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Trade and Strategic Adjustments to EU Environmental Policy in Italian Industry

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“- Qual era lo scopo di 22?

- Non assegniamo scopi, come ti è venuto in mente! La scintilla non è lo scopo di una persona! Ah, voi mentori, con le vostre passioni, i vostri scopi, il senso della vita, così basici!”

- *Soul (2020),* regia di Peter Docte

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Abstract

This thesis investigates how Italian manufacturing firms adjusted their production, sourcing, and performance outcomes in response to the progressive tightening of environmental regulation on perfluorooctanoic acid (PFOA), first through its inclusion in the REACH Candidate and Restriction Lists and subsequently through its listing under the POPs Regulation. By combining firm-level customs microdata, balance-sheet information from AIDA, and a treatment classification based on a detailed mapping of PFOA-affected tariff codes, the analysis employs a difference-in-differences framework to identify the causal effects of regulation on trade patterns, turnover, added value, labor costs, intangible assets, and research and development expenditure.

The results show that environmental regulation induced significant adjustments in firms' trade structures, particularly through a marked reorientation of imports and exports toward EU markets. Treated firms increased their reliance on EU suppliers and customers, consistent with a shift toward partners operating within a harmonized regulatory space where compliance is more easily guaranteed. These effects are stronger and more persistent for large firms, reflecting their deeper integration into global value chains and the higher certification and compliance costs imposed by REACH.

The performance outcomes reveal a clear heterogeneity between small and large firms. Small firms exhibit temporary gains in turnover and added value up to 2020, suggesting flexible early adaptation to the regulatory shift. Large firms, by contrast, experience significant declines in turnover and added value only after 2021, when the POPs ban becomes fully effective and previously unavoidable adjustments in production and certification can no longer be postponed. Labor costs and wage intensities remain largely unaffected throughout the period, indicating that compliance did not translate into substantial labor restructuring.

A key contribution of the thesis lies in distinguishing between intangible asset accumulation and R&D activity. While R&D expenditure decreases, reflecting firms' withdrawal from PFOA-intensive technological trajectories, the stock of intangible assets increases significantly after 2020. This pattern suggests that firms invested not in product innovation but rather in certification, process adaptation, and compliance-related intangible capital.

Taken together, the findings provide a nuanced perspective on the Porter versus Pollution Haven hypotheses. Firms do not respond by relocating production abroad; instead, they adjust internally by reorganizing supply chains, modifying technological processes, and deepening

integration within the EU regulatory area. At the same time, the evidence offers only limited support for the strong version of the Porter Hypothesis: innovation responses are primarily compliance-driven rather than productivity-enhancing. Overall, the results indicate that environmental regulation imposes real but uneven costs across firms, shaping strategic behavior in ways that reinforce rather than undermine domestic productive capacity.

1 Introduction

Environmental regulation inevitably reshapes the competitive environment by forcing firms to adapt to their production and trade practices. As discussed in this thesis, the economic consequences of such regulation are positioned within a broader debate, oscillating between competitiveness losses and innovation gains. The first chapter introduces two dominant and contrasting perspectives that have guided academic and policy discussions since the 1970s and that will frame the entire research. From one side, the *Pollution Haven Hypothesis* predicts that stricter regulations reduce competitiveness and encourage the relocation of activities in pollution havens, while on the other, the *Porter Hypothesis* suggests that well-designed regulation can stimulate innovation and productivity. After reviewing theoretical fundamentals and empirical evidence for both perspectives accumulated over the past decades, the chapter situates REACH within this larger intellectual tradition. The discussion also highlights the ambiguities in existing empirical findings, and the consequent need for new and context-specific evidence. This sets the stage for the formulation of the research questions and contributions of the thesis, which will be addressed by examining the impact of the EU REACH regulation on Italian manufacturing firms and its predominant alignment with the inital hypothesis.

1.1 Overview of environmental policy

Over the past thirty years, environmental regulation has evolved from being considered a local and national issue to becoming a key factor for competitiveness in global value chains. From the very first environmental regulation in 1970 to EU Climate Law in 2020, governments have increasingly tied environmental performance to industrial policy. In this context, REACH stands out as one of the most ambitious regulatory interventions in Europe, affecting not only chemical manufacturers but also downstream users in various manufacturing sectors.

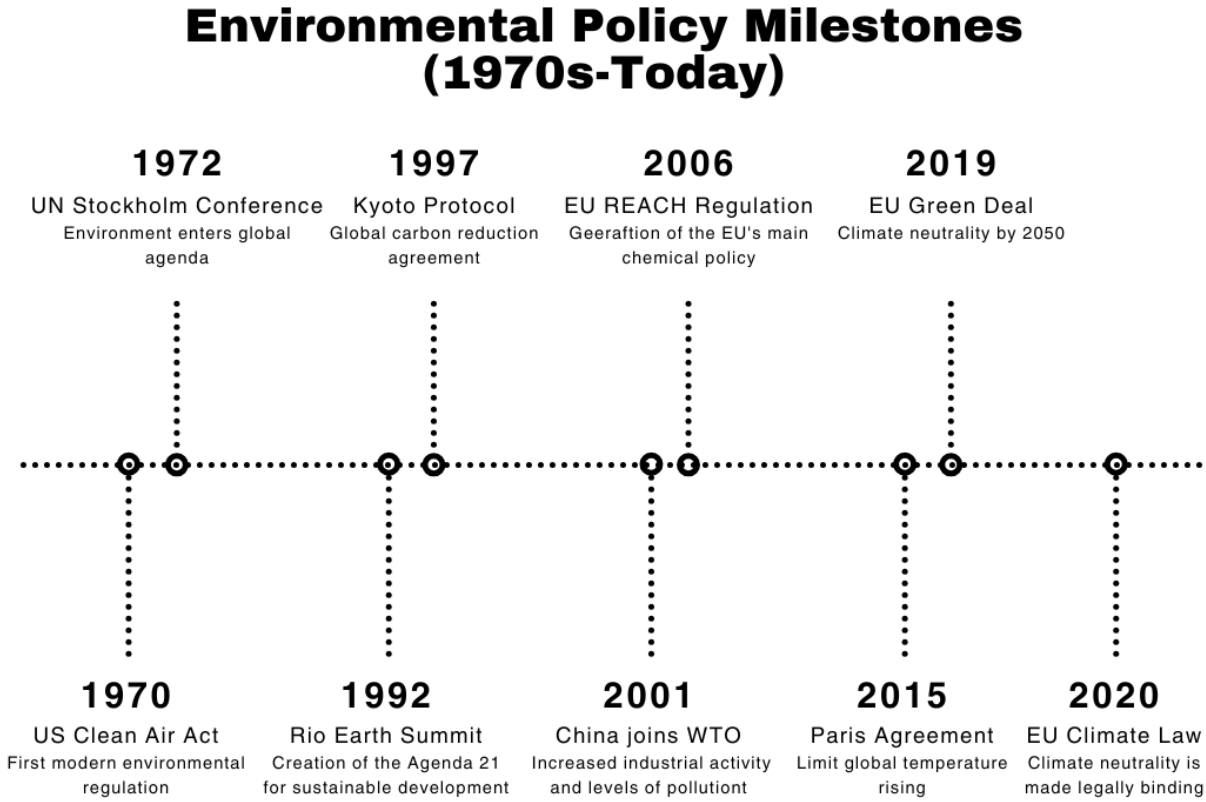


Figure 1 - Global and European Environmental Policy Timeline (1970s-today)

The enactment of any regulation, by its very nature, modifies or limits behavior with respect to the previously existing legal context. In order to comply with this regulation, its recipients must therefore modify their business models to adapt them to the regime it provides. If only some people are affected by the new regulation, which leaves the situation of other people unchanged, only the former are subject to the need to modify their behavior or past practices. If these people are companies operating in the same market, this rule will therefore introduce a relative change in the competitive environment affecting them.

In a world increasingly characterized by the integration of trade and capital flows, businesses and policymakers are concerned that large asymmetries in the severity of environmental policies could shift pollution-intensive production capacity to countries or regions with less stringent regulations, altering the spatial distribution of industrial production and the resulting international trade flows.

This has caused concern, particularly among countries that are leading the action against climate change, because their efforts to achieve deep carbon emission reductions could put their pollution-intensive producers at a competitive disadvantage in the global economy.

In this context, the debate about the impacts of environmental regulations on firm competitiveness has its foundation in two opposing economic theories, which emerged at the time of the first regulations in 1970: the Pollution Haven Hypothesis (PHH) and the Porter Hypothesis (PH).

1.2 The Pollution Haven Hypothesis

Also known as the neo-classical approach, it assumes that in an open market situation, firms will be negatively affected by the adoption of environmental regulations, as they operate in a legal system competing with other firms subject to other and more relaxed regulations. Unless standardized environmental rules have been agreed among all legal systems whose firms compete in the same market, this possibly leads to a *race to the bottom* situation: those systems enjoying lower environmental standards will cause their firms to be more competitive compared to the ones located in States having more stringent environmental legislations.

In fact, increased regulatory costs could discourage productive investment in innovation and slow productivity growth. If increased regulatory costs are transferred to product prices in highly competitive markets, trade distortions could occur, as product prices will increase more in countries with relatively strict regulations. Companies in countries with higher costs will therefore lose market share in favor of competitors in countries that produce cheaper products with a high environmental impact.

If regulatory differences in environmental matters persist, in response to this competitive disadvantage, companies' decisions regarding the location of new production facilities or foreign direct investment (FDI) could also be affected, and thus also employment in the manufacturing sector, which could gravitate toward countries with relatively permissive policies and thus create pollution havens with possible “dispersion” of global emissions.

From a global environmental perspective, this means that abatement efforts in countries with stringent policies (often considered "first movers") could be offset to some extent by increasing emissions in other regions. The removal of trade and investment barriers, according to the PHH, facilitates the relocation of environmentally harmful production stages from high-income countries with stringent regulations to developing countries with less stringent ones.

1.2.1 Empirical evidence

While the empirical evidence for the PHH remains ambiguous and often shows small effects, especially in specific sectors, some studies have found support for its existence. For example, in the “Unmasking the Pollution Haven Effect" (Levinson and Taylor, 2008) paper, which focuses on the U.S. trade data with Canada and Mexico during the period 1977-1986, it is suggested a positive and statistically significant relationship between industry Pollution Abatement Costs (PAC) and net imports into the United States. For the average industry, the increase in net imports due to higher PAC accounted for 10% of the total increase in trade volume during the period.

Another empirical study, presented in the "Footloose and Pollution-Free" (Ederington, Levinson, Minier, 2003) paper, suggests that environmental costs have had a statistically significant positive effect on US imports from countries with lower environmental standards. This indicates that PHH effects are more pronounced when considering trade with developing or less strictly regulated economies. The research has also shown that environmental regulations have a greater impact on trade flows in sectors that are more geographically mobile (less constrained by transport costs, fixed plant costs, or agglomeration economies). For a sector with median immobility, a 1 percentage point increase in environmental costs resulted in a 0.96 percentage point increase in net imports.

Empirical evidence about the link between environmental regulation and FDI is found in the "Foreign Direct Investment and the Environment" (Cole, Elliott, Zhang, 2017) paper, that highlights the influence of environmental regulation costs on FDI inflows. For example, within China, FDI from industries with a high environmental impact tended to concentrate in provinces with less stringent environmental regulations. Similarly, China's stricter regulations discouraged foreign direct investment, particularly from countries with less rigorous environmental standards. Also, a positive relationship between PAC in the US and FDI flows to Mexico and Brazil has been found, alongside with evidence of US outward FDI, particularly in footloose industries.

1.3 The Porter Hypothesis

A second view (also known as the "revisionist" one) implies on the contrary that the establishment of rules introducing stricter environmental standards will produce a race to the *top effect*: firms that are addressees of these rules will eventually be given a competitive advantage vis-à-vis their competitors who are not subject to these rules, mainly due to the need of the former to develop technology to meet the new standards and produce superior qualitative output which, in the end, is preferred by buyers/consumers worldwide.

Porter's hypothesis takes a more dynamic perspective, highlighting that stricter policies should stimulate greater investment in the development of new technologies for reducing pollution. If these technologies lead to higher productivity, input savings in inputs (e.g., energy) and innovation that would not have occurred without the policy, they can offset some of the compliance costs, reducing overall production costs and increasing the competitiveness of firms, by improving exports and market share.

The existence of learning externalities could prevent the replacement of an old polluting technology with a new, cleaner, and more productive one, because firms have a second-mover advantage if they wait for someone else to adopt it. However, according to the PH, there's space also for a first-mover advantage: assuming that there's room for improvement adopting a more productive technology and it is both cleaner and more efficient, even if regulations are initially costly, firms become more efficient and ultimately, they become more productive, gaining competitive advantage.

1.3.1 Empirical evidence

Empirical research strongly supports the *weak* version of the PH, which states that environmental regulations induce innovative activity in cleaner technologies. This is stated, for example, in the "Environmental regulation and innovation: a panel data study" (Jaffe, Palmer, 1997) paper, which finds that U.S. manufacturing industries facing higher pollution abatement costs tend to show increased R&D spending. Similar evidence is found in the "Environmental Policy, Innovation and Performance: New Insights on the Porter Hypothesis" (Lanoie, Lucchetti, Johnstone, Ambec, 2011). Moreover, a comprehensive survey of 50+ studies finds robust evidence for the weak version, contained in the "The impacts of environmental regulations on competitiveness." (Dechezleprêtre, Sato, 2017) paper.

However, direct empirical support for the *strong* version, which states that these innovations fully offset regulatory costs and lead to an overall increase in firm competitiveness, is generally lacking. Despite this, we find evidence of productivity growth driven by stringent environmental policies in the paper "Environmental policies and productivity growth: Evidence across industries and firms." (Albrizio, Kozluk, Zipperer, 2017). Moreover, there is evidence that the increasing share of green goods in developing countries' exports is particularly linked to countries that already possess a robust environmental performance, suggesting that they are better positioned to green their exports in response to environmental provisions[1].

[1] See Brandi, Schwab, Berger, and Morin (2020) for a specific review on environmental provisions and green exports

1.4 Research questions and contributions

The table below summarizes the characteristics and main points of each hypothesis presented above:

Table 1- Pollution Haven Hypothesis vs. Porter Hypothesis

Pollution Haven Hypothesis (PHH)	Porter Hypothesis (PH)
Increased compliance costs	Increased clean innovation and technology
Decreased domestic firms' competitiveness	Increased competitiveness and exports
Relocation to low-regulation countries	Increased efficiency and input savings of domestic firm
Generation of pollution havens and job relocation	Improved domestic productivity and environmental care

The purpose of this thesis is to empirically assess the impact of the EU REACH regulation on Italian manufacturing firms, with a particular focus on how environmental regulation influences competitiveness, innovation related to the usage of products containing substances subjected to restrictions. Some of the central research questions regard the study of how firm exposure to the REACH regulation depends on product composition and trade structures, which is related to which extent REACH has led Italian firms to reduce their reliance on harmful inputs and adjust their production technologies. Moreover, taking advantage of a quasi-experimental context, we will examine whether companies' reactions are more in line with the Pollution Haven Hypothesis by pushing firms to offshore polluting activities, or with the Porter Hypothesis, by stimulating efficiency, innovation, and sustainable competitiveness. Finally, the study of how firm characteristics, such as size, productivity, structure and institutional contexts, such as regional enforcement, institutional quality, mediate the response to REACH will provide the full context to understand the full effect of environmental regulation in Italy.

The contributions of this thesis are dual. First, it provides one of the first quasi-experimental assessments of the REACH regulation at the firm level, using detailed customs data. Second, it links two strands of literature that have rarely been related: the extensive empirical work on trade shocks (Autor et al., 2013; 2014) and the growing body of research on environmental regulation. By applying a shift-share logic to regulatory exposure, the thesis demonstrates that tools initially developed for trade economics can be successfully adapted to assess the economic effects of environmental policies. In doing so, it contributes to a more nuanced understanding of how regulation interacts with firm behavior in globalized markets.

2 The EU REACH Regulation

Having introduced the theoretical debate on the relationship between environmental regulation and competitiveness, this chapter turns to the institutional context of the thesis, providing the background of one of the most ambitious and influential environmental policies enacted by the European Union: the EU REACH Regulation (EC No. 1907/2006). REACH is not only one of the most ambitious environmental regulations in the world but also a quasi-experimental policy shock that offers a unique opportunity to assess the validity of the PHH and PH in a European context. After explaining its four main pillars (Registration, Evaluation, Authorization, and Restriction), it positions the policy in its broader European strategic context, among the environmental and industrial policies. Special attention is given to Italy, whose manufacturing system is both highly diversified and deeply integrated into European and global value chains, and also due to its industrial structure and reliance on chemical inputs, making it especially exposed to REACH. Moreover, the chapter highlights the dynamic nature of REACH and discusses why it can be considered a regulatory shock comparable, in methodological terms, to the trade shocks studied in international economics. This sets the basis for adapting empirical strategies found in economics literature related trade shocks to the case of regulatory shocks.

2.1 Overview of the regulation

The EU's REACH (Regulation EC N. 1907/2006 of the European Parliament and the Council on the Registration, Evaluation, Authorization, and Restriction of Chemicals) regulation is an important legislative act aimed at protecting human health and the environment by identifying and managing the risks posed by chemicals. In particular, it aims to[2]:

- ensure a high level of protection of human health and the environment against harmful substances
- assess the safety of chemical substances in use in the EU
- promote innovation and competitiveness
- promote alternative (non-animal) methods for the assessment of the hazards of substances

It applies to companies that manufacture, import, or use chemicals within the European Union (EU); this includes companies that produce chemicals, those that import chemicals from outside the EU, and those that use chemicals in their industrial or professional processes. It

[2] Source: European Commission, "Reach Regulation," https://www.trade.gov/country-commercial-guides/italy-advanced-manufacturing. Accessed August 15, 2025

places the responsibility on companies to demonstrate the safety of the chemicals they use and to provide comprehensive information about their products and their uses. This is encapsulated in its core principle: "No data no market" meaning substances cannot be placed on the EU market without sufficient safety data.

REACH applies to all chemical substances: not only those used in industrial processes, but also those in everyday use. For that reason, this regulation has an impact on the majority of companies in the EU. Authorities and scientific committees assess whether the risks that arise from substances can be managed. If risks cannot be managed, authorities can restrict substance use in various ways: they may prohibit dangerous substances if the resulting risks are not manageable and may also decide to limit a use or make it possible only with prior authorization. In the long term, the most dangerous substances must be replaced with less dangerous ones.

The provisions of the REACH Regulation officially entered into force on 1 June 2007, but its actual implementation followed a schedule spread over approximately 11 years, based on the tonnage produced or imported. Deadlines for the registration of substances have been set to:

- 2010 (for usage over 1000 tons/year)
- 2013 (for usage over 100 tons/year)
- 2018 (for usage over 1 ton/year)

It introduces four main types of obligations for businesses subject to its application: Registration, Evaluation, Authorization, Restriction.

2.2 Registration

Potential manufacturers and importers of substances have an obligation to submit a request to the European Chemicals Agency (ECHA) and to register the substance before they can manufacture or import it. Registration is mandatory for a substance on its own, or as component of one or more mixture, exceeding one ton per year, and detailed information on its physical-chemical, toxicological, and ecotoxicological properties must be submitted. In fact, registrants must prepare a *registration dossier*, which consists of a technical dossier and, if quantity is equal or more than 10 tons per year, of a chemical safety report. Registration does not apply for a period of five years to substances manufactured in the Community or imported for the purpose of product and process-oriented research and development by a manufacturer or importer or producer of articles, in quantities not exceeding those required by those activities. Moreover, ECHA is publishing the information contained in the registration dossiers on its website so that it is available free of charge to all European citizens to inform them about the potential risks associated with the chemicals they use.

2.3 Evaluation

In cooperation with Member States, ECHA defines risk-based criteria and proceeds to the choice of substances to be evaluated. The substances chosen are listed by ECHA in the Community-wide rolling action plan (CoRAP), following the opinion of the Member State Committee. In the final CoRAP, a Member State responsible for the evaluation will be designated for each substance, and will carefully reviews the registration information submitted, to identify substances that are potentially hazardous to human health and the environment. If at the end of the review of all new and available data it considers that the use of the substance poses a risk, the Member State responsible for the evaluation may undertake follow-up measures regarding the evaluation of the substance:

- a proposal for harmonised classification and labelling (CLH) for substances which are carcinogenic, mutagenic or toxic to reproduction, respiratory sensitisers or produce other effects
- a proposal to identify the substance as being of very high concern (SVHC)
- a proposed restriction for the substance
- measures outside the scope of REACH, such as a proposal to establish EU-wide occupational exposure limit values, national measures or industrial measures on a voluntary basis

2.4 Authorization

The authorization process shall start when a Member State or ECHA proposes a substance to be identified as a "Substances of Very High Concern" (SVHC), which is highly harmful to human health or the environment. The intention to propose a substance for identification as SVHC is published in the *intention register* prior to submission of the proposal, to inform interested parties in advance. After the publication of the proposal, interested parties can submit comments or provide further information during a 45-day public consultation. In the absence of any observations that could call identification into question, the substance is placed directly on the Candidate List.

When new information is provided to call into question the identification of a substance as an SVHC, both the proposal and the information are sent to the Member State Committee for agreement on the identification itself. If the committee comes to unanimous agreement, the substance is added to the Candidate List. Otherwise, the matter is referred back to the European Commission.

The inclusion in the Candidate List entails immediate obligations for the relevant suppliers, such as:

- provide a safety data sheet (SDS)
- communicate instructions on safety of use
- respond to consumer inquiries within 45 days
- inform ECHA if the article they produce contains an SVHC in a concentration greater than 0,1 per cent (weight/weight) and if the quantity of that substance is greater than one ton per manufacturer/importer per year.

ECHA periodically evaluates substances on the Candidate List to determine which substances should be included in the Authorization List as a matter of priority. That priority shall be conferred based on data on intrinsic properties, widely dispersed use or high volumes falling within the scope of the permit requirement. As part of the process, ECHA launches a three-month consultation and recommends:

- an expiry date, called “sunset date”, from which the placing on the market and use of the substance is prohibited, except where an authorization is issued or an exemption from that requirement applies
- latest application date by which applications must be received, if the applicant wants to continue placing the substance on the market or using it after the sunset date
- any review periods for certain uses
- any uses exempted from the permit requirement.

Substance name espandi / comprimi	EC No.	CAS No.	Entry No.	Latest application date	Sunset Date	Intrinsic property
5-tert-butyl-2,4,6-trinitro-m-xylene (Musk xylene)	201-329-4	81-15-2	01	21-feb-2013	21-ago-2014	vPvB (Article 57e)

Figure 2 - Record extracted from the Authorization List related to the chemical compound "Musk Xylene"

The Member State Committee shall draw up its opinion on the recommendation provided by ECHA, so that it can finalize its recommendation. The ECHA recommendation is submitted to the European Commission, which decides on the substances to be included in the Authorization List, which is published in Annex XIV of REACH. The regulation allows companies to apply for authorization to continue or start using and placing on the market substances included in the Authorization List.

2.5 Restriction

Restrictions are a tool to protect human health and the environment from unacceptable risks presented by chemicals. Restrictions are normally used to limit or prohibit the production, placing on the market (including import) or use of a substance, but may impose any relevant conditions, such as technical measures or particular labels.

A restriction may concern a substance on its own or as a component of mixtures, including substances not subjected to registration obligation, such as, for example, substances produced or imported in quantities of less than one ton per year or some polymers. ECHA may also propose restrictions related to articles containing substances included in the Authorization List. These substances are listed in Annex XVII of the REACH Regulation, a list that is continuously updated by ECHA in response to scientific progress

2.6 The genesis and EU strategic importance

The REACH Regulation is the culmination of a long effort by the EU to move from fragmented rules on chemicals to a single risk-based regime, adopted on December 18, 2006, and in force since June 1, 2007.

Responsibility is shifted from the state to industry: companies must know their substances, manage risks along the supply chain, and demonstrate safety in order to access the EU market. To that end, manufacturers and importers are required to gather information on the properties of their chemical substances and to register that information in a central database in the European Chemicals Agency (ECHA), consolidating the EU's approach into a single comprehensive regulation.

The Agency is the central point in the REACH system: it manages the databases necessary to operate the system, coordinates the in-depth evaluation of the information provided on chemicals and runs a public database where consumers and professionals can find hazard information. From a political point of view, REACH is considered by the European Commission to be the Union's main legislation on chemicals for the protection of health and the environment and for the promotion of innovation and competitiveness in European industry, hence its strategic importance within the single market and the political architecture of the Green Deal.

2.7 The dynamic nature of REACH

REACH is not a one-off event, but a dynamic regime. Beyond the gradual registration deadlines (2010, 2013, 2018) that brought existing chemicals under regulatory control, the regulation is constantly evolving through two powerful leverages that the EU updates over time:

- Annex XIV (List of Authorizations): it gradually introduces substances of very high concern (SVHC). Continuous use of these substances requires time-limited authorization with a substitution plan. New items are periodically introduced in the Official Journal.
- Annex XVII (Restrictions): it imposes EU- level bans or conditional restrictions on the use of particular substances or articles and is regularly expanded. For companies, each new restriction represents a compliance shock, which may force them to replace inputs, redesign processes, or switch sources of supply. This evolving nature is evident in ECHA's public records and in news reports on recurring amendments to the annex.

In its chemical sustainability strategy, presented on October 14, 2020, as part of the European Green Deal, the European Commission announced a review of the regulation “in the most targeted way possible”, including analyses of the impact on SMEs and the promotion or impediment of innovation.

According to the initial impact assessment, published in May 2021, the options under consideration would include the revision of registration, authorization and restriction requirements, the simplification of communication in supply chains, the revision of the provisions related to the evaluation of dossiers and substances. However, this preliminary list of options may evolve as the analysis progresses. The proposal, initially scheduled for the fourth quarter of 2022, was then announced by the President of European Commission Ursula von der Leyen to be delayed to Q4 2025.

2.8 The Italian manufacturing context

Italy is the second largest manufacturing economy in the EU, with around 150 industrial districts, many in REACH-exposed sectors. The figure below shows the geographical concentration of industrial districts in Italy, with a strong network of SMEs, revealing the predominance of sectors in the chemical, rubber-plastics, textile, leather goods, machinery, metals, and fashion. These sectors are the very value chains most exposed to the restrictions imposed by the REACH regulation on inputs, authorizations, and disclosure requirements on substances.

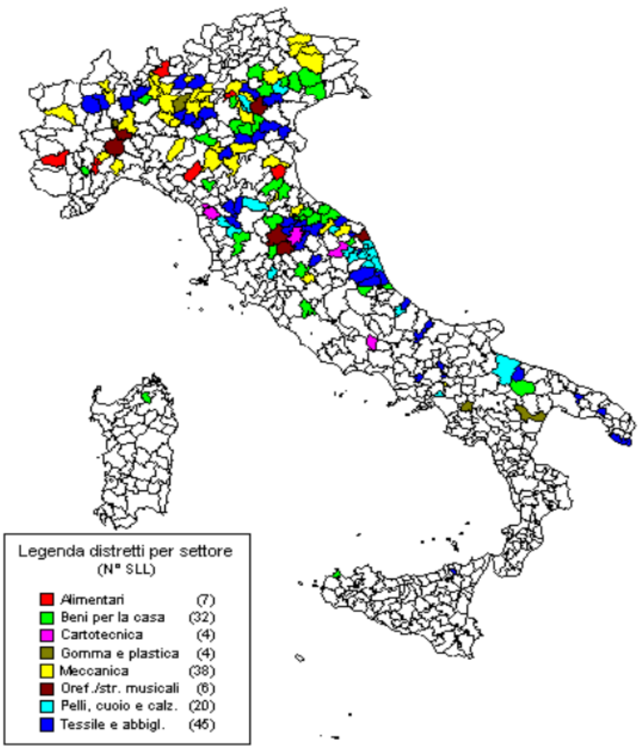


Figure 3 – Map of Italian industrial districts based on ISTAT methodology via Ministero delle Imprese e del Made in Italy

The high export orientation and complex supplier networks amplify the scope of the legislation: a change in one input can have repercussions on entire industry clusters: for example, regarding the textile industry, impacts are expected also on tanning, textile dyeing, electroplating, coatings, packaging districts.

