$\begin{aligned}
\Pi_j &= \int_0^\infty \pi_j(\varphi)\, M_j\, \mu_j(\varphi)\, d\varphi \\
&= \int_0^\infty \left[\frac{1}{\sigma} r_j(\tilde{\varphi}_j) \left(\frac{\varphi}{\tilde{\varphi}_j}\right)^{\sigma-1} - F_j\right] M_j\, \mu_j(\varphi)\, d\varphi \\
&= \frac{M_j}{\sigma} r_j(\tilde{\varphi}_j) \tilde{\varphi}_j^{1-\sigma} \underbrace{\int_0^\infty \varphi^{\sigma-1} \mu_j(\varphi)\, d\varphi}_{\tilde{\varphi}_j^{\sigma-1}} - F_j M_j \underbrace{\int_0^\infty \mu_j(\varphi)\, d\varphi}_{1} \\
&= \frac{M_j}{\sigma}\, r_j(\tilde{\varphi}_j) - F_j M_j \\
&= M_j \underbrace{\left(\frac{r_j(\tilde{\varphi}_j)}{\sigma} - F_j\right)}_{\pi(\tilde{\varphi}_j)} \\
&= M_j \pi(\tilde{\varphi}_j)
\end{aligned}$$

## S5.2 Policy Implementation

**Fixed cost and the relative price of the treated firm**

We start with the expression for the price of firm $j$ relative to all other firms:

$$\frac{P_j}{P_{-j}} = \frac{M_j^{-\frac{1}{\sigma-1}}\, \tilde{\varphi}_j^{-1}}{\left(\sum_{m \neq j} \left[M_m^{-\frac{1}{\sigma-1}}\, \tilde{\varphi}_m^{-1}\right]^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}}$$

$$\frac{\partial}{\partial F_j}\ln\left(\frac{P_j}{P_{-j}}\right) = -\frac{1}{\sigma-1}\frac{1}{M_j}\frac{\partial M_j}{\partial F_j} - \frac{1}{\tilde{\varphi}_j}\frac{\partial \tilde{\varphi}_j}{\partial F_j} - \frac{1}{1-\varepsilon}\frac{1}{\sum_{m\neq j}\left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right]^{1-\varepsilon}}\frac{\partial}{\partial F_j}\left(\sum_{m\neq j}\left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right]^{1-\varepsilon}\right)$$

Then take the inner derivatives:

$$\frac{\partial}{\partial F_j}\left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right]^{1-\varepsilon} = (1-\varepsilon)\left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right]^{-\varepsilon}\frac{\partial}{\partial F_j}\left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right]$$

where

$$\frac{\partial}{\partial F_j}\left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right] = \left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right]\left[\frac{1}{\sigma-1}\frac{1}{M_m}\frac{\partial M_m}{\partial F_j} - \frac{1}{\tilde{\varphi}_m}\frac{\partial \tilde{\varphi}_m}{\partial F_j}\right]$$

Bringing this back to the original derivative gives:

$$\begin{aligned}\frac{\partial}{\partial F_j}\ln\left(\frac{P_j}{P_{-j}}\right) &= -\frac{1}{\sigma-1}\frac{1}{M_j}\frac{\partial M_j}{\partial F_j} - \frac{1}{\tilde{\varphi}_j}\frac{\partial \tilde{\varphi}_j}{\partial F_j} \\ &\quad - \frac{\sum_{m\neq j}\left[M_m^{-\frac{1}{\sigma-1}}\tilde{\varphi}_m^{-1}\right]^{1-\varepsilon}\left[-\frac{1}{\sigma-1}\frac{1}{M_m}\frac{\partial M_m}{\partial F_j} - \frac{1}{\tilde{\varphi}_m}\frac{\partial \tilde{\varphi}_m}{\partial F_j}\right]}{\sum_{k\neq j}\left[M_k^{-\frac{1}{\sigma-1}}\tilde{\varphi}_k^{-1}\right]^{1-\varepsilon}} \\ &= -\frac{1}{\sigma-1}\frac{1}{M_j}\frac{\partial M_j}{\partial F_j} - \frac{1}{\tilde{\varphi}_j}\frac{\partial \tilde{\varphi}_j}{\partial F_j} \\ &\quad - \sum_{m\neq j}\frac{R_m}{R_{-j}}\left[-\frac{1}{\sigma-1}\frac{1}{M_m}\frac{\partial M_m}{\partial F_j} - \frac{1}{\tilde{\varphi}_m}\frac{\partial \tilde{\varphi}_m}{\partial F_j}\right]\end{aligned}$$

**Aggregate Expenditure Closure**

As a closure, we hold nominal expenditure on the modeled economy fixed throughout the policy analysis:

$$\frac{\partial \ln R}{\partial F_j} = 0$$

A fixed expenditure aggregate together with an endogenous price index is standard in heterogeneous-firm models. In multi-industry models, Cobb–Douglas preferences across in-

dustries assign a constant share of aggregate expenditure to each industry, as in Bernard et al. (2007). In the one-industry models of Melitz (2003) and Bernard et al. (2011), aggregate expenditure is instead pinned down by labor-market clearing and free entry, while the aggregate price index remains endogenous. We impose the same fixed-expenditure environment directly, interpreting the modeled economy as the regulated manufacturing part of a larger economy and abstracting from feedback to economy-wide nominal income. The reform therefore reallocates a fixed amount of expenditure and product variety across firms, while the aggregate price index $P$ and real consumption $Q = R/P$ remain endogenous.

**Sign of the different Impact Channels**

In this section, we show the sign for the entry-flow, selection and composition channels. This requires showing the sign for:

$$\frac{d\varphi_j^*}{dF_j} \quad , \quad \frac{\partial \tilde{\varphi}_j}{\partial \varphi_j^*} \quad \text{and} \quad \frac{\partial n_j}{\partial F_j}$$

We start with using the ZPC and the free entry condition:

$$\bar{\pi}_j = F_j \left[ \left( \frac{\tilde{\varphi}_j}{\varphi_j^*} \right)^{\sigma-1} - 1 \right] \quad (\textbf{ZPC})$$

$$\bar{\pi}_j = \frac{\delta f_{e,j}}{1 - G(\varphi_j^*)} \quad (\textbf{FE})$$

They can be equated, which yields the following equation:

$$F_j \left[ \left( \frac{\tilde{\varphi}_j}{\varphi_j^*} \right)^{\sigma-1} - 1 \right] = \frac{\delta f_{e,j}}{1 - G(\varphi_j^*)} \tag{S2}$$

We will use this expression to take the derivative of $\varphi_j^*$ with respect to $F_j$. To do this, we will apply the Implicit Function Theorem.

**Left hand side:**

$$\frac{\partial}{\partial F_j} \{F_j[\cdots]\} = \left( \frac{\tilde{\varphi}_j}{\varphi_j^*} \right)^{\sigma-1} - 1 + F_j \frac{\partial \varphi_j^*}{\partial F_j} \frac{\partial}{\partial \varphi_j^*} \left[ \left( \frac{\tilde{\varphi}_j(\varphi_j^*)}{\varphi_j^*} \right)^{\sigma-1} - 1 \right]$$

We have two inner derivatives:

$$\frac{\partial}{\partial \varphi_j^*}\left[\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-1}-1\right]=(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-2}\underbrace{\frac{\partial}{\partial \varphi_j^*}\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)}_{\frac{\tilde{\varphi}_j'(\varphi_j^*)\,\varphi_j^*-\tilde{\varphi}_j(\varphi_j^*)}{(\varphi_j^*)^2}}$$

Therefore, the LHS becomes:

$$\frac{\partial}{\partial F_j}\{F_j[\cdots]\}=\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-1}-1+F_j(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-2}\frac{\tilde{\varphi}_j'\varphi_j^*-\tilde{\varphi}_j}{(\varphi_j^*)^2}\frac{\partial \varphi_j^*}{\partial F_j}$$

**Right hand side:**

$$\frac{\partial}{\partial F_j}\frac{\delta f_{e,j}}{1-G(\varphi_j^*)}=\frac{\delta f_{e,j}\,g(\varphi_j^*)}{[1-G(\varphi_j^*)]^2}\frac{d\varphi_j^*}{dF_j}$$

Now we can combine both sides and solve for $\frac{d\varphi_j^*}{dF_j}$:

$$\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-1}-1+F_j(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-2}\frac{\tilde{\varphi}_j'\varphi_j^*-\tilde{\varphi}_j}{(\varphi_j^*)^2}\frac{d\varphi_j^*}{dF_j}=\frac{\delta f_{e,j}\,g(\varphi_j^*)}{[1-G(\varphi_j^*)]^2}\frac{d\varphi_j^*}{dF_j}.$$

$$\Rightarrow \frac{d\varphi_j^*}{dF_j}=\frac{\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-1}-1}{\frac{\delta f_{e,j}\,g(\varphi_j^*)}{[1-G(\varphi_j^*)]^2}-F_j(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-2}\frac{\tilde{\varphi}_j'\varphi_j^*-\tilde{\varphi}_j}{(\varphi_j^*)^2}}$$

