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## Three essays on firms in international markets

Irene Iodice

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DOCTORAL THESIS

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**Three essays on firms  
in international markets**

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for the joint doctoral degree  
in Economics*



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*“The most amazing combinations can result if you shuffle the pack enough.”*

— Mikhail Bulgakov, *The Master and Margarita*

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# Introduction

In the EU only about 4.5% of firms are engaged in exporting. Among large firms this figure increases tenfold. Even within exporting firms, a substantial heterogeneity persists, with the bulk of sales concentrated in a handful of firms. The top 10 European exporters account alone, on average, for between 10% and 20% of the total export share. While economists have usually read trade patterns through the lens of the comparative advantage of countries, increasing returns to scale and consumer love of variety, only recently the attention has moved to the fundamental driver of trade flows - the firm. This shift has brought new understanding of the implications of the various episodes of tariff liberalization that have characterized the second half of the last century as well as the early 2000s. The trade environment in which firms operate has, however, quickly changed. Contemporary trade agreements go now much beyond traditional trade restrictions at the border. They cover regulatory standards, health and safety rules, investment, banking and finance, intellectual property, labour, the environment, and many other subjects. Understanding of how such trade environment interacts with firm characteristics brings in fresh challenges to scholars in the international trade.

**The contribution of a micro-perspective.** Since the mid-90s, the rising availability of micro-dataset with disaggregated trade flows has brought to light a bunch of facts on how firms mediate the trade of a country (Bernard and Jensen, 1995). These studies have shown that trading firms differ substantially from firms that operate uniquely in the domestic market. Across a wide range of countries and industries, exporters are larger, more diversified, more productive, more skill- and capital-intensive, and they pay higher wages than non exporting firms.<sup>1</sup> These facts have challenged traditional theories of trade based on comparative advantages and differentiated products, which predict that all firms in a given sector would be either exporters or non-exporters. It has also allowed to shed new light on aggregate phenomena, such as trends in workforce composition and wages, which has motivated and supported new theories.

In the first chapter of this thesis, in a joint work with Chiara Tomasi, we show that one needs a micro-perspective to find an explanation of why Italy, a country with a comparative advantage in low skilled industries, underwent an increase in the skill composition of its workforce during the period of trade integration of the

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<sup>1</sup>For comprehensive surveys of this theoretical and empirical literature, see Bernard et al., 2007a; Melitz and Trefler, 2012; Melitz and Redding, 2014; Bernard et al., 2018a.

early 2000s.<sup>2</sup> Standard theories predict countries with a more unskilled labor force to specialize in industries which use that factor more intensively. As a result of an expansion of trade, workers should move from contracting industries to expanding ones, changing the aggregate ratio between skilled and unskilled workers and their relative wages. Our exercise, while confirming movements of workers from skilled to unskilled manufacturing industries, points to the fact that most of the changes in the Italian workforce composition has occurred within industries, and mainly within firms, where one observes a skill upgrade. This is similar to what observed for the US in Bernard et al., 2007a and supports models that accommodate intra-industry heterogeneity and firm level adjustments. For example, Bustos, 2011 predicts that larger trade openness, by increasing market access, incentives the most competitive firms to incur in technology upgrading.<sup>3</sup> In our sample, the most productive and the largest firms are indeed those that contribute the most in the rise of the skill intensity. On the other hand, we find that the price of skilled labor has not adjusted positively. On the contrary, the annual wage premium has fallen, which means that the wage gap between skilled and unskilled labor narrows. This is at odds with what observed in UK, US and Germany over the same period, while is in line with what reported for France (Naticchioni, Ragusa, and Massari, 2014). For the latter, Verdugo, 2014 has explained the decrease in wage differential as due to changes in the composition of education and experience groups in the workforce.<sup>4</sup> While we could not test this argument, we have run out the possibility that the fall in the annual wage premium is driven by an adjustment at the intensive margin, on the hours worked by employee. This could have had a consequence of the increased labor flexibility introduced in the early 2000s.

**The characteristics of firm heterogeneity** The shift of focus from countries and industries to firms introduces new mechanisms for international trade to shape aggregate patterns via the interaction of firm characteristics and the export orientation of the firm. The seminal work of Melitz, 2003 predicts that even with a fixed heterogeneity in firms' productivity, openness to trade spurs the aggregate productivity, via a reallocation mechanism that selects the best firms.<sup>5</sup> Subsequent research has

<sup>2</sup>This work is published in Iodice and Tomasi, 2016.