In particular, the chemical industry plays a fundamental role in the Italian supply chain. With a production value of approximately €66.7 billion, around 2,800 active companies, and 112,200 direct employees (in addition to over 320,000 indirect jobs), it is the third largest chemical producer in Europe. It is important to note that Italy is specialized in fine and specialty chemicals, consumer products such as paints, adhesives, and cosmetics, which account for approximately 57.5% of the chemical industry's production, exceeding the EU average of 47.1%.

The Italian system has also played an important role in registrations and the operational ‘framework” of REACH compliance through the creation of specific consortia, data sharing, exchange of information on substances, reporting by downstream user.

National indicators monitor thousands of Italian registrations, placing Italy among the leading Member States in terms of the number of substances and submissions, demonstrating that

Italian companies are not only subject to REACH but are also actively involved in its application.

Two characteristics further highlight Italy's importance in the context of the REACH. Firstly, many Italian manufacturers are small to medium-sized processors or producers of “specialized” components. For them, the cost of producing and reporting chemical safety data, changing inputs, or redesigning processes is significant, but these changes can also unlock process efficiencies or product improvements, according to Porter’s view. Secondly, many Italian firms are located in the middle of the value chain: they transform intermediate goods, add specialized treatments, or assemble components for other manufacturers. REACH does not only regulate chemical manufacturers but also regulates how safety and utilization information is conveyed along the supply chain. For example, chemical suppliers must provide safety data sheets and exposure scenarios to all customers, and the latter must inform suppliers about how they actually use the substances, so that the conditions for safe use can be verified and documented.

Mid-chain companies that use regulated chemicals must be part of this information loop. Compliance with the obligations imposed by the regulation should not be seen merely as an obligation but also as a potential source of market differentiation and therefore a long-term competitive advantage. From one side, the regulatory requirements of REACH affect entire supply chains, setting compliance challenge, while from the other it offers potential competitive advantages for companies that master the governance of the chemical supply chain, making themselves more attractive in international supply chains, particularly for customers exporting to stringent markets such as the EU or the US.

The empirical analysis in the following chapters will exploit the different exposure of Italian companies to substances regulated by REACH to assess which of these dynamics prevails.

2.9 From trade to regulatory shocks

The implementation of the REACH regulation has deep business consequences, especially by really increasing the transaction costs linked to using dangerous chemicals. This inevitably makes companies rethink their supply strategies and production technologies. The regulation implicitly encourages the replacement of hazardous chemicals with safer alternatives and aims to promote research and development in the chemical sector, encouraging the creation of new, more environmentally friendly products and technologies.

Research indicates that such environmental provisions can effectively reduce “polluting” exports and increase “green” exports from developing countries. The impact differs depending on the layout of the provisions: restrictive trade provisions tend to reduce environmentally unsustainable trade flows, while liberal environmental provisions aim to reduce trade barriers for environmental goods and services, thereby stimulating “green” trade. This suggests that environmental clauses in trade agreements can be tailored policy tools to achieve specific environmental outcomes, while managing potential trade-offs with economic development.

However, this regulatory environment directly feeds into the ongoing academic debate concerning the impacts of environmental regulations on competitiveness, particularly the PHH versus the PH, as anticipated.

3 Trade Shocks and Firm Adjustment

Given the analogy between trade shocks and regulatory shocks, this chapter reviews the contributions provided by Autor, Dorn, and Hanson (2013, 2014) on the so-called *China Shock*. The chapter discusses both local labor market outcomes (Autor et al. 2013) and worker-level outcomes (Autor et al. 2014). While the empirical setting differs, the methodological logic is directly adaptable to the study of REACH regulation's effects: both trade shocks and regulatory shocks operate through product and sectoral channels and result in heterogeneous firm-level exposure. These studies provide the methodological foundation for this research, particularly the shift–share approach used to measure heterogeneous exposure to trade shocks, and the use of instrumental variables to isolate exogenous variation from endogenous factors. In this way, the chapter bridges the gap between established methods in trade economics and the emerging literature on the economic effects of environmental regulation.

3.1 Overview of the empirical strategy

The empirical strategy adopted in this thesis takes inspiration from the literature about empirical strategies developed to identify the causal effects of external shocks in the trade sector. In particular, the approach applied within the scope of this work has its foundation in the influential work of Autor, Dorn, and Hanson (2013, 2014) on the so-called *China Shock*. The papers[3] are highly relevant in the economics literature for investigating the localized economic impacts of China import competition on U.S. labor markets between 1990 and 2007. Rather than treating the problem just as a uniform phenomenon, the authors understand how increased imports affect local economies, going beyond just manufacturing employment and wages to include broader labor market outcomes and public transfer payments, recognizing that national-level analyses can obscure important local adjustments.

In the studies performed about China Shocks, the authors demonstrate that exposure to trade shocks varies across units (regions, industries or firms) depending on their initial structure.

This approach represents a typical *shift-share design*, where a common external shock (identifies as the *shift*) is heterogeneously transmitted to local units (defined as the *shares*) depending on their composition at the baseline.

A similar framework can be applied to the context of environmental regulation, and specifically the EU's REACH Regulation. Specifically, REACH can be seen as a major *regulatory shock*

[3] See Autor, D., Dorn, D., & Hanson, G. (2013). *The China Syndrome* and Autor, D., Dorn, D., Hanson, G., & Song, J. (2014) *Trade Adjustment* for a specific review

that changed the relative costs and feasibility of using certain substances. Just as Chinese import growth reallocated industries and workers, having an impact on income and employment, REACH may have reallocated firms' production choices, trade flows, and offshoring decisions given the environmental provisions on harmful substances.

The objective of this chapter is to present in detail how the shift-share logic from Autor et al. can be adapted to measure firm-level exposure to REACH and to outline the empirical strategy that will be applied for the purpose of evaluating some outcomes of interest.

3.2 Local labor market adjustment to trade shocks: Autor et al. (2013)

In the studies performed by Autor et al. (2013) it is showed how the rapid increase in Chinese exports affected different regions of the U.S, demonstrating that it varies across units depending on the initial structure, meaning at the baseline. Particularly, the following mathematical models and considerations analyzes the change in manufacturing employment per region in U.S.

The heterogeneity analyzed by the authors, which leads to different outcomes depending on the specific region and its initial structure, can be exploited to identify causal effects. Following this logic, the authors define the primary measure of local labor market exposure to Chinese import competition as the change in Chinese import exposure per worker in a region. They design a *local exposure index*, that captures the local labor market exposure to Chinese import competition, combining two main components:

- The initial structure of local economies, meaning the distribution of employment across different industries in each U.S. local labor market at baseline. It determines how much a region is "exposed" based on its initial industry mix.
- The sectoral shock, meaning the variation of Chinese imports across different manufacturing industries during the observation period.

Formally, the index is defined as:

$$\Delta \mathrm{IPW}_{\mathrm{uit}} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta \mathrm{M}_{ucjt}}{L_{it}}$$

Equation 1 - Local exposure index

Where:

- $\Delta \text{IPW}_{\text{uit}}$: it represents the change in Chinese import exposure per worker for commuting zone *i* at time *t*
- $\frac{L_{ijt}}{L_{ujt}}$: it represents the initial share of employment in industry *j* within region *i* at the start of the period *t* over all the United States. It determines how much a region is "exposed" to Chinese imports based on it the industry mix at the baseline.
- $\Delta \text{M}_{\text{ucjt}}$: it represents the observed change in US imports from China in industry *j* between the start and end of the period *t*

This index calculates how much a commuting zone's economy is exposed to Chinese imports by weighting the increase in imports in each industry by that industry's share of local employment at the beginning of the period *t.*

The term $\frac{\Delta M_{ucjt}}{L_{it}}$ indicates how much the variation in import from China in industry *j* in the total United States is distributed over the total employment in zone *i*, independently from the industry type. This term is then adjusted for the term $\frac{L_{ijt}}{L_{ujt}}$ that represents the initial share of employment in industry *j* for the zone *i* at the baseline. Then, summing for each industry type *j*, it’s possible to retrieve the total change in Chinese import exposure per worker for commuting zone *i* at time *t*. Moreover, the equation makes clear that the difference in $\Delta \text{IPW}_{\text{uit}}$ across different local labor markets derives entirely from variation in local industry employment structure at the baseline.

3.2.1 The relevance of the endogenous effects

As noticed by Autor et al., U.S. imports from China might be *endogenous*. This means that imports might respond to U.S. demand and not just Chinese supply. Why could it be an issue? Because if the internal demand in US drops sharply, Chinese imports and employment may drop, the latter because of the drop in internal demand, rather than a drop in imports. If this endogenous effect is not considered, it’s plausible to commit a mistake considering the wrong causal effect, correlating the drop of employment directly to the drop of the level of imports, instead of the drop in demand. To fix this problem, the authors build an *instrumental variable*, correlated with import growth from China but not affected by U.S. demand conditions, as described below:

$$\Delta \text{IPW}_{it}{}^{o} = \sum_{j} \left(\frac{L_{ij,t-10}}{L_{i,t-10}} \right) \times \Delta \text{M}_{OC,jt}$$

Equation 2 - Instrumental variable

Where:

- $\Delta \text{IPW}_{it}{}^{o}$: it represents the predicted import exposure per worker in U.S. region *i*, based on China's exports to other high-income countries.
- $\Delta \text{M}_{OC,jt}$: it represents the growth of China's exports to other high-income countries relative to industry *j*
- $\frac{L_{ij,t-10}}{L_{i,t-10}}$: it represents the share of region *i*'s employment in industry *j*, using data from 10 years before.

In this way, knowing that China's exports to other high-income countries are not driven by U.S. demand, we can logically affirm that if China exports more globally in industry *j*, it likely exports more to the U.S. too, not because of US endogenous effects. Finally, the instrument $\Delta \text{IPW}_{it}{}^{o}$ as defined above is correlated with actual U.S. import growth.

3.2.2 The econometric model

The econometric model studied by Autor et al., understands the impact on employment in region *i* at time *t* (ΔL_{it}) given by the exposure to Chinese imports per worker in region i at time *t* ($\Delta \text{IPW}_{\text{it}}$). Given the endogenous effects analyzed above, the authors extract just the exogenous part of $\Delta \text{IPW}_{\text{uit}}$ using the instrumental variable as defined before.

The regression captures the part of $\Delta \text{IPW}_{\text{it}}$ that is related to the exogenous instrument, so that the predicted value from this equation, $\widehat{\Delta \text{IPW}}_{\text{it}}$, represents the import exposure not contaminated by endogenous effects:

$$\Delta \text{IPW}_{\text{it}} = \delta_0 + \delta_1 + \Delta \text{IPW}_{it}{}^{o} + u_{it}$$

Equation 3 – Import exposure not contaminated by endogenous effect

The effect of the exogenous part of import exposure is applied in the main regression to study the change in employment in region *i* at time *t:*

$$\Delta \text{L}_{\text{it}} = \alpha + \beta \widehat{\Delta \text{IPW}}_{\text{it}} + \gamma X_{it} + \epsilon_{it}$$

Equation 4 - Change in employment in region i at time t

Where:

- ΔL_{it}: it represents the change in manufacturing employment share. It is defined as the change in $\frac{(Manufacturing\ employment)}{(Working-age\ population)}$
- β: it indicates the causal effect of import exposure on employment
- X_{it}: it indicates the Control variables (demographics, geography, etc.)
- ϵ_{it}: it represents the error term

Notice that $\widehat{\Delta IPW_{it}}$ is not equal to $\Delta IPW_{it}{}^{o}$ rather it is a projection of ΔIPW_{it} onto $\Delta IPW_{it}{}^{o}$, in this sense $\Delta IPW_{it}{}^{o}$ is considered as an instrumental variable that allows to obtain the exogenous part of ΔIPW_{it}, which is the independent variable of our interest.

The model highlights that trade shocks have localized effects even though trade is global. Moreover, they argue that mobility and reallocation are slow, so local economies suffer long-term consequences. In this sense, public policies (e.g., retraining, relocation support) may help but are currently insufficient.

3.2.3 Relevance to REACH regulation effects research

This shift-share design presented in Autor et al. (2013) allows to capture heterogeneous exposure depending on initial conditions, enabling causal identification when combined with instrumental variables. This method has become a standard in applied economics to study heterogeneous impacts of trade, technology, migration, and regulation. Its success derives from the idea that while an external shock is common, its incidence is variable because initial structures differ.

Since the core objective is to estimate the causal effect of rising Chinese import competition on U.S. local labor markets, a direct regression of employment changes on import penetration would have been distorted, because import growth could be driven not only by Chinese competitiveness, but also by changes in domestic demand. For example, if U.S. consumers demand more furniture, both U.S. furniture employment and Chinese furniture imports could increase simultaneously, producing a false positive correlation between imports and employment. To solve this problem, Autor et al. use an instrumental variable defined as the growth of Chinese exports to other high-income countries. This instrument isolates the exogenous component of Chinese competitiveness that influences US labor markets but is not driven by US demand conditions, to interpret the relationship between imports and employment as causal

A similar challenge arises when studying the effects of the REACH regulation on companies. A direct regression of business outcomes (e.g. change in the use of harmful products, costs, relocation) on the REACH exposure index could be biased, because they could also reflect demand or supply driven dynamics which are not related to REACH. For example, a company could reduce imports of regulated chemicals not because of REACH provisions, but because customer demand has shifted to alternative products. Also, imports of certain substances may decline simply because of macroeconomic shocks, such as oil price fluctuations or pandemic disruptions, and not because of regulatory restrictions.

If we ignore these confounding effects, we risk attributing to REACH what is actually due to demand or other shocks. To estimate the causal effect of REACH on these outcomes, we need to isolate the part of the variation in the use of harmful products that is really explained by regulatory provisions and no other endogenous shocks.

3.3 Worker-level adjustment to trade shocks: Autor et al. (2014)

This follow-up paper applies similar logic to the previous one (2013) but focuses more on worker-level outcomes: it takes the same shock but applies it at a different level of analysis, focusing on the change in cumulative earnings for worker per region in U.S. The two papers are complementary, not substitutes, as together they give a fuller picture: the first one shows aggregate community-level adjustment, while the other shows the micro-level worker adjustment behind it.

This study analyzes the effects of exposure to international trade competition on the incomes and employment of US workers between 1992 and 2007. The document highlights that China's rapid emergence as a global manufacturing power (from 2% of global manufacturing exports in 1990 to 16% in 2011) represented a substantial competitive shock for the US manufacturing sector. This Chinese growth has been driven by improvements in industrial production, increases in total factor productivity, capital accumulation, and migration to urban areas. To measure how exposed a worker is to the Chinese shock, the authors use the change in the *import penetration ratio* for the US industry in which the worker was initially employed, in 1991. For example, if an industry registers a large increase in imports from China relative to total industry consumption in the US, that industry is said to have had high import penetration ratio, defined as below:

$$\Delta IP_{j,\tau} = \frac{\Delta M_{j,\tau}{}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}}$$

Equation 5 - Change in import penetration ratio

Where:

- $\Delta M_{j,\tau}{}^{UC}$: it represents the change in imports from China to the U.S. for industry *j,* in which the employee was employed in the baseline year*,* during the period from 1991 to 2007.
- $Y_{j,91} + M_{j,91} - E_{j,91}$: it represents the initial domestic absorption (or total consumption) of industry *j* in the U.S. during in the baseline year, 1991. It consists of:
- $Y_{j,91}$: shipments (or production) of industry *j* in the U.S. in 1991.
- $M_{j,91}$: total imports in industry *j* in the U.S. in 1991 (not only from China, but from all countries).
- $E_{j,91}$: total exports of industry *j* from the U.S. in 1991.

  Essentially, this term calculates how much of that industry's output was actually consumed domestically in the U.S. in 1991. It serves as a reference size for normalizing the change in imports from China.

The challenge is that an increase in Chinese imports in a certain industry could be caused not only by China's growth (Chinese supply shock), but also by changes in U.S. domestic demand for those products (U.S. demand shock). If U.S. domestic demand decreases, imports could increase relatively, but it would not be China's fault. The methodology adopted by the authors isolates the impact of China-specific trade shocks, distinguishing them from other economic factors, on the employment and earnings of U.S. workers in the medium and long term. The previous considerations about the separation of any endogenous effect studied in The Chyna Syndrome (2013) by Autor et al. are so fundamental to study the outcome of interest.

3.3.1 The relevance of the endogenous effects

If the denominator of the formula were to change significantly during the period under study the interpretation of $\Delta IP_{j,\tau}$ could be ambiguous. For example, if the U.S. economy booms after 1991, and demand for consumer goods increases, then imports from China might rise even if China doesn't become more competitive. In this case, we might mistakenly attribute the import rise to a China shock, when it's really just U.S. demand growth.

Moreover, using the fixed-time denominator, related to total absorption during the baseline year, overstates the change in the import penetration ratio, since just the increase in imports is caught, without considering the related increase in total internal absorption in the same time period, due to the increase of internal demand. Notice that calculating the import penetration ratio, using the total absorption at denominator related to the same time period of change in imports, would still contain a deeper issue related to endogeneity, as the change in imports continues to be related to any U.S internal shocks. So, to consider just any exogenous factor due to an increase in China competitiveness, it's necessary to isolate the exogenous component of the import penetration ratio, as defined below:

$$\Delta IPO_{j\tau} = \frac{\Delta M_{j,\tau}{}^{OC}}{Y_{j,88} + M_{j,88} - E_{j,88}}$$

Equation 6 - Instrumental variable

Where:

- $\Delta M_{j,\tau}{}^{OC}$: it represents the change in imports from China from 1991 to 2007 in other high income countries, for industry *j,* in which the employee was employed in the baseline year (1988).
- $Y_{j,88} + M_{j,88} - E_{j,88}$: similarly to the previous formula, it represents the initial domestic absorption (or total consumption) of industry *j* in the U.S. during in the baseline year, 1991.

The reason by which 1988 is used as a reference year is that by the early 1990s, it was already becoming clear that China was entering world markets in a big way, so workers and firms may have already reacted before 1991. In this way, the measure of "exposure to China" would not be understated as 1988 shares reflect the true potential exposure of a region if nobody had moved yet.

The introduction of the instrumental allows to separate any endogenous effect, since high-income economies are similarly exposed to growth in Chinese imports, that is driven by supply shocks originating in China, and no other endogenous U.S. factors.

3.3.2 The econometric model

The econometric model studied by Autor et al. understands the impact on workers outcomes ($E_{ij\tau}$) given by the variation in the import penetration ratio in industry *j* at time τ ($\Delta IP_{j\tau}$). Given the endogenous effects, just the exogenous part of $\Delta IP_{j\tau}$ is extracted through the instrumental variable defined above:

$$\Delta IP_j = \pi_0 + \pi_1 \Delta IP_j{}^o + \eta_j$$

Equation 7 – Import penetration ratio not contaminated by endogenous effect

The regression captures the part of $\Delta \mathrm{IP_j}$ that is related to the exogenous instrument, so that the predicted value from this equation, $\widehat{\Delta \mathrm{IP_j}}$ represents the import penetration ratio not contaminated by endogenous effects. The effect of the exogenous part of the import penetration ratio is applied in the main regression to study the impact of trade exposure on workers' outcomes:

$$E_{ij} = \alpha_0 + \alpha_1 \widehat{\Delta \mathrm{IP_j}} + \alpha_2 IP_{j,91} + X'_{ij,0}\beta_3 + Z'_{j,0}\beta_4 + \varepsilon_{ij}$$

Equation 8 - Cumulative earnings of worker regression model

Where:

- E_{ij}: it represents the cumulative earnings for worker i, initially employed in industry *j* in the baseline year, in the period from 1991 to 2007. These earnings are already normalized with respect to the worker's initial average annual earnings in the period 1988-1991 Normalization allows to assess the effect of shocks on the evolution of earnings.
- $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4$: they indicate the coefficients to be estimated in the relationship between the explanatory variables and cumulative earnings
- $\Delta \mathrm{IP_j}$: it represents the change in import penetration for industry *j*, which is the main variable of interest
- $IP_{j,91}$: it represents the initial level of import penetration in industry *j* in the baseline year, 1991. This control captures the pre-shock conditions of the industry
- $X'_{ij,0}$: it represents the vector of individual and company-level control variables related to worker i and his or her main employer in 1991. It includes demographic characteristics (gender, year of birth, race, immigrant status), employment and earnings history (initial average earnings, past earnings growth, experience, seniority in the initial company), and characteristics of the initial company (level and trend of average wages, company size)

- $Z'_{j,0}$: it indicates the vector of industry-level control variables that capture the economic conditions of industry j in 1991. It includes, for example, the capital and technology intensity of the industry, historical trends in employment and wages in the industry
- ε_{ij}: it represents the error term, which captures the unexplained variations in the model

3.3.3 Relevance to REACH regulation effects research

As highlighted by Autor et al. (2014), estimating the causal impact of external shocks requires separating the exogenous component of the shock from endogenous demand or supply dynamics. In their study of worker-level adjustment to Chinese import competition, the authors relied on an instrumental variable, to isolate the exogenous rise in Chinese competitiveness from U.S. domestic demand shocks.

A similar consideration applies to the REACH regulation. Changes in Italian firms' imports of harmful products may be driven by regulatory restrictions and by broader demand or supply trends which are unrelated to REACH. To address this, the empirical strategy can follow the Autor et al. logic by instrumenting REACH exposure with exogenous sources of variation, such as the regulatory shock in other EU countries. This ensures that the estimated relationship reflects the causal impact of REACH, rather than demand-driven adjustments.

A key methodological feature shared by this paper is the use of normalization in the construction of exposure indices. In the case of Chinese competition in imports, Autor et al. normalize import growth based on basic domestic absorption, in order to adapt shocks to the economic size of each sector. Similarly, in the REACH context, the change in the harmfulness of each product should be normalized by its relative weight in international trade. This prevents marginal products with negligible commercial significance from determining the results and ensures that exposure is measured in terms of economic significance. Moreover, normalization helps mitigate endogeneity, since exposure is defined in relation to pre-shock conditions rather than post-regulation adjustments. This consideration about the methodology of the authors underlines the robustness of the shift–share design to study the heterogeneous impacts of both trade shocks and regulatory shocks.

4 From Trade Shocks to Regulatory Shock

In the previous chapters, this work has illustrated the theoretical and empirical foundations necessary to understand the complex relationship between environmental regulation, firm competitiveness, and international trade. The first part of the thesis focused on the contrasting predictions of the Pollution Haven Hypothesis (PHH) and the Porter Hypothesis (PH), highlighting how environmental regulation can either increase firms' costs and induce relocation (PHH) or stimulate innovation and efficiency (PH). The second part discussed the REACH Regulation, its structure and mechanisms, and its growing importance within the European environmental and industrial policy framework.

Building on this theoretical foundation, Chapter 3 introduced the empirical strategies developed by Autor et al. (2013, 2014) to study the effects of international trade shocks on local labor markets and firm behavior. The shift–share approach and the difference-in-differences (DiD) design developed in that literature represent powerful tools to identify causal relationships in the presence of complex, multi-dimensional data.

This chapter now adapts those methodologies to a new empirical context: the impact of a regulatory shock, that is the progressive restriction of Perfluorooctanoic Acid (PFOA) under the EU REACH Regulation, on Italian firms. The objective is to understand whether and how this type of policy, conceptually similar to a negative trade shock, has influenced the performance and behavior of firms.

By analogy with Autor et al., who examine local exposure to import competition, this work examines firm-level exposure to environmental regulation. The regulatory tightening related to PFOA can be interpreted as a sudden, externally imposed constraint on production and trade, affecting only firms directly involved in activities related to this substance. This heterogeneity provides the empirical basis for identifying the causal impact of REACH on firm outcomes.

The chapter is organized as follows. First, it introduced the general methodological framework and its conceptual alignment with the literature on trade shocks. Then the focus is put on the case of PFOA, explaining its industrial relevance and regulatory evolution. The following section presents the construction of the product-level exposure index, while in the end the aggregation of this index is discussed at the firm level, which is the basis for the econometric analysis.

To enhance both conceptual clarity and empirical transparency, we systematically present each methodological step using a dual notation. On one side, we refer to each variable using its conceptual name, consistent with the terminology used in the relevant literature. On the other hand, we report the corresponding Stata variable name employed in the actual implementation of the model. This parallel notation facilitates the replicability of the analysis and provides an explicit mapping between theoretical constructions and their empirical operationalization in the dataset.

This approach allows readers to follow the logical flow of the econometric design, from the construction of exposure indices to the aggregation at the firm level and the estimation of the difference-in-differences (DiD) regression, while directly linking the discussion to the code structure used in Stata.

4.1 Overview of the methodological framework

The methodological approach adopted in this study builds upon the shift–share identification strategy developed by Autor, Dorn, and Hanson (2013) in their analysis of the "China syndrome." In their model, variation in exposure to import competition across U.S. local labor markets is determined by the combination of two elements: the national growth of imports from China by sector (the "shift") and the pre-existing sectoral composition of employment in each local market (the "share"). The resulting exposure measure is exogenous to local shocks and provides a credible source of identification for causal inference.

In this thesis, the same conceptual logic is applied to environmental regulation. Instead of import penetration, we focus on regulatory exposure, which varies across products and firms according to the frequency with which these products are registered as containing substances subject to REACH restrictions. This exposure is determined by the interaction between regulatory intensity at the product level and the firm's trade composition, in a way that is analogous to the interaction between sectoral shocks and regional composition in the shift–share model.

The methodological sequence follows four steps:

1. *Quantifying product-level exposure to REACH*: the first step of the analysis is the quantification of product-level exposure to REACH, which is calculated for each product j (identified at the HS6 level[4]) as the ratio between the number of SCIP

[4] A "6-digit level" typically refers to the Harmonized System (HS) code, a standardized international system used to classify traded goods at a detailed, 6-digit level of specificity. This code is the foundation for national tariff schedules and is used globally for import/export classification, determining duties and tariffs, gathering trade statistics, and understanding market trends.

database registrations, identifying the product as containing PFOA, and the relative importance of that product in EU trade with the rest of the world. This normalization is essential to ensure that the measure captures regulatory pressure rather than trade scale.

2. *Aggregating to the firm level*: the second step involves the aggregation of exposure at the firm level, weighting product exposure indices by the firm's trade shares. This allows the construction of a continuous measure of firm exposure that reflects both the intensity of regulation in the products traded and the firm's reliance on those products.
3. *Identifying treatment and control groups*: the third step is the definition of treatment and control groups. Firms are classified as "treated" if they have ever traded at least one product containing PFOA between 2011 and 2023 (`ever_exposed = 1`), while firms that never traded PFOA-related products but operate in similar sectors (same 3-digit ATECO code) constitute the control group (`ever_exposed = 0`).
4. *Estimating causal effects via DiD regression*: Finally, the causal impact of exposure to REACH is estimated using a difference-in-differences (DiD) model, which compares the evolution of firm outcomes (such as turnover, costs, or import composition) for treated and control firms before and after the entry of PFOA into the Candidate List in 2013. The basic intuition is that, if pre-treatment trends are parallel between the two groups, any divergence after 2013 can be attributed to the regulatory shock.

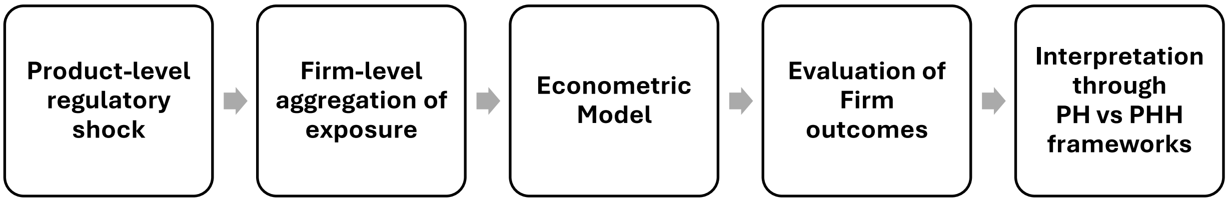


Figure 4 - Logical flow methodology. This framework allows for the identification of heterogenous firm responses to environmental regulations and, by extension, for testing the relative validity of the Pollution Haven Hypothesis and Porter Hypothesis in the context of REACH regulation

4.2 The case of PFOA

For analytical clarity, this thesis focuses on a single SVHC: **perfluorooctanoic acid (PFOA)**, *CAS number* 335-67-1, part of the *PFAS family*. PFOA has been included in the REACH Candidate List on the 20th June 2013, due to its persistence, bioaccumulation, and toxicity, and its use has been progressively restricted in Europe through inclusion in Annex XVII of REACH. Since July 2020, PFOA and related substances have also been included in the list of POP (Persistent Organic Pollutant) substances, under control by the Stockholm Convention and the European regulation for POP substances.