Using Equation S2, we can replace the numerator by $\frac{\delta f_{e,j}}{F_j[1-G(\varphi_j^*)]}$ and get the general form:

$$\begin{aligned}\frac{d\varphi_j^*}{dF_j}&=\frac{\frac{\delta f_{e,j}}{F_j[1-G(\varphi_j^*)]}}{\frac{\delta f_{e,j}g(\varphi_j^*)}{[1-G(\varphi_j^*)]^2}-F_j(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-2}\frac{\tilde{\varphi}_j'\varphi_j^*-\tilde{\varphi}_j}{(\varphi_j^*)^2}}\\&=\frac{\frac{\delta f_{e,j}}{F_j[1-G]}}{\frac{\delta f_{e,j}g}{[1-G]^2}}\frac{1}{1-\frac{F_j[1-G]^2}{\delta f_{e,j}g}(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-2}\frac{\tilde{\varphi}_j'\varphi_j^*-\tilde{\varphi}_j}{(\varphi_j^*)^2}}\end{aligned}$$

$$\Rightarrow \frac{d\varphi_j^*}{dF_j}=\frac{1-G(\varphi_j^*)}{g(\varphi_j^*)}\frac{1}{F_j}\frac{1}{1-\frac{F_j[1-G(\varphi_j^*)]^2}{\delta f_{e,j}g(\varphi_j^*)}(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-2}\frac{\tilde{\varphi}_j'\varphi_j^*-\tilde{\varphi}_j}{(\varphi_j^*)^2}} \tag{S3}$$

Equation S3 is the general condition. In the following, we will assume a Pareto tail distribution, which simplifies the Equation S3 and allows us to recover the sign of both $\frac{\partial \varphi_j^*}{\partial F_j}$ and $\frac{\partial \tilde{\varphi}_j}{\partial \varphi_j^*}$. The Pareto tail distribution has the following properties:

Table S11: Pareto Tail Distribution

| **Object** | **Expression** | **Interpretation** |
|---|---|---|
| $G(\varphi)$ | $1 - \left(\frac{\varphi_{\min}}{\varphi}\right)^{\theta}$ | CDF |
| $g(\varphi)$ | $\theta \frac{\varphi_{\min}^{\theta}}{\varphi^{\theta+1}}$ | PDF |

We now examine the implications of this assumption for $\tilde{\varphi}$ in several steps. Recall that its definition is given by:

$$\tilde{\varphi}_j = \left[ \frac{1}{1 - G(\varphi_j^*)} \int_{\varphi_j^*}^{\infty} \varphi^{\sigma-1} g(\varphi)\, d\varphi \right]^{\frac{1}{\sigma-1}}$$

We start with the integral:

$$\int_{\varphi_j^*}^{\infty} \varphi^{\sigma-1} g(\varphi)\, d\varphi = \theta\, \varphi_{\min}^{\theta} \int_{\varphi_j^*}^{\infty} \varphi^{\sigma-\theta-2}\, d\varphi = \frac{\theta}{\theta + 1 - \sigma}\, \varphi_{\min}^{\theta}\, (\varphi_j^*)^{\sigma-\theta-1}$$

We also know that $1 - G(\varphi_j^*) = \left(\frac{\varphi_{\min}}{\varphi_j^*}\right)^{\theta}$, so we use this combined with the previous equation:

$$\frac{1}{1 - G(\varphi_j^*)} \int_{\varphi_j^*}^{\infty} \varphi^{\sigma-1} g(\varphi)\, d\varphi = \frac{\theta}{\theta + 1 - \sigma}\, (\varphi_j^*)^{\sigma-1}$$

$$\Rightarrow \tilde{\varphi}_j = \left[ \frac{1}{1 - G(\varphi_j^*)} \int_{\varphi_j^*}^{\infty} \varphi^{\sigma-1} g(\varphi)\, d\varphi \right]^{\frac{1}{\sigma-1}} = \left( \frac{\theta}{\theta + 1 - \sigma} \right)^{\frac{1}{\sigma-1}} \varphi_j^*$$

We can take the derivative with respect to $\varphi_j^*$:

$$\frac{\partial \tilde{\varphi}_j}{\partial \varphi_j^*} = \left( \frac{\theta}{\theta + 1 - \sigma} \right)^{\frac{1}{\sigma-1}} \tag{S4}$$

With the Pareto tail distribution, $\frac{\partial \tilde{\varphi}_j}{\partial \varphi_j^*}$ becomes a constant. This property simplifies Equation

S3 significantly. Note first that:

$$\tilde{\varphi}'_j\varphi^*_j - \tilde{\varphi}_j = \left(\frac{\theta}{\theta+1-\sigma}\right)^{\frac{1}{\sigma-1}}\varphi^*_j - \left(\frac{\theta}{\theta+1-\sigma}\right)^{\frac{1}{\sigma-1}}\varphi^*_j = 0$$

$$\Rightarrow \frac{\partial\varphi^*_j}{\partial F_j} = \frac{1-G(\varphi^*_j)}{g(\varphi^*_j)}\frac{1}{F_j}\frac{1}{1-\frac{F_j[1-G(\varphi^*_j)]^2}{\delta f_{e,j}g(\varphi^*_j)}(\sigma-1)\left(\frac{\tilde{\varphi}_j}{\varphi^*_j}\right)^{\sigma-2}\underbrace{\frac{\tilde{\varphi}'_j\varphi^*_j-\tilde{\varphi}_j}{(\varphi^*_j)^2}}_{=0}}$$

$$= \frac{1-G(\varphi^*_j)}{g(\varphi^*_j)}\frac{1}{F_j} = \frac{1}{F_j}\frac{1}{\frac{g(\varphi^*_j)}{1-G(\varphi^*_j)}} = \frac{1}{F_j}\frac{1}{\frac{\theta}{\varphi^*_j}}$$

$$\Rightarrow \frac{\partial\varphi^*_j}{\partial F_j} = \frac{\varphi^*_j}{\theta F_j} > 0 \tag{S5}$$

With Equations S4 and S5, we can show that the **selection channel** and the **composition channel** have the sign as stated in the main text. Now, we are left with the **entry-flow channel**. The sign of this channel depends on the sign of $\frac{dn_j}{dF_j}$.

The entry flow is determined by free entry and stationarity. The free-entry condition in Equation (10) and the stationarity condition imply

$$\bar{\pi}_j = \frac{\delta f_{e,j}}{1-G(\varphi^*_j)}, \qquad M_j = \frac{n_j}{\delta}\left[1-G(\varphi^*_j)\right],$$

and therefore

$$M_j\bar{\pi}_j = n_j f_{e,j}$$

To express entry in terms of firm revenue, note that $R_j = M_j\bar{r}_j$ and $\bar{\pi}_j = \bar{r}_j/\sigma - F_j$. From the zero-profit condition in Equation (9),

$$\bar{\pi}_j = F_j\left[\left(\frac{\tilde{\varphi}_j}{\varphi^*_j}\right)^{\sigma-1} - 1\right], \qquad \bar{r}_j = \sigma F_j\left(\frac{\tilde{\varphi}_j}{\varphi^*_j}\right)^{\sigma-1}$$

Under the Pareto distribution,

$$\left(\frac{\tilde{\varphi}_j}{\varphi^*_j}\right)^{\sigma-1} = \frac{\theta}{\theta+1-\sigma},$$

so average operating profit is a constant fraction of average revenue:

$$\frac{\bar{\pi}_j}{\bar{r}_j} = \frac{\sigma - 1}{\sigma\theta}$$

Combining this result with $M_j\bar{\pi}_j = n_j f_{e,j}$ and $M_j\bar{r}_j = R_j$ gives

$$n_j = \frac{\sigma - 1}{\sigma\theta f_{e,j}} R_j, \qquad \frac{\partial \ln n_j}{\partial F_j} = \frac{\partial \ln R_j}{\partial F_j}$$

Because the entry flow moves proportionally with firm revenue, determining the sign of the entry response requires determining how $R_j$ responds to $F_j$. Firm-level CES demand is

$$R_i = R\left(\frac{P_i}{P}\right)^{1-\varepsilon}$$

Taking logs and differentiating with respect to $F_j$ gives, for firm $j$,

$$\frac{\partial \ln R_j}{\partial F_j} = \frac{\partial \ln R}{\partial F_j} + (1-\varepsilon)\left(\frac{\partial \ln P_j}{\partial F_j} - \frac{\partial \ln P}{\partial F_j}\right),$$

and, for any firm $m \neq j$,

$$\frac{\partial \ln R_m}{\partial F_j} = \frac{\partial \ln R}{\partial F_j} + (1-\varepsilon)\left(\frac{\partial \ln P_m}{\partial F_j} - \frac{\partial \ln P}{\partial F_j}\right)$$

Subtracting the second expression from the first eliminates aggregate expenditure and the aggregate price index:

$$\frac{\partial}{\partial F_j}\ln\left(\frac{R_j}{R_m}\right) = (1-\varepsilon)\frac{\partial}{\partial F_j}\ln\left(\frac{P_j}{P_m}\right) \tag{S6}$$

To evaluate the relative price response in Equation (S6), we first derive the response of each firm-level price index. Equation (6) gives

$$P_i = M_i^{-\frac{1}{\sigma-1}} p_i(\tilde{\varphi}_i)$$

The pricing rule implies that $p_i(\tilde{\varphi}_i)$ is proportional to $\tilde{\varphi}_i^{-1}$. The policy experiment changes $F_j = f_{\text{fix}} - x_j\tau$ through $x_j$, while holding $w$, $P_e$, and $\tau$ fixed. Hence, the common variable-cost term $\Psi$ is unaffected, so $\partial \ln \Psi / \partial F_j = 0$. Taking logs and differentiating therefore gives

$$\frac{\partial \ln P_i}{\partial F_j} = -\frac{1}{\sigma - 1}\frac{\partial \ln M_i}{\partial F_j} - \frac{\partial \ln \tilde{\varphi}_i}{\partial F_j}$$