<sup>3</sup>Bustos, 2011 indeed observes that the increase in exports due to trade liberalization in Argentina has impacted on firms' behavior generating a technology and skill upgrading. Other empirical studies confirming the causal impact of trade on labor market outcomes are Frias, Kaplan, and Verhoogen, 2012 and Verhoogen, 2008. Based on French firm level data, Harrigan, Reshef, and Toubal, 2016 found exporting to cause a within-firm polarization: faster growth in the share of managers and skill downgrading within production workers.

<sup>4</sup>Verdugo, 2014 indeed found a strong negative co-variation between changes in the skill premium and the relative supply of skills within experience groups. A review of the evolution of French wage differentials is discussed in Charnoz, Coudin, and Gaini, 2013.

<sup>5</sup>The same framework can be extended to accommodate several endogenous decisions that affect firm productivity, including technology adoption (Bustos, 2011; Lileeva and Trefler, 2010), innovation (Atkeson and Burstein, 2010; Perla, Tonetti, and Waugh, 2015; Sampson, 2016), endogenous changes in workforce composition Helpman, Itskhoki, and Redding, 2010; Helpman et al., 2017 and endogenous changes in product mix (Bernard, Redding, and Schott, 2010; Bernard, Redding, and Schott, 2011).

introduced a link between productivity and the ability of firms to expand into different margins of trade, such as the number of export markets to serve (Eaton, Kortum, and Kramarz, 2011a), the number of products to supply to each export market (Bernard, Redding, and Schott, 2010; Bernard, Redding, and Schott, 2011; Hottman, Redding, and Weinstein, 2016), the number of country from which to source intermediate inputs and which inputs to import from each source country (Antras, Fort, and Tintelnot, 2017; Berman, Rebeyrol, and Vicard, 2019). If firm decisions over these margins of participation are interdependent then initial exogenous differences across firms can get magnified in the international economy (Bernard et al., 2018a). This mechanism might explain why we observe few very large exporters who dominate trade across a wide range of countries and sectors. For example, Freund and Pierola, 2015 report that among 32 countries, the top firm accounts for an average of 14% of a country's total (non-oil) exports and the top five firms make up 30%.

In the second chapter we contribute to the recently growing literature in trade that investigates how micro behavior aggregates into macro patterns. The interest finds motivation in Arkolakis, Costinot, and Rodríguez-Clare, 2012, which proves a lack of implication of the recent literature for aggregate trade. Eaton, Kortum, and Sotelo, 2012 argues that a primary reason why models of heterogeneous producers deliver so little in the way of modification of how we think about aggregates is the device of treating the set of products as a continuum, which was initiated by Dornbusch, Fischer, and Samuelson, 1977. The feature of measure-zero varieties, embraced by the heterogeneous firm literature, is convenient for modelling. By invoking the law of large numbers, one can consider what affects the aggregate level to be driven by the parameters defining the distributions of the outcomes affecting individual units, but not on the realizations of those outcomes themselves. In presence of granularity instead - term coined by Gabaix, 2011 to represent the skewed nature of firm size distributions - shocks on big firms "carry on" to the aggregate.<sup>6</sup> To account for this, Eaton, Kortum, and Sotelo, 2012 and Gaubert and Itskhoki, 2018 propose to look at the number of firms that export to a destination as generated by Poisson stochastic mechanism, already proposed in Bernard et al., 2003, and therefore as a finite number. In these works, the realized market shares of firms can thus differ from those obtained in a continuum world. In a similar spirit, in our framework, we describe an industry (in an origin country) where an aggregate relationship, here the set of products exported towards a destination country by the industry, is viewed as the outcome of decisions made by a finite group of heterogeneous firms. We show that differently from from what happens with the intensive margin, the aggregate product set is not generated by summation but by the union of the baskets of products exported by each firm. We formalize a conceptual framework that features a discrete number of firms that export potentially heterogeneous product sets towards a country and we study how firms product choices aggregates. We show