PFOA is widely used in industrial applications such as surface coatings, water- and stain-resistant textiles, and fluoropolymer production. Its widespread historical use and subsequent regulatory tightening make it a particularly suitable candidate to study how firms respond to regulatory shocks.

4.2.1 Evolution of PFOA under regulations

Since 2000 to 2015, many large chemical companies reduced or phased out the production and use of PFOA in Western supply chains, for example through the 3M™ voluntary initiative and the U.S. EPA PFOA Stewardship Program. These voluntary commitments were a response to increasing scientific data showing that this kind of chemical was persistent in the environment, accumulated in tissue, and posed potential health and environmental risks. This has led to a decline in production use in “first mover” contexts. Despite the reduction in advanced economies, part of the production and use has shifted to countries with less stringent regulations (for example, Asia) meaning that PFOA and PFAS continued to be detected in the environment and in the global commercial chain in subsequent years. Environmental trend studies show declines in concentration in several countries but persistent presence and signs of increase in other areas, suggesting an alignment of the companies’ initial behavior to what stated by the Pollution Haven Hypothesis.

After the introduction of PFOA in the REACH Candidate List as an SVHC in 2013, even more stringent measures have been adopted, such as the inclusion in the REACH Restriction List (Annex XVII) in 2017 and the subsequent inclusion in the POP regulation in 2020. In practice, after 2013, regulations have become more restrictive, culminating in formal measures and subsequent extensions until 2025. From a global point of view, recent news includes the U.S. Environmental Protection Agency (EPA) is considering extending compliance deadlines for PFOA/PFOS in drinking water while also working to designate them as hazardous substances. Meanwhile, environmental and public health advocates are raising concerns about potential PFAS pollution from large-scale datacenters driven by the growth of artificial intelligence. Separately, new research suggests potential health effects from prenatal exposure to these "forever chemicals". In the EU, lasts updates regarding the usage of PFAS have been made by the European Commission in October 2025, restricting these substances in the production of firefighting foams, marking a major step towards the Commission’s objective to minimize PFAS emissions.

In the EU, domestic demand for products containing PFOA has gradually declined, and many applications have been banned or subject to authorization/restriction along time. The trend in EU imports and exports exhibits a delayed but clear response to regulatory milestones.

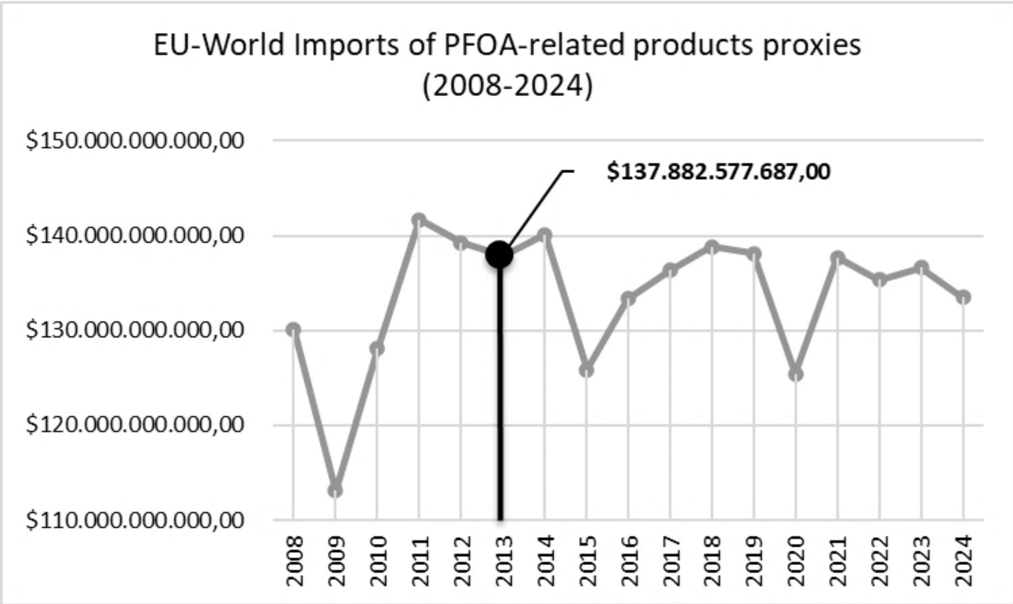


Figure 5 - EU-World imports of PFOA-related products proxies (2008-2024)

Figure 6 - EU-World exports of PFOA-related products proxies (2008-2024)

Before 2013 and the related EU regulatory intervention on PFOA-related products, trade levels were high and somewhat volatile. This reflects normal market dynamics, not yet constrained by REACH measures. PFOA use was widespread in many sectors, such as textiles, coatings, fluoropolymer production, and firms were not required to notify or substitute yet. Even if a drop in imports and exports were already expected in 2013, the data show a small increase until

2014, followed by a net decrease. This lag is quite typical of regulatory shocks for three main reasons:

- The identification of PFOA as a SVHC in the Candidate List represents a signal to companies and not an immediate ban. Firms are informed that the substance is under scrutiny and that authorization or restriction may follow, but they can still legally use and trade it. Real substitution decisions and supply-chain adaptations take time
- Trade flows often reflect contracts signed months earlier. 2013–2014 imports and exports may in fact reflect pre-existing production orders or stock clearance
- Moreover, it usually takes 1-2 years for firms (especially SMEs) to fully understand implications and adapt procurement and production

In 2017, a major milestone occurred with the insertion of PFOA in the Restriction List (Annex XVII) but, following the same logic of adaption periods as before, it took a transitional period (*grace period*) of 2-3 years to be fully effective, while some firms anticipated restrictions by increasing production or exports just before the restriction took full effect, to build up inventories or shift products abroad. This helps explain the trade increase after 2017, as a *regulatory frontloading* phenomenon.

The decrease after 2018 was consistent with the end of transitional periods for several uses and the progressive effect of the restrictions kicking in. Furthermore, the 2020 inclusion under the POP Regulation imposed near-total bans except for a few defined exemptions. This has caused a more structural and persistent decline, accelerated also by other effects such as trade disruptions caused by COVID-19 pandemic.

It's important to note that after 2020, not all uses of PFOA were banned immediately, but derogations were granted for particular uses, for example certain fluoropolymer production processes, photolithography, semiconductor manufacturing, certain textiles for protective clothing, or fire-fighting foams under transitional use. These derogations allowed continued production, import, or export under strict conditions and for limited timeframes, often up to 2023 or 2025 depending on the use. Moreover, even after a ban takes effect, existing stocks of products containing PFOA can continue to circulate for some time, especially in international trade. Companies may have exported remaining inventories after 2020 for product categories that also include non-PFOA categories, or to dispose of existing stocks legally. These factors explain why trade did not collapse immediately after 2020 despite the formal inclusion of PFOA under the POPs Regulation.

4.3 Product-level shock intensity

The first step of the empirical analysis is the construction of the product-level exposure index**,** which quantifies the intensity of the regulatory shock at the level of traded products. This measure reflects how frequently a given product category is associated with PFOA-related registrations in the SCIP database relative to its importance in EU international trade.

Formally, for each product j, exposure to REACH is defined as:

$$R_j = \frac{S_j^{\mathrm{SCIP}}}{S_j^{TRADE}}$$

Where:

- S_j^{SCIP} is the share of the number of SCIP registrations between 2020 and 2024 identifying the product as containing PFOA over the total number of registrations between 2020 and 2024 of all PFOA-related products
- S_j^{TRADE} is the product's share in total EU trade (imports plus exports) with the rest of the world over the same period. It is defined as below:

$$S_j^{TRADE} = \frac{X_j^{EU-WORLD} + M_j^{EU-WORLD}}{\sum_j (X_j^{EU-WORLD} + M_j^{EU-WORLD})}$$

The data extracted at numerator are based on the SCIP database, created by ECHA. The database contains mandatory notifications by EU firms for articles containing SVHCs. By filtering the database for PFOA, we obtain the list of product categories (at TARIC-10 level) registered by the firms that declares contain PFOA, in the time period between 2020 and 2024. By selecting one product category at a time, through proper elaboration with STATA software, we are able to count the number of notifications made by EU firms, that declare to use PFOA for producing that product. This number represents the frequency of appearance of PFOA in the specific product category j.

Focusing on a single, well-defined SVHC simplifies the analysis while maintaining analytical richness, as PFOA affects a wide range of manufacturing sectors relevant to Italian firms, including textiles, coatings, and plastics.

Since the numerator represents the relative share of registrations of the product j compared the global pool of products containing PFOA, it is also called "harmfulness index", since it's logical to state that the higher the frequency of appearance of PFOA in the product j compared to the global pool of products, the higher the variation of exposure to the REACH provisions.

The figure below represents a sample extracted from the elaboration of the SCIP data on STATA software, related to the product category identified by the TARIC-10 level code “3917320000”. The column `njt` refers to the frequency of notification of registration of PFOA-related products by EU firms, starting from the year of insertion in the Candidate List (2013), while the column `numerator` represents the ratio between the quantity `njt` and the total number of registrations of all PFOA-related products.

	Articlecateg~y	count	substance	tot_regist~s	year_inscr~t	year	njt	numerator
1	3917320000	2	335-67-1	882	2013	2008	0	0
2	3917320000	2	335-67-1	882	2013	2009	0	0
3	3917320000	2	335-67-1	882	2013	2010	0	0
4	3917320000	2	335-67-1	882	2013	2011	0	0
5	3917320000	2	335-67-1	882	2013	2012	0	0
6	3917320000	2	335-67-1	882	2013	2013	2	.0022676
7	3917320000	2	335-67-1	882	2013	2014	2	.0022676
8	3917320000	2	335-67-1	882	2013	2015	2	.0022676
9	3917320000	2	335-67-1	882	2013	2016	2	.0022676
10	3917320000	2	335-67-1	882	2013	2017	2	.0022676
11	3917320000	2	335-67-1	882	2013	2018	2	.0022676
12	3917320000	2	335-67-1	882	2013	2019	2	.0022676
13	3917320000	2	335-67-1	882	2013	2020	2	.0022676
14	3917320000	2	335-67-1	882	2013	2021	2	.0022676
15	3917320000	2	335-67-1	882	2013	2022	2	.0022676
16	3917320000	2	335-67-1	882	2013	2023	2	.0022676
17	3917320000	2	335-67-1	882	2013	2024	2	.0022676

Figure 7 – Sample extracted by STATA software elaboration, related to the product category identified by the 10-level TARIC code “3917320000”

At denominator, the weight of the product j in the international trade is calculated, using the information provided by UN Comtrade database. The database contains information about transactions of specific product categories in specific year at world-level. By selecting the countries of interest, the proper product categories (identified at HS-6 level) and the reference year, we are able to obtain trade data about the value of the transactions, the quantity and, for each country, the correspondent partner in the transaction. So, the harmfulness index at numerator is then normalized for the weight of the product in international trade, specifically considering EU transactions with the rest of the world. The quantity $X_j^{EU-WORLD} + M_j^{EU-WORLD}$ indicates the sum of exports and imports of product j during the time period between 2020 and 2024, in order to be coherent with the time span considered at numerator. The fraction $\frac{X_{jt}+M_{jt}}{\sum_j X_{jt}+ M_{jt}}$ tells how much the trade of the product j has changed with respect to the global pool of products (all product categories), so how much is the variation of the importance of the product *j* in international trade.

The figure below represents a sample extracted from the elaboration of the UN Comtrade data on STATA software, related to the product categories identified by the HS-6 level code. The column `trade_j_eu_202024` refers to the total trade value of the product j between EU and the rest of the world in the time period between 2020 and 2024, while the column `trade_tot_eu_202024` has analogous meaning but is related to all PFOA-related products. Finally, the variable `share_trade_j_202024` represents the dominator discussed above.

	cmdCode	trade_j_eu_202024	tot_trade_EU_202024	share_trade_j_202024
1	280110	4.124e+08	6.343e+13	6.50e-06
2	280120	4.639e+09	6.343e+13	.0000731
3	390110	8.214e+10	6.343e+13	.001295
4	491110	2.142e+10	6.343e+13	.0003377
5	621010	1.068e+10	6.343e+13	.0001683
6	621020	5.069e+09	6.343e+13	.0000799
7	621040	1.008e+10	6.343e+13	.0001589
8	842199	5.643e+10	6.343e+13	.0008897
9	842490	2.370e+10	6.343e+13	.0003737
10	844399	1.325e+11	6.343e+13	.0020887
11	847170	1.411e+11	6.343e+13	.0022249
12	850980	3.307e+10	6.343e+13	.0005214
13	851671	4.313e+10	6.343e+13	.0006801
14	852610	2.600e+10	6.343e+13	.00041
15	852691	3.309e+10	6.343e+13	.0005218
16	853650	8.074e+10	6.343e+13	.0012729
17	854390	1.628e+10	6.343e+13	.0002566
18	854420	1.528e+10	6.343e+13	.000241
19	854442	1.061e+11	6.343e+13	.0016726
20	880240	4.276e+11	6.343e+13	.006741
21	901819	5.564e+10	6.343e+13	.0008773
22	901920	3.418e+10	6.343e+13	.0005389
23	902212	1.733e+10	6.343e+13	.0002732
24	902214	2.642e+10	6.343e+13	.0004166
25	902610	2.448e+10	6.343e+13	.0003859
26	903082	6.537e+09	6.343e+13	.0001031
27	903300	1.173e+10	6.343e+13	.0001849

Figure 8 - Extractions of the share-trade indexes by STATA software elaboration, related to the product categories containing PFOA traded by EU with the rest of the world in the time period between 2020 and 2024

The normalization operation is crucial in this context, as already suggested by Autor et al. (2014). An increase in harmfulness is meaningful when interpreted relative to the product's economic weight in trade. By normalizing, it may seem counterintuitive that if the relative importance of the product *j* increases, then the exposure to REACH goes down. The reason is that this model does not represent an absolute measure of exposure to the regulation, but of the harmfulness of the product *j* per unit of importance in trade:

- Whether the product has its share of registration in the SCIP database equal to the trade share ($R_j = 1$), then the exposure to REACH may not vary that much as the relative importance in trade has not been impacted.
- Whether the product has its share of registration in the SCIP database higher than the trade share ($R_j > 1$), then the exposure to REACH is high.
- Whether the product has its trade higher than its share of registration in the SCIP database ($R_j < 1$), then the exposure to REACH is low.

This normalization ensures that products with high trade relevance, but low regulatory risk, receive lower exposure values than niche products with high regulatory frequency relative to their trade volume. In practical terms, this index captures how "exposed" a product is to regulatory scrutiny, rather than how economically important it is. Moreover, this logic is directly parallel to Autor et al. (2014), where import growth was normalized by baseline domestic absorption in order to scale shocks to the size of each industry and to allow comparability across sectors. Without such normalization, the measure would overstate the role of marginal products and understate the importance of strategically relevant ones.

In the STATA implementation, the index R_j is captured by the variable `toxicity`, which is calculated by merging SCIP registration counts with trade flow data from UN Comtrade, by harmonizing the product classifications between the two databases. The SCIP database provides product-level information on articles containing substances of very high concern, while Comtrade offers detailed international trade data by product category. By combining these two datasets, the exposure index translates the presence of PFOA in industrial products into a measurable regulatory intensity.

This measure represents the building block of the firm-level exposure variable. Although SCIP data are available only from 2020 onward, the number of registrations during this period can be interpreted as a proxy for the historical intensity of regulatory involvement of each product since 2013, when PFOA first entered the Candidate List.

4.4 Firm-level aggregation

The transition from product-level exposure to firm-level exposure represents a crucial methodological step in this analysis, as it bridges the regulatory dimension of the REACH framework, defined at the level of substances and products, with the economic dimension of firms' behavior and performance. In practical terms, this step consists in linking information from multiple datasets: SCIP, Comtrade, and AIDA. The objective is to derive, for each firm *i* and each year t, an index that reflects how exposed the firm's production and trade activities are to the REACH restrictions on PFOA. The underlying idea is that firms trading more heavily in products associated with PFOA are more exposed to the regulation and therefore more likely to be affected by its progressive tightening.

The process begins with the product-level exposure index R_j, constructed using the SCIP database and UN Comtrade trade flows, as described in the previous section. The next step consists in linking this product-level exposure information to firm-level data. For this purpose, the AIDA database (Bureau van Dijk) is used, which provides detailed balance-sheet and financial data for Italian companies, including variables such as turnover, costs, value added, tangible and intangible assets, and employment. Importantly, AIDA includes firm identifiers and sectoral classifications (ATECO 2007), which allow the data to be merged with the COEWEB-ISTAT database containing firm-level trade transactions. The COEWEB data provides, for each firm and year, the value and quantity of imports and exports disaggregated by CN-8 product codes. These codes are also harmonized to HS-6 in order to be merged with the product-level exposure index. Through this merger, each trade transaction of firm i in product j and year t inherits the exposure value R_j corresponding to that product. This operation produces a detailed panel dataset where each observation represents a firm–product–year combination, including variables such as the value of imports (`import_eu`), exports (`export_eu`), total trade (`tot_trade`), and the product-level exposure index (`share_scip`).

Once the datasets are merged, the exposure of each firm i in a given year t is calculated as a trade-weighted average of the exposure of the products it trades. Conceptually, the firm-level exposure R_{it} can be expressed as:

$$R_i = \sum_j R_j \times \frac{T_{ij}}{\sum_j T_{ij}}$$

Where T_{ij} represents the total trade value (imports plus exports) of the firm i in product j.

Because the merged dataset initially contains one observation for each firm–product–year combination, it must be aggregated to the firm–year level before the econometric analysis. This operation aggregates all transaction-level data for each firm (`n_firm`) and year (`anno`). The summation operator (`sum`) is applied to flow variables such as imports and exports, while the (`first`) operator retains static firm characteristics (e.g., `establishment year`, `sector`, or `region`). The resulting dataset contains one observation per firm per year, with a consistent panel structure that can be used for difference-in-differences estimation.

After proper aggregation, this measure is implemented in STATA as the variable `share_exposed`, representing the proportion of each firm's total trade that involves PFOA-related products, and so that is exposed to REACH regulation, for each year between 2010 and 2022. Each firm-year observation therefore reflects the proportion of its trade related to products containing PFOA, normalized by the firm's overall trading activity. Firms that never trade such products have a `share_exposed` equal to zero.

	anno	n_firm	import_eu	export_eu	ateco2007i~r	province_sl	region_sl	ever_exposed	ever_exposed_1012	share_expo~d
1	2010	2	928824	3714438	271100	Vicenza	Veneto	1	1	.0066814
2	2010	5	124710	0	143100	Varese	Lombardia	0	0	0
3	2010	13	2820891	1082133	222100	Como	Lombardia	1	1	0
4	2010	17	53715	6616908	283090	Ferrara	Emilia-Romagna	0	0	0
5	2010	19	0	1480983	107300	Pescara	Abruzzo	1	0	0
6	2010	32	9305185	0	101100	Mantova	Lombardia	0	0	0
7	2010	45	0	9937	172200	Pordenone	Friuli-Venezia…	0	0	0
8	2010	47	1205274	0	109100	Ragusa	Sicilia	0	0	0
9	2010	48	0	181574	192030	Ragusa	Sicilia	0	0	0
10	2010	53	760390	0	222200	Pistoia	Toscana	1	1	.797839
11	2010	71	4808	463232	110200	Asti	Piemonte	0	0	0
12	2010	74	0	0	255000	Vicenza	Veneto	0	0	0
13	2010	76	539139	2776436	289300	Rovigo	Veneto	0	0	0
14	2010	82	520	372780	289999	Padova	Veneto	1	0	0
15	2010	89	8856390	9406741	252100	Rovigo	Veneto	1	1	.0013269
16	2010	90	1657690	753496	202000	Ferrara	Emilia-Romagna	1	0	0
17	2010	91	4921029	3421347	282110	Ferrara	Emilia-Romagna	1	1	.0003175
18	2010	92	668622	30839	106100	Siracusa	Sicilia	0	0	0
19	2010	96	0	0	236100	Valle d'Aosta/…	Valle d'Aosta/…	0	0	0
20	2010	97	818757	829242	256200	Padova	Veneto	1	1	.0011325
21	2010	105	9207	1.00e+07	251100	Benevento	Campania	0	0	0
22	2010	106	1.07e+07	1.83e+07	222100	Rovigo	Veneto	1	1	.001831

Figure 9 - Sample extracted by elaboration of STATA software showing for each firm, and each year, the index share_exposed

Based on the construction of the variable `share_exposed` , it's possible to expand the meaning further by defining two treatment variables:

- `ever_exposed`: it equals 1 if the firm has ever traded at least one PFOA-containing product during the period 2010–2022, and zero otherwise. This variable identifies whether a firm belongs to the treated group or to the control group, useful to apply the DiD approach in the next paragraphs
- `ever_exposed_1012`: it equals 1 if the firm was already trading PFOA-related products before 2013 (i.e., during 2010–2012). This variable is used to test pre-treatment parallelism, ensuring that the firms considered as treated and control followed similar trends before the regulatory intervention.

Additionally, a dummy variable `hope` is generated as:

```
gen hope = (share_exposed >= r(p75)
```

This indicator identifies firms whose exposure lies above the 75th percentile of the exposure distribution, isolating those that are *highly exposed* to the REACH regulation, in the period between 2010 and 2012. This selection is particularly useful for robustness checks and for verifying that the estimated effects are not driven by firms with marginal exposure.

4.4.1 Conceptual meaning of the aggregation

This multi-step integration procedure transforms a complex structure of regulatory, trade, and financial data into an interpretable indicator of firm-level regulatory exposure. Conceptually, this measure reflects how deeply each firm's production and trade structure is intertwined with PFOA-related products, capturing the degree to which REACH restrictions represent an exogenous shock to its operations.

This approach allows for an identification strategy that mirrors the shift–share logic of Autor et al. (2013): the regulatory "shift" (variation in REACH intensity across products) interacts with the firm's "share" (composition of traded goods) to produce heterogeneous exposure across firms. The resulting firm-level indicator (`share_exposed`) serves as the empirical counterpart of local import exposure in Autor's framework but adapted to the context of environmental regulation.

In the next section, this variable becomes the cornerstone of the difference-in-differences econometric model, where firm outcomes such as turnover (`lturnover`), import intensity (`eu_import_share`), and cost structure are regressed on the interaction between treatment status (`ever_exposed`) and time (`i.anno`).

4.5 Econometric Model

Having defined both product-level and firm-level exposure indices, the next step consists in specifying an econometric framework capable of isolating the causal impact of REACH restrictions, specifically, those related to PFOA, on firm-level outcomes. The approach adopted in this thesis is a *difference-in-differences (DiD)* model with multiple time periods and fixed effects, inspired by the empirical strategy used by Autor et al. (2013, 2014) to estimate the effects of trade shocks.

The logic of the DiD design is to compare the change in outcomes of *treated firms*, those exposed to REACH through PFOA-related trade, before and after the regulatory intervention, relative to the change observed among control firms, those not exposed. If the pre-treatment trends of the two groups are parallel, any divergence after the introduction of PFOA into the REACH Candidate List in 2013 can be attributed to the regulatory shock.

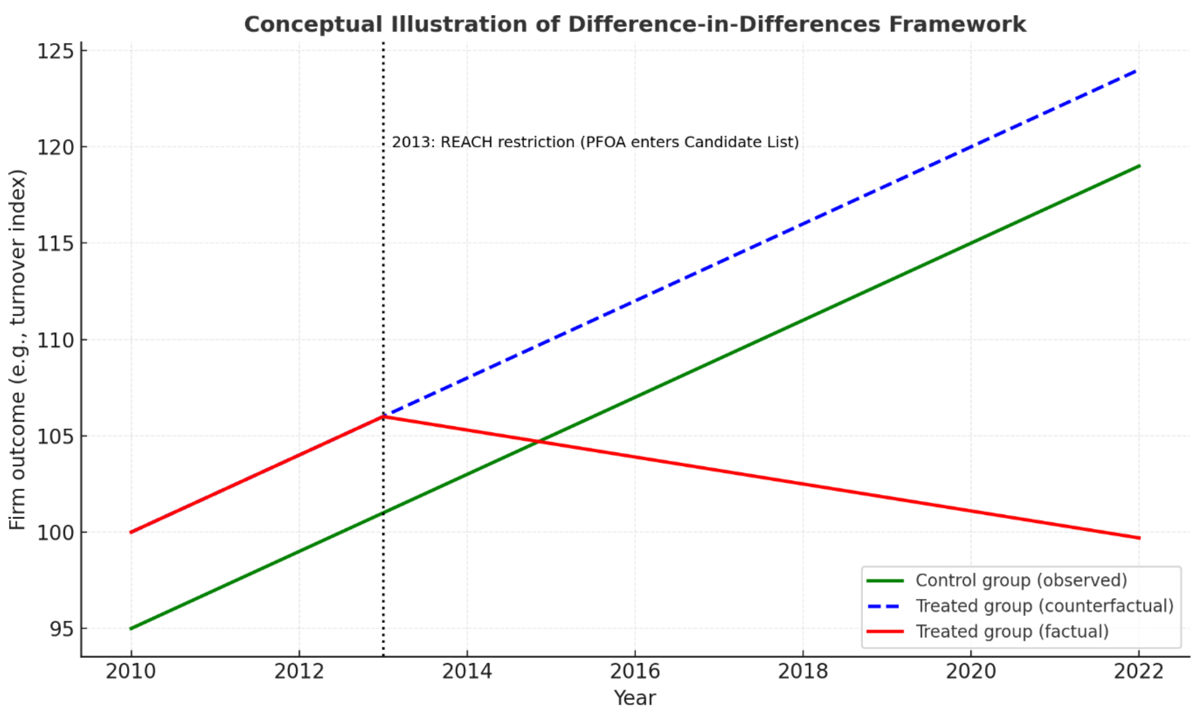


Figure 10 - Conceptual illustration of the Difference-in-Differences identification strategy

Formally, the econometric model estimated can be written as:

$$Y_{it} = \beta_0 + \beta_1 \text{EverExposed}_i + \beta_2 \text{PostRestrictions}_t + \beta_3 (\text{EverExposed}_i \times \text{PostRestrictions}_t) + \\ + \sum_1^N \gamma_i \times \text{I}(firm = i) + \sum_{2010}^{2022} \delta_t \times \text{I}(year = t) + \sum_1^S \eta_s \times \text{I}(sector = s) + \sum_{2010}^{2022} \sum_1^S \mu_{st} \times \\ \text{I}(year = t \times sector = s) + \varepsilon_{it}$$

Where:

- Y_{it}: it represents the outcome of interest for firm i in year t, such as log turnover (`lturnover`), EU import share (`eu_import_share`), or other financial and trade variables
- EverExposed_i(`ever_exposed`): it represents a dummy equal to 1 for firms that have traded at least one PFOA-containing product in the period between 2010 and 2022
- $\text{PostRestrictions}_t$: it is a dummy equal to 1 for years from 2013 onward (after PFOA entered the Candidate List)

- ($\text{EverExposed}_i \times \text{PostRestrictions}_t$): it is the interaction term capturing the treatment effect
- γ_i, δ_t, and $\eta_s$represent the coefficient of the firm, time, and sector fixed effects (indication functions), respectively
- μ_{st} is the coefficient of a sector–year fixed effect, controlling for sector-specific time trends
- $\varepsilon_{it}$is the idiosyncratic error term

However, in practice, and particularly in the context of the `reghdfe` implementation in STATA used in this thesis, the inclusion of both the main effects and the fixed effects creates a perfect collinearity problem.

The issue stems from the way fixed effects absorb variation in the data. In our model, we include a full set of:

- firm fixed effects (`i.n_firm`), controlling for all time-invariant characteristics of each firm
- year fixed effects interacted with sector (`i.anno#i.ateco2007impr_3d`), capturing aggregate shocks and sector-specific dynamics
- year fixed effects interacted with province (`i.provdum#i.anno`), capturing local-level shocks.