Thus, the price index responds through the mass of active product lines and the productivity composition of those lines. For firm $j$, stationarity implies

$$M_j = \frac{n_j}{\delta}\left[1 - G(\varphi_j^*)\right]$$

Taking logs and differentiating,

$$\frac{\partial \ln M_j}{\partial F_j} = \frac{\partial \ln n_j}{\partial F_j} + \frac{\partial \ln[1 - G(\varphi_j^*)]}{\partial F_j}$$

Under the Pareto distribution,

$$1 - G(\varphi_j^*) = \left(\frac{\varphi_{\min}}{\varphi_j^*}\right)^{\theta},$$

and therefore

$$\begin{aligned}\frac{\partial \ln[1 - G(\varphi_j^*)]}{\partial F_j} &= -\theta \frac{\partial \ln \varphi_j^*}{\partial F_j} \\ &= -\theta \frac{1}{\theta F_j} = -\frac{1}{F_j}\end{aligned}$$

Using $\partial \ln n_j / \partial F_j = \partial \ln R_j / \partial F_j$, we obtain

$$\frac{\partial \ln M_j}{\partial F_j} = \frac{\partial \ln R_j}{\partial F_j} - \frac{1}{F_j}$$

Moreover, under the Pareto distribution, $\tilde{\varphi}_j$ is proportional to $\varphi_j^*$. Equation (S5) therefore implies

$$\frac{\partial \ln \tilde{\varphi}_j}{\partial F_j} = \frac{\partial \ln \varphi_j^*}{\partial F_j} = \frac{1}{\theta F_j}$$

Substituting the responses of $M_j$ and $\tilde{\varphi}_j$ into the firm-level price-index equation gives

$$\begin{aligned}\frac{\partial \ln P_j}{\partial F_j} &= -\frac{1}{\sigma - 1}\left(\frac{\partial \ln R_j}{\partial F_j} - \frac{1}{F_j}\right) - \frac{1}{\theta F_j} \\ &= -\frac{1}{\sigma - 1}\frac{\partial \ln R_j}{\partial F_j} + \left(\frac{1}{\sigma - 1} - \frac{1}{\theta}\right)\frac{1}{F_j}\end{aligned}$$

The first term captures the revenue–entry feedback. The second combines the direct loss of product variety with the increase in average productivity caused by selection. It is positive under the maintained assumption $\theta > \sigma - 1$. For every firm $m \neq j$, the fixed cost $F_m$ and

therefore its survival cutoff are unchanged. Hence,

$$\frac{\partial \ln \tilde{\varphi}_m}{\partial F_j} = 0$$

Its survival probability is also unchanged, so stationarity and the proportionality between entry and revenue imply

$$\frac{\partial \ln M_m}{\partial F_j} = \frac{\partial \ln n_m}{\partial F_j} = \frac{\partial \ln R_m}{\partial F_j}$$

Consequently,

$$\frac{\partial \ln P_m}{\partial F_j} = -\frac{1}{\sigma - 1} \frac{\partial \ln R_m}{\partial F_j}$$

Unlike firm $j$, firm $m$ has no direct selection or composition response to $F_j$; its price index responds only through the revenue–entry feedback. Subtracting the price-index response of firm $m$ from that of firm $j$ yields

$$\frac{\partial}{\partial F_j} \ln \left( \frac{P_j}{P_m} \right) = -\frac{1}{\sigma - 1} \frac{\partial}{\partial F_j} \ln \left( \frac{R_j}{R_m} \right) + \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j}$$

Substituting this expression into Equation (S6) gives

$$\frac{\partial}{\partial F_j} \ln \left( \frac{R_j}{R_m} \right) = (1 - \varepsilon) \left[ -\frac{1}{\sigma - 1} \frac{\partial}{\partial F_j} \ln \left( \frac{R_j}{R_m} \right) + \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j} \right]$$

Using $1 - \varepsilon = -(\varepsilon - 1)$ and collecting the relative-revenue response on the left-hand side,

$$\left[ 1 - \frac{\varepsilon - 1}{\sigma - 1} \right] \frac{\partial}{\partial F_j} \ln \left( \frac{R_j}{R_m} \right) = -(\varepsilon - 1) \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j}$$

Since

$$1 - \frac{\varepsilon - 1}{\sigma - 1} = \frac{\sigma - \varepsilon}{\sigma - 1},$$

we obtain

$$\frac{\partial}{\partial F_j} \ln \left( \frac{R_j}{R_m} \right) = -\frac{(\varepsilon - 1)(\sigma - 1)}{\sigma - \varepsilon} \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j} < 0$$

The inequality follows from $\sigma > \varepsilon > 1$ and $\theta > \sigma - 1$. Thus, a higher fixed cost reduces the revenue of firm $j$ relative to every firm $m \neq j$. A decline in relative revenue does not by itself imply that the absolute revenue of firm $j$ falls, since $R_j$ could increase less than the revenue of the other firms. Under the aggregate expenditure closure introduced above,

$$\frac{\partial \ln R}{\partial F_j} = 0$$

For each firm $m \neq j$, the reform leaves its productivity cutoff and average productivity unchanged. Moreover, free entry and stationarity imply that its entry flow and mass of product lines move proportionally with its revenue. Hence,

$$\frac{\partial \ln P_m}{\partial F_j} = -\frac{1}{\sigma - 1} \frac{\partial \ln R_m}{\partial F_j}.$$

This relationship is common to all firms $m \neq j$. Combined with the demand equation

$$\frac{\partial \ln R_m}{\partial F_j} = (1 - \varepsilon) \left( \frac{\partial \ln P_m}{\partial F_j} - \frac{\partial \ln P}{\partial F_j} \right),$$

it implies that all firms $m \neq j$ have the same proportional revenue and price-index responses, although they may differ in levels and primitives. Let $s_j = R_j/R$ denote the expenditure share of firm $j$. Differentiating aggregate expenditure therefore gives

$$0 = s_j \frac{\partial \ln R_j}{\partial F_j} + (1 - s_j) \frac{\partial \ln R_m}{\partial F_j}$$

Solving for the revenue response of the other firms yields

$$\frac{\partial \ln R_m}{\partial F_j} = -\frac{s_j}{1 - s_j} \frac{\partial \ln R_j}{\partial F_j}$$

Hence,

$$\frac{\partial}{\partial F_j} \ln \left( \frac{R_j}{R_m} \right) = \frac{\partial \ln R_j}{\partial F_j} - \frac{\partial \ln R_m}{\partial F_j} = \frac{1}{1 - s_j} \frac{\partial \ln R_j}{\partial F_j}$$

Equivalently, the absolute revenue response of firm $j$ is

$$\frac{\partial \ln R_j}{\partial F_j} = (1 - s_j) \frac{\partial}{\partial F_j} \ln \left( \frac{R_j}{R_m} \right)$$

Substituting the relative-revenue response derived above gives

$$\frac{\partial \ln R_j}{\partial F_j} = -(1 - s_j) \frac{(\varepsilon - 1)(\sigma - 1)}{\sigma - \varepsilon} \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j} < 0$$

The inequality follows from $\sigma > \varepsilon > 1$, $\theta > \sigma - 1$, and $s_j < 1$. Finally, because free entry and stationarity imply that the entry flow is proportional to firm revenue,

$$\frac{\partial \ln n_j}{\partial F_j} = \frac{\partial \ln R_j}{\partial F_j} < 0$$

Since $n_j > 0$, this also implies

$$\frac{\partial n_j}{\partial F_j} < 0$$

Thus, a higher fixed operating cost reduces firm $j$'s absolute revenue and, consequently, the equilibrium flow of entry attempts. These pairwise results also determine the relative price index that appears in Equation 11 of the main text. The price index of all firms other than $j$ is

$$P_{-j} = \left( \sum_{m \neq j} P_m^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}}$$

Differentiating gives

$$\frac{\partial \ln P_{-j}}{\partial F_j} = \sum_{m \neq j} \frac{R_m}{R_{-j}} \frac{\partial \ln P_m}{\partial F_j}$$

As shown above, all firms $m \neq j$ have the same proportional price-index response. The weighted average therefore equals this common response,

$$\frac{\partial \ln P_{-j}}{\partial F_j} = \frac{\partial \ln P_m}{\partial F_j}$$

It follows that

$$\frac{\partial}{\partial F_j} \ln \left( \frac{P_j}{P_{-j}} \right) = \frac{\partial}{\partial F_j} \ln \left( \frac{P_j}{P_m} \right) > 0$$

The general equilibrium spillovers in Equation 11 correspond to the response of $P_m$. As shown above, the revenue reallocated toward the other firms raises their entry and their mass of product lines, which lowers $P_m$ and thereby amplifies the increase in the relative price index of firm $j$ beyond its direct effect.