<sup>6</sup>The skewed distribution of sales across firms was already subject of much attention in the industrial organization literature, e.g. Axtell, 2001; Sutton, 1997a. The effects of a granular economy has been studied in (Gabaix, 2011; Di Giovanni, Levchenko, and Mejean, 2014)

that the relation between the aggregate and firm level diversification is mediated by the extent to which firms product sets overlap. In particular, we show that the average number of product overlaps per firm can be conveniently decomposed into three factors: the normalized number of firms exporting, the average product scope of firms - computed excluding the most diversified firm, and an index of product sets similarity. We interpret firms' product set similarity by building on early contributions on the theory of the firm. These suggest that firms grows by diversifying across new activities (Marris, 1964) while gaining productive capabilities that can be used to produce new product varieties (Penrose, 1955). Different products require different know how or input capabilities, and firms differ in the capabilities they have. Capabilities are tied to the firm as they often cannot be bought 'off the shelf' (Teece, 1980; Teece et al., 1994; Sutton, 2012).<sup>7</sup> By comparing firms based on what they sell one can investigate the extent to which sectoral diversification reflects characteristics that are common to all firms in a given sector — such as the availability of specific human capital, infrastructure, and technology — versus idiosyncratic contribution of individual firms, driven by their idiosyncratic know-how and managerial talent.

**A new trade environment** The reallocation of the economic activity across firms, as in Melitz, 2003, and within firms across product varieties, as in Mayer, Melitz, and Ottaviano, 2014, spurs aggregate productivity and offer a nontraditional source of welfare gains from trade. When trade policy barriers fall or transportation costs decline, high-productivity exporting firms (high-quality product) survive and grow, while lower-productivity non-exporting firms (low-quality product varieties) are more likely to fail (to be dropped). This tendency to view trade agreements as an example of efficiency-enhancing policies has been prominent in the trade literature and used to promote several episodes of tariff cuts and reduction of quotas. However, "We are no longer negotiating just the reduction of tariffs, but also the reduction of non-tariff barriers, which have gained enormous importance."<sup>8</sup> Contemporary trade agreements go now much beyond traditional trade restrictions at the border.<sup>9</sup> They seek deep integration among nations rather than shallow integration, to use the distinction proposed by Lawrence, 2000. They include for example regulatory standards, health and safety rules, investment, banking and finance, intellectual

<sup>7</sup>More recently, Bernard, Redding, and Schott, 2010 find that firms are much more likely to produce in certain pairs of industries suggesting complementarities exist across activities. Dosi, Grazzi, and Moschella, 2017 find firms are much more diversified in terms of products than in terms of technologies, with their main products more related to the exploitation of their innovative knowledge. Boehm, Dhingra, and Morrow, 2019 shows that input-output tables suggest firms co-produce in industries that share intermediate inputs, proposing input capabilities drive multiproduct production patterns.

<sup>8</sup>Quoting Pascal Lamy, an ex-director of the WTO, during his farewell speech on the 24th of July 2013.

<sup>9</sup>Rodrik, 2018 compares the The US-Israel Free Trade Agreement, which went into force in 1985 with the The US- Singapore Free Trade Agreement went into effect in 2004. The first contains 22 articles and three annexes, the bulk of which are devoted to free-trade issues such as tariffs, agricultural restrictions, import licensing, and rules of origin. The second is nearly ten times as long. Of its 20 chapters, only seven cover conventional trade topics. Other chapters deal with behind-the-border topics.

property, labor, the environment, and many other subjects. Different types of measures exist and, owing to the UNCTAD recent coding system, Non-Tariff Measures (NTMs) can be classified according to their promoted objective (Cadot, Malouche, and Sáez, 2012). Among them, Technical barriers to trade (TBTs) constitute the bulk of NTMs, applying to a wide range of products. These instruments can concern the features or quality of a product or the procedures for testing, certification, labelling etc. They should be designed to achieve public policy goals, such as to protect human safety and health, the environment, as well as national security. However, these are complex policy tools and, despite their official status, they can also be used for political economy reasons, becoming unnecessary barriers to trade (WTO, 2012). The poor data availability and the difficult quantification of these policies makes it particularly difficult to detect their discriminatory application against trade partners. Surveys of exporters across OECD countries report technical regulations among the most reported non tariff barriers (OECD Report p.24, 2005). Interestingly, more than technical regulation itself, EU exporters mostly complain about the procedural obstacles to comply with it (ITC Report 2016 Table B5).

The third chapter investigates procedural obstacles and their effect on the exporting activity of firms. For this purpose we use newly introduced technical regulations that have been contested by exporting countries at the WTO through a soft law mechanism called Specific Trade Concern (STC). We construct a novel database using the content of the STCs which is available as text documentation through the WTO portal. These documents have been automatically parsed while detecting the dates of implementation of the regulations that have been contested. This procedure allows us to identify when and how a contested technical regulation has been introduced in a country. Based on whether the new regulation has been properly disclosed, we introduce the concept of 'Surprise' vs 'Announced' measures. We interpret these differences in terms of the different timing in which firms evaluate whether to adopt the new technical requirement as well as the information at disposal when taking this decision.