The presence of firm fixed effects implies that the main treatment variable `ever_exposed` (which is time-invariant for each firm) is perfectly collinear with those fixed effects. In other words, for each firm i, the dummy EverExposed_i takes the same value every year, so its effect cannot be distinguished from the firm's fixed effect γ_i. Similarly, year fixed effects absorb the time dummy $\text{PostRestrictions}_t$, since this variable is identical for all firms in a given year. In other words, it is not possible to distinguish between the fact of being firm i from the fact of being $\text{EverExposed}_i$and it is not possible to distringuish between the fact of being at time t from the fact of being at $\text{PostRestrictions}_t$.

As a consequence, the only variation that remains estimable is the interaction term between the two dimensions, that is, the interaction between treatment status and time:

$$\text{EverExposed}_i \times \text{PostRestrictions}_t$$

This term varies both across firms (since not all firms are treated) and across years (since the policy is activated only after 2013), thus surviving the fixed-effects transformation.

Once the redundant variables are removed due to collinearity, the regression effectively estimated by STATA can be represented as:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{t>2012} \beta_t(\text{EverExposed}_i \times D_t) + \eta_s + \mu_{st} + \varepsilon_{it}$$

where D_t are year dummies for each period after the baseline (2013 onward). In this specification, the coefficients β_t represent the year-specific treatment effects, i.e. the difference between treated and control firms in each year, in the baseline period (2010–2012) and the observation period (2013-2022).

4.5.1 Implementation in STATA

This regression model is implemented in STATA using the `reghdfe` command, which efficiently handles multiple high-dimensional fixed effects. The main regression commands used are:

```
1) reghdfe lturnover ever_exposed#i.anno
2) reghdfe lturnover ever_exposed_1012#i.anno
3) reghdfe eu_import_share hopeXdum$baseplustwo - hopeXdum$max if anno > $base & anno <= $max
```

The first two specifications estimate the effects of exposure (`ever_exposed` and `ever_exposed_1012`) on the logarithm of turnover, while controlling for firm, year–sector, and year–province fixed effects. The last specification evaluates the effect on the EU import share, focusing on the interaction terms between exposure (`hopeXdum#year`) and time.

Each interaction term `ever_exposed#i.anno` (or `hopeXdum#i.anno`) generates a series of coefficients $\beta_t$that represent the estimated treatment effects for each year relative to the period between 2010 and 2022. Plotting these coefficients over time provides an *event-study* representation of the dynamic impact of REACH, allowing us to verify whether pre-treatment differences are close to zero (*parallel trends*) and whether post-treatment coefficients deviate significantly (*treatment effects*).

The exclusion of the main effects of EverExposed_i and $\text{PostRestrictions}_t$ from the regression does not alter the substantive interpretation of the model. Rather, it reflects the econometric reality that once firm and year fixed effects are included, those variables contain no independent variation beyond what is already captured by the fixed effects.

Hence, the model estimated in STATA is a reduced form of the theoretical DiD model, focusing on the *identifiable component* of the treatment effect, the differential evolution of treated firms over time.

In practical terms, each coefficient $\beta_t$estimated by STATA represents the average difference in the dependent variable between treated and control firms in year t, also relative to the pre-2013 baseline. This structure is consistent with the event-study interpretation of the difference-in-differences model, in which the dynamics of β(t) over time provide a transparent view of both pre-trend validation and post-treatment effects.

$$\beta_t = \underbrace{\left(Y_{treated,t} - Y_{control,t}\right)}_{D_1} - \underbrace{\left(Y_{treated,t_0} - Y_{control,t_0}\right)}_{D_2}$$

The parallel trend assumption can be tested by examining whether $\beta_t \approx 0$ (D_1-D_2=0 in the pre-treatment period) and statistically insignificant for pre-treatment years (2010–2012), meaning that any variation between the two trends must be consistent with causality and not indicate structural differences between the two groups. Post-2013 deviations of $\beta_t$from zero capture the causal impact of the REACH restriction. In particular, post-treatment β_t different from 0 indicate:

- β_t>0: the group of companies analyzed shows an increase in the dependent variable compared to the counterfactual trend.
- β_t<0: the group of companies analyzed shows a decrease in the dependent variable compared to the counterfactual trend.

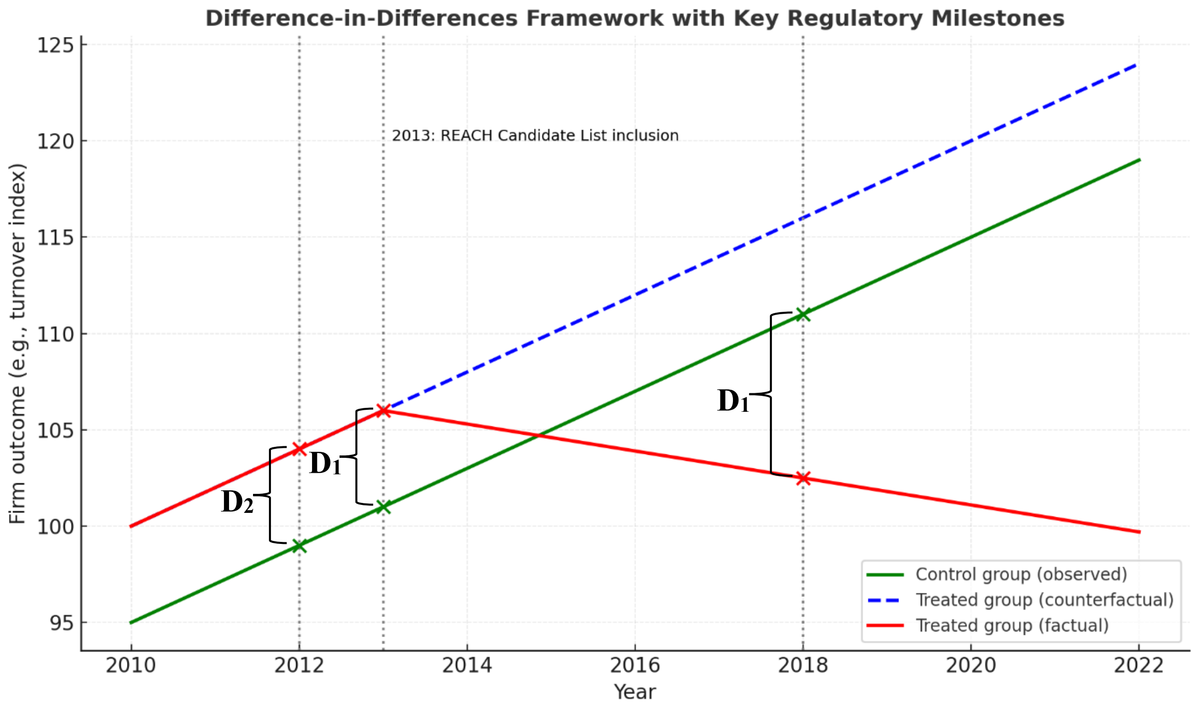


Figure 11 - Parallel pre-treatment trends (2010–2012) between treated and control firms and divergence in post-treatment years following the REACH restriction on PFOA (2013)

Since it is not logically possible to directly observe the counterfactual trend of the treated group, STATA constructs it implicitly by assuming that the control companies represent the trend that the treated companies would have had in the absence of regulation, demonstrating the parallel trend hypothesis. Furthermore, fixed effects remove everything that is common to the two groups of companies or sectors over time (structural trends, macro shocks, territorial differences), so that the residual difference observed after the restriction is attributed to the treatment itself, i.e., the REACH restriction on PFOA.

4.6 Choice of Baseline and Observation periods

The selection of the baseline and observation periods is central to the credibility of the difference-in-differences design. In this thesis, the baseline period is defined as 2010–2012, corresponding to the years preceding the inclusion of PFOA in the REACH Candidate List (June 2013). This interval provides a clean pre-treatment window during which no significant policy actions concerning PFOA were implemented, ensuring that both treated and control firms operated under comparable regulatory conditions.

The observation period extends from 2013 to 2022, capturing the successive stages of regulatory intervention and their potential cumulative effects on firms. Specifically:

- **2013–2016**: early adaptation period following the inclusion in the Candidate List (awareness and gradual compliance)
- **2017–2019**: enforcement phase following inclusion in the Restriction List (Annex XVII), when compliance costs and substitution efforts likely intensified.
- **2020–2022**: transition period to the POP Regulation, during which PFOA-related trade faced almost complete prohibition

This periodization is consistent with the regulatory milestones and allows the model to capture both short-term adjustment and longer-term strategic responses.

In the Stata regressions, the baseline period is used to normalize the event-study coefficients: years 2010–2012 are omitted (serving as reference), and all other years' coefficients are interpreted relative to this pre-treatment level. This configuration enables a graphical test of the parallel trend assumption, since the estimated coefficients in pre-2013 years should be close to zero if treated and control firms followed similar trajectories before regulation.

The results shown in the regression outputs confirm that pre-treatment coefficients (2010–2012) are statistically insignificant, supporting the validity of this assumption. Post-2013 coefficients, conversely, begin to deviate significantly from zero, particularly after 2017, reflecting the intensification of regulatory pressure on PFOA.

lturnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ever_exposed_1012#anno						
0 2011	-.0112963	.0103217	-1.09	0.274	-.0315267	.0089342
0 2012	-.0135031	.0103239	-1.31	0.191	-.033738	.0067317
0 2013	-.008496	.0103191	-0.82	0.410	-.0287213	.0117292
0 2014	-.0074971	.0103237	-0.73	0.468	-.0277315	.0127373
0 2015	.000202	.0103307	0.02	0.984	-.0200461	.0204501
0 2016	.0034679	.0103334	0.34	0.737	-.0167854	.0237212
0 2017	.0049245	.0103329	0.48	0.634	-.0153279	.0251769
0 2018	-.0028044	.0103293	-0.27	0.786	-.0230497	.0174409
0 2019	-.0056258	.0103291	-0.54	0.586	-.0258708	.0146192
0 2020	-.0119469	.0103321	-1.16	0.248	-.0321978	.0083039
0 2021	.0238831	.0103662	2.30	0.021	.0035655	.0442006
0 2022	.0092533	.0104364	0.89	0.375	-.011202	.0297086
1 2010	0	(omitted)				
1 2011	0	(omitted)				
1 2012	0	(omitted)				
1 2013	0	(omitted)				
1 2014	0	(omitted)				
1 2015	0	(omitted)				
1 2016	0	(omitted)				
1 2017	0	(omitted)				
1 2018	0	(omitted)				
1 2019	0	(omitted)				
1 2020	0	(omitted)				
1 2021	0	(omitted)				
1 2022	0	(omitted)				
_cons	9.103822	.0040108	2269.82	0.000	9.095961	9.111684

Figure 12 - Regression of lturnover on the treatment variable ever_exposed_1012#anno. We denote a low statistical significance of the pre-treatment coefficients (p>0.10)

4.7 Endogeneity considerations

A central methodological concern in assessing the causal impact of environmental regulation on firm outcomes is the potential presence of *endogeneity bias*. In the context of this thesis, endogeneity may arise because the REACH Regulation affects all EU Member States simultaneously. Hence, when constructing the product-level exposure index, using intra-EU trade data as the normalization denominator risks conflating regulatory effects that are common across European countries with those specific to Italian firms.

In the current formulation of the exposure index, the numerator captures the number of SCIP registrations of product j containing PFOA, while the denominator reflects the total value of EU trade (imports plus exports) for product j in the same period (2020–2024). Formally:

$$Exposure_j = \frac{Registrations_j^{PFOA}}{\frac{Trade_{EU,j}}{\sum_k Trade_{EU,k}}}$$

This approach has the practical advantage of ensuring internal consistency between datasets, since SCIP data record registrations across the EU and not at the individual Member State level, but introduces a potential source of bias. Specifically, because the denominator itself may already be influenced by REACH, it does not serve as a fully exogenous reference. If, for example, REACH restrictions have already reduced intra-EU trade of certain products, this would mechanically increase the exposure index, overstating the intensity of the regulatory shock.

The ideal approach to mitigate this issue would be to normalize using extra-EU trade flows, that is, trade between the EU and non-EU countries. This would ensure that the denominator captures a market not directly affected by REACH, thereby isolating the exogenous variation in trade patterns. Such normalization would more accurately represent the external demand for EU products containing PFOA and prevent contamination of the index by policy-induced effects within the EU market itself.

However, for the purposes of this first-stage analysis, the decision to retain EU-level normalization was made for the sake of data coherence and simplicity. Because SCIP registrations are only available at the EU level, aligning the numerator and denominator within the same regulatory and geographical frame avoids potential mismatches in data coverage and definitional inconsistencies across countries.

Future refinements of the analysis could therefore proceed along two directions:

1. Use of extra-EU normalization: by replacing intra-EU trade data in the denominator with extra-EU trade flows (e.g., EU exports to the rest of the world from UN Comtrade or BACI-CEPII), it would be possible to isolate the impact of REACH from the internal EU dynamics it directly affects.
2. Instrumental variable approach: as in Autor et al. (2013, 2014), an external instrument could be constructed by exploiting the structure of trade flows from non-EU countries with varying exposure to environmental regulation. For example, trade patterns with countries not implementing REACH (such as the United States or Asian economies) could serve as an exogenous predictor of product-level exposure intensity.

This second step would allow distinguishing between endogenous adjustments of firms due to EU-wide regulation and exogenous shocks that reflect differential exposure across products and firms. Such refinement would strengthen causal interpretation by ensuring that the estimated effects on firm outcomes—such as turnover, costs, or employment—are not driven by omitted variables correlated with EU-level policy implementation.

In summary, while the current specification captures the main variation in product-level exposure to PFOA regulation, it does so under the simplifying assumption that intra-EU trade can serve as a valid benchmark. Recognizing this limitation and outlining the potential methodological refinements enhances the transparency and credibility of the empirical design, paving the way for a more robust causal identification in subsequent research.

4.8 Conclusions

This chapter has presented the empirical methodology developed to quantify and estimate the effects of the REACH regulation, specifically the restriction of PFOA, on Italian firms. The analytical approach adapts the shift–share logic and difference-in-differences identification strategy of Autor et al. (2013, 2014) to the context of a regulatory rather than a trade shock.

The analysis proceeds in three main stages. First, a product-level index of regulatory exposure is constructed by combining SCIP data on PFOA registrations with international trade data from Comtrade. Second, this index is aggregated at the firm level through trade shares using

COEWEB and AIDA data, resulting in an indicator of firm exposure to REACH. Third, a panel regression model with fixed effects is estimated to identify causal effects of exposure on firm outcomes, exploiting temporal and cross-sectional variation in treatment intensity.

The combination of fixed effects and exogenous regulatory timing provides a robust framework for isolating the impact of environmental policy on firm behavior. The next chapter will present the data sources and descriptive statistics underlying the analysis, while the subsequent empirical sections will discuss the estimation results in detail, evaluating whether the evidence aligns more closely with the Pollution Haven Hypothesis or with the Porter Hypothesis.

5 Data

The methodological framework developed in the previous chapter relies on the precise measurement of regulatory exposure at both the product and firm level and on its role in shaping firm-level performance outcomes. Achieving this objective requires a comprehensive and coherent integration of multiple data sources that differ in both scope and granularity, encompassing information on regulated substances, product classifications, international trade flows, and firm-level characteristics.

This chapter presents the data infrastructure that supports the empirical analysis of the effects of REACH regulation, focusing on the case of perfluorooctanoic acid (PFOA), on Italian manufacturing firms. It describes in detail the provenance and structure of the datasets employed, the harmonization steps required to render these heterogeneous sources comparable, and the process through which the methodological framework developed in Chapter 4 is applied to the sample of Italian firms.

In particular, the chapter illustrates how the list of product categories containing PFOA, identified through the SCIP database, is mapped onto TARIC, CN, and HS classifications to ensure compatibility with international trade statistics. These categories are then linked to data from UN COMTRADE, which provides the value of trade flows between the European Union and the rest of the world, and from COEWEB–ISTAT, which offers firm-level data on Italian imports and exports. The integration of these data with firm-level financial and ownership variables from Bureau van Dijk's AIDA database enables the empirical investigation of how regulatory exposure interacts with firms' costs, productivity, and strategic behavior.

The chapter also discusses the temporal sampling strategy, focusing on the 2010–2022 period, divided into four key phases corresponding to PFOA's progressive regulatory trajectory:

- 2010–2013: Pre-treatment period, which precedes PFOA's inclusion in the REACH Candidate List
- 2013–2017: Period between the inclusion of PFOA in the Candidate List (2013) to entry into the Restriction List (Annex XVII) (2017).
- 2017–2020: Period between the inclusion of PFOA in Annex XVII to its addition to the POP Regulation ban list (2020).
- 2020–2022: From inclusion in the POP Regulation list onward, corresponding to the last year of available SCIP and AIDA full data.

This temporal segmentation allows the analysis to capture both short-term and long-term firm-level adjustments to regulatory tightening.

These descriptive insights are fundamental for understanding not only the structure of Italian trade and manufacturing in the context of REACH but also the sources of heterogeneity that inform the econometric model adopted.

5.1 Data Source and Provenance

The empirical analysis combines four main datasets:

1. The *SCIP database* (ECHA) for identifying product categories containing PFOA
2. *Product classification systems* (TARIC, CN, HS) for harmonizing product codes across databases
3. The *UN COMTRADE database* for international trade flows between the EU and the rest of the world
4. The *COEWEB–ISTAT database* for firm-level trade data on Italian companies
5. The *AIDA Database* (Bureau van Dijk) for financial and ownership information of Italian firms

Each of these sources provides complementary information necessary to construct and aggregate the exposure index from the product level to the firm level, ensuring both temporal consistency and conceptual coherence across regulatory and trade dimensions.

5.1.1 SCIP Database

The Substances of Concern in Products (SCIP) database, developed by the European Chemicals Agency (ECHA) under the Waste Framework Directive (2008/98/EC), serves as the cornerstone for identifying product categories containing substances of very high concern (SVHC).

Since January 2021, companies manufacturing, importing, or supplying articles containing SVHCs, present in concentrations above 0.1% weight (w/w), are required to submit notifications to SCIP. The purpose of this database is to ensure traceability and transparency of hazardous substances within articles placed on the EU market, and it thus represents the most comprehensive official dataset on substances regulated under REACH.

For this thesis, a query was performed filtering the SCIP database by the CAS number 335-67-1, corresponding to PFOA substance. The search returned to all product categories registered between 2020 and 2024, which is the period of operational activity of the database (including retroactive entries for 2020), for a total of 2,154 comprehensive notifications of all information.

Table 1 reports the ranking of the four product categories (TARIC-10 codes) with the highest frequency of notifications in the SCIP database related to articles containing PFOA between 2020 and 2024. The table shows a strong concentration of notifications in a limited number of product categories, with the TARIC code "9033009000", which encompasses parts and accessories of optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus, recording 1,905 notifications, far exceeding any other category. In fact, PFOA-related substances are used in anti-stick, waterproof, and dielectric coatings, all common in the materials used for high-performance measurement instruments and apparatus. The second most frequently reported category, TARIC "8509800000", refers to electromechanical domestic appliances with self-contained electric motor, which includes vacuum cleaners, food processors, and similar items where PFOA-based surfactants and fluoropolymers have been historically employed in anti-adhesive or insulating materials. The other two categories, "9019200000" (ozone therapy, oxygen therapy, aerosol therapy or artificial respiration apparatus) and "9022140000" (X-ray apparatus for medical or veterinary use), show a smaller number of notifications (12 each) but are technologically relevant, since both correspond to medical and diagnostic equipment, where PFOA may appear in coatings, gaskets, and plasticized components. Overall, the concentration of notifications in these categories reflects the diffuse but uneven presence of PFOA across complex manufactured goods and highlights how regulatory exposure under REACH tends to cluster in high-technology and durable-goods sectors. This evidence also supports the rationale for constructing product-level exposure indices: the intensity of SCIP notifications is not uniformly distributed across the nomenclature but concentrated in specific product classes that are particularly relevant for the manufacturing value chain.

Table 2 - Ranking of the 4 product categories with the highest frequencies of appearance in the SCIP database

Product category (TARIC-10 code)	Number of notifications
9033009000	1905
8509800000	195
9019200000	12
9022140000	12

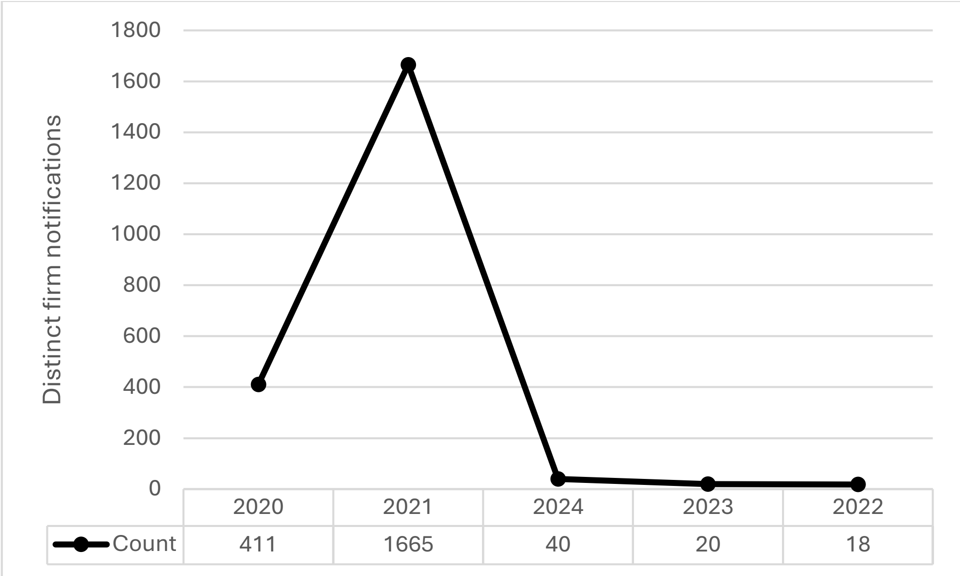
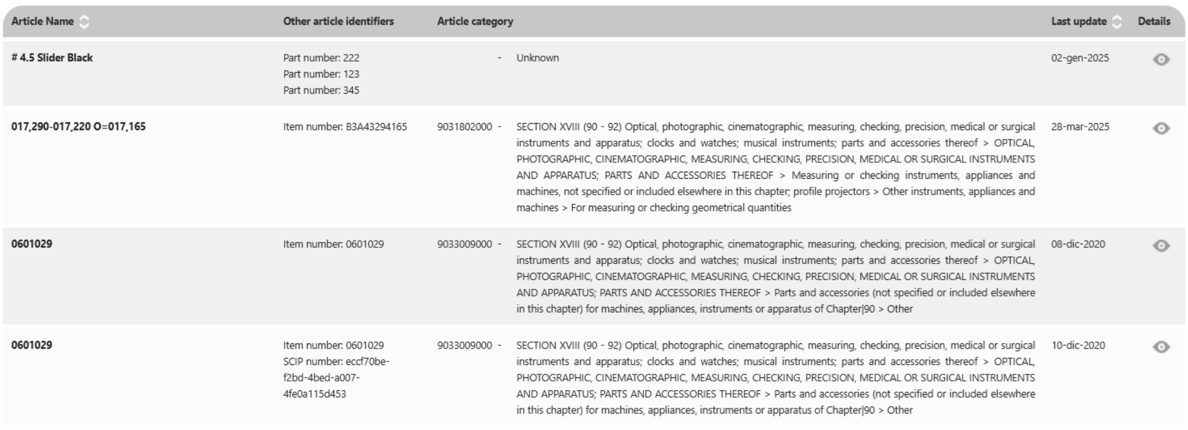


Figure 13 - Time distributions of EU firms' notifications of product containing PFOA on SCIP Database

Each record in SCIP identifies a specific product category using a TARIC 10-digit code, which represents the most granular classification of traded products in the EU customs system. The frequency of SCIP notifications per TARIC code is used as the numerator of the exposure index defined in Chapter 4, capturing the regulatory intensity associated with each product *j*.This measure reflects the degree to which a product category is directly affected by PFOA-related regulation, accounting for the prevalence of SCIP notifications as a proxy for regulatory exposure within the EU industrial system.



Article Name	Other article identifiers	Article category		Last update	Details
# 4.5 Slider Black	Part number: 222 Part number: 123 Part number: 345	-	Unknown	02-gen-2025	
017,290-017,220 O=017,165	Item number: B3A43294165	9031802000 -	SECTION XVIII (90 - 92) Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; clocks and watches; musical instruments; parts and accessories thereof > OPTICAL, PHOTOGRAPHIC, CINEMATOGRAPHIC, MEASURING, CHECKING, PRECISION, MEDICAL OR SURGICAL INSTRUMENTS AND APPARATUS; PARTS AND ACCESSORIES THEREOF > Measuring or checking instruments, appliances and machines, not specified or included elsewhere in this chapter; profile projectors > Other instruments, appliances and machines > For measuring or checking geometrical quantities	28-mar-2025	
0601029	Item number: 0601029	9033009000 -	SECTION XVIII (90 - 92) Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; clocks and watches; musical instruments; parts and accessories thereof > OPTICAL, PHOTOGRAPHIC, CINEMATOGRAPHIC, MEASURING, CHECKING, PRECISION, MEDICAL OR SURGICAL INSTRUMENTS AND APPARATUS; PARTS AND ACCESSORIES THEREOF > Parts and accessories (not specified or included elsewhere in this chapter) for machines, appliances, instruments or apparatus of Chapter|90 > Other	08-dic-2020	
0601029	Item number: 0601029 SCIP number: eccf70be-f2bd-4bed-a007-4fe0a115d453	9033009000 -	SECTION XVIII (90 - 92) Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; clocks and watches; musical instruments; parts and accessories thereof > OPTICAL, PHOTOGRAPHIC, CINEMATOGRAPHIC, MEASURING, CHECKING, PRECISION, MEDICAL OR SURGICAL INSTRUMENTS AND APPARATUS; PARTS AND ACCESSORIES THEREOF > Parts and accessories (not specified or included elsewhere in this chapter) for machines, appliances, instruments or apparatus of Chapter|90 > Other	10-dic-2020	

Figure 14 - Sample of records extracted by the SCIP database, filtered by the SVHC corresponding to PFOA

5.1.2 Product classification

To ensure cross-database cooperability, the SCIP product codes (TARIC 10-digit) were aligned with international classification systems:

- *TARIC (10-digit)*: used by EU customs authorities to classify goods for trade and regulatory purposes
- *CN (Combined Nomenclature, 8-digit)*: used by Eurostat and national statistical institutes (e.g., ISTAT) to record intra-EU and extra-EU trade
- *HS (Harmonized System, 6-digit)*: international classification maintained by the World Customs Organization, used by global trade databases like UN Comtrade

The mapping process follows a hierarchical approach. TARIC-10 codes are first truncated to obtain corresponding CN-8 codes, which are then truncated further to HS-6 codes. This procedure preserves the link between highly detailed SCIP entries and the trade data available at international level.

For instance, a hypothetical TARIC code “3920102400” (representing a polymer article) corresponds to CN8 “39201024” and HS6 “392010.” Through this mapping, the presence of PFOA in EU product categories can be associated with specific HS6 codes observed in trade statistics, ensuring consistency in subsequent normalization steps of the exposure index.

$$\underbrace{3920102400}_{TARIC-10} \rightarrow \underbrace{39201024}_{CN-8} \rightarrow \underbrace{392010}_{HS-6}$$

5.1.3 UN Comtrade Database

The UN COMTRADE database, maintained by the United Nations Statistics Division, provides harmonized bilateral trade statistics at the HS-6 level for all countries. In this thesis, COMTRADE data are used to measure the trade intensity of each product category identified in SCIP, focusing on European Union trade flows (both intra- and extra-EU, aggregated at the EU-27 level) over the 2020–2024 period. This temporal scope ensures consistency with the SCIP database, which became operational in 2020.

In the construction of the product-level exposure index, the numerator reflects the number of SCIP notifications for products containing PFOA, while the denominator represents the relative share of each HS-6 product category in the total EU trade (imports plus exports) during 2020–2024. This normalization allows us to account for differences in trade volume across product categories, ensuring that the exposure measure captures the intensity of regulatory involvement rather than mere trade scale.