**Dominance of Entry-flow and Selection Channel**

Now that we are sure about the sign of each of the channels that affect $\frac{P_j}{P}$, we show under which conditions the selection and entry-flow channels dominate the composition channel. We start from the stationarity condition and take the derivative with respect to $F_j$:

$$\frac{\partial \ln M_j}{\partial F_j} = \frac{\partial \ln n_j}{\partial F_j} + \frac{\partial}{\partial F_j} \ln[1 - G(\varphi_j^*)]$$

Using the earlier result $\partial \varphi_j^* / \partial F_j = \varphi_j^* / (\theta F_j)$, and $\frac{\partial}{\partial F_j} \ln[1 - G(\varphi_j^*)] = -\frac{g}{1-G} \frac{d\varphi_j^*}{dF_j} = -\frac{1}{F_j}$, from

the Pareto tail distribution, we can write:

$$\frac{1}{M_j}\frac{\partial M_j}{\partial F_j} = \frac{1}{n_j}\frac{\partial n_j}{\partial F_j} - \frac{1}{F_j}$$

We also showed above that:

$$\frac{\partial \ln \tilde{\varphi}_j}{\partial F_j} = \frac{1}{\varphi_j^*}\frac{\partial \varphi_j^*}{\partial F_j} = \frac{1}{\theta F_j}$$

We can plug those two expressions in the bracket of Equation 11:

$$\begin{aligned}\frac{\partial}{\partial F_j}\ln\left(\frac{P_j}{P_{-j}}\right) &= \left[-\frac{1}{\sigma-1}\left(\frac{1}{n_j}\frac{\partial n_j}{\partial F_j} - \frac{1}{F_j}\right) - \frac{1}{\theta F_j}\right] + (\text{GE spillover}) \\ &= \left[\underbrace{\frac{1}{\sigma-1}\left(-\frac{1}{n_j}\frac{\partial n_j}{\partial F_j} + \frac{1}{F_j}\right)}_{\text{Selection and Entry}} + \underbrace{\left(-\frac{1}{\theta F_j}\right)}_{\text{composition (via } \tilde{\varphi}_j)}\right] + (\text{GE spillover})\end{aligned}$$

The selection and entry effect dominates iff:

$$\begin{aligned}&\frac{1}{\sigma-1}\left(-\frac{1}{n_j}\frac{\partial n_j}{\partial F_j} + \frac{1}{F_j}\right) > \frac{1}{\theta F_j}. \\ &\Leftrightarrow -\frac{1}{n_j}\frac{\partial n_j}{\partial F_j} > \frac{(\sigma-1)-\theta}{\theta}\frac{1}{F_j}\end{aligned}$$

As shown above, $\frac{\partial n_j}{\partial F_j} < 0$. That implies that the LHS is positive, so this inequality holds unconditionally under the maintained assumption $\theta > \sigma - 1$.

**General Equilibrium Spillover**

We start from:

$$\frac{\partial}{\partial F_j}\ln\left(\frac{P_j}{P_{-j}}\right) = \left[-\frac{1}{\sigma-1}\frac{1}{M_j}\frac{\partial M_j}{\partial F_j} - \frac{1}{\tilde{\varphi}_j}\frac{\partial \tilde{\varphi}_j}{\partial F_j}\right] - \underbrace{\sum_{m\neq j}\frac{R_m}{R}\left[-\frac{1}{\sigma-1}\frac{1}{M_m}\frac{\partial M_m}{\partial F_j} - \frac{1}{\tilde{\varphi}_m}\frac{\partial \tilde{\varphi}_m}{\partial F_j}\right]}_{\text{GE effects}}$$

The second sum represents the *general-equilibrium effects*. Inside it, two channels appear:

$$\frac{\partial M_m}{\partial F_j}, \qquad \frac{\partial \tilde{\varphi}_m}{\partial F_j}$$

In this section, we show that $\frac{\partial \tilde{\varphi}_m}{\partial F_j} = 0$ and $\frac{\partial M_m}{\partial F_j} > 0$. Therefore, the GE effects amplify the increase of the relative price $\frac{P_j}{P}$. Consider first:

$$\frac{\partial \tilde{\varphi}_m}{\partial F_j} = \frac{\partial \tilde{\varphi}_m}{\partial \varphi_m^*} \frac{\partial \varphi_m^*}{\partial F_j}$$

The cutoff $\varphi_m^*$ is pinned down by the zero-profit and free-entry conditions:

$$F_m \left[ \left( \frac{\tilde{\varphi}_m}{\varphi_m^*} \right)^{\sigma - 1} - 1 \right] = \frac{\delta f_{e,m}}{1 - G(\varphi_m^*)}$$

Importantly, this equation contains *only* firm-$m$ objects and parameters. It does not depend on $F_j$ for $j \neq m$ and it does not include variables that would transmit GE effects into $\varphi_m^*$. Since $\tilde{\varphi}_m = \tilde{\varphi}_m(\varphi_m^*)$ and $\varphi_m^*$ is independent of $F_j$ for $m \neq j$, we obtain

$$\frac{\partial \tilde{\varphi}_m}{\partial F_j} = 0, \qquad m \neq j$$

Thus, all GE effects for $m \neq j$ operate through $M_m$ only:

$$\frac{\partial M_m}{\partial F_j} = \frac{\partial M_m}{\partial R_m} \frac{\partial R_m}{\partial F_j}$$

As established in the derivation of the entry response above, free entry and stationarity imply that the mass of product lines of every firm moves proportionally with its revenue. Since neither the survival cutoff nor the survival probability of firm $m \neq j$ responds to $F_j$, the proportionality factor is unaffected by the reform, and

$$\frac{\partial \ln M_m}{\partial F_j} = \frac{\partial \ln R_m}{\partial F_j}$$

We are left with the effect of $F_j$ on $R_m$, $\frac{\partial R_m}{\partial F_j}$. Revenues satisfy the CES demand system:

$$R_i = R \left( \frac{P_i}{P} \right)^{1-\varepsilon}, \qquad P = \left( \sum_{m=1}^{N} P_m^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}}$$

We differentiate $\ln R_m$ w.r.t. $F_j$ for $m \neq j$:

$$\frac{\partial \ln R_m}{\partial F_j} = \underbrace{\frac{\partial \ln R}{\partial F_j}}_{=0} + (1 - \varepsilon) \left( \frac{\partial \ln P_m}{\partial F_j} - \frac{\partial \ln P}{\partial F_j} \right)$$

where the first term vanishes under the aggregate expenditure closure introduced above. Moreover,

$$P_m = M_m^{-\frac{1}{\sigma-1}} p_m(\tilde{\varphi}_m)$$

Since $\frac{\partial \tilde{\varphi}_m}{\partial F_j} = 0$, it follows that

$$\frac{\partial \ln P_m}{\partial F_j} = -\frac{1}{\sigma-1}\frac{\partial \ln M_m}{\partial F_j} = -\frac{1}{\sigma-1}\frac{\partial \ln R_m}{\partial F_j}$$

Substituting this expression into the CES demand equation gives

$$\begin{aligned}
\frac{\partial \ln R_m}{\partial F_j} &= (1-\varepsilon)\left(-\frac{1}{\sigma-1}\frac{\partial \ln R_m}{\partial F_j} - \frac{\partial \ln P}{\partial F_j}\right) \\
&= \frac{\varepsilon-1}{\sigma-1}\frac{\partial \ln R_m}{\partial F_j} + (\varepsilon-1)\frac{\partial \ln P}{\partial F_j} \\
\Leftrightarrow \left(1-\frac{\varepsilon-1}{\sigma-1}\right)\frac{\partial \ln R_m}{\partial F_j} &= (\varepsilon-1)\frac{\partial \ln P}{\partial F_j} \\
\Leftrightarrow \frac{\sigma-\varepsilon}{\sigma-1}\frac{\partial \ln R_m}{\partial F_j} &= (\varepsilon-1)\frac{\partial \ln P}{\partial F_j} \\
\Leftrightarrow \frac{\partial \ln R_m}{\partial F_j} &= \frac{(\varepsilon-1)(\sigma-1)}{\sigma-\varepsilon}\frac{\partial \ln P}{\partial F_j}
\end{aligned}$$

Using the expression derived above in $\frac{\partial \ln P_m}{\partial F_j}$, we obtain

$$\frac{\partial \ln P_m}{\partial F_j} = -\frac{1}{\sigma-1}\left[\frac{(\varepsilon-1)(\sigma-1)}{\sigma-\varepsilon}\frac{\partial \ln P}{\partial F_j}\right]$$

$$\Leftrightarrow \frac{\partial \ln P_m}{\partial F_j} = -\frac{\varepsilon-1}{\sigma-\varepsilon}\frac{\partial \ln P}{\partial F_j}$$

Since $\sigma > \varepsilon > 1$, the coefficient $\frac{\varepsilon-1}{\sigma-\varepsilon}$ is positive. Hence, the price index of firm $m$ moves in the opposite direction to the aggregate price index. To determine the sign of this response, we next derive the effect of $F_j$ on the aggregate price index $P$. We first consider the price response of the treated firm $j$. Using the same decomposition as above, the mass of product lines in firm $j$ can be written as

$$M_j = \frac{R_j}{\sigma\left(F_j + \frac{\delta f_{e,j}}{1-G(\varphi_j^*)}\right)}$$

From the zero-profit and free-entry conditions,

$$\frac{\delta f_{e,j}}{1-G(\varphi_j^*)} = F_j\left[\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-1} - 1\right] \Leftrightarrow F_j + \frac{\delta f_{e,j}}{1-G(\varphi_j^*)} = F_j\left(\frac{\tilde{\varphi}_j}{\varphi_j^*}\right)^{\sigma-1}$$

Under the Pareto distribution,

$$\frac{\tilde{\varphi}_j}{\varphi_j^*} = \left(\frac{\theta}{\theta+1-\sigma}\right)^{\frac{1}{\sigma-1}},$$

which is constant with respect to $F_j$. Hence,

$$\frac{\partial \ln M_j}{\partial F_j} = \frac{\partial \ln R_j}{\partial F_j} - \frac{1}{F_j}$$

The firm-level price index satisfies

$$P_j = M_j^{-\frac{1}{\sigma-1}} p_j(\tilde{\varphi}_j)$$

Since

$$\frac{\partial \ln \tilde{\varphi}_j}{\partial F_j} = \frac{1}{\theta F_j},$$

we obtain

$$\frac{\partial \ln P_j}{\partial F_j} = -\frac{1}{\sigma-1}\frac{\partial \ln R_j}{\partial F_j} + \left(\frac{1}{\sigma-1} - \frac{1}{\theta}\right)\frac{1}{F_j}$$