Previous empirical literature has found transparency in trade policy to boost trade and investment flows (Francois, 2001; Helble, Shepherd, and Wilson, 2009; Lejarraga and Shepherd, 2013). Metrics used in these type of works are very broad in scope – they are built on perception-based indices or on general transparency provisions within regional trade agreements. An exception, is a recent work by Ing, Cadot, and Walz, 2018 which proposes an index based on what governments actually do in the area of Non Tariff Measures (NTMs). Their index includes the number of NTMs that are notified by a country. We share with this work the focus on Non Tariff Measures, since NTMS, and TBTs in particular, are complex legal instruments which can impose substantial procedural obstacles. In our work we use the procedure of implementation of these regulations, to capture not only whether, as in the case of Ing, Cadot, and Walz, 2018, but also *how* countries announce and disclose these type of regulations. In doing so we provide transparency with a definition

along one fundamental attribute: predictability.<sup>10</sup>

Our work thus refers to the literature that studies the role of trade policy uncertainty on investment decisions of international firms. Recent theoretical contributions (Handley and Limao, 2015; Coelli, 2018) have combined intuitions from trade models with firm heterogeneity (Melitz, 2003) with those from the real options literature (Dixit and Pindyck, 1994). In presence of an irreversible investment and the possibility to wait, uncertainty on the trade environment incentives firms to delay the investment decision on whether to enter a market (Handley and Limao, 2015) or to undergo technology upgrading (Handley and Limão, 2017; Coelli, 2018). These studies test their predictions by exploiting the enforcement of trade Agreements as episodes of changes in policy uncertainty and using variation in the gap between applied and bounds tariffs (similarly also Carballo, Handley, and Limão, 2018). Instead, we use episodes of changes in TBTs, with and without formal Notification, to identify the effect of uncertainty on the export investment decision of foreign firms.

## Resume of the Three Essays

### Chapter 1

The first chapter of the thesis is an extension of Iodice and Tomasi, 2016. This work investigates the evolution of the employment and wage structure of Italian manufacturing firms in the early 2000s. In particular, we perform a decomposition analysis and break down the variation in the skilled-wage bill ratio into employment and wage movements. Our technique disentangles aforementioned structure into inter- and intra-sector shifts, and between or within firms. We provide a methodological framework that simultaneously takes into account changes in the skill intensity and the wage gap. The results suggest that most of the changes are reported within firms, where one observes a skill-upgrading effect not followed by a price adjustment. The increase in the relative employment of skilled workers and the decrease in the wage gap between high- skilled and low-skilled workers can be substantially attributed to changes within exporters and importers, and in more productive firms. Finally, the paper further accounts for changes in the hourly wage premium and skill intensity, and it shows that the annual wage gap is induced by a substantial fall in the hourly wage premium and by an increase in the numbers of hours worked by the skilled factor.

### Chapter 2

The second chapter builds on the joint work with Lionel Fontagné and Angelo Secchi. We describe an industry (in an origin country) where an aggregate relationship,

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<sup>10</sup>Helble, Shepherd, and Wilson, 2009 identify two dimensions of transparency: predictability (reducing the cost of uncertainty) and simplification (reducing information costs). As acknowledged by the authors, their indexes are not able to disentangle the two but instead try to account for both sources together.

the set of products exported towards a destination country by an industry, is viewed as the outcome of decisions made by a finite group of heterogeneous firms. We show that the relation between the aggregate and firm level diversification is mediated by the extent to which firms product sets overlap. In particular, we show that the average number of product overlaps per firm can be conveniently decomposed into three factors: the normalized number of firms exporting, the average number of products of firms - computed excluding the most diversified firm and an index of product sets similarity. We use a sample of French exporters between 1995-2011 and compute the contribution of these three components to the variation in the number of overlaps per firms across destinations and industries. Product set similarity account for half of the variation. The distribution of the average product scope across industry-destination is found to be significantly affected by the removal of the most diversified firm. We compute the RCAs of French industries with and without the top exporter and we find that a 10% increase in the product set similarity index is associated to a reduction of 3.4% in the probability of loosing the RCA due to the removal of the largest exporter. We interpret this evidence suggesting that the similarity of firms' product sets reflects the extent to which the aggregate performance of the industry are driven by fundamental rather than firm-specific forces.