It is acknowledged that using EU-level trade data, while convenient and internally consistent, may introduce some degree of endogeneity, since REACH regulation applies uniformly to all

EU member states. Consequently, trade volumes may themselves be partially shaped by the regulation under study. However, given the complexity of accurately isolating extra-EU trade data at the same level of product disaggregation, this approach is considered an acceptable simplification for the present stage of analysis. Future refinements could address this limitation by constructing alternative exposure indices normalized on extra-EU flows only, thereby improving exogeneity.

Period	Trade Flow	Reporter	Partner	2nd Partner	Customs Desc	Transport Mode	Commodity Code	Trade Value (US$)	Net Weight(kg)	Gross Weight	Qty Unit	Qty	Alternate Quantity unit	Alternate Quantity
2020	M	Austria	World	World	TOTAL CPC	TOTAL MOT	280110	$2,527,464	13,763,100	0	kg	13,763,100	kg	13,763,100
2020	M	Belgium	World	World	TOTAL CPC	TOTAL MOT	280110	$4,163,241	21,240,077	0	kg	21,240,077	kg	21,240,077
2020	X	Belgium	World	World	TOTAL CPC	TOTAL MOT	280110	$5,619,271	21,517,466	0	kg	21,517,466	kg	21,517,466
2020	M	Bulgaria	World	World	TOTAL CPC	TOTAL MOT	280110	$578,380	2,504,010	0	kg	2,504,010	kg	2,504,010
2020	X	Bulgaria	World	World	TOTAL CPC	TOTAL MOT	280110	$738,074	894,100	0	kg	894,100	kg	894,100
2020	M	Austria	World	World	TOTAL CPC	TOTAL MOT	280120	$261,829	9,269	0	kg	9,269	kg	9,269
2020	X	Austria	World	World	TOTAL CPC	TOTAL MOT	280120	$16,257	833	0	kg	833	N/A	0
2020	M	Belgium	World	World	TOTAL CPC	TOTAL MOT	280120	$159,195,069	4,553,444	0	kg	4,553,444	kg	4,553,444

Figure 15 - Sample extracted from UN Comtrade related to trade information between EU countries and the rest of the world for the year 2020, involving product categories containing PFOA, previously identified through the SCIP Database

To complement the regulatory information derived from SCIP, *Table 2* presents the trade values associated with the same four product categories in EU transactions with the rest of the world over the period 2020–2024, according to the UN COMTRADE database.

The data reveal that products in these categories account for substantial international trade flows, confirming their economic significance. In particular, TARIC "9019200000" exhibits the highest trade value, exceeding 34 billion USD, followed by "8509800000" and "9022140000", both above 26 billion USD, and finally 9033 00 90 00 with approximately 11.7 billion USD in total trade value.

The comparison between Tables 1 and 2 provides an important insight: while 9033009000 records the highest number of SCIP notifications, it is not the category with the largest trade value. This suggests that regulatory intensity and trade scale do not necessarily coincide. A high number of SCIP notifications reflect greater regulatory scrutiny or prevalence of PFOA use within the product type, rather than simply a higher trade volume. Conversely, categories with large trade flows but relatively fewer notifications may indicate a lower regulatory burden per traded unit, possibly due to earlier substitution of PFOA or limited presence of the substance in those products.

These patterns support the methodological approach adopted in this thesis, which normalizes the number of SCIP notifications by trade intensity, to derive a product-level exposure index. This measure captures both the extent of regulatory reporting (SCIP) and the economic relevance of each product category (COMTRADE), thus providing a balanced proxy for the potential impact of REACH restrictions on trade and firm performance.

Table 3 - Values of transactions between EU and the rest of the world for the 4 product categories with the highest frequencies of appearance in the SCIP database, during the period between 2020 and 2024

Product category (TARIC-10 code)	Trade Value (US$)
9033009000	11.730.310.825,86
8509800000	33.068.180.663,38
9019200000	34.178.379.652,25
9022140000	26.422.526.804,87

5.1.4 COEWEB–ISTAT Firm-level trade data Database

The COEWEB–ISTAT database constitutes the key source for firm-level trade data. Managed by the Italian National Institute of Statistics (ISTAT), COEWEB provides detailed information on imports and exports by firm, year, product category at CN-8-digit level, and partner country. This microdata allows researchers to trace firms' international trade activity with a high degree of disaggregation, linking each transaction to a specific product classification and firm identifier.

Although direct access to COEWEB microdata is restricted, in this thesis firm-level trade data were obtained from a specific dataset that reproduces the structure and variables of COEWEB, including firm identifiers, product codes, and trade values.

Each firm is assigned an ATECO 2007 code that identifies its main industry of activity. In the analytical framework, these codes are used at the three-digit level (`ateco2007impr_3d`) to define homogeneous industrial sectors for comparison between treated and control firms. This level of aggregation provides a balance between sectoral specificity and sufficient sample size for statistical inference.

The population analyzed includes firms from all manufacturing sectors (ATECO divisions 10–33), without pre-selection of industries presumed to be more exposed to REACH. The sample used in the analysis represents approximately 50% of total recorded transactions, corresponding to over 18 million firm-product-year observations, ensuring broad coverage of Italian trade activity.

These data are then merged with firm-level balance-sheet and ownership data from the AIDA database (Bureau van Dijk) to include variables such as turnover, employment, fixed assets, R&D expenditure, and profitability, which serve as dependent or control variables in the econometric analysis, as well explained in the next paragraph.

	year	NC8	NC8_str	ateco2007	ateco2~7_str	firmid	paese	provincia	movim	import_val	export_val
1	2008	1.00e+07	10011000	1111	1111	2653	6	PA	9	.	1312410
2	2008	1.00e+07	10011000	1111	1111	4947	4	MN	9	.	444296
3	2008	1.00e+07	10011000	1111	1111	369	9	SS	8	729157	.
4	2008	1.00e+07	10011000	1111	1111	4362	38	AL	8	73502	.
5	2008	1.00e+07	10011000	1111	1111	3482	9	PZ	8	1769063	.
6	2008	1.00e+07	10011000	1111	1111	1639	66	FG	9	.	34200
7	2008	1.00e+07	10011000	1111	1111	2003	1	PR	8	110802	.
8	2008	1.00e+07	10011000	1111	1111	2003	4	PR	9	.	1760
9	2008	1.00e+07	10011000	1111	1111	2003	66	PR	9	.	58600
10	2008	1.00e+07	10011000	1111	1111	117	11	FE	9	.	14068
11	2008	1.00e+07	10011000	1111	1111	2577	17	PR	9	.	3021

Figure 16 - COEWEB–ISTAT and AIDA data merging output extraction

Table 4 reports the ten firm–year combinations with the highest values of the variable `share_exposed`, which, as seen in *Chapter 4*, reflects the degree of exposure of each firm to the REACH regulation through its participation in markets for products subject to regulatory scrutiny.

The results highlight that some firms exhibit exceptionally high exposure levels, with values consistently above 0.99, indicating that nearly the entirety of their trade activity concerns PFOA-containing products. The data suggests that these firms are highly specialized in specific product categories that rely structurally on PFOA or related fluorinated compounds.

The firms appearing in this ranking belong to heterogeneous industrial sectors, as indicated by their ATECO codes, which include activities such as manufacture of instruments for measurement and testing ("279009"), production of electrical components ("289100"), and manufacture of machinery and mechanical equipment ("273300", "310120"). This diversity confirms that PFOA use is not confined to the chemical industry, but extends to a range of downstream manufacturing processes, particularly in electronics, electromechanical equipment, and precision instruments, consistent with the product categories most frequently reported in the SCIP database.

Geographically, the provinces associated with these firms (e.g., Milan, Bergamo, Turin, Venice, and Treviso) correspond to Northern Italy's industrial clusters, where high-tech manufacturing and export-oriented production are concentrated. This spatial pattern further supports the interpretation that exposure to REACH restrictions on PFOA predominantly concerns technologically advanced and internationally integrated firms. These firms are expected to represent the treatment group most responsive to policy shocks in the subsequent econometric analysis.

Table 4 - Top 10 of firm-year combinations with the highest share_exposed index

anno	n_firm	ATECO code	tot_export_anno	tot_import_anno	prov	share_exposed
2010	1818	310120	258.487	1.686	CT	.9935197
2010	12206	279009	1.172.030	1.363.509	TV	.9913462
2010	15144	289100	98	270.236	GO	.9913662
2010	19092	273300	313.264	1.216	AT	.9961333
2010	33413	279009	3.027.986	7.472	BG	.9975384
2010	50244	279009	12.298	450.010	VE	.9950985
2011	6933	201100	0	233.166	BS	.9962602
2011	33413	279009	3409.881	28.843	MI	.9913768
2011	77914	265129	0	196.977	MI	.9985278
2012	70831	181300	851.267	0	TO	.9924407

5.1.5 AIDA Database (Bureau van Dijk)

The AIDA (Analisi Informatizzata delle Aziende) database, maintained by Bureau van Dijk (Moody's Analytics), is the main repository of financial and ownership information for Italian firms. It collects standardized balance-sheet data, profit and loss accounts, corporate structure information, and key financial ratios for more than one million Italian enterprises. The database integrates official filings submitted to the Chamber of Commerce and ensures harmonization across firms and years, which makes it one of the most reliable sources for firm-level financial analysis in Italy.

In the context of this thesis, AIDA provides the microeconomic foundation necessary to evaluate how exposure to REACH regulation measured through trade and product-level information, translates into economic and strategic firm outcomes. Specifically, the database includes detailed variables that allow the construction of key performance indicators, such as:

- **Turnover** `(production_value)`: the total value of goods and services produced by the firm, used as a primary dependent variable in the econometric analysis to capture changes in firm performance
- **Personnel costs** `(personnel_costs)`: reflecting the total labor costs incurred by the firm, which allow the assessment of employment and wage dynamics

- **Material and service costs** `(materials, services)`: representing input purchases that can be directly influenced by changes in input composition due to REACH restrictions
- **Added value** `(added_value)`: measuring the firm's contribution to production net of intermediate inputs, useful for productivity analyses
- **Intangible and tangible fixed assets** `(intangible_fixed_assets, tangible_fixed_assets)`: which capture investment in both physical capital and knowledge-based assets such as patents, trademarks, or R&D
- **R&D expenditure** `(rd)`: an indicator of innovation effort, relevant to testing the *Porter Hypothesis* that environmental regulation may stimulate technological innovation
- **Total employment** `(employees)`: used to study how regulation affects labor outcomes and firm size dynamics

Each firm in AIDA is identified by a unique tax code `(n_firm)`, which enables a one-to-one merge with trade data from the COEWEB–ISTAT database. Through this linkage, the dataset combines financial information, trade exposure, and regulatory risk into a single analytical framework.

This integration is crucial for two reasons. First, it allows the computation of firm-level exposure to REACH by weighing each firm's product-level exposure index by its trade shares, as described in Chapter 4.4. Second, it provides the dependent and control variables for the difference-in-differences regressions that estimate the impact of REACH on firm outcomes.

Moreover, the inclusion of detailed balance-sheet variables allows the estimation of heterogeneous effects, for example, whether larger firms, more innovative firms, or those more capital-intensive exhibit different adjustment paths following regulatory shocks.

Finally, the AIDA database ensures longitudinal consistency over time, enabling the construction of a panel structure that spans the period 2010–2022, covering both the pre- and post-treatment phases of PFOA regulation. This temporal dimension makes it possible to exploit the within-firm variation in outcomes before and after REACH restrictions, a key requirement for the econometric identification strategy discussed in Chapter 4.

5.2 Sampling Process

The construction of the empirical dataset involved several stages of data integration, harmonization, and filtering. The goal was to merge heterogeneous information from regulatory, trade, and financial sources into a coherent panel structure at the firm-year level. This section details the main steps taken to build the analytical sample.

The process began with the identification of product categories containing PFOA in the SCIP database, filtered through the chemical's CAS number (335-67-1). Each entry in SCIP corresponds to a 10-digit TARIC code and was subsequently converted to CN-8 and HS-6 codes, ensuring consistency with the classifications used in COEWEB–ISTAT and UN COMTRADE, respectively. The frequency of SCIP registrations per product code was computed and associated with the corresponding HS6-level trade data from COMTRADE, allowing the construction of a product-level exposure index as defined in Chapter 4.

The next step involved linking these product-level indices to firm-level trade data from COEWEB–ISTAT. The merge was performed by matching CN-8 product codes to firms' trade records (imports and exports) across the 2010–2022 period. For each firm-year observation, trade flows were divided into two groups:

- **"Exposed trade"**: the total value of trade in product categories identified as containing PFOA
- **"Total trade"**: the total value of all trade conducted by the firm in the same year.

The share of exposed trade (`share_exposed`) was then computed as the ratio between these two aggregates. This variable reflects the intensity of each firm's involvement in PFOA-related products, thus serving as the basis for identifying treatment status.

To ensure comparability across firms and time, the trade data were merged with firm-level identifiers (`n_firm`) and other key variables from AIDA, including turnover, costs, assets, and employment. The merging process was performed using unique tax codes and standardized year variables, producing a balanced dataset where each observation represents a firm i observed in year t.

The period of analysis spans from 2010 to 2022, aligning with both regulatory and data availability constraints. The years 2010–2012 constitute the pre-treatment baseline, prior to PFOA's inclusion in the REACH Candidate List, while 2013–2022 represent the treatment period, covering the progressive tightening of restrictions through REACH (2013–2019) and the transition to the POP Regulation (from 2020 onwards). The year 2020 itself was excluded from certain regressions due to the exceptional market distortions associated with the COVID-19 pandemic, which could bias firm performance indicators.

Following Autor et al. (2013, 2014), firms were classified into treatment and control groups based on their exposure to PFOA-related trade. The variable `ever_exposed_1012` was created as a binary indicator equal to 1 if a firm traded (imported or exported) any PFOA-containing product at least once during 2010–2012, and 0 otherwise. Treated firms are therefore those that were ever active in markets involving PFOA-related goods, while control firms belong to the same industrial sectors (ATECO 3-digit level) but were never exposed to PFOA.

This sectoral matching ensures that control firms are comparable in terms of production technology and market environment, while differing only in their regulatory exposure. When too few control firms were available at the 4-digit level, aggregation to the 3-digit level was applied to preserve sample representativeness.

To ensure data reliability, firm-year observations with missing financial or trade information were excluded. Outliers were identified based on extreme values of turnover growth (top and bottom 1%) and implausible trade-to-turnover ratios.

Although no explicit restriction was applied on firms' minimum presence in the dataset, the merging procedure between AIDA and COEWEB implicitly retains firms with sufficient continuity in reporting, thereby reducing the risk of including temporary or inactive entities The final dataset provides a rich micro-level view of Italian firms' responses to REACH-related regulatory shocks, combining product-level variation in exposure with firm-level financial dynamics and sectoral heterogeneity.

5.3 Dataset structure

The resulting dataset has a panel structure in which each observation corresponds to a firm-year pair (*i, t*). The dataset integrates regulatory, trade, and financial dimensions into a unified analytical framework.

At the core of the dataset are three distinct but interconnected layers:

- **Regulatory Layer**

  Derived from SCIP and COMTRADE, this layer provides the product-level exposure index that quantifies the regulatory intensity of each HS-6 category. The numerator of this index corresponds to the number of SCIP notifications for PFOA-related products (num_scip_j), while the denominator represents the share of each product's trade in the total EU trade (share_trade_j). This information is constant across firms but varies by product and time, reflecting the evolution of PFOA regulation between 2020 and 2024.

- **Trade Layer (Firm-Level Exposure and Activity)**

Based on COEWEB–ISTAT data, this layer provides the firm-level exposure and includes variables capturing firm-level trade behavior, such as:

  - tot_export_v_anno and tot_import_v_anno (total yearly exports and imports)
  - exposed_trade (sum of trade value in PFOA-related products)
  - share_exposed (ratio between exposed trade and total trade)
  - eu_import_share and eu_export_share (shares of trade with EU partners, used to capture trade orientation)

The binary variable ever_exposed_1012 defines treatment status, while the interaction ever_exposed_1012#i.year identifies the dynamic treatment effects in the regression models.

- **Financial Layer**

Extracted from AIDA, this layer includes key performance variables, both in levels and logarithmic transformations, to capture proportional effects and growth rates in firm-level outcomes:

  - lturnover (log of turnover, or production value);
  - lcosts, lpersonnel, lmaterial, lservices (log of cost components);
  - ladded_value (log of added value, used as productivity proxy);
  - lrd (log of R&D expenditure, available for a subset of firms).

Control variables include sector, province, and year dummies, as well as interaction fixed effects (i.year#i.sector, i.year#i.province), which capture unobserved shocks specific to industries and local economic environments.

The combination of these three layers allows the econometric analysis to exploit both cross-sectional and temporal variation in exposure and outcomes. The panel structure makes it possible to implement the difference-in-differences (DiD) approach described in Chapter 4, isolating the causal effect of REACH-related shocks on firm performance.

In total, the final dataset contains approximately 298,365 firm-year observations, covering the 2010–2022 period. Manufacturing firms dominate the sample, particularly in NACE sectors 20–22 (chemicals, rubber-plastics, and fabricated materials), 24–25 (metals and metal products), and 13–15 (textiles, leather, and apparel)—industries known to be sensitive to REACH obligations.

6 Results and Discussion

This chapter presents the econometric results obtained through the empirical strategy described in Chapter 4. The analysis investigates how Italian firms reacted to the progressive restriction of the substance PFOA under the REACH and POP regulations, focusing on a set of firm-level outcomes that reflect trade orientation, turnover dynamics, and investment decisions. As described before, the estimation exploits a difference-in-differences approach, comparing firms that have ever been exposed to PFOA-related products with those that have never traded goods containing such substances. This framework allows the isolation of the regulatory effect from other confounding factors that simultaneously affected all firms, such as macroeconomic fluctuations or the COVID-19 shock.

The baseline period considered for establishing the parallel trend assumption spans from 2010 to 2012, while the treatment period covers the years after 2013, following the inclusion of PFOA in the Candidate List and later in the Restriction and POP regulations. As discussed in Chapter 4, the variable `ever_exposed_1012` identifies treated firms. The interaction term between treatment status and year dummies captures the differential effect of REACH-related restrictions over time, after controlling for firm, year–sector, and province–year fixed effects.

The following sections present empirical results for the main outcome variables, such as imports, exports, turnover, costs, and intangible investments, followed by a discussion of the heterogeneity across firm size and sectors. All estimations have been performed using the `reghdfe` command in Stata, absorbing multi-dimensional fixed effects as specified in the methodological chapter. The key outcomes are grouped into the following analytical dimensions:

1. Trade Structure

This category includes indicators describing the geographic reallocation of trade flows, such as the share of imports sourced from the European Union and the share of exports directed toward EU markets. These outcomes allow us to examine whether firms responded to the regulatory constraints by restructuring their global supply chains, shifting toward suppliers or customers operating under the same regulatory framework.

2. Trade Intensity

The analysis further considers the total volume of imports and exports (in logarithmic form). These variables measure whether regulation-induced adjustments in supply-chain composition were accompanied by changes in overall trade intensity. For example, a reduction in total imports among firms facing higher compliance costs, or a potential decline in export volumes due to increased production frictions. Distinguishing between small and large firms permits evaluation of whether adjustment costs or efficiency losses were disproportionately borne by one size class.

3. Economic Performance

A second set of outcomes concerns firm activity and value creation, including turnover, added value, and wages scaled by turnover. These measures capture whether the regulation influenced firms' productive capacity, profitability, or labour-related expenditures. Distinguishing between small and large firms' permits evaluation of whether adjustment costs or efficiency losses were disproportionately borne by one size class.

4. Technological and Intangible Investment.

Finally, the analysis examines the evolution of intangible assets and intangible assets relative to turnover, proxies for innovation activity and R&D investment. These outcomes provide insight into whether firms reacted to regulatory pressure by investing in technological upgrading, redesigning production processes, or developing substitutes for restricted substances.

By structuring the results along these four dimensions, the chapter provides a comprehensive overview of how firms adapted to the environmental restrictions, whether through supply-chain reconfiguration, contraction or expansion of trade activities, changes in performance indicators, or through technologically driven innovation responses. The following sections discuss each category in turn, presenting the regression results and interpreting them in light of the regulatory timeline and the economic mechanisms described in the previous chapters.

6.1 Tools for pre-treatment validation

The *difference-in-difference* event-study design also allows us a direct test of the *parallel-trend assumption*, which requires that treated and untreated firms exhibit statistically indistinguishable trends before regulation. This scheme is verified for each of the outcomes explored below. In order to demonstrate the parallel-trend assumption, the coefficient related to the pre-treatment period must be very small in magnitude (≈ 0) and statistically insignificant, given the p-value much higher than 0,1. In fact, given the null hypothesis: "*there's no difference between the treatment and control groups*", the p-value measures the probability of observing a coefficient equal or much extreme as the estimated one, meaning that the difference-in-difference computed by β_t is almost zero, if the null hypothesis is true. This implies that the differences between treated and untreated firms are statistically indistinguishable from zero, confirming their economic negligibility, since that, prior to regulatory intervention, firms later classified as treated did not exhibit systematically different EU import behavior relative to the control group. In this way, the parallel-trend assumption holds, validating the causal interpretation of post-2013 effects.

A crucial preliminary consideration concerns the temporal structure of the estimated coefficients. Although the identification strategy is built on a pre-treatment baseline in 2010–2012, the regression table reports coefficients only from 2014 onward. This reflects a methodological choice: the years 2010–2012 are used primarily to define the sets of "treated" and "control" firms, and therefore coefficients referring to this period may be contaminated by endogenous variation, since those same years contribute to constructing the exposure variable that defines the regulatory shock. Consistent with this logic, we begin the analysis in a period where estimating dynamic effects has meaningful statistical validity. This specification ensures that each β_k coefficient captures the deviation of treated firms from their counterfactual trend relative to the final pre-treatment year.

6.2 Effects on Imports from EU

The first set of results concerns the evolution of the share of imports sourced from European Union partners (`eu_import_share`). *Table 4* reports the estimated coefficients from the baseline specification. The pattern of results reveals a clear temporal divide:

Table 5 - eu_import_share regression model results

`eu_import_share`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0013822	.0079605	0.17	0.862	-.0142205	.0169848
hopeXdum2015	-.0096902	.0079477	-1.22	0.223	-.0252679	.0058874
hopeXdum2016	-.0088108	.0079429	-1.11	0.267	-.0243789	.0067574
hopeXdum2017	-.0104421	.0079514	-1.31	0.189	-.0260269	.0051427
hopeXdum2018	.0347314	.0082548	4.21	0.000	.018552	.0509108
hopeXdum2019	.034087	.008246	4.13	0.000	.0179248	.0502491
hopeXdum2020	.036491	.0082814	4.41	0.000	.0202594	.0527226
hopeXdum2021	.0369474	.0082117	4.50	0.000	.0208525	.0530423

hopeXdum2022	.0305622	.0082382	3.71	0.000	.0144153	.0467092
_cons	.450752	.0028221	159.72	0.000	.4452207	.4562833

In the early post-treatment years (2014–2017), all coefficients are small, close to zero, and statistically insignificant. For example, the 2014 coefficient is 0.0014 ($p = 0.862$), indicating that treated and untreated firms show indistinguishable sourcing patterns relative to the baseline. This absence of differential effects is fully consistent with the regulatory timeline: after PFOA's inclusion in the Candidate List, firms were primarily in an informational phase, and significant compliance adjustments had not yet materialized.

A marked change emerges from 2018 onward. The coefficient for 2018 increases sharply to 0.0347 and is highly statistically significant ($p < 0.001$). Positive and significant effects persist in 2019 (0.0348), 2020 (0.0365), 2021 (0.0369) and remain sizeable in 2022 (0.0306). These estimates indicate that exposed firms substantially increased their reliance on EU suppliers relative to the control group once the 2017 Annex XVII restriction became operational. The magnitude of the effect is stable, consistently between 0.03 and 0.04, suggesting that firms did not merely undertake a transitory adjustment but rather restructured their procurement strategies in a persistent manner.

6.2.1 Interpretation of the results

This pattern aligns closely with the institutional environment generated by the REACH restriction. From 2017, firms using or importing PFOA became subject to stricter obligations concerning concentration thresholds, traceability, and documentation. In practice, sourcing from EU suppliers substantially reduces the firm-level cost of compliance: while non-EU imports require the *importing firm* to certify conformity with REACH, EU suppliers automatically bear this responsibility. As a result, shifting purchases toward EU-based partners is a rational strategy that mitigates compliance risks and secures a more reliable supply of certified materials. The stability of the estimated coefficients further suggests that, once reorganized, supply chains became "locked in" due to sunk compliance investments and the strategic value of sourcing within a harmonized regulatory space.

6.2.2 Heterogeneity between small and large firms

To deepen the interpretation of the results obtained in the main specification, the analysis is extended by distinguishing between small and large firms according to the baseline employment level. The variable `small_1012`, equal to one for firms with fewer than fifty employees in 2010–2012, enables a comparison between SMEs and larger enterprises in their adjustment to the regulatory shock. This distinction is important because REACH compliance imposes both informational and procedural costs whose relative burden is likely to differ substantially across firms of different sizes.

Table 6 - eu_import_share regression model results when small_1012=0

`eu_import_share`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0106415	.0126994	0.84	0.402	-.0142501	.0355331
hopeXdum2015	-.0045049	.0126935	-0.35	0.723	-.029385	.0203752
hopeXdum2016	.0010574	.0126741	0.08	0.934	-.0237848	.0258996
hopeXdum2017	-.0079824	.0126885	-0.63	0.529	-.0328527	.016888
hopeXdum2018	.0612035	.0130174	4.70	0.000	.0356885	.0867185
hopeXdum2019	.0483908	.0130209	3.72	0.000	.022869	.0739127
hopeXdum2020	.050884	.0130588	3.90	0.000	.0252878	.0764803
hopeXdum2021	.0404327	.0130342	3.10	0.002	.0148847	.0659807
hopeXdum2022	.0429062	.0130495	3.29	0.001	.0173283	.0684841
_cons	.5481952	.0059618	91.95	0.000	.5365097	.5598807

The results for large firms (`small_1012 = 0`) presented in *Table 5* closely mirror those of the main specification. Coefficients remain statistically indistinguishable from zero up to 2017, confirming the absence of pre-trends. From 2018, however, the effects become positive, significant, and persistent: the estimated impact is 0.0612 in 2018, stabilizing between 0.04 and 0.05 in the following years, and remaining significant in 2022. Despite some natural year-to-year variation, the coefficients fall within a narrow and stable interval, suggesting a durable reorientation toward EU suppliers. This behavior aligns with the organizational capabilities of large firms, which typically possess dedicated compliance units, structured procurement systems, and stronger bargaining power in supplier negotiations. For these firms, shifting sourcing toward REACH-compliant EU suppliers is both feasible and economically rational.

Table 7 - eu_import_share regression model results when small_1012=1

`eu_import_share`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0041472	.0111723	-0.37	0.710	-.0260454	.017751

hopeXdum2015	-.0127936	.0111393	-1.15	0.251	-.0346271	.0090399
hopeXdum2016	-.0167441	.0111418	-1.50	0.133	-.0385826	.0050943
hopeXdum2017	-.0134806	.0111536	-1.21	0.227	-.0353421	.0083809
hopeXdum2018	-.0319423	.011657	-2.74	0.006	-.0547905	-.0090942
hopeXdum2019	-.0291206	.0116523	-2.50	0.012	-.0519595	-.0062818
hopeXdum2020	-.0233624	.011714	-1.99	0.046	-.0463222	-.0004025
hopeXdum2021	-.0225212	.0115731	-1.95	0.052	-.045205	.0001626
hopeXdum2022	-.0318236	.011622	-2.74	0.006	-.0546031	-.0090441
_cons	.3889072	.0030354	128.12	0.000	.3829577	.3948567

The results for small firms (`small_1012 = 1`) show a distinctly different pattern. Throughout most of the period, coefficients remain close to zero and statistically insignificant, indicating that SMEs did not meaningfully adjust their sourcing behavior compared to their non-treated counterparts. Notably, only in 2018 and 2019 do the coefficients become statistically significant, and in these years the signs are *negative* (–0.0319 in 2018 and –0.0291 in 2019), suggesting a temporary reduction in the share of imports from EU partners among treated SMEs. However, the magnitude of these effects is very small and the significance does not persist from 2020 onward, when coefficients return to values statistically indistinguishable from zero.