Using CES demand and $\frac{\partial \ln R}{\partial F_j} = 0$ gives

$$\frac{\partial \ln R_j}{\partial F_j} = (1-\varepsilon)\left(\frac{\partial \ln P_j}{\partial F_j} - \frac{\partial \ln P}{\partial F_j}\right)$$

Substituting this expression into the previous equation yields

$$\frac{\partial \ln P_j}{\partial F_j} = \frac{\varepsilon-1}{\sigma-1}\left(\frac{\partial \ln P_j}{\partial F_j} - \frac{\partial \ln P}{\partial F_j}\right) + \left(\frac{1}{\sigma-1} - \frac{1}{\theta}\right)\frac{1}{F_j}$$

$$\Leftrightarrow \frac{\partial \ln P_j}{\partial F_j} = \frac{\sigma-1}{\sigma-\varepsilon}\left(\frac{1}{\sigma-1} - \frac{1}{\theta}\right)\frac{1}{F_j} - \frac{\varepsilon-1}{\sigma-\varepsilon}\frac{\partial \ln P}{\partial F_j}$$

We can now use the aggregate CES price index. Differentiating gives

$$\frac{\partial \ln P}{\partial F_j} = \frac{R_j}{R}\frac{\partial \ln P_j}{\partial F_j} + \sum_{m\neq j}\frac{R_m}{R}\frac{\partial \ln P_m}{\partial F_j}$$

For all $m \neq j$, we derived above that

$$\frac{\partial \ln P_m}{\partial F_j} = -\frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j}$$

Since

$$\sum_{m \neq j} \frac{R_m}{R} = 1 - \frac{R_j}{R},$$

we obtain

$$\begin{aligned} \frac{\partial \ln P}{\partial F_j} = \frac{R_j}{R} \frac{\sigma - 1}{\sigma - \varepsilon} \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j} \\ - \frac{R_j}{R} \frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j} \\ - \left( 1 - \frac{R_j}{R} \right) \frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j} \end{aligned}$$

Combining the last two terms gives

$$\frac{\partial \ln P}{\partial F_j} = \frac{R_j}{R} \frac{\sigma - 1}{\sigma - \varepsilon} \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j} - \frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j}$$

$$\Leftrightarrow \left( 1 + \frac{\varepsilon - 1}{\sigma - \varepsilon} \right) \frac{\partial \ln P}{\partial F_j} = \frac{R_j}{R} \frac{\sigma - 1}{\sigma - \varepsilon} \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j}$$

$$\Leftrightarrow \frac{\partial \ln P}{\partial F_j} = \frac{R_j}{R} \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j}$$

Under the maintained assumption $\theta > \sigma - 1$,

$$\frac{\partial \ln P}{\partial F_j} > 0$$

We can now sign the general-equilibrium responses of the other firms. From the expression derived above,

$$\frac{\partial \ln R_m}{\partial F_j} = \frac{(\varepsilon - 1)(\sigma - 1)}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j}$$

Since $\sigma > \varepsilon > 1$ and $\frac{\partial \ln P}{\partial F_j} > 0$, it follows that

$$\frac{\partial \ln R_m}{\partial F_j} > 0$$

Since $M_m$ is proportional to $R_m$, we also have

$$\frac{\partial \ln M_m}{\partial F_j} = \frac{\partial \ln R_m}{\partial F_j} > 0$$

Thus, the increase in the fixed cost of firm $j$ shifts demand toward the other firms and increases their mass of active product lines. For their price indices, we derived

$$\frac{\partial \ln P_m}{\partial F_j} = -\frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j}$$

Hence,

$$\frac{\partial \ln P_m}{\partial F_j} < 0, \qquad m \neq j$$

The increase in product variety among the other firms therefore lowers their firm-level price indices. We can now determine the response of the aggregate price index of all firms other than $j$. Since

$$P_{-j} = \left( \sum_{m \neq j} P_m^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}},$$

differentiating gives

$$\frac{\partial \ln P_{-j}}{\partial F_j} = \sum_{m \neq j} \frac{R_m}{R_{-j}} \frac{\partial \ln P_m}{\partial F_j}$$

Using the expression for $\frac{\partial \ln P_m}{\partial F_j}$ derived above and $\sum_{m \neq j} \frac{R_m}{R_{-j}} = 1$, we obtain

$$\frac{\partial \ln P_{-j}}{\partial F_j} = -\frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j} < 0$$

Finally, consider the relative price index of the treated firm:

$$\frac{\partial}{\partial F_j} \ln \left( \frac{P_j}{P_{-j}} \right) = \frac{\partial \ln P_j}{\partial F_j} - \frac{\partial \ln P_{-j}}{\partial F_j}$$

Using

$$\frac{\partial \ln P_j}{\partial F_j} = \frac{\sigma - 1}{\sigma - \varepsilon} \left( \frac{1}{\sigma - 1} - \frac{1}{\theta} \right) \frac{1}{F_j} - \frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j}$$

and

$$\frac{\partial \ln P_{-j}}{\partial F_j} = -\frac{\varepsilon - 1}{\sigma - \varepsilon} \frac{\partial \ln P}{\partial F_j},$$

the aggregate-price terms cancel, leaving

$$\frac{\partial}{\partial F_j} \ln\left(\frac{P_j}{P_{-j}}\right) = \frac{\sigma - 1}{\sigma - \varepsilon}\left(\frac{1}{\sigma - 1} - \frac{1}{\theta}\right)\frac{1}{F_j}$$

Under $\theta > \sigma - 1$ and $\sigma > \varepsilon$, this expression is strictly positive:

$$\frac{\partial}{\partial F_j} \ln\left(\frac{P_j}{P_{-j}}\right) > 0.$$

Thus, general-equilibrium adjustments reinforce the relative-price effect. Higher fixed costs in firm $j$ shift expenditure toward other firms, raising their revenues and product variety. The resulting decline in their price indices further increases the price index of firm $j$ relative to the rest of the economy.

## S5.3 Policy Announcement

### Emissions and Technology Adoption

The cleaner technology lowers emissions per unit of revenue, but it also lowers marginal costs and raises demand for the adopting product line. We therefore need to account for this rebound effect when determining the effect of adoption on total emissions. Starting from Equation 14, taking logs and differentiating with respect to $\ln \kappa$ gives

$$\frac{\partial \ln[\kappa e_j(\varphi)]}{\partial \ln \kappa} = 1 - \frac{\tau\kappa}{P_e + \tau\kappa} + \frac{\partial \ln r_j(\varphi)}{\partial \ln \kappa}$$

To characterize the revenue response, note from the pricing rule that $p(\kappa;\varphi) \propto (P_e + \tau\kappa)^{1-\alpha}$. Hence

$$\frac{\partial \ln p(\kappa;\varphi)}{\partial \ln \kappa} = (1-\alpha)\frac{\tau\kappa}{P_e + \tau\kappa}$$

For the adoption decision of a single product line, the measure-zero argument above implies that $R_j$ and $P_j$ remain unchanged. Using $r_j(\varphi) = R_j\left(\frac{p_j(\varphi)}{P_j}\right)^{1-\sigma}$ therefore yields

$$\frac{\partial \ln r_j(\varphi)}{\partial \ln \kappa} = (1-\sigma)(1-\alpha)\frac{\tau\kappa}{P_e + \tau\kappa}$$

A lower emission factor thus lowers the product price and raises revenue. Substituting this response above gives

$$\frac{\partial \ln[\kappa e_j(\varphi)]}{\partial \ln \kappa} = \underbrace{\frac{P_e}{P_e + \tau\kappa}}_{\text{emission-intensity effect}} \underbrace{- (\sigma - 1)(1 - \alpha)\frac{\tau\kappa}{P_e + \tau\kappa}}_{\text{rebound effect}} \tag{S7}$$

Since adoption corresponds to a reduction in $\kappa$, total emissions fall if this derivative is positive, which requires

$$P_e > (\sigma - 1)(1 - \alpha)\tau\kappa \tag{S8}$$

The first term in Equation S7 captures the decline in emissions per unit of revenue from a cleaner technology, while the second captures the increase in revenue induced by its lower price. The condition is more likely to hold when $P_e$ is large relative to the carbon-cost component $\tau\kappa$. The rebound effect becomes stronger when products are more substitutable ($\sigma$ is larger), when energy has a larger cost share ($1 - \alpha$ is larger), or when carbon costs are larger. For the discrete change from $\kappa_\ell$ to $\kappa_h$, it is sufficient that Equation S8 holds over $[\kappa_h, \kappa_\ell]$; since the right-hand side is increasing in $\kappa$, it is sufficient to impose it at $\kappa_\ell$.