### Chapter 3

The third chapter discusses in detail the (unpublished) working paper Iodice, 2019. This chapter investigates the protective nature of newly introduced technical regulations that are not properly disclosed at the international level. We begin by building a novel database which identifies the process of adoption of those Technical Barriers to Trade (TBTs) that have been contested to the WTO through a Specific Trade Concern (STC). We then cross-reference this database with a firm-level panel of French exporters and we carry out an event study. We find that in more than 1/3 of the studied cases, countries have adopted the underlying regulations without previously announcing the change to other members. In these cases, the new regulation hampers exporters by causing a temporary halt of their activity. This stop lasts from one to two semesters, and it is shorter in the case the content of the new TBT is eventually disclosed by governments. While large firms are able to wait until more information is available, small firms exit the market. We interpret this evidence as suggesting that countries can effectively hinder foreign competitors by raising the uncertainty about the profitability of the market. This in turn raises firms real option to delay their investment decision on whether to export there.



## Chapter 1

# Skill upgrading and wage gap

## A decomposition analysis for Italian manufacturing firms

The material of this chapter is based on the publication: Iodice, I. and Tomasi, C. Skill upgrading and wage gap: a decomposition analysis for Italian manufacturing firms. In *Economia Politica* 33.2 (2016): 201–232.

The increasing share of skilled workers in the labor force and the widening of the wage gap over the last three decades have been largely documented for many OECD countries. These issues are today much debated, and several studies have concentrated on the drivers of movements in the relative demand for skills. The early empirical literature, based on industry data, agreed that technical change was mainly responsible for the skill upgrading and the rising wage gap. This conclusion has been supported by the finding that most of the variation observed in skill utilization has occurred within, rather than between, sectors.<sup>1</sup> Indeed, according to the skill-biased technical change (SBTC) view, rapid technological change, especially when associated with the introduction of computers and automatizing processes, modifies the workforce composition within sectors, increasing the employment share of skilled workers and reducing the demand for unskilled workers and hence their wages. By contrast, explanations based on product demand shifts, such as international trade as modeled in standard trade theories, predict shifts of workers between sectors. Countries with a more skilled labor force specialize in industries which use that factor more intensively. As a result of an expansion of trade, workers should move from contracting industries to expanding ones, changing the aggregate ratio between skilled and unskilled workers and their relative wages.

The conclusions derived from industry-level analyses, however, have been recently challenged by a new stream of empirical studies based on firm-level data.<sup>2</sup> Research based on micro data suggests that most of the movements in labor composition and relative wages happen within firms and that, at least some of these changes, are due to the differences in firms' involvement in international trade. This paper contributes to this emerging literature by providing new evidence on the firm-level

<sup>1</sup>See Section 1.1 for a review of the literature.

<sup>2</sup>See, in particular, Bernard and Jensen, 1997; Biscourp and Kramarz, 2007; Manasse and Stanca, 2006.

dynamics in labor market outcomes underlying the industry-level patterns. Using micro-level data, it investigates the employment structure and the wage dynamic for Italian manufacturing firms in the early 2000s. The use of firm-level data enables us to assess whether the employment and wage movements have taken place between or within sectors, and within sectors, between or within firms.

To investigate the labor market dynamics, we implement a decomposition analysis that breaks the variation in the skilled wage bill ratio down into employment and wage changes. We innovate with respect to the existing literature by proposing a methodology that takes simultaneous account of variations in the skill intensity and the wage gap and that consistently combines the industry-level analysis with the firm-level one. Moreover, to detect the role of technology or international competition in driving firms' skill reallocation and wage premium changes, we run the decomposition analysis for different categories of firms depending on their technological efficiency and international involvement. Finally, we also consider changes in the hourly wage premium and skill intensity. In fact, firms may modify the structure of the workforce by changing the relative number of hours worked and the hourly wage of skilled workers. The results obtained by using annual data may therefore conceal additional movements on the hourly margin. Changes in the average hours worked at the firm would eventually be accounted for in factor prices (annual wages) rather than in quantity movements (total hours employed). The main findings of the empirical analysis are summarized as follows.

The decomposition analysis confirms the importance of within firm changes in explaining the labor market outcomes: most of the movements are reported within sectors, and within