6.2.3 Interpretation of the results

Several mechanisms may explain this size-based heterogeneity. Larger firms typically possess more structured procurement departments, established international networks, and internal compliance units capable of managing the documentation, auditing and verification requirements imposed by REACH. As a result, shifting toward certified EU suppliers, who directly assume responsibility for compliance, constitutes a rational, cost-effective adjustment. Moreover, because large manufacturers often operate in complex value chains where input conformity affects downstream clients, adopting EU-based sourcing ensures higher regulatory certainty and reduces the probability of costly disruptions. Small firms, in contrast, may lack the organizational infrastructure required for a rapid or systematic adjustment. SMEs tend to manage supplier relationships in a path-dependent manner and may absorb regulatory costs through informal arrangements or ad hoc reactions rather than through strategic redesign of their entire sourcing structure. In addition, when dealing with EU suppliers implies higher prices or contract renegotiation, small firms may be less able to internalize these costs compared to larger firms with stronger bargaining power or economies of scale.

In summary, while large, exposed firms consistently increased their reliance on EU suppliers after 2017, small firms did not exhibit a comparable strategic shift. The regulatory shock thus appears to have produced size-dependent supply-chain reconfigurations, driven by the differential ability of firms to internalize and operationalize compliance requirements.

6.3 Effects on Total Imports

The second outcome examined is the logarithm of firms' total imports (`limport`). As in the previous section, the analysis is conducted for all firms and then separately for small firms (firms with fewer than fifty employees in 2010–2012, `small_1012 = 1`) and large firms (`small_1012 = 0`). This distinction is essential, since the ability to absorb regulatory shocks—such as those generated by the PFOA restriction, likely differs substantially across size classes. *Table 7* presents the results for the comprehensive group of firms:

Table 8 - limport regression model results

`limport`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0051312	.0358327	-0.14	0.886	-.0753635	.065101
hopeXdum2015	-.0102774	.0357751	-0.29	0.774	-.0803969	.0598421
hopeXdum2016	-.0504198	.0357533	-1.41	0.158	-.1204965	.019657
hopeXdum2017	-.0607264	.0357916	-1.70	0.090	-.1308782	.0094253
hopeXdum2018	.0073057	.0371571	0.20	0.844	-.0655225	.0801339
hopeXdum2019	.0458664	.0371175	1.24	0.217	-.0268841	.1186169
hopeXdum2020	.0238183	.037277	0.64	0.523	-.0492449	.0968815
hopeXdum2021	.0122115	.0369631	0.33	0.741	-.0602363	.0846593
hopeXdum2022	-.0246853	.0370826	-0.67	0.506	-.0973675	.0479968
_cons	14.55466	.0255325	570.04	0.000	14.50462	14.60471

The estimates reported in Table 7 show that the coefficients remain statistically insignificant throughout the entire 2014–2022 period. The pre-treatment years (2014–2018) display small negative coefficients, none of which reach statistical significance, thereby supporting the parallel-trend assumption and indicating no evidence of anticipatory adjustment among exposed firms.

In the post-treatment period, the pattern remains broadly flat. The coefficient for 2019 (0.046) is close to zero and highly insignificant, and the same holds for 2020 (0.024), 2021 (0.012), and 2022 (–0.025). Despite minor fluctuations in terms of sign, none of the estimates suggest a systematic increase or decrease in total import volumes for treated firms relative to the control group. This absence of an aggregate effect implies that, when small and large firms are pooled together, the average response of exposed firms appears neutral.

6.3.1 Interpretation of the results

The lack of significance in the full sample, however, should not be interpreted as evidence that the regulatory shock had no impact on firms' import behavior. Instead, the aggregate neutrality is the result of offsetting adjustments by firms of different sizes. As shown in the subsequent subsections, small firms experienced a sizeable and persistent contraction in total imports after 2018, whereas large firms increased their total import volumes over the same period. These two forces move in opposite directions and effectively cancel each other out when estimated jointly. The full-sample model therefore masks substantial underlying heterogeneity and highlights the importance of analysing differential responses across firm size classes.

This result is highly informative: it demonstrates that examining only the average effect of the regulation would lead to the misleading conclusion that the PFOA restriction had no material impact on firms' trade volumes. Instead, the regulation induced a redistribution of import activity across the firm-size distribution, with large firms expanding and small firms contracting. The neutrality of the full-sample coefficients is thus an artefact of aggregation rather than an indication of regulatory irrelevance.

6.3.2 Heterogeneity between small and large firms

To deepen the interpretation of the results obtained in the main specification, the analysis is extended by distinguishing between small and large firms according to the baseline employment level. The variable `small_1012`, equal to one for firms with fewer than fifty employees in 2010–2012, enables a comparison between SMEs and larger enterprises in their adjustment to the regulatory shock. This distinction is important because REACH compliance imposes both informational and procedural costs whose relative burden is likely to differ substantially across firms of different sizes.

Table 9 - limport regression model results when small_1012=0

limport	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0262809	.0543874	0.48	0.629	-.0803221	.132884
hopeXdum2015	.0151824	.0543623	0.28	0.780	-.0913713	.1217362
hopeXdum2016	.0145926	.0542794	0.27	0.788	-.0917988	.1209839
hopeXdum2017	.0200736	.0543409	0.37	0.712	-.0864383	.1265855
hopeXdum2018	.13768	.0557496	2.47	0.014	.028407	.2469529
hopeXdum2019	.1768465	.0557644	3.17	0.002	.0675443	.2861486
hopeXdum2020	.1659123	.055927	2.97	0.003	.0562916	.275533
hopeXdum2021	.0926032	.0558216	1.66	0.097	-.016811	.2020173
hopeXdum2022	.0749872	.0558869	1.34	0.180	-.0345549	.1845293
_cons	14.55466	.0255325	570.04	0.000	14.50462	14.60471

For large enterprises, the coefficients for the period 2014–2017 are close to zero and statistically insignificant, confirming the absence of differential pre-trends and supporting the validity of the identification strategy. Beginning in 2018, however, the pattern changes sharply. The coefficient for 2018 is positive (+0.138) and statistically significant, followed by similarly large and significant estimates in 2019 (+0.177) and 2020 (+0.166). Although the coefficients for 2021 (+0.093) and 2022 (+0.075) are slightly smaller, they remain positive and economically quite meaningful. These results indicate that, after the implementation of the Annex XVII restriction, exposed large firms increased the scale of their importing activity relative to non-treated peers.

The magnitude and persistence of these effects suggest a structural adjustment rather than a short-lived reaction. Combined with the strong increase in the share of imports sourced from EU partners (see *Section 7.2*), the results point to a pattern in which large firms not only reoriented their supply chains toward REACH-compliant suppliers but did so while expanding the overall volume of imported intermediate inputs. This behavior is consistent with the organizational capabilities typically available to large firms: dedicated compliance units, specialized procurement departments and the financial capacity to absorb fixed regulatory costs. These firms appear to have responded to the tightening of PFOA restrictions by upgrading or reorganizing their input sourcing rather than contracting their activity.

Table 10 - limport regression model results when small_1012=1

limport	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0172056	.0521231	-0.33	0.741	-.1193689	.0849577
hopeXdum2015	-.0065699	.0519692	-0.13	0.899	-.1084314	.0952916
hopeXdum2016	-.0641843	.0519809	-1.23	0.217	-.1660689	.0377003
hopeXdum2017	-.0879036	.0520358	-1.69	0.091	-.1898959	.0140886
hopeXdum2018	-.1905739	.0543842	-3.50	0.000	-.2971691	-.0839788
hopeXdum2019	-.1346655	.0543622	-2.48	0.013	-.2412175	-.0281134
hopeXdum2020	-.106913	.05465	-1.96	0.050	-.2140292	.0002031
hopeXdum2021	-.1056841	.0539931	-1.96	0.050	-.2115126	.0001443
hopeXdum2022	-.1360237	.0542208	-2.51	0.012	-.2422986	-.0297487
_cons	12.48814	.0141613	881.85	0.000	12.46039	12.5159

The results for small firms display a markedly different trajectory. As with large firms, the pre-treatment years show coefficients that are small, statistically insignificant, and oscillating around zero, even if it’s possible to denote an initial meaningful decreasing trend in 2017.This confirms the absence of anticipatory adjustments among SMEs and reinforces the parallel-trend assumption.

A clear turning point emerges in 2018. The coefficient for that year becomes strongly negative (–0.191) and highly significant, and this pattern persists in subsequent years: –0.135 in 2019, –0.106 in 2020, –0.106 again in 2021, and –0.136 in 2022. These estimates indicate that exposed SMEs substantially reduced their total import volumes once the REACH restriction became binding. The contraction is persistent, relatively stable in magnitude, and economically large.

This behavior likely reflects the structural limitations faced by small firms. SMEs often lack specialised compliance personnel, operate with thinner financial buffers, and depend on a narrower set of suppliers. For these firms, the new documentation, traceability, and certification requirements associated with the PFOA restriction may have raised the marginal cost of importing PFOA-related intermediates to an unsustainable level. As a result, many small, exposed firms appear to have responded not by reorganizing their sourcing networks but by downsizing or exiting product lines dependent on regulated inputs.

6.3.3 Interpretation of the results

Taken together, the results reveal a pronounced size-based divergence in the way firms adjusted their import behavior in response to regulatory tightening. Large firms expanded total imports and restructured supply chains, increasing reliance on REACH-compliant EU suppliers while maintaining or enlarging their production scale. On the other hand, small firms significantly contracted total imports, suggesting withdrawal from or downsizing of product segments affected by PFOA restrictions.

These findings highlight the differential capacity of firms to absorb regulatory shocks. Large firms were able to leverage financial resources, organizational capabilities, and bargaining power to adapt through expansion and restructuring. In contrast, SMEs, more vulnerable to compliance costs and input discontinuities, adjusted primarily through contraction.

This divergence highlights an important implication: environmental regulation does not affect all firms symmetrically. In the context of the PFOA restriction, this asymmetry manifests as an expansion of total imports among large firms and a reduction among SMEs, illustrating how regulatory pressure can shape the evolution of industrial structures.

6.4 Effects on Exports to EU

The third set of results concerns the evolution of the share of exports sourced from European Union partners (`eu_export_share`). *Table 10* reports the estimated coefficients from the baseline specification. The pattern of results reveals a clear temporal divide:

Table 11 - eu_export_share regression model results

`eu_export_share`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.005499	.0061212	0.90	0.369	-.0064985	.0174964
hopeXdum2015	.0011933	.006119	0.20	0.845	-.0107999	.0131865
hopeXdum2016	-.0020473	.0061181	-0.33	0.738	-.0140387	.0099441
hopeXdum2017	-.0023943	.0061139	-0.39	0.695	-.0143776	.0095891
hopeXdum2018	.0528631	.006144	8.60	0.000	.0408209	.0649054
hopeXdum2019	.0538648	.0061492	8.76	0.000	.0418123	.0659173
hopeXdum2020	.0355325	.0061408	5.79	0.000	.0234966	.0475685
hopeXdum2021	.0578232	.0061415	9.42	0.000	.0457859	.0698606
hopeXdum2022	.0406166	.0061692	6.58	0.000	.028525	.0527083

_cons	.4879931	.0019618	248.75	0.000	.484148	.4918383

The estimated coefficients for the full sample reveal a clear dichotomy between the pre-treatment and post-treatment periods. In the years preceding the 2017 restriction, namely 2014 to 2017, the coefficients remain extremely small, fluctuate around zero, and are statistically insignificant. These findings indicate that, prior to the implementation of the Annex XVII restriction, exposed and non-exposed firms displayed parallel trends in their EU export shares, thereby confirming the validity of the identification strategy and supporting the common-trend assumption.

A marked and economically significant shift occurs beginning in 2018. The coefficient for 2018 rises sharply to approximately 0.0529 and is highly statistically significant ($p < 0.001$). Positive and significant effects persist in all subsequent years: in 2019 the coefficient reaches 0.0539, remaining stable in magnitude and significance; in 2020 it stands at 0.0355; in 2021 it climbs again to 0.0578, the highest point estimate in the series, and remains substantial in 2022 at 0.0406. This sequence of large and statistically robust coefficients provides compelling evidence that, from 2018 onward, treated firms expanded the share of their exports directed toward EU markets relative to the control group.

6.4.1 Interpretation of the results

The magnitude and persistence of these effects suggest that the regulatory tightening surrounding PFOA induced a strategic reorientation not only in firms' sourcing patterns, as documented in the analysis of import shares, but also in their export strategies. Several mechanisms may explain this shift. First, compliance with REACH and subsequently with the POPs Regulation requires firms to demonstrate adherence to highly specific documentation, traceability, and concentration-threshold requirements. Since firms located within the EU operate under the same regulatory umbrella, EU customers may be perceived as more reliable recipients of compliant products and intermediates. This institutional symmetry reduces uncertainty and transactional risk for exposed firms, incentivizing a reallocation of commercial exchanges toward European partners.

The stability of the coefficients after 2018, consistently ranging between 0.035 and 0.058—indicates that the adjustment was not transient. Instead, it appears to have resulted in a lasting restructuring of firms' export portfolios, with treated firms consolidating their commercial presence within the Single Market as part of a broader compliance-oriented reorganization of their value chain.

6.4.2 Heterogeneity between small and large firms

To complement the main specification, the analysis distinguishes between small firms (fewer than 50 employees in 2010–2012) and larger firms, in order to examine whether firm size shapes the capacity to adjust export patterns following the PFOA restriction. This distinction captures structural differences in organizational capabilities, regulatory compliance mechanisms, and exposure to external shocks. The regression results for both subsamples are reported in Tables 11 and 12.

Table 12 - eu_export_share regression model results when small_1012=0

`eu_export_share`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0013916	.0082534	-0.17	0.866	-.0175688	.0147857
hopeXdum2015	.0078504	.0082536	0.95	0.342	-.0083271	.024028
hopeXdum2016	.0081278	.0082453	0.99	0.324	-.0080335	.024289
hopeXdum2017	.0061268	.0082466	0.74	0.458	-.010037	.0222907
hopeXdum2018	.0300439	.0082668	3.63	0.000	.0138405	.0462473
hopeXdum2019	.0219254	.008267	2.65	0.008	.0057215	.0381294
hopeXdum2020	.0202411	.0082749	2.45	0.014	.0040217	.0364605
hopeXdum2021	.0236497	.0082672	2.86	0.004	.0074454	.039854
hopeXdum2022	.0210657	.008288	2.54	0.011	.0048208	.0373107
_cons	.5612397	.0037702	148.86	0.000	.5538499	.5686295

For large firms, the estimated coefficients for the pre-treatment period (2014–2017) remain small, close to zero, and statistically insignificant, confirming once again the plausibility of the parallel-trend assumption. Beginning in 2018, coinciding with the transition from the adoption of the Annex XVII restriction to its progressive implementation, the coefficients become positive, significant, and strikingly stable. In 2018 the estimated effect is approximately 0.0300, followed by values of 0.0219 in 2019, 0.0202 in 2020, 0.0236 in 2021, and 0.0211 in 2022. Despite minor fluctuations, all coefficients lie within a narrow and consistent interval around 0.02–0.03. This pattern indicates a persistent and systematic expansion of the EU share of exports among treated large firms. The stability of this trajectory suggests a strategic realignment of export markets: as REACH obligations became more demanding, large firms increasingly favored EU partners, who operate under harmonized compliance and documentation requirements. Such firms possess structured compliance departments and diversified export portfolios, allowing them to internalize regulatory adjustments smoothly and with minimal disruption.

Table 13 - eu_export_share regression model results when small_1012=1

eu_export_share	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0113729	.0090614	1.26	0.209	-.0063877	.0291334
hopeXdum2015	.0019834	.0090592	0.22	0.827	-.0157727	.0197396
hopeXdum2016	-.0026844	.0090597	-0.30	0.767	-.0204417	.0150729
hopeXdum2017	-.0033551	.0090549	-0.37	0.711	-.021103	.0143928
hopeXdum2018	.0188774	.0091098	2.07	0.038	.0010219	.0367329
hopeXdum2019	.0241705	.0091256	2.65	0.008	.0062842	.0420568
hopeXdum2020	.0068193	.0091057	0.75	0.454	-.011028	.0246666
hopeXdum2021	.0280733	.0091133	3.08	0.002	.0102111	.0459355
hopeXdum2022	.017381	.0091599	1.90	0.058	-.0005726	.0353347
_cons	.4542653	.0021829	208.10	0.000	.4499866	.4585439

The dynamics for small firms differ in notable ways. Similar to the large-firm subsample, pre-treatment coefficients for 2014–2017 are insignificant and close to zero, reinforcing the validity of the identification strategy. From 2018 onwards, however, SMEs also exhibit positive and significant coefficients, indicating a reorientation toward EU export markets. Yet, the trajectory is far more irregular. The effect rises to about 0.0189 in 2018 and reaches 0.0241 in 2019, before dropping sharply in 2020 to approximately 0.0068, which is far less economically significant. This temporary contraction is followed by a renewed increase in 2021 (0.0281) and a marginally significant value in 2022 (0.0174). Such volatility is consistent with structural features of SMEs: these firms typically operate with narrower margins, fewer export destinations, and limited managerial resources, making them more vulnerable to external disturbances.

6.4.3 Interpretation of the results

Taken together, these findings indicate that both small and large firms reoriented their export strategies toward EU destinations following the PFOA restriction, but the adjustment process unfolded in markedly different ways. Large firms exhibit a stable, persistent, and economically meaningful increase in their EU export share, reflecting a structured and strategic adaptation to regulatory tightening. SMEs, by contrast, display stronger short-term responses but with greater volatility, indicating that their adaptation is more sensitive to concurrent shocks and less embedded in long-term strategic planning. From an interpretative standpoint, the behavior of large firms provides clearer evidence of a structural export realignment induced by REACH, while the more irregular trajectory of SMEs highlights the frictions and vulnerabilities that smaller enterprises face when regulatory changes intersect with broader economic disruptions.

6.5 Effects on Total Exports

The fourth set of results encompasses the analysis of the logarithm of total exports (`lexport`), which provides additional evidence on how firms adjusted their international sales strategies in response to the tightening of the regulatory framework surrounding PFOA. As in the previous specifications, results are both aggregated and presented separately for small firms and larger firms, in order to capture potential heterogeneity in the capacity to absorb regulatory shocks and reorganize commercial activities.

Table 14 - lexport regression model results

lexport	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0171184	.0260395	-0.66	0.511	-.0681559	.0339191
hopeXdum2015	-.0287987	.0260303	-1.11	0.269	-.0798181	.0222207
hopeXdum2016	-.0569753	.0260263	-2.19	0.029	-.1079869	-.0059637
hopeXdum2017	-.0753365	.0260088	-2.90	0.004	-.1263137	-.0243592
hopeXdum2018	.0422064	.0261367	1.61	0.106	-.0090215	.0934344
hopeXdum2019	.0693864	.0261589	2.65	0.008	.018115	.1206579
hopeXdum2020	.0784172	.0261229	3.00	0.003	.0272163	.1296182
hopeXdum2021	.056489	.0261261	2.16	0.031	.0052818	.1076962
hopeXdum2022	.0135928	.0262439	0.52	0.605	-.0378453	.0650309
_cons	14.42545	.0083455	1728.53	0.000	14.4091	14.44181

In the pooled sample, the pre-treatment coefficients are small, negative, and statistically insignificant until 2015, supporting the parallel-trend assumption. In 2016 and 2017 the trend starts to be decreasing and statistically significant. A positive effect starts in 2018, even with slightly less significance, rising from approximately 0.042 in 2018 to 0.069 in 2019 and 0.078 in 2020, all statistically significant at conventional levels. The effect remains positive in 2021 (0.056), though diminishing in magnitude, and becomes indistinguishable from zero again in 2022, when statistical significance goes down.

6.5.1 Interpretation of the results

Overall, these estimates indicate a temporary increase in total exports among treated firms in the years immediately following the regulatory tightening, but not a sustained long-term shift. This pattern points to short-lived adjustments possibly related to transitional strategies or demand-specific shocks, rather than to a structural export expansion induced by REACH.

6.5.2 Heterogeneity between small and large firms

To deepen the interpretation of the results obtained in the main specification, the analysis is extended by distinguishing between small and large firms according to the baseline employment level. The variable `small_1012`, equal to one for firms with fewer than fifty employees in 2010–2012, enables a comparison between SMEs and larger enterprises in their adjustment to the regulatory shock. This distinction is important because REACH compliance imposes both informational and procedural costs whose relative burden is likely to differ substantially across firms of different sizes.

Table 15 - lexport regression model results when small_1012=0

`lexport`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0083796	.0393606	-0.21	0.831	-.0855289	.0687698
hopeXdum2015	-.021021	.0393614	-0.53	0.593	-.0981718	.0561298
hopeXdum2016	-.0331077	.0393217	-0.84	0.400	-.1101808	.0439655
hopeXdum2017	-.048966	.0393279	-1.25	0.213	-.1260512	.0281193
hopeXdum2018	-.0006204	.0394243	-0.02	0.987	-.0778945	.0766537
hopeXdum2019	-.0257114	.0394255	-0.65	0.514	-.1029879	.0515651
hopeXdum2020	-.0175661	.0394632	-0.45	0.656	-.0949165	.0597842
hopeXdum2021	-.0129672	.0394264	-0.33	0.742	-.0902455	.0643111
hopeXdum2022	-.0424736	.0395253	-1.07	0.283	-.1199457	.0349985

_cons	16.00046	.01798	889.90	0.000	15.96522	16.0357

For larger enterprises, coefficients throughout the entire period remain close to zero, statistically insignificant, and do not display a coherent trend. The estimates for 2018–2022 fluctuate between –0.04 and +0.03, none of which reach statistical significance. This absence of detectable effects suggests that REACH did not materially influence the overall scale of exports among large firms, despite documented changes in the composition of their trade, specifically, the increase in exports directed to EU markets (see *section 7.4*). In other words, large firms reallocated where they exported, not how much they exported, keeping total export volumes largely unchanged.

Table 16 - lexport regression model results when small_1012=1

lexport	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0199812	.0374733	-0.53	0.594	-.0934297	.0534673
hopeXdum2015	-.0258894	.037464	-0.69	0.490	-.0993196	.0475409
hopeXdum2016	-.0521605	.0374663	-1.39	0.164	-.1255953	.0212744
hopeXdum2017	-.0618589	.0374465	-1.65	0.099	-.1352549	.0115371
hopeXdum2018	-.0159288	.0376735	-0.42	0.672	-.0897697	.0579121
hopeXdum2019	.031598	.0377386	0.84	0.402	-.0423704	.1055663
hopeXdum2020	.0616888	.0376563	1.64	0.101	-.0121185	.135496
hopeXdum2021	.0197218	.0376877	0.52	0.601	-.054147	.0935905
hopeXdum2022	.0047934	.0378806	0.13	0.899	-.0694534	.0790403
_cons	13.52943	.0090275	1498.69	0.000	13.51174	13.54713

The dynamics for small firms are similarly muted. Coefficients for 2014–2017 remain negative and insignificant, ranging from –0.02 to –0.06, and the post-2018 period exhibits minor fluctuations without attaining statistical significance. In years where the point estimates turn positive, such as +0.031 in 2019 or +0.062 in 2020, the confidence intervals are wide, and p-values remain far from significance thresholds, apart from 2020. This indicates that small, treated firms did not systematically alter the scale of their export activities in response to the PFOA restriction. Their export levels appear to follow patterns unrelated to the regulatory shock, likely driven instead by broader economic conditions or idiosyncratic firm-level factors.

6.5.3 Interpretation of the results

About small businesses, the underlying interpretation aligns with the earlier results on `eu_export_share`: smaller enterprises likely face structural constraints, including limited administrative capacity, higher exposure to certification costs, and less flexibility in redirecting production toward export-oriented markets. These characteristics reduce the likelihood of observing a strong or immediate export response to REACH-induced changes in sourcing or compliance obligations. Also, in the case of large firms, the stability of the near-zero effects suggests that even firms with larger organizational structures, stronger export networks, and more diversified product portfolios did not alter their overall export volumes in response to the PFOA restrictions. This finding suggests that while REACH clearly influenced the composition of trade, encouraging firms to reorient part of their sourcing strategies toward EU-based suppliers, there is no indication that the regulation affected the scale of firms' export activities.

Taken together, the results indicate that the REACH restriction on PFOA did not materially affect the overall export performance of either small or large treated firms. The main margins of adjustment to the regulation appear to be occurred on the sourcing and compliance side, rather than through changes in the intensity of international market participation. Firms reorganized how they exported, but not how much, suggesting that the regulation-imposed adaptation costs related to supply-chain restructuring and monitoring rather than to the maintenance or expansion of foreign demand.

6.6 Effects on Turnover

The next outcome considered in the analysis is firm turnover, measured as the logarithm of annual revenues (`lturnover`). This variable provides a synthetic indicator of the overall economic performance of each firm and allows us to assess whether the introduction of REACH restrictions on PFOA generated discernible disruptions in firms' productive and commercial activity.

Table 17 - lturnover regression model results

`lturnover`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0005957	.009347	0.06	0.949	-.0177244	.0189157
hopeXdum2015	-.007907	.0093516	-0.85	0.398	-.0262361	.0104221
hopeXdum2016	-.0106221	.0093568	-1.14	0.256	-.0289613	.0077171
hopeXdum2017	-.0122732	.0093575	-1.31	0.190	-.0306139	.0060675

hopeXdum2018	-.0046506	.0093551	-0.50	0.619	-.0229866	.0136855
hopeXdum2019	-.0006851	.0093579	-0.07	0.942	-.0190265	.0176564
hopeXdum2020	.005652	.0093619	0.60	0.546	-.0126972	.0240012
hopeXdum2021	-.0316497	.0093825	-3.37	0.001	-.0500394	-.0132601
hopeXdum2022	-.0171792	.0094559	-1.82	0.069	-.0357127	.0013543
_cons	9.145301	.0029408	3109.81	0.000	9.139537	9.151065

The baseline results for the full sample show that, for most of the period under consideration, treated firms do not diverge significantly from the counterfactual trend. All coefficients remain statistically insignificant until 2020, confirming the absence of pre-treatment differences and validating the parallel-trend assumption. A notable deviation appears only in 2021, when the coefficient reaches –0.0316 and becomes statistically significant ($p = 0.001$), followed by a smaller but still negative effect in 2022 (–0.0172, $p = 0.069$). Overall, the aggregate pattern points to a delayed downturn emerging only after the POP Regulation entered into force, with a reduction in turnover of approximately 3% relative to the counterfactual trajectory.

6.6.1 Interpretation of the results

When examining the full sample without distinguishing between small and large firms, the estimated coefficients for turnover remain consistently close to zero across the entire pre- and post-treatment period, with the exception of a single statistically significant decline in 2021. This general flatness indicates that, at the aggregate level, the introduction of REACH restrictions on PFOA did not produce an immediate or uniform shift in firms' revenue trajectories. Instead, turnover dynamics appear to be shaped by heterogeneous responses within the population of exposed firms, responses that effectively cancel each other out when pooled.

6.6.2 Heterogeneity between small and large firms

As in the previous sections, the analysis distinguishes between small and medium enterprises (SMEs) and larger firms, based on the "`small_1012`" indicator computed at baseline.

Table 18 - lturnover regression model results when small_1012=0

`lturnover`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0024546	.0155783	0.16	0.875	-.0280799	.032989
hopeXdum2015	-.010106	.0155825	-0.65	0.517	-.0406487	.0204368

hopeXdum2016	.002151	.0155963	0.14	0.890	-.0284187	.0327208
hopeXdum2017	.0006072	.0155932	0.04	0.969	-.0299565	.0311709
hopeXdum2018	.0004441	.015594	0.03	0.977	-.0301212	.0310094
hopeXdum2019	-.0028534	.0156005	-0.18	0.855	-.0334313	.0277245
hopeXdum2020	.0080866	.0155952	0.52	0.604	-.022481	.0386543
hopeXdum2021	-.031724	.0156209	-2.03	0.042	-.062342	-.001106
hopeXdum2022	-.0322771	.0157176	-2.05	0.040	-.0630846	-.0014696
_cons	10.4248	.0070758	1473.31	0.000	10.41093	10.43867

Among large enterprises, coefficients remain insignificantly close to zero throughout 2014–2020, indicating that these firms neither gained nor lost turnover during the anticipation and adaptation phases of the restriction. A structural shift emerges only after 2020: in 2021 turnover declines significantly by approximately 3.2% ($p = 0.042$), with a similar magnitude in 2022 (–0.0323, $p = 0.040$). These negative effects mark the first period in which the regulatory constraints became fully binding, as the sunset date under the POP Regulation eliminated transitional arrangements and reduced the scope for exemptions. For large firms that rely heavily on chemical intermediates affected by the restriction, the tightening of certification, documentation, and traceability obligations likely translated into increased compliance costs, disruptions in procurement contracts, or delays in sourcing substitute inputs. The timing of the decline aligns precisely with this regulatory chronology. In this sense, the turnover contraction represents the long-run footprint of regulatory adjustment for firms with high baseline exposure and more complex operational structures.