**Technology Adoption Cutoff**

We start with the expression for revenue of a given product line:

$$r_j(\varphi) = R_j \left( \frac{p_j(\varphi)}{P_j} \right)^{1-\sigma}$$

If one variant $\varphi_0$ would adopt the technology, it now has the new price: $p'_j(\varphi_0) = m\, p_j(\varphi_0)$. Given that product lines are atomistic, the set $\{\varphi_0\}$ has measure zero. Thus, the integrals above would not change ($P'_j = P_j$). This is a unilateral-deviation argument. It characterizes the gain of a single product line from adopting, taking the behavior of all other product lines as given. The same argument underlies the emissions decomposition above. The adjustment of the firm-level price index when a positive mass of product lines adopts in equilibrium is analyzed at the end of this appendix. Therefore:

$$\frac{r'_j(\varphi_0)}{r_j(\varphi_0)} = \left( \frac{p'_j(\varphi_0)/P'_j}{p_j(\varphi_0)/P_j} \right)^{1-\sigma} = \left( \frac{m\, p_j(\varphi_0)/P_j}{p_j(\varphi_0)/P_j} \right)^{1-\sigma} = m^{1-\sigma}$$

and

$$r_h(\varphi) = m^{1-\sigma} r_\ell(\varphi) \tag{S9}$$

This allows us to calculate the gain for a product line from adoption. We know that the variable costs for $s \in \{\ell, h\}$ can be expressed as $vc_s(\varphi) = \frac{\sigma-1}{\sigma} p_s(\varphi) q_s(\varphi) = \frac{\sigma-1}{\sigma} r_s(\varphi)$. We then have:

$$\begin{aligned}
\pi_j(p) &= p_j\, q_j(\varphi) - c_u(\varphi) q_j(\varphi) - F_j \\
&= r_s(\varphi) - vc_s(\varphi) - F_j \\
&= r_s(\varphi) \left(1 - \frac{\sigma - 1}{\sigma}\right) - F_j \\
&= \frac{1}{\sigma} r_s(\varphi) - F_j
\end{aligned}$$

$$\Rightarrow \pi_s(\varphi) = \frac{1}{\sigma} r_s(\varphi) - F_j \qquad s \in \{\ell, h\} \tag{S10}$$

Using this definition of profits, we can derive the gain from adoption:

$$\begin{aligned}
\Delta\pi(\varphi) \equiv \pi_h(\varphi) - \pi_\ell(\varphi) &= \left[\frac{1}{\sigma} r_h(\varphi) - F_j\right] - \left[\frac{1}{\sigma} r_\ell(\varphi) - F_j\right] \\
&= \frac{1}{\sigma} [r_h(\varphi) - r_\ell(\varphi)]
\end{aligned}$$

Now, we can use the Equation S9 to express everything in terms of $r_\ell(\varphi)$:

$$\begin{aligned}
\Delta\pi(\varphi) &= \frac{1}{\sigma} [m^{1-\sigma} r_\ell(\varphi) - r_\ell(\varphi)] \\
&= \frac{1}{\sigma} (m^{1-\sigma} - 1) r_\ell(\varphi)
\end{aligned}$$

This gives the additional profit that a product line receives from adopting the technology (equation 15 in the main text). We can put this in terms of present value of the firm:

$$\Delta v(\varphi) = \frac{\Delta\pi(\varphi)}{\delta}$$

To decide to adopt or not, this has to be related to the cost of adoption $K$. The product line will adopt the new technology if and only if the gain in net present value exceeds the

sunk cost $K$:

$$\Delta v(\varphi) \geq K \iff \frac{\Delta\pi(\varphi)}{\delta} \geq K \iff \Delta\pi(\varphi) \geq \delta K$$

Now, we can use Equation 15:

$$\frac{1}{\sigma}(m^{1-\sigma}-1)r_\ell(\varphi) \geq \delta K$$
$$r_\ell(\varphi) \geq \frac{\sigma\delta K}{m^{1-\sigma}-1}$$

Using the revenue ladder $r_\ell(\varphi) = r(\varphi_j^*)\left(\frac{\varphi}{\varphi_j^*}\right)^{\sigma-1}$, we get:

$$r(\varphi_j^*)\left(\frac{\varphi}{\varphi_j^*}\right)^{\sigma-1} \geq \frac{\sigma\,\delta K}{m^{1-\sigma}-1} \Leftrightarrow \left(\frac{\varphi}{\varphi_j^*}\right)^{\sigma-1} \geq \frac{\sigma\delta K}{r(\varphi_j^*)[m^{1-\sigma}-1]}$$
$$\Leftrightarrow \frac{\varphi}{\varphi_j^*} \geq \left[\frac{\sigma\delta K}{r(\varphi_j^*)[m^{1-\sigma}-1]}\right]^{1/(\sigma-1)} \Leftrightarrow \varphi \geq \underbrace{\varphi_j^*\left[\frac{\sigma\delta K}{r(\varphi_j^*)[m^{1-\sigma}-1]}\right]^{1/(\sigma-1)}}_{\varphi_A}$$

This gives us the firm-level adoption cutoff (equation 16 in the main text):

$$\varphi_j^A = \varphi_j^*\left[\frac{\sigma\delta K}{r(\varphi_j^*)(m^{1-\sigma}-1)}\right]^{1/(\sigma-1)}$$

We next consider how the adoption cutoff responds to a change in the fixed operating cost $F_j$. Using the zero-profit condition $r_\ell(\varphi_j^*) = \sigma F_j$, the adoption cutoff can be rewritten as

$$\varphi_j^A = \varphi_j^*\left[\frac{\delta K}{F_j(m^{1-\sigma}-1)}\right]^{\frac{1}{\sigma-1}}.$$

We next consider how the fixed operating cost $F_j$ affects technology adoption. As shown in Equation (S5), under the Pareto productivity distribution a higher fixed cost raises the survival cutoff:

$$\frac{\partial \ln \varphi_j^*}{\partial \ln F_j} = \frac{1}{\theta} > 0$$

Hence, an increase in $F_j$ causes the least productive product lines to exit. This selection also affects the revenue of the product lines that remain active. To see this, combine the revenue ladder with the zero-profit condition $r_\ell(\varphi_j^*) = \sigma F_j$. For any surviving product line

with productivity $\varphi$,

$$r_\ell(\varphi) = \sigma F_j \left(\frac{\varphi}{\varphi_j^*}\right)^{\sigma-1}$$

Holding the productivity $\varphi$ of a given surviving product line fixed and differentiating with respect to $F_j$ gives

$$\frac{\partial \ln r_\ell(\varphi)}{\partial \ln F_j} = 1 - (\sigma - 1)\frac{\partial \ln \varphi_j^*}{\partial \ln F_j} = 1 - \frac{\sigma - 1}{\theta} > 0$$

where the inequality follows from the maintained assumption $\theta > \sigma - 1$. Thus, although a higher fixed cost raises the survival cutoff and reduces the set of active product lines, it increases the equilibrium revenue of a given product line that remains active. Economically, this captures the demand reallocation generated by product exit. When the least productive product lines disappear, part of their demand is reallocated toward the remaining varieties. In the nested CES demand system, varieties within a firm are more substitutable than firms are across each other ($\sigma > \varepsilon$), so this within-firm reallocation works against the decline in firm-level demand and raises the revenue of surviving product lines. This increase in survivor revenue strengthens the incentive to adopt the cleaner technology. From the expression for the gain from adoption,

$$\Delta\pi(\varphi) = \frac{1}{\sigma}\left(m^{1-\sigma} - 1\right) r_\ell(\varphi),$$

the return to adoption is proportional to product-line revenue. Hence, for a given surviving product line,

$$\frac{\partial \ln \Delta\pi(\varphi)}{\partial \ln F_j} = 1 - \frac{\sigma - 1}{\theta} > 0$$

We can express the corresponding effect on the adoption cutoff directly. Using the zero-profit condition in the cutoff derived above gives

$$\varphi_j^A = \varphi_j^* \left[\frac{\delta K}{F_j(m^{1-\sigma} - 1)}\right]^{\frac{1}{\sigma-1}}$$

Taking logs and using Equation (S5),

$$\begin{aligned}\frac{\partial \ln \varphi_j^A}{\partial \ln F_j} &= \frac{1}{\theta} - \frac{1}{\sigma - 1} \\ &= -\frac{1}{\sigma - 1}\left(1 - \frac{\sigma - 1}{\theta}\right) < 0 \end{aligned} \tag{S11}$$

The negative response of the adoption cutoff is therefore the counterpart of the positive revenue response of surviving product lines. Higher fixed costs induce the exit of marginal product lines and increase the revenue available to those that remain. Since the cost of adopting the cleaner technology is fixed, this raises the return to adoption and makes adoption profitable at a lower productivity level.

**Anticipation**

The increase in value of a given product line due to the adoption of the high-efficiency technology can be calculated using Equation S10, and it depends on the increase in revenue of the remaining product lines. At $t = 0$, profits remain unchanged and are equal to $\pi_0$. At $t = 1$, they change and then stay at the new level $\pi_1$ for all upcoming periods:

$$\begin{aligned}\Delta v_0(\varphi) &= \Delta\pi_0(\varphi) + (1-\delta)\Delta\pi_1(\varphi) + (1-\delta)^2\Delta\pi_1(\varphi) + \dots \\ &= \Delta\pi_0(\varphi) + \frac{1-\delta}{\delta}\Delta\pi_1(\varphi). \\ &= \frac{1}{\sigma}(m^{1-\sigma} - 1)\left[r_\ell^0(\varphi) + \frac{1-\delta}{\delta} r_\ell^1(\varphi)\right]\end{aligned}$$

We know that product lines adopt at $t = 0$, if and only if $\Delta v_0(\varphi) \geq K$:

$$\begin{aligned}\frac{1}{\sigma}(m^{1-\sigma} - 1)\left[r_\ell^0(\varphi) + \frac{1-\delta}{\delta} r_\ell^1(\varphi)\right] &\geq K \\ r_\ell^0(\varphi) + \frac{1-\delta}{\delta} r_\ell^1(\varphi) &\geq \frac{\sigma K}{m^{1-\sigma} - 1}\end{aligned}$$

Defining $\Phi_j \equiv \frac{r_\ell^1(\varphi)}{r_\ell^0(\varphi)}$, we can rewrite the expression:

$$\begin{aligned} r_\ell^0 + \frac{1-\delta}{\delta}\Phi_j\, r_\ell^0 &\geq \frac{\sigma K}{m^{1-\sigma} - 1} \\ \Leftrightarrow r_\ell^0\left(1 + \frac{1-\delta}{\delta}\Phi_j\right) &\geq \frac{\sigma K}{m^{1-\sigma} - 1} \\ \Leftrightarrow r_\ell^0(\varphi) &\geq \frac{\sigma K}{m^{1-\sigma} - 1}\frac{1}{1 + \frac{1-\delta}{\delta}\Phi_j}\end{aligned}$$

Note that if $\Phi_j = 1$, so that the revenues of today and tomorrow are equal, we arrive at the same expression as before: $r_\ell^0 \geq \frac{\sigma K}{m^{1-\sigma}-1}\frac{1}{1+\frac{1-\delta}{\delta}} = \frac{\sigma K}{m^{1-\sigma}-1}\delta$. Again, we can get today's adoption cutoff (equation 17) in the main text:

$$\left(\frac{\varphi_A^0}{\varphi_j^{*0}}\right)^{\sigma-1} = \frac{\sigma K}{r_\ell^0(\varphi)(m^{1-\sigma}-1)}\frac{1}{1+\frac{1-\delta}{\delta}\Phi_j}$$

$$\Leftrightarrow \varphi_A^0 = \varphi_j^{*0}\left[\frac{\sigma K}{r_\ell^0(\varphi)(m^{1-\sigma}-1)}\frac{1}{1+\frac{1-\delta}{\delta}\Phi_j}\right]^{\frac{1}{\sigma-1}}$$

Taking the derivative with respect to the announcement parameter $\Phi_j$ shows that an increase in revenue next period decreases the adoption productivity cutoff:

$$\frac{\partial \varphi_A^0}{\partial \Phi_j} = -\varphi_A^0 \frac{1}{\sigma-1}\frac{(1-\delta)/\delta}{1+\frac{1-\delta}{\delta}\Phi_j} < 0$$

What determines $\Phi_j$? To see how firm $j$ is affected by the announcement effect relative to all other firms $m \neq j$, we look closer at the relative revenue change of a product line due to the announcement. Starting from the revenue ladder:

$$\frac{r_\ell^1(\varphi)}{r_\ell^0(\varphi)} = \frac{R_j^1}{R_j^0}\left(\frac{p(\varphi)/P_j^1}{p(\varphi)/P_j^0}\right)^{1-\sigma} = \frac{R_j^1}{R_j^0}\left(\frac{P_j^0}{P_j^1}\right)^{1-\sigma}$$

$$\Rightarrow \frac{r_\ell^1(\varphi)}{r_\ell^0(\varphi)} = \frac{R_j^1}{R_j^0}\left(\frac{P_j^1}{P_j^0}\right)^{\sigma-1} \tag{S12}$$

We can express the firm revenue via the top nest using:

$$R_j^t = R^t\left(\frac{P_j^t}{P^t}\right)^{1-\varepsilon}$$

$$\Rightarrow \frac{R_j^1}{R_j^0} = \frac{R^1}{R^0}\left(\frac{P_j^1/P^1}{P_j^0/P^0}\right)^{1-\varepsilon} = \frac{R^1}{R^0}\left(\frac{P_j^1}{P_j^0}\right)^{1-\varepsilon}\left(\frac{P^0}{P^1}\right)^{1-\varepsilon}$$

We plug this into Equation S12 to get:

$$\begin{aligned}\frac{r_\ell^1(\varphi)}{r_\ell^0(\varphi)} &= \frac{R^1}{R^0}\left(\frac{P_j^1}{P_j^0}\right)^{(1-\varepsilon)+(\sigma-1)}\left(\frac{P^0}{P^1}\right)^{1-\varepsilon} \\ &= \underbrace{\frac{R^1}{R^0}}_{\text{aggregate expenditure}} \quad \underbrace{\left(\frac{P_j^1}{P_j^0}\right)^{\sigma-\varepsilon}}_{\text{within-firm reallocation}} \quad \underbrace{\left(\frac{P^1}{P^0}\right)^{\varepsilon-1}}_{\text{economy-wide price index}}\end{aligned}$$

We can see that we have three components here. The **aggregate expenditure** captures the fact that the revenue of a product line increases when aggregate expenditure rises, for example due to higher income of households. In this case, every product line in the economy sees an increase in their revenue of its share in the economy. Consistent with the aggregate expenditure closure introduced in Appendix S5.2, we assume that the reform leaves aggregate expenditure unchanged, $\frac{R^1}{R^0} = 1$: the reform reallocates expenditure across firms rather than changing its level.

The **economy-wide price effect** captures how changes in firm-level price indices affect the aggregate price index $P$. An increase in $P_j$ raises $P$ directly, while the general-equilibrium expansion of other firms and the resulting decline in their price indices work in the opposite direction. We do not need to determine the sign of this aggregate response. Under the aggregate-expenditure closure, it affects the revenue of all product lines through the common term $(P^1/P^0)^{\varepsilon-1}$ and therefore cancels when we compare the anticipated revenue change of product lines in firm $j$ with that in any other firm $m \neq j$.

Finally, the **within-firm reallocation** is based on channels that define the announcement effect. First, the within-firm demand increases the demand for the variants remaining in the market. As discussed in the last Section, the reform will increase the price level of firm $j$ at $t = 1$, since higher fixed cost decreases the mass of product lines $M_j$, which makes it harder to reach a given utility due to love-of-variety preferences. The pricing rule of a product line, however, is independent of fixed costs. Therefore, a given product line becomes cheaper relative to the firm level price index $P_j$ and has, therefore, a higher revenue. That positive effect on a line's revenue has strength $\sigma - 1$.

Second, given the higher firm-level price index $P_j$, firm $j$ will lose some revenue to other firms $m \neq j$. That is given by the $1 - \varepsilon$. Therefore, for each product line, we see a change in revenue based on the change in $P_j$ from $t = 0$ to $t = 1$ based on $\sigma - \varepsilon$.

We are especially interested in the effect of the announcement on the productivity cutoff for adoption in the treated firm $j$, relative to all other firms $m \neq j$. We first look at the ratio:

$$\frac{\Phi_j}{\Phi_m} = \frac{\frac{R^1}{R^0}\left(\frac{P_j^1}{P_j^0}\right)^{\sigma-\varepsilon}\left(\frac{P^1}{P^0}\right)^{\varepsilon-1}}{\frac{R^1}{R^0}\left(\frac{P_m^1}{P_m^0}\right)^{\sigma-\varepsilon}\left(\frac{P^1}{P^0}\right)^{\varepsilon-1}}$$

$$= \underbrace{\frac{R^1/R^0}{R^1/R^0}}_{=1} \times \frac{\left(\frac{P_j^1}{P_j^0}\right)^{\sigma-\varepsilon}}{\left(\frac{P_m^1}{P_m^0}\right)^{\sigma-\varepsilon}} \times \underbrace{\frac{\left(\frac{P^1}{P^0}\right)^{\varepsilon-1}}{\left(\frac{P^1}{P^0}\right)^{\varepsilon-1}}}_{=1}$$

$$\Rightarrow \frac{\Phi_j}{\Phi_m} = \left(\frac{P_j^1/P_j^0}{P_m^1/P_m^0}\right)^{\sigma-\varepsilon} \tag{S13}$$

From our previous analysis, we know that with the implementation of the reform, $\frac{P_j^1}{P_j^0} > 1$. Moreover, the GE spillovers suggest that $\frac{P_m^1}{P_m^0} < 1$. This effect is most likely much smaller and only amplifies the main effect on the price index of the treated firm. Therefore, given that $\sigma > \varepsilon$, we can conclude that:

$$\frac{\partial}{\partial F_j^1}\ln\left(\frac{\Phi_j}{\Phi_m}\right) = (\sigma-\varepsilon)\left(\frac{\partial \ln P_j^1}{\partial F_j^1} - \frac{\partial \ln P_m^1}{\partial F_j^1}\right)$$

This has implications for the relative change in the productivity cutoff:

$$\frac{\varphi_{A,j}^0}{\varphi_{A,m}^0} = \left(\frac{1+\frac{1-\delta}{\delta}\Phi_m}{1+\frac{1-\delta}{\delta}\Phi_j}\right)^{\frac{1}{\sigma-1}}$$

Taking logs and differentiating gives:

$$\ln\left(\frac{\varphi_{A,j}^0}{\varphi_{A,m}^0}\right) = \frac{1}{\sigma-1}\Big[\ln\big(\delta+(1-\delta)\Phi_m\big) - \ln\big(\delta+(1-\delta)\Phi_j\big)\Big]$$

$$\Rightarrow \frac{\partial}{\partial F_j^1}\ln\left(\frac{\varphi_{A,j}^0}{\varphi_{A,m}^0}\right) = \frac{1}{\sigma-1}\left[\frac{(1-\delta)\frac{\partial \Phi_m}{\partial F_j^1}}{\delta+(1-\delta)\Phi_m} - \frac{(1-\delta)\frac{\partial \Phi_j}{\partial F_j^1}}{\delta+(1-\delta)\Phi_j}\right]$$

Note that prior to the announcement, $\Phi_j = \Phi_m = 1$. We evaluate the derivative using this:

$$\begin{aligned}
\frac{\partial}{\partial F_j^1} \ln\left(\frac{\varphi_{A,j}^0}{\varphi_{A,m}^0}\right)\Bigg|_{\Phi_j=\Phi_m=1} &= \frac{1-\delta}{\sigma-1}\left[\frac{\partial \Phi_m}{\partial F_j^1} - \frac{\partial \Phi_j}{\partial F_j^1}\right] \\
\frac{\partial}{\partial F_j^1} \ln\left(\frac{\Phi_j}{\Phi_m}\right)\Bigg|_{\Phi_j=\Phi_m=1} &= \left(\frac{1}{\Phi_j}\frac{\partial \Phi_j}{\partial F_j^1} - \frac{1}{\Phi_m}\frac{\partial \Phi_m}{\partial F_j^1}\right)\Bigg|_{\Phi_j=\Phi_m=1} \\
&= \frac{\partial \Phi_j}{\partial F_j^1} - \frac{\partial \Phi_m}{\partial F_j^1} \\
\frac{\partial}{\partial F_j^1} \ln\left(\frac{\varphi_{A,j}^0}{\varphi_{A,m}^0}\right)\Bigg|_{\Phi=1} &= -\frac{1-\delta}{\sigma-1}\frac{\partial}{\partial F_j^1} \ln\left(\frac{\Phi_j}{\Phi_m}\right)\Bigg|_{\Phi=1}
\end{aligned}$$

This, together with Equation S13, gives us Equation 19:

$$\frac{\partial}{\partial F_j^1} \ln\left(\frac{\varphi_{A,j}^0}{\varphi_{A,m}^0}\right)\Bigg|_{\Phi=1} = -\frac{1-\delta}{\sigma-1}(\sigma-\varepsilon)\left(\underbrace{\frac{1}{P_j^1}\frac{\partial P_j^1}{\partial F_j^1}}_{+} \underbrace{-\frac{1}{P_m^1}\frac{\partial P_m^1}{\partial F_j^1}}_{+}\right)$$

**Equilibrium Adoption and the Cannibalization Feedback**

The adoption cutoff in Equation 16 is derived from a unilateral deviation: a single product line adopts while the firm-level aggregates remain unchanged. In equilibrium, however, all product lines above the adoption cutoff adopt, which is a set of positive mass. Their adoption lowers the firm-level price index and thereby reduces the revenue gain from adoption for all other product lines. This section accounts for this cannibalization feedback. It shows that the equilibrium adoption cutoff is higher than the unilateral-deviation cutoff and that adoption decisions are strategic substitutes. The feedback attenuates the announcement response, but it does not reverse it. At implementation, the firm-level aggregates cancel between the adoption and survival conditions, leaving the previously derived elasticity unchanged.

To isolate the cannibalization channel, we hold the survival cutoff $\varphi_j^*$ and the mass of product lines $M_j$ fixed. Aggregate expenditure $R$ is fixed under the aggregate-expenditure closure introduced in Appendix S5.2, while the aggregate price index $P$ remains endogenous. We also hold the price indices of firms $m \neq j$ fixed in this auxiliary exercise.

Suppose all product lines with productivity above a candidate cutoff $\varphi_j^A$ adopt the cleaner

technology. The firm-level price index is then computed over the two technologies:

$$P_j^{1-\sigma} = M_j \left(\frac{\sigma}{\sigma-1}\Psi\right)^{1-\sigma} \left[\int_{\varphi_j^*}^{\varphi_j^A} \varphi^{\sigma-1}\mu(\varphi)\,d\varphi + m^{1-\sigma}\int_{\varphi_j^A}^{\infty} \varphi^{\sigma-1}\mu(\varphi)\,d\varphi\right]$$

Since $m^{1-\sigma} > 1$, adoption lowers the firm-level price index relative to the no-adoption benchmark. Differentiating with respect to the candidate cutoff gives

$$\frac{\partial \ln P_j}{\partial \ln \varphi_j^A} = \frac{(m^{1-\sigma}-1)\left(\varphi_j^A\right)^{\sigma}\mu\left(\varphi_j^A\right)}{(\sigma-1)\left[\int_{\varphi_j^*}^{\varphi_j^A} \varphi^{\sigma-1}\mu(\varphi)\,d\varphi + m^{1-\sigma}\int_{\varphi_j^A}^{\infty} \varphi^{\sigma-1}\mu(\varphi)\,d\varphi\right]} > 0$$

A higher candidate cutoff means that fewer product lines adopt, so the firm-level price index rises. Since $P$ remains endogenous, this change also affects the aggregate price index. Holding the price indices of firms $m \neq j$ fixed, the aggregate C.E.S. price index implies

$$\frac{\partial \ln P}{\partial \ln P_j} = s_j, \qquad s_j \equiv \frac{R_j}{R}$$

Combining within-firm demand, $r_{\ell,j}(\varphi) = R_j\left(p_{\ell,j}(\varphi)/P_j\right)^{1-\sigma}$, with firm-level demand, $R_j = R\left(P_j/P\right)^{1-\varepsilon}$, and the pricing rule gives

$$r_{\ell,j}(\varphi) \propto \varphi^{\sigma-1} P_j^{\sigma-\varepsilon} P^{\varepsilon-1}$$

Therefore,

$$\frac{\partial \ln r_{\ell,j}(\varphi)}{\partial \ln \varphi_j^A} = [\sigma - \varepsilon + (\varepsilon-1)s_j]\frac{\partial \ln P_j}{\partial \ln \varphi_j^A} > 0$$

Hence, less adoption by other product lines raises the revenue of a given line. The first component, $\sigma-\varepsilon$, captures the direct effect through the firm-level price index. The additional term $(\varepsilon-1)s_j$ arises because the increase in $P_j$ also raises the aggregate price index $P$, which further increases demand for firm $j$.

Now define the best-response cutoff $\widehat{\varphi}_j^A$ as the productivity at which an individual product line is indifferent between adopting and not adopting, given that all other lines adopt above the candidate cutoff $\varphi_j^A$:

$$\frac{1}{\sigma}\left(m^{1-\sigma}-1\right) r_{\ell,j}\left(\widehat{\varphi}_j^A; \varphi_j^A\right) = \delta K$$

Differentiating this condition with respect to the candidate cutoff gives

$$\frac{\partial \ln \widehat{\varphi}_j^A}{\partial \ln \varphi_j^A} = -\frac{\sigma - \varepsilon + (\varepsilon - 1)s_j}{\sigma - 1} \frac{\partial \ln P_j}{\partial \ln \varphi_j^A} < 0$$

Adoption decisions are therefore strategic substitutes within the firm: when fewer other lines adopt, product-line revenue is higher and adoption becomes attractive at a lower productivity. Allowing the aggregate price index to adjust strengthens this strategic-substitutes feedback relative to the case in which $P$ is held fixed.

The equilibrium adoption cutoff is the fixed point

$$\varphi_j^A = \widehat{\varphi}_j^A \left(\varphi_j^A\right)$$

When the candidate cutoff is such that no product line adopts, the best-response cutoff equals the unilateral-deviation cutoff in Equation 16. Since the best response is strictly decreasing in the candidate cutoff, the fixed point is unique and lies strictly above the value in Equation 16. Cannibalization therefore makes adoption less widespread than the unilateral-deviation cutoff suggests.

More generally, let $z$ denote a shifter of the adoption incentive, holding the candidate cutoff fixed. Totally differentiating the fixed-point condition gives

$$\frac{d \ln \varphi_j^A}{d \ln z} = \frac{\dfrac{\partial \ln \widehat{\varphi}_j^A}{\partial \ln z}}{1 - \dfrac{\partial \ln \widehat{\varphi}_j^A}{\partial \ln \varphi_j^A}}$$

Since the feedback derivative in the denominator is negative, the denominator exceeds one. The equilibrium response therefore has the same sign as the direct response and is smaller in absolute value. The cannibalization feedback attenuates, but cannot reverse, the effect of an adoption shifter. A reversal would require adoption decisions to be strong strategic complements. The nested C.E.S. demand structure rules this out: one product line's price reduction lowers the revenues of other lines and therefore makes their adoption less attractive. This attenuation applies in particular to the announcement effect, where higher expected future revenue shifts the current adoption incentive.

At implementation, however, the equilibrium conditions imply an additional cancellation. The marginal surviving line and the marginal adopting line face the same firm-level and

aggregate price indices. Dividing the adoption indifference condition

$$\left(m^{1-\sigma}-1\right) r_{\ell,j}\left(\varphi_j^A\right) = \sigma\delta K$$

by the zero-profit condition

$$r_{\ell,j}\left(\varphi_j^*\right) = \sigma F_j$$

and using the revenue ladder yields

$$\left(\frac{\varphi_j^A}{\varphi_j^*}\right)^{\sigma-1} = \frac{\delta K}{F_j\left(m^{1-\sigma}-1\right)}$$

All firm-level and aggregate price indices cancel from this ratio. The cannibalization feedback scales the revenues of the marginal surviving and marginal adopting lines by the same proportional factor and therefore leaves their relative revenue unchanged. Consequently, the distance between the adoption and survival cutoffs responds to the fixed operating cost with elasticity

$$\frac{\partial}{\partial \ln F_j} \ln\left(\frac{\varphi_j^A}{\varphi_j^*}\right) = -\frac{1}{\sigma-1}$$

Combining this with the survival-cutoff response, $\partial \ln \varphi_j^* / \partial \ln F_j = 1/\theta$, reproduces the implementation elasticity derived above:

$$\frac{\partial \ln \varphi_j^A}{\partial \ln F_j} = \frac{1}{\theta} - \frac{1}{\sigma-1} < 0$$

The cancellation applies to the implementation margin because the survival and adoption conditions are evaluated in the same equilibrium. At announcement, current survival is instead compared with future product-line revenue, so the strategic-substitutes attenuation derived above remains relevant. Finally, this exercise isolates the cannibalization feedback by holding the survival cutoff, the mass of product lines, and the price indices of other firms fixed. Adoption may additionally affect survival, entry, and the equilibrium responses of other firms; we do not characterize these further feedbacks.