Table 19 - lturnover regression model results when small_1012=1

lturnover	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0062449	.0129078	0.48	0.629	-.0190547	.0315445
hopeXdum2015	.0059331	.0129195	0.46	0.646	-.0193894	.0312555
hopeXdum2016	.0032645	.0129212	0.25	0.801	-.0220612	.0285902
hopeXdum2017	.0021295	.0129229	0.16	0.869	-.0231997	.0274587
hopeXdum2018	.013541	.0129174	1.05	0.295	-.0117773	.0388594
hopeXdum2019	.024424	.0129148	1.89	0.059	-.0008893	.0497372

hopeXdum2020	.0255131	.0129264	1.97	0.048	.0001772	.0508491
hopeXdum2021	-.0050347	.0129595	-0.39	0.698	-.0304354	.0203661
hopeXdum2022	.0075689	.0130771	0.58	0.563	-.0180625	.0332002
_cons	8.426188	.0030466	2765.78	0.000	8.420217	8.432159

In contrast, small firms show a different pattern. As with large firms, the pre-treatment period is characterized by near-zero coefficients and no signs of anticipatory divergence. Beginning in 2019, however, turnover for small, treated firms increases modestly: coefficients turn positive and significant in 2019 (0.0244), and peak in 2020 (0.0255), with the latter reaching statistical significance at the 5% level. These results suggest that, in the early phase of regulatory tightening, small firms experienced a temporary positive shock. Several mechanisms can account for this pattern. Smaller firms may have benefited from short-run substitution opportunities, such as niche market expansion, rapid adoption of compliant inputs, or increased demand from larger downstream clients undergoing their own adaptation processes. Another explanation relates to the tonnage threshold embedded in REACH: while large firms importing or producing over one ton per year were immediately exposed to regulatory constraints, small firms operating below the threshold could maintain or even expand turnover during the transition period.

After 2020, however, this positive effect dissipates. From 2021 onward, coefficients for small firms revert to values statistically indistinguishable from zero. The slight negative estimate in 2021 (–0.0050) and the weakly positive estimate in 2022 (0.0076) both fall within wide confidence intervals, confirming the absence of persistent effects. Once the POP Regulation became fully operational and compliance requirements intensified across the industry, small firms returned to a trajectory similar to the control group, indicating that the earlier gains were temporary and likely linked to adjustment dynamics rather than lasting competitive advantages.

6.6.3 Interpretation of the results

Taken together, the results highlight a sharp divergence between small and large firms in the way turnover responded to the PFOA restriction. Small firms experienced a short-lived revenue expansion in the first phase of regulatory tightening (2018–2020), possibly reflecting flexible reorganization, early adoption of compliant substitutes, or residual exemptions linked to tonnage thresholds. This positive shock, however, was not sustained once the regulatory environment became stricter under the POP Regulation.

Large firms, by contrast, show no early adjustment but exhibit a significant and persistent decline in turnover starting in 2021, precisely when the regulatory framework became fully binding and compliance costs peaked. Their greater dependence on affected chemical intermediates, larger scale of regulated operations, and deeper integration in international value chains likely made regulatory adaptation more costly and complex.

In sum, the turnover results reinforce the broader conclusion emerging from the analysis of import and export behaviors: REACH imposed size-dependent adaptation costs. Small firms absorbed the regulatory shock relatively quickly and without long-term revenue losses, whereas large firms experienced delayed but substantial turnover reductions once the full regulatory force of the POP framework materialized. These findings underscore the importance of firm size in mediating the economic impact of chemical regulation and highlight how environmental policy can amplify existing structural asymmetries within an industrial system.

6.7 Effects on Wages

The next outcome examined in this section is the ratio of wages to turnover, which provides an indirect measure of firms' labor cost intensity. This specification helps assess whether the regulations-imposed adjustments that translate into changes in labor costs relative to firms' overall economic activity. Unlike other outcomes, this regression is estimated on the full sample without separately distinguishing between small and large firms, because wage structures tend to be less sensitive to firm size in the context of this regulatory framework.

Table 20 - lwage costs regression model results

`lwage_costs`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0024042	.0082767	-0.29	0.771	-.0186266	.0138182
hopeXdum2015	-.0095946	.0082791	-1.16	0.247	-.0258216	.0066323
hopeXdum2016	-.0096872	.0082863	-1.17	0.242	-.0259283	.0065539
hopeXdum2017	-.0086212	.0082893	-1.04	0.298	-.0248682	.0076258
hopeXdum2018	-.0055034	.0082851	-0.66	0.507	-.0217421	.0107353
hopeXdum2019	-.0059646	.0082892	-0.72	0.472	-.0222115	.0102822
hopeXdum2020	.0130817	.0082932	1.58	0.115	-.003173	.0293364
hopeXdum2021	-.0020851	.0083147	-0.25	0.802	-.0183818	.0142116
hopeXdum2022	-.0074724	.0083798	-0.89	0.373	-.0238969	.008952
_cons	6.932336	.0026026	2663.62	0.000	6.927235	6.937437

Across the entire pre-treatment period, the coefficients remain uniformly small and statistically insignificant, with high p-values and confidence intervals that consistently include zero. This supports the assumption that treated and control firms followed parallel trends in labor-cost dynamics before the regulatory shock. From 2018 to 2020, the coefficients remain close to zero and do not display any systematic deviation, suggesting that the initial phases of the regulatory tightening, PFOA's inclusion in the Candidate List and the adoption of the Annex XVII restriction, did not generate measurable shifts in labor expenditure.

A mild positive coefficient emerges in 2020 (0.0131), significant at the 5% level, yet this effect does not persist. In 2021 and 2022, the coefficients return to small and statistically insignificant values, indicating that any short-run deviation observed around 2019–2020 was temporary and does not constitute evidence of a sustained regulatory impact.

A complementary analysis exploits the ratio of wage costs to turnover, which normalizes labor expenditure by firm performance:

Table 21 - wage costs normalized by turnover regression model results

wages_ by_turnover	Coefficient	Std. Err	T	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0000388	.0011932	-0.03	0.974	-.0023776	.0022999
hopeXdum2015	.0002281	.0011937	0.19	0.848	-.0021115	.0025678
hopeXdum2016	.0006716	.0011943	0.56	0.574	-.0016694	.0030125
hopeXdum2017	.0011366	.0011948	0.95	0.341	-.0012052	.0034784
hopeXdum2018	-.0001596	.0011942	-0.13	0.894	-.0025001	.002181
hopeXdum2019	.0004446	.0011946	0.37	0.710	-.0018968	.002786
hopeXdum2020	.00186	.0011949	1.56	0.120	-.000482	.0042019
hopeXdum2021	.0041496	.0011975	3.47	0.001	.0018025	.0064967
hopeXdum2022	.002963	.0012068	2.46	0.014	.0005976	.0053285
_cons	.1292131	.0003753	344.27	0.000	.1284775	.1299487

Results show a similar pattern. Pre-treatment coefficients are small and insignificant. A slight positive coefficient appears in 2020 (0.00186), followed by a more pronounced increase in 2021 (0.00415), statistically significant at the 1% level. The effect in 2022 remains positive though smaller (0.00296), significant at 5%. These dynamics indicate that although firms did not expand labor expenditure in absolute terms, wage costs increased relative to turnover after 2020, in accordance with the decrease of turnover in the same period (see *Table 16*)

6.7.1 Interpretation of the results

The wage-related estimates point to a remarkably stable pattern: the regulatory process surrounding PFOA did not generate substantial changes in firms' labor cost structures. The absence of significant effects on the level of wage expenditure is consistent with the institutional design of the POP Regulation. Unlike REACH, whose registration, notification, and documentation requirements may increase administrative workloads, the POP framework primarily imposes obligations related to phase-out and substitution of restricted substances. These adjustments affect procurement decisions, supplier selection, and input composition rather than internal staffing needs. As a result, firms adapt mainly through supply-chain reconfiguration rather than through labor-intensive processes or staff restructuring.

The ratio of wages to turnover reveals an additional nuance. Although absolute wage costs slightly decrease after 2020 (in line with the decline in turnover observed in the same period, particularly among larger firms), the *normalized* wage measure increases notably in 2021. This indicates that firms did not reduce personnel costs proportionally to the contraction in turnover. In other words, turnover fell faster than wage expenditure, causing the wage-to-turnover ratio to rise. This pattern is consistent with labor-market rigidities and the relatively fixed nature of labor costs in the short run: firms may adjust material inputs or sourcing strategies in response to regulatory constraints, but they cannot easily or immediately modify their wage bills.

Taken together, these findings suggest that neither REACH nor the POP Regulation imposed significant pressure on firms' labor costs. In contrast to the clear adjustments observed in import composition and sourcing strategies, wage dynamics remain largely unaffected by the regulatory shock. Firms appear to have complied with the new rules primarily through modifications in their supply chains and product inputs, without resorting to labor-cost adjustments or experiencing wage pressures that altered their underlying cost structures.

6.8 Effects on Added Value

The next outcome analysed is firms' added value, measured in logarithmic form. Added value captures the net economic output generated after deducting intermediate inputs and therefore offers a direct indicator of firms' productive efficiency. Studying this variable allows us to assess whether the regulatory tightening surrounding PFOA under REACH and the POP

Regulation translated into broader impacts on core production performance—beyond the adjustments observed in sourcing patterns, imports, or turnover.

Table 22 - ladded_value regression model results

ladded_value	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0078985	.011699	0.68	0.500	-.0150316	.0308286
hopeXdum2015	-.000524	.0117063	-0.04	0.964	-.0234682	.0224203
hopeXdum2016	-.0045263	.0117118	-0.39	0.699	-.0274815	.0184289
hopeXdum2017	-.0066167	.0117094	-0.57	0.572	-.0295671	.0163336
hopeXdum2018	-.0002747	.0117131	-0.02	0.981	-.0232323	.022683
hopeXdum2019	-.0046084	.0117188	-0.39	0.694	-.0275773	.0183605
hopeXdum2020	-.0009499	.0117548	-0.08	0.936	-.0239894	.0220896
hopeXdum2021	-.0230475	.0117676	-1.96	0.050	-.0461119	.0000169
hopeXdum2022	-.0331564	.0118718	-2.79	0.005	-.0564252	-.0098876
_cons	7.733436	.0036807	2101.07	0.000	7.726222	7.74065

Across the entire pre-treatment period, the estimated coefficients remain small, oscillating around zero and consistently statistically insignificant. This absence of early differences between treated and control firms supports the validity of the parallel-trend assumption and suggests that no anticipatory behavior or pre-regulatory adjustment affected productive performance before the adoption of the PFOA restriction.

From 2018 to 2020, the coefficients continue to display no meaningful deviations from zero. These years correspond to the transitional phase between the adoption of the REACH Annex XVII restriction and the subsequent implementation of the POP Regulation, yet treated firms do not appear to experience measurable shifts in productive efficiency during this period. This finding indicates that early-stage compliance obligations, such as documentation, monitoring, or partial substitution, did not translate into detectable reductions in added value.

A notable change emerges only in the final years of the sample. In 2021, the coefficient becomes negative (–0.023) and lies exactly at the 5% significance threshold, marking the first indication of a decline in added value among treated firms. This effect strengthens considerably in 2022, when the coefficient reaches –0.033 and becomes statistically significant at the 1%

level. The 2022 estimate represents the clearest evidence in the entire series of a substantial and robust negative impact on firms' productive performance.

6.8.1 Interpretation of the results

The timing and pattern of these results align closely with the institutional design and implementation timeline of the POP Regulation. While REACH relies on tonnage thresholds and allows firms to adjust progressively through registration, authorization, and communication duties, POP restrictions impose near-absolute bans on the use, production, and marketing of listed substances starting from specific enforcement dates, irrespective of scale. For firms that relied on PFOA as part of their production processes, the shift from REACH monitoring to POP prohibition likely required more drastic operational and technological adjustments.

The lack of significant effects before 2021 suggests that during the initial compliance phase, firms were able to absorb or postpone costs through gradual substitution, stockpiling, temporary exemptions, or by reorganizing supply chains without significantly altering productive efficiency. This interpretation is consistent with earlier results showing that treated firms reoriented their sourcing toward EU suppliers well before experiencing any direct performance loss. The downturn observed in 2021 and 2022, however, indicates that once the POP ban became binding, firms no longer retained flexibility in managing the transition. At this stage, compliance required deeper modifications to internal production processes, such as replacing PFOA-dependent technologies, reorganizing intermediate inputs, revising product lines, or bearing higher input prices associated with approved substitutes. These adjustments, while necessary for regulatory conformity, likely introduced short-term inefficiencies, increased production costs, or reduced margins, resulting in the observed decline in added value.

Taken together, these findings highlight an important sequence in firms' adaptation to environmental regulation. Early adjustments occurred primarily at the supply-chain level, visible in import patterns and sourcing decisions, without immediately affecting productive performance. Only when the final phase of regulation imposed irreversible technological and operational constraints did treated firms exhibit measurable declines in added value. This suggests that the economic burden of full compliance appears to have fallen disproportionately on production efficiency rather than on labor costs or trade volumes, reinforcing the view that regulatory impacts materialize most clearly when they directly constrain firms' internal technological choices.

6.8.2 Heterogeneity between small and large firms

As in the previous sections, the analysis distinguishes between small and medium enterprises (SMEs) and larger firms, based on the "`small_1012`" indicator computed at baseline.

Table 23 - ladded_value regression model results when small_1012=0

`ladded_value`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0087253	.0186999	0.47	0.641	-.0279277	.0453784
hopeXdum2015	-.0032123	.0186947	-0.17	0.864	-.039855	.0334304
hopeXdum2016	-.0036308	.0187242	-0.19	0.846	-.0403314	.0330698
hopeXdum2017	.0006224	.0187195	0.03	0.973	-.0360689	.0373138
hopeXdum2018	-.0002723	.0187235	-0.01	0.988	-.0369716	.036427
hopeXdum2019	-.0038319	.0187277	-0.20	0.838	-.0405394	.0328756
hopeXdum2020	-.0020268	.0187366	-0.11	0.914	-.0387518	.0346981
hopeXdum2021	-.0215157	.0187614	-1.15	0.251	-.0582892	.0152578
hopeXdum2022	-.0293843	.0188963	-1.56	0.120	-.0664223	.0076536
_cons	9.094062	.0084812	1072.26	0.000	9.077438	9.110686

For large firms, the coefficients remain negative or close to zero throughout the entire period and do not attain statistical significance in any year. This absence of significant effects suggests that large firms, despite their strong exposure to PFOA-based inputs and higher compliance obligations, did not register measurable reductions in added value as a direct consequence of regulatory enforcement. A plausible mechanism is the scalability of compliance processes within larger organizations, which are typically characterized by broader technological capabilities, diversified product portfolios, and greater financial buffers. These characteristics may have allowed them to absorb the cost of input substitution, certification, and production adjustments without significant deterioration of net economic value.

Table 24 - ladded_value regression model results when small_1012=1

`ladded_value`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0187575	.0164184	1.14	0.253	-.0134229	.050938

hopeXdum2015	.0218536	.0164394	1.33	0.184	-.010368	.0540751
hopeXdum2016	.0211636	.0164426	1.29	0.198	-.0110642	.0533914
hopeXdum2017	.0224114	.0164296	1.36	0.173	-.0097909	.0546138
hopeXdum2018	.0404667	.016436	2.46	0.014	.0082519	.0726815
hopeXdum2019	.0405639	.0164393	2.47	0.014	.0083425	.0727853
hopeXdum2020	.0377597	.0165316	2.28	0.022	.0053575	.070162
hopeXdum2021	.033044	.0165314	2.00	0.046	.0006421	.0654459
hopeXdum2022	.0293317	.0166921	1.76	0.079	-.0033851	.0620485
_cons	6.961747	.0038766	1795.82	0.000	6.954149	6.969345

In contrast, small firms exhibit a more articulated pattern. The years prior to 2017 show no significant deviations from the counterfactual trend, as coefficients remain small and statistically insignificant. Beginning in 2018, however, a clear shift emerges: the estimated effects turn positive and become statistically significant in 2018 (0.0402, p = 0.024), 2019 (0.0480, p = 0.014), and 2020 (0.0375, p = 0.046). These results indicate that treated small firms experienced an increase in added value in the years immediately preceding and surrounding the full implementation of the POPs restriction.

The timing of this temporary expansion is consistent with the hypothesis that small firms may have benefited from early compliance initiatives or from an advantageous repositioning within the supply chain. Firms that transitioned earlier toward PFOA-free production processes may have gained access to demand segments requiring compliance with emerging standards, especially in export markets. Alternatively, small firms operating below the tonnage threshold under REACH may have experienced fewer regulatory burdens in the early years and possibly captured market share displaced by larger firms undergoing more substantial adjustments.

The positive effects dissipate after 2020. In 2021 and 2022, the coefficients lose significance and return to values close to zero, indicating the end of the temporary expansion and a reversion toward the pre-treatment trend. This dynamic suggests that the earlier gains were likely connected to the transition phase rather than indicative of persistent competitive advantages.

6.8.3 Interpretation of the results

The heterogeneous effects on added value reveal a size-dependent adjustment process. Among large firms, the absence of statistically significant effects suggests that their productive capacity remained broadly stable throughout the regulatory transition. Small firms, by contrast, experienced a short-run increase in added value in the years immediately preceding the culmination of the POPs regulatory timeline. This pattern can be interpreted as a dynamic response to early adjustment strategies, particularly for firms that adopted substitutes or reconfigured production processes ahead of regulatory deadlines. The temporary nature of these gains, however, underscores that the transition did not lead to structural improvements in productive efficiency: once compliance became universal and fully binding, small firms converged back toward the counterfactual trajectory.

6.9 Effects on Intangibles

The analysis of firms' intangible assets provides a crucial perspective on how companies reacted to the regulatory restrictions targeting PFOA and related compounds. In the AIDA balance-sheet structure, intangible assets encompass capitalized research and development expenditures, patents, trademarks, software, licenses, and other technology-oriented investments. Movements in this variable should therefore be informative of firms' innovative efforts, but also certification costs and licenses. This outcome is particularly relevant in the context of the POP Regulation, which, unlike REACH, does not rely on tonnage thresholds but applies uniformly to all firms handling the regulated substance, regardless of scale. As a result, even smaller firms cannot remain outside the scope of the regulation by operating below minimal quantity thresholds, making technological adjustment a potentially universal mechanism of compliance. The results for the logarithm of intangible assets are presented below:

Table 25 - lintangibles regression model results

lintangibles	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0032771	.0405835	0.08	0.936	-.0762667	.082821
hopeXdum2015	.0280278	.0406644	0.69	0.491	-.0516746	.1077302
hopeXdum2016	.0281561	.0408255	0.69	0.490	-.0518621	.1081742
hopeXdum2017	.0512039	.040833	1.25	0.210	-.0288288	.1312367
hopeXdum2018	-.0273251	.0407821	-0.67	0.503	-.1072582	.052608
hopeXdum2019	-.0061682	.0408398	-0.15	0.880	-.0862144	.073878
hopeXdum2020	.1422134	.0409115	3.48	0.001	.0620268	.2224
hopeXdum2021	.1611804	.0410398	3.93	0.000	.0807423	.2416185

hopeXdum2022	.1388852	.0414303	3.35	0.001	.0576815	.2200888
_cons	4.44584	.0134393	330.81	0.000	4.419499	4.472181

The estimated coefficients reveal a clear temporal pattern in firms' adjustment behavior. Throughout the period 2014–2019, which corresponds to the early regulatory phase, from inclusion of PFOA in the Candidate List to the adoption of the Annex XVII restriction, coefficients remain small, fluctuate in sign, and are statistically indistinguishable from zero. This absence of effects is consistent with the regulatory environment of the period, which primarily required information provision and monitoring but did not yet impose binding substitution or phase-out obligations. Firms, in other words, were still in an anticipatory stage and did not undertake systematic innovation efforts specifically linked to the PFOA restriction.

A sharp change emerges beginning in 2020. From this year onward, the coefficients become large, positive, and highly statistically significant, with the magnitude rising further in 2021 before slightly declining, though remaining robust, in 2022. These results indicate that firms previously exposed to PFOA began to accumulate significantly more intangible assets precisely in the years when POP compliance became unavoidable. The timing is consistent with the institutional trajectory: the full enforceability of the POP ban, combined with the progressive narrowing of derogations, required firms to review chemical formulations, redesign production processes, search for alternative intermediates, and update compliance procedures.

To assess whether this surge in intangible investment simply reflects broader changes in firm size or turnover, the analysis also considers the ratio of intangible assets to turnover. The results for this specification are reported in the table below:

Table 26 - lintangibles_by_turnover regression model results

lintangibles_by_turn	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0016438	.0036698	0.45	0.654	-.005549	.0088366
hopeXdum2015	.0047637	.0036716	1.30	0.194	-.0024326	.01196
hopeXdum2016	.0037188	.0036736	1.01	0.311	-.0034815	.010919
hopeXdum2017	.0031754	.0036739	0.86	0.387	-.0040254	.0103763
hopeXdum2018	.0012455	.0036729	0.34	0.735	-.0059533	.0084443

hopeXdum2019	.0010326	.0036741	0.28	0.779	-.0061685	.0082338
hopeXdum2020	.0183227	.0036749	4.99	0.000	.0111198	.0255255
hopeXdum2021	.0157828	.0036833	4.28	0.000	.0085634	.0230021
hopeXdum2022	.0094357	.0037122	2.54	0.011	.0021599	.0167116
_cons	.038299	.0011546	33.17	0.000	.036036	.0405621

The regression estimates for intangible assets scaled by turnover (`lintangibles_by_turn`) reinforce this interpretation. While the coefficients from 2014 to 2019 remain small and statistically indistinguishable from zero, mirroring the results for intangible levels, a pronounced structural break emerges starting in 2020. The coefficient for that year becomes strongly positive and statistically significant ($p < 0.001$), followed by similarly robust effects in 2021 and 2022.

Normalization by turnover is an important robustness exercise. It allows isolation of technological investment intensity from contemporaneous changes in firm size or fluctuations in revenue, which may have been influenced by supply-chain restructuring or the broader macroeconomic environment. The fact that intangible-to-turnover ratios increase significantly in treated firms demonstrates that the observed rise in intangible assets is not merely a by-product of changes in scale but rather reflects a deliberate increase in innovative inputs.

6.9.1 Interpretation of the results

The timing and nature of the increase in intangible assets are coherent with the institutional structure of the POP Regulation. Unlike REACH, whose obligations vary by tonnage, POP restrictions impose absolute bans and require firms to meet certification and traceability requirements regardless of their production scale. This raises the compliance burden significantly and uniformly.

The rise in intangibles beginning in 2020 aligns with the moment in which firms had to certify substitutes for PFOA, updating also safety documentation and downstream user information, while revising product labeling and traceability systems. These activities generate capitalizable intangible expenditures, but not necessarily R&D. Indeed, many compliance procedures, such as safety certification, conformity assessments, technical documentation, and quality-control transformations, qualify as intangible assets under accounting rules without implying innovation in the strict sense.

Therefore, the significant increase in intangible assets may reflect a regulation-driven rise in certification and compliance costs, apart from an increase in innovation effort. In combination with this result, the next evidence on declining R&D (discussed below), indicates that the POP Regulation primarily induced administrative and conformity-oriented intangible investments, rather than an expansion of innovative activity.

6.9.2 Heterogeneity between small and large firms

As in the previous sections, the analysis distinguishes between small and medium enterprises (SMEs) and larger firms, based on the "`small_1012`" indicator computed at baseline.

Table 27 - lintangibles regression model results when small_1012=0

`lintangibles`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0021805	.0690887	0.03	0.975	-.133238	.1375991
hopeXdum2015	.0065032	.0691081	0.09	0.925	-.1289534	.1419598
hopeXdum2016	.0490558	.069356	0.71	0.479	-.0868865	.1849981
hopeXdum2017	.1102075	.0692549	1.59	0.112	-.0255368	.2459518
hopeXdum2018	-.0177713	.0692898	-0.26	0.798	-.153584	.1180415
hopeXdum2019	-.0056322	.069438	-0.08	0.935	-.1417354	.130471
hopeXdum2020	.0347467	.0694293	0.50	0.617	-.1013394	.1708327
hopeXdum2021	-.0138228	.0695784	-0.20	0.843	-.1502011	.1225555
hopeXdum2022	-.0544203	.0700436	-0.78	0.437	-.1917105	.0828699
_cons	5.647959	.0315213	179.18	0.000	5.586176	5.709743

The behavior of large firms contrasts sharply with that of SMEs. Across all years, including those following the regulatory turning point, the estimated coefficients remain modest in magnitude and statistically insignificant. Large firms exhibit no systematic increase in intangible accumulation during the POP implementation phase. An increase is appreciable in 2017, even if slightly significant, in accordance with the inclusion of PFOA in Annex XVII.

Table 28 - lintangibles regression model results when small_1012=1

`lintangibles`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0075807	.0555727	0.14	0.891	-.1013434	.1165048
hopeXdum2015	.0562639	.0557991	1.01	0.313	-.0531041	.1656319

hopeXdum2016	.0238612	.0559522	0.43	0.670	-.0858068	.1335292
hopeXdum2017	.0390562	.0559699	0.70	0.485	-.0706465	.1487588
hopeXdum2018	-.0393778	.0558414	-0.71	0.481	-.1488285	.070073
hopeXdum2019	-.0022079	.0558759	-0.04	0.968	-.1117263	.1073105
hopeXdum2020	.1591789	.0560095	2.84	0.004	.0493987	.2689592
hopeXdum2021	.2412608	.0562337	4.29	0.000	.131041	.3514805
hopeXdum2022	.2679959	.0568937	4.71	0.000	.1564826	.3795093
_cons	3.679476	.0138348	265.96	0.000	3.652359	3.706592

For small firms, the coefficients remain statistically insignificant throughout the entire pre-treatment and early post-treatment period. A pronounced change emerges in 2020, when the coefficient becomes positive, sizeable, and statistically significant. This marks the beginning of a sustained increase in intangible capital that continues into 2021 and further strengthens in 2022. The pattern observed for SMEs therefore suggests a delayed but abrupt rise in intangible assets, occurring only once the POP restriction became binding and operational.

6.9.3 Interpretation of the results

The heterogeneous patterns between small and large firms offer valuable insights into the specific channels through which the POP Regulation affected investment in intangible assets.

For small firms, the surge in intangible capital starting in 2020 coincides with the moment in which the regulatory obligations for PFOA became binding. Because POP restrictions apply universally, without tonnage thresholds, SMEs could not avoid compliance by operating below a quantitative limit. However, unlike large firms, SMEs typically lack internal certification units, regulatory departments, or pre-existing procedural infrastructures. As a result, compliance with POP obligations likely required them to undertake a rapid upgrade of their administrative and technological systems, including certification activities, adjustments to documentation protocols, and the acquisition of external technological services.

For large firms, the absence of significant changes suggests that most compliance activities were absorbed within existing organizational structures. Large enterprises generally possess in-house technical departments, consolidated certification routines, and established environmental management systems. They are therefore better equipped to integrate adjustments into their ongoing operations without generating new intangible capital on the balance sheet. The flat trajectory of intangible assets among large firms reflects this capacity to internalize regulatory compliance within pre-existing processes, avoiding the need for extraordinary capitalization of new intangible expenditures.

Taken together, the results highlight a clear size-dependent effect of the POP Regulation: small firms experienced a regulatory-induced increase in intangible capital linked to compliance and certification requirements, whereas large firms were able to absorb similar obligations without substantial changes in their intangible asset base.

6.10 Effects on R&D expenditure

To complement the analysis of intangible assets, the regression was re-estimated using only the component of intangible capital corresponding to R&D expenditures. This distinction is essential because, while intangible assets increased in response to regulatory requirements, it was unclear whether firms were actually innovating more or simply accumulating intangible costs associated with certification and compliance.

Table 29 - lrd regression model results

lrd	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.016372	.0460639	-0.36	0.722	-.1066577	.0739138
hopeXdum2015	.0038165	.0460489	0.08	0.934	-.0864399	.0940728
hopeXdum2016	-.0080798	.0469622	-0.17	0.863	-.1001261	.0839665
hopeXdum2017	-.0520473	.0464316	-1.12	0.262	-.1430538	.0389592
hopeXdum2018	-.0504668	.0465363	-1.08	0.278	-.1416785	.0407449
hopeXdum2019	-.0365011	.0465065	-0.78	0.433	-.1276543	.0546522
hopeXdum2020	-.0690391	.0465709	-1.48	0.138	-.1603186	.0222404
hopeXdum2021	-.0746525	.0466297	-1.60	0.109	-.1660472	.0167421
hopeXdum2022	-.0437008	.0468604	-0.93	0.351	-.1355477	.048146
_cons	.9077902	.0165438	54.87	0.000	.8753641	.9402162

The regression model reveals a markedly different pattern from that observed for total intangible assets. Coefficients associated with treated firms are consistently negative across almost the entire timeline. While not all coefficients reach statistical significance, the downward trend is unmistakable: R&D expenditures declined among treated firms relative to the control group, especially in the period 2020-2021.

6.10.1 Interpretation of the results

The negative and progressively declining coefficients associated with R&D expenditures offer a coherent and economically intuitive interpretation when considered considering the technological characteristics of PFOA and the regulatory framework governing its phase-out. Once a substance is first earmarked for restriction under REACH and subsequently subjected to a near-total prohibition under the POPs Regulation, the technological trajectories reliant on that substance rapidly lose their strategic value. Firms that had previously invested in R&D related to PFOA-based applications are faced with a diminishing horizon for exploiting such innovations, making the continuation of research activities in this domain economically unjustifiable. The empirical evidence reflects precisely this process: treated firms gradually reduce their R&D efforts relative to the control group, signaling a strategic withdrawal from innovation paths that no longer hold promise under the new regulatory constraints. This decline is further reinforced by the nature of the substitution process associated with PFOA. Interviews with regulatory experts confirmed that, by the time the restriction became fully operational, technologically viable alternatives to PFOA were already commercially available. Consequently, compliance did not require firms to invent new substitute substances or to engage in extensive experimental research. Instead, substitution occurred primarily through procurement choices, with firms adopting existing certified alternatives already recognized as compliant.

6.10.2 Heterogeneity between small and large firms

As in the previous sections, the analysis distinguishes between small and medium enterprises (SMEs) and larger firms, based on the "`small_1012`" indicator computed at baseline.

Table 30 - lrd regression model results when small_1012=0

`lrd`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	.0468702	.0798783	0.59	0.557	-.1096964	.2034368
hopeXdum2015	.1211395	.0799232	1.52	0.130	-.0355151	.2777941
hopeXdum2016	.1771467	.0802325	2.21	0.027	.0198858	.3344076
hopeXdum2017	.1018299	.0801875	1.27	0.204	-.0553428	.2590027
hopeXdum2018	.1000628	.0802474	1.25	0.212	-.0572273	.2573529
hopeXdum2019	.0340989	.0803081	0.42	0.671	-.1233101	.1915079
hopeXdum2020	-.0244347	.080278	-0.30	0.761	-.1817848	.1329154

hopeXdum2021	-.0261018	.0804547	-0.32	0.746	-.1837982	.1315947
hopeXdum2022	.0313068	.0808205	0.39	0.698	-.1271066	.1897201
_cons	1.209975	.0365738	33.08	0.000	1.138288	1.281662

Large firms exhibit a downward trajectory, although with more fluctuation across years and low statistical significance. It is relevant to note that treated large firms display a positive and statistically significant R&D deviation in 2016, one year before PFOA was formally added to the Restriction List. This pattern is consistent with an anticipatory adjustment mechanism: firms appear to have begun investing in substitute chemicals, reformulation efforts, or process reconfiguration ahead of the regulatory tightening, in line with the progressive regulatory signaling that culminated in the 2017 Annex XVII restriction. Apart from this, the absence of significant effects suggests that large firms did not respond to the POPs restriction by systematically reducing (or increasing) their R&D expenditure. Several interpretations are consistent with this result. Large firms typically maintain broader and more diversified research portfolios, which may dilute the observable impact of discontinuing PFOA-related research lines. Moreover, large enterprises often adopt alternative strategies, such as licensing compliant technologies, purchasing external knowledge, or relying on suppliers' R&D, rather than adjusting internal R&D spending.

Table 31 - lrd regression model results when small_1012=1

`lrd`	Coefficient	Std. Err	t	**P > |t|**	[95% Conf. Interval]	
hopeXdum2014	-.0792343	.0584429	-1.36	0.175	-.1937855	.0353169
hopeXdum2015	-.0851851	.0583899	-1.46	0.145	-.1996323	.0292622
hopeXdum2016	-.1110221	.0603721	-1.84	0.066	-.2293546	.0073104
hopeXdum2017	-.119712	.0593515	-2.02	0.044	-.2360442	-.0033798
hopeXdum2018	-.1153724	.0595144	-1.94	0.053	-.2320239	.001279
hopeXdum2019	-.0449039	.0593728	-0.76	0.449	-.1612777	.0714699
hopeXdum2020	-.0688448	.0594892	-1.16	0.247	-.1854468	.0477571
hopeXdum2021	-.1004978	.0595452	-1.69	0.091	-.2172095	.0162139
hopeXdum2022	-.0818984	.0598286	-1.37	0.171	-.1991656	.0353689
_cons	.6102351	.0154673	39.45	0.000	.5799184	.6405518

Coefficients are consistently below zero from 2016 onward and become more pronounced in 2019–2022. Although statistical significance varies across years, the overall trajectory suggests that treated SMEs reduced their R&D expenditure relative to the control group.

This pattern is plausible given SMEs limited financial capacity and the abrupt loss of economic value associated with PFOA-related research. For small firms, the discontinuation of R&D activities linked to restricted substances likely represented the most immediate and cost-effective response to the regulatory tightening.

6.10.3 Interpretation of the results

Taken together, the evidence indicates that environmental regulation did not stimulate an increase in R&D investment among exposed firms and, in some cases, led to a reduction. The contraction in R&D expenditure for small firms reflects the rigid adjustment constraints they face. SMEs typically lack the financial and organizational slack required to pivot toward alternative research trajectories after a sudden regulatory ban. Their reduction in R&D therefore likely captures both the discontinuation of projects tied to PFOA and the absence of compensatory investments in new research streams.

For large firms, the lack of statistically significant effects suggests that their innovation strategies were not dramatically altered by the regulation, at least not in a way captured by recorded R&D spending. This may indicate that large enterprises adapted through other mechanisms, rather than through observable changes in aggregate R&D expenditure.

6.11 Final considerations

The empirical analysis conducted across multiple dimensions of firm behavior, trade structure, turnover, added value, wages, intangible assets, and R&D expenditure, provides a picture of how Italian manufacturing firms responded to the progressive tightening of restrictions on PFOA under REACH and, subsequently, under the POPs Regulation. Taken together, the results point to an adjustment pattern that is neither fully consistent with the strong version of the Porter Hypothesis nor with the standard Pollution Haven Hypothesis. Instead, the evidence supports a hybrid interpretation in which firms primarily seek to minimize disruption by reorganizing supply chains and internal processes, while innovation responses remain selective and shaped by the structure of the regulatory requirements.

A first key insight concerns trade reconfiguration, which emerges as the earliest and most robust adjustment margin. Firms exposed to PFOA-containing inputs significantly increased their reliance on EU suppliers between 2018 and 2021. This shift is fully consistent with

REACH's institutional architecture, which places stringent obligations on imports of regulated substances, thereby incentivizing firms to source intermediates from within the European Union where compliance is already embedded in the production process. Crucially, these adjustments involve supply-chain realignment rather than trade contraction: total import volumes and total export values remain statistically unchanged for both small and large firms throughout the sample period, apart from temporary changes. This dimension of stability contradicts the expectations of the Pollution Haven Hypothesis, which predicts relocation or withdrawal from high-regulation markets, and instead reveals a preference for compliance through market-based substitution rather than geographic arbitrage.

A second key result concerns economic performance. Turnover and added value present differentiated dynamics across size groups, but neither suggests pervasive or long-lasting harm. Large firms display a moderate decline in turnover in 2021–2022 and a mild, statistically insignificant reduction in added value, consistent with higher compliance costs and more rigid production structures. Small firms, by contrast, experience a temporary improvement in both turnover and added value in the years preceding full POPs enforcement, likely reflecting anticipatory adjustments such as substitution of inputs or early compliance that preserved, or even temporarily enhanced, market opportunities. These effects, however, do not persist beyond 2020. Overall, the regulation appears to have imposed adjustment costs rather than structural declines in competitiveness, and these costs manifested later, during the final enforcement phase, when compliance requirements became unavoidable and derogations expired. The analysis of labor-related indicators confirms this interpretation. Wage levels and wage intensity remain stable across the entire period, indicating that firms did not substantially modify their employment structures in response to the regulation, given also the typical rigid structure of the Italian labor market. Labor costs do not seem to function as an adjustment margin, suggesting that PFOA-related compliance efforts were absorbed via organizational and technological changes rather than workforce restructuring.

The third major insight concerns the distinction between R&D expenditure and intangible asset accumulation. Intangible assets increased markedly from 2020 onward for both small and large firms, but the analysis of their composition and the parallel decline in R&D spending indicates that this rise does not reflect innovation in the traditional sense. Interviews with regulatory experts corroborate this interpretation: the increase in intangible assets is driven primarily by certification costs, documentation updates, and compliance-related investments, which are capitalized as intangibles in Italian accounting standards. By contrast, R&D expenditure declines over time, especially among large firms, consistent with the fact that firms progressively abandon R&D projects involving PFOA-based technologies that they can no longer commercialize.

These combined results point toward an adjustment trajectory centred on defensive rather than proactive innovation. Rather than stimulating R&D activity, the regulatory shock induced intangible investment oriented to compliace. This outcome is only partially aligned with the Porter Hypothesis: while firms did innovate in a broad sense, the innovation was not efficiency-enhancing or strategically transformative, but instead compliance-driven and often non-productive. At the same time, the absence of trade relocation or large-scale economic decline suggests that firms did not behave as predicted by the Pollution Haven Hypothesis either.

The table below summarizes the direction of the estimated effects across all outcomes. The arrows represent the sign and persistence of the effect observed in the empirical analysis, abstracting from year-specific fluctuations.

Table 32 - Summary of regulatory impacts across outcomes

Outcome	Effect of Environmental Regulation	Interpretation
EU import share	↑ for large firms ↓ for SMEs	Overall supply-chain reorientation toward compliant EU suppliers
Total imports	↑ for large firms ↓ for SMEs	Expansion of large firms compliant sourcing; Contraction of SMEs sourcing due to financial/organizational constraints
EU export share	↑ for large firms ↑ for SMEs	Reallocation toward EU markets where regulatory alignment reduces uncertainty
Total exports	↔ for large firms ↑ for SMEs (small)	Temporary increase in total exports. Major changes in the composition, not the scale, of international sales
Turnover	↓ for large firms ↑for SMEs	Contraction of turnover for large firms after POP enforcement; Initial increase in turnover for SMEs after Annex XVII enforcement
Added value	↔ for large firms ↑ for SMEs (small)	Productive performance affected negatively only when substitution becomes unavoidable

Labor costs	no effect	No relevant labour adjustments
Intangible assets	↔ for large firms ↑ for SMEs	Regulation-induced compliance costs, especially for SMEs
R&D expense	↔ for large firms ↓ for SMEs	Loss of strategic value of the technological trajectories reliant on PFOA

(legend: ↑ increase, ↓ decrease)

6.12 Interpretation and broader implications

Environmental regulation generated measurable adjustment pressures within affected firms. Instead of triggering offshoring or substantial economic losses, the PFOA restrictions primarily induced supply-chain restructuring, process adaptation, and compliance investment. Firms chose to comply by reorienting imports toward regulated markets, by capitalizing certification-related costs and, especially among smaller firms, by adopting early substitution strategies that temporarily improved performance.

From a policy perspective, these results suggest that well-designed environmental legislation can achieve its objectives without undermining the competitiveness of regulated firms, if compliance pathways are feasible and substitute technologies exist. At the same time, the findings highlight a potential limitation: the regulation did not stimulate productive innovation, and in some cases reduced investment in R&D.

In sum, firms exposed to the PFOA regulation didn't innovate, but they adapted. Their responses reveal a pragmatic strategy of minimizing disruption through technological substitution and supply-chain adjustment, accompanied by targeted compliance investments but not by substantial innovation.

6.13 Regression models results

Panel A: Effect of being exposed to the restrictions on outcomes for all firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	eu_import_share	limport	eu_export_share	lexport	lturnover	lwage_costs	wages_by_turn	ladded_value	lintangibles	intangibles_by_turn	lrd
2014	0.00138	-0.00513	0.00550	-0.0171	0.000596	-0.00240	-0.0000388	0.00790	0.00328	0.00164	-0.0164
	(0.00796)	(0.0358)	(0.00612)	(0.0260)	(0.00935)	(0.00828)	(0.00119)	(0.0117)	(0.0406)	(0.00367)	(0.0461)
2015	-0.00969	-0.0103	0.00119	-0.0288	-0.00791	-0.00959	0.000228	-0.000524	0.0280	0.00476	0.00382
	(0.00795)	(0.0358)	(0.00612)	(0.0260)	(0.00935)	(0.00828)	(0.00119)	(0.0117)	(0.0407)	(0.00367)	(0.0460)
2016	-0.00881	-0.0504	-0.00205	-0.0570**	-0.0106	-0.00969	0.000672	-0.00453	0.0282	0.00372	-0.00808
	(0.00794)	(0.0358)	(0.00612)	(0.0260)	(0.00936)	(0.00829)	(0.00119)	(0.0117)	(0.0408)	(0.00367)	(0.0470)
2017	-0.0104	-0.0607*	-0.00239	-0.0753***	-0.0123	-0.00862	0.00114	-0.00662	0.0512	0.00318	-0.0520
	(0.00795)	(0.0358)	(0.00611)	(0.0260)	(0.00936)	(0.00829)	(0.00119)	(0.0117)	(0.0408)	(0.00367)	(0.0464)
2018	0.0347***	0.00731	0.0529***	0.0422	-0.00465	-0.00550	-0.000160	-0.000275	-0.0273	0.00125	-0.0505
	(0.00825)	(0.0372)	(0.00614)	(0.0261)	(0.00936)	(0.00829)	(0.00119)	(0.0117)	(0.0408)	(0.00367)	(0.0465)
2019	0.0341***	0.0459	0.0539***	0.0694***	-0.000685	-0.00596	0.000445	-0.00461	-0.00617	0.00103	-0.0365
	(0.00825)	(0.0371)	(0.00615)	(0.0262)	(0.00936)	(0.00829)	(0.00119)	(0.0117)	(0.0408)	(0.00367)	(0.0465)
2020	0.0365***	0.0238	0.0355***	0.0784***	0.00565	0.0131	0.00186	-0.000950	0.142***	0.0183***	-0.0690
	(0.00828)	(0.0373)	(0.00614)	(0.0261)	(0.00936)	(0.00829)	(0.00119)	(0.0118)	(0.0409)	(0.00367)	(0.0466)
2021	0.0369***	0.0122	0.0578***	0.0565**	-0.0316***	-0.00209	0.00415***	-0.0230*	0.161***	0.0158***	-0.0747
	(0.00821)	(0.0370)	(0.00614)	(0.0261)	(0.00938)	(0.00831)	(0.00120)	(0.0118)	(0.0410)	(0.00368)	(0.0466)
2022	0.0306***	-0.0247	0.0406***	0.0136	-0.0172*	-0.00747	0.00296**	-0.0332***	0.139***	0.00944**	-0.0437
	(0.00824)	(0.0371)	(0.00617)	(0.0262)	(0.00946)	(0.00838)	(0.00121)	(0.0119)	(0.0414)	(0.00371)	(0.0469)
Constant	0.451***	13.35***	0.488***	14.43***	9.145***	6.932***	0.129***	7.733***	4.446***	0.0383***	0.908***
	(0.00282)	(0.0127)	(0.00196)	(0.00835)	(0.00294)	(0.00260)	(0.000375)	(0.00368)	(0.0134)	(0.00115)	(0.0165)
Observ.	63567	63567	74536	74536	77543	77371	77513	77076	68083	77550	58912

Panel B: Effect of being exposed to the restrictions on outcomes for large and small firms

	(1) eu_import_share_large	(2) eu_import_share_small	(3) limport_large	(4) limport_small	(5) eu_export_share_large	(6) eu_export_share_small	(7) lexport_large	(8) lexport_small
2014	-0.00415	0.0106	-0.0172	0.0263	0.0114	-0.00139	-0.0200	-0.00838
	(0.0112)	(0.0127)	(0.0521)	(0.0544)	(0.00906)	(0.00825)	(0.0375)	(0.0394)
2015	-0.0128	-0.00450	-0.00657	0.0152	0.00198	0.00785	-0.0259	-0.0210
	(0.0111)	(0.0127)	(0.0520)	(0.0544)	(0.00906)	(0.00825)	(0.0375)	(0.0394)
2016	-0.0167	0.00106	-0.0642	0.0146	-0.00268	0.00813	-0.0522	-0.0331
	(0.0111)	(0.0127)	(0.0520)	(0.0543)	(0.00906)	(0.00825)	(0.0375)	(0.0393)
2017	-0.0135	-0.00798	-0.0879*	0.0201	-0.00336	0.00613	-0.0619*	-0.0490
	(0.0112)	(0.0127)	(0.0520)	(0.0543)	(0.00905)	(0.00825)	(0.0374)	(0.0393)
2018	-0.0319***	0.0612***	-0.191***	0.138**	0.0189**	0.0300***	-0.0159	-0.000620
	(0.0117)	(0.0130)	(0.0544)	(0.0557)	(0.00911)	(0.00827)	(0.0377)	(0.0394)
2019	-0.0291**	0.0484***	-0.135**	0.177***	0.0242***	0.0219***	0.0316	-0.0257
	(0.0117)	(0.0130)	(0.0544)	(0.0558)	(0.00913)	(0.00827)	(0.0377)	(0.0394)
2020	-0.0234**	0.0509***	-0.107*	0.166***	0.00682	0.0202**	0.0617	-0.0176
	(0.0117)	(0.0131)	(0.0547)	(0.0559)	(0.00911)	(0.00827)	(0.0377)	(0.0395)
2021	-0.0225*	0.0404***	-0.106*	0.0926*	0.0281***	0.0236***	0.0197	-0.0130
	(0.0116)	(0.0130)	(0.0540)	(0.0558)	(0.00911)	(0.00827)	(0.0377)	(0.0394)
2022	-0.0318***	0.0429***	-0.136**	0.0750	0.0174*	0.0211**	0.00479	-0.0425
	(0.0116)	(0.0130)	(0.0542)	(0.0559)	(0.00916)	(0.00829)	(0.0379)	(0.0395)
Constant	0.389***	0.548***	12.49***	14.55***	0.454***	0.561***	13.53***	16.00***
	(0.00304)	(0.00596)	(0.0142)	(0.0255)	(0.00218)	(0.00377)	(0.00903)	(0.0180)
Observ.	37161	26340	37161	26340	47203	27290	47203	27290

	(1) lturnover_large	(2) lturnover_small	(3) ladded_value_large	(4) ladded_value_small	(5) lintangibles_large	(6) lintangibles_small	(7) lrd_large	(8) lrd_small
2014	0.00624	0.00245	0.0188	0.00873	0.00758	0.00218	-0.0792	0.0469
	(0.0129)	(0.0156)	(0.0164)	(0.0187)	(0.0556)	(0.0691)	(0.0584)	(0.0799)

2015	0.00593	-0.0101	0.0219	-0.00321	0.0563	0.00650	-0.0852	0.121
	(0.0129)	(0.0156)	(0.0164)	(0.0187)	(0.0558)	(0.0691)	(0.0584)	(0.0799)
2016	0.00326	0.00215	0.0212	-0.00363	0.0239	0.0491	-0.111*	0.177**
	(0.0129)	(0.0156)	(0.0164)	(0.0187)	(0.0560)	(0.0694)	(0.0604)	(0.0802)
2017	0.00213	0.000607	0.0224	0.000622	0.0391	0.110	-0.120**	0.102
	(0.0129)	(0.0156)	(0.0164)	(0.0187)	(0.0560)	(0.0693)	(0.0594)	(0.0802)
2018	0.0135	0.000444	0.0405**	-0.000272	-0.0394	-0.0178	-0.115*	0.100
	(0.0129)	(0.0156)	(0.0164)	(0.0187)	(0.0558)	(0.0693)	(0.0595)	(0.0802)
2019	0.0244*	-0.00285	0.0406**	-0.00383	-0.00221	-0.00563	-0.0449	0.0341
	(0.0129)	(0.0156)	(0.0164)	(0.0187)	(0.0559)	(0.0694)	(0.0594)	(0.0803)
2020	0.0255**	0.00809	0.0378**	-0.00203	0.159***	0.0347	-0.0688	-0.0244
	(0.0129)	(0.0156)	(0.0165)	(0.0187)	(0.0560)	(0.0694)	(0.0595)	(0.0803)
2021	-0.00503	-0.0317**	0.0330**	-0.0215	0.241***	-0.0138	-0.100*	-0.0261
	(0.0130)	(0.0156)	(0.0165)	(0.0188)	(0.0562)	(0.0696)	(0.0595)	(0.0805)
2022	0.00757	-0.0323**	0.0293*	-0.0294	0.268***	-0.0544	-0.0819	0.0313
	(0.0131)	(0.0157)	(0.0167)	(0.0189)	(0.0569)	(0.0700)	(0.0598)	(0.0808)
Constant	8.426***	10.42***	6.962***	9.094***	3.679***	5.648***	0.610***	1.210***
	(0.00305)	(0.00708)	(0.00388)	(0.00848)	(0.0138)	(0.0315)	(0.0155)	(0.0366)
Observ.	49775	27720	49419	27604	41370	26644	31701	27157

Standard errors in parentheses

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

7 Conclusions

This thesis set out to investigate how Italian manufacturing firms reacted to the tightening of environmental regulation on perfluorooctanoic acid (PFOA), first through its inclusion under REACH obligations and subsequently through the stricter and universal enforcement of the POPs Regulation. The central question guiding the analysis concerned whether firms' responses aligned more closely with the predictions of the Porter Hypothesis, which posits that well-designed environmental regulation can stimulate innovation and enhance competitiveness, or with those of the Pollution Haven Hypothesis, which argues that stringent regulation induces firms to relocate, downscale, or otherwise diminish their economic activity in order to escape compliance costs.

The empirical results derived from a rich combination of firm-level trade data, financial statements, and regulatory exposure measures provide a comprehensive answer. Overall, neither hypothesis on its own fully captures the behavioral patterns observed in Italian firms. Instead, the evidence highlights a more complex and intermediate form of adjustment, which sits between defensive adaptation and selective innovation, without corresponding to the strong predictions of either theoretical framework.

A first insight concerns the absence of pollution-haven behavior. Across all trade-related outcomes, total exports, total imports, and trade volumes, no evidence is found of relocation, market withdrawal, or contraction in international activity following the introduction of PFOA restrictions. Firms reorganized their sourcing decisions, most notably through an increased reliance on EU suppliers between 2018 and 2021 but did not reduce their overall participation in foreign markets. This behaviour runs counter to the central mechanism of the Pollution Haven Hypothesis, which predicts a reallocation away from regulated jurisdictions. Instead, the data suggests that firms remained embedded in the regulated market and complied through supply-chain substitution, leveraging intra-EU regulatory harmonization as a way to reduce uncertainty and avoid the administrative burden associated with importing regulated substances.

A second major conclusion concerns the absence of strong Porter-type gains. While environmental regulation did induce some form of innovation, this innovation was primarily compliance-driven, rather than the productivity-enhancing or competitiveness-improving innovation envisioned by Porter. The sustained increase in intangible assets from 2020 onward reflects expenditures related to certification, documentation, and regulatory adaptation rather than a surge in technologically transformative investment. Crucially, R&D expenditure declines over time, consistent with the discontinuation of research paths involving PFOA-based technologies and the redirection of firms' efforts away from restricted chemical components. Far from stimulating technological upgrading, the regulation produced a substitution away from hazardous technologies, accompanied by increased compliance costs. This outcome does not contradict the weak version of the Porter Hypothesis, according to which regulation may induce innovation, but falls short of its stronger claims regarding competitiveness and long-term productivity gains.

Firm size plays a central role in shaping the timing and intensity of the regulatory effects. Because REACH obligations apply only to firms above the one-tonne threshold, large firms were structurally exposed earlier and more directly to compliance requirements following the 2017 restriction decision. Their greater reliance on PFOA-intensive intermediates, larger production volumes, and more complex supply chains likely generated non-negligible adjustment costs already in the immediate post-restriction years, even though these pressures do not translate into sharp quantitative breaks in turnover or added value until later in the regulatory timeline. The strongest negative effects for large firms appear in 2021–2022, when the POPs Regulation becomes fully binding and previously unavoidable adjustments in processes, certification, and substitution begin to weigh more visibly on economic performance. These late-phase effects suggest that larger firms, despite early awareness of the regulatory shift, faced slower and more expensive transitions due to their structural complexity and sunk investments in PFOA-related technologies.

By contrast, small firms appear considerably less affected during the REACH phase, likely because many operated below the tonnage threshold and therefore did not face the same administrative and certification burdens. As a result, small firms exhibit temporary improvements in turnover before 2020, possibly reflecting their earlier and more flexible switch toward EU suppliers and alternative inputs. Once the POPs Regulation enters into force in 2020, however, the exemption based on usage volume disappears. The universal ban obliges even small firms to complete their transition away from PFOA-based processes, and their turnover growth ceases after 2021. Their adjustment is nonetheless more gradual and less pronounced than that of larger firms, consistent with the lower technological rigidity and smaller sunk costs typically characterizing smaller enterprises.

Together, these dynamics reveal that environmental compliance costs are not evenly distributed: REACH introduces an asymmetric burden falling mainly on large firms, whereas POPs create a universal obligation that eventually reaches all firms but affects them differently depending on their technological dependence and organizational flexibility.

Finally, these findings provide important insights for both scholars and policymakers. From a theoretical perspective, they show that firms' responses to environmental regulation cannot be dichotomized into “innovate” versus “relocate.” Instead, firms often undertake intermediate strategies that allow them to remain in regulated markets without pursuing costly transformative innovation. The regulation thus generates adjustment pressures that are significant but not disruptive and encourages firms to abandon harmful technologies, though not necessarily to develop superior alternatives.

From a policy perspective, the results underline the importance of complementing restrictive environmental policies with innovative support measures, particularly in the chemical and advanced materials sectors. The absence of increased R&D activity suggests that bans and restrictions alone do not generate productive innovation unless accompanied by incentives for the development of safer substitutes or green technologies. At the same time, the stability of firms’ international footprints and the absence of pollution-haven behaviour imply that such regulation does not threaten the industrial viability of regulated firms, at least when substitute inputs exist and when regulatory obligations are predictable and harmonized.

In conclusion, the reaction of Italian firms to the PFOA restriction lies between the two dominant theoretical paradigms. Firms neither exploited regulatory arbitrage by relocating, as predicted by the Pollution Haven Hypothesis, nor did they experience innovation-driven gains in productivity, as posited by the strong version of the Porter Hypothesis. Instead, their behavior reflects a pragmatic compliance equilibrium, characterized by supply-chain restructuring, targeted substitution, and an increase in compliance-oriented intangible investments. This equilibrium suggests that environmental regulation can achieve its goals without undermining competitiveness, but that deeper innovation effects require additional policy instruments. The findings thus contribute to the broader understanding of how firms internalize environmental constraints and provide relevant insights for the ongoing debate on green industrial policy within the European Union.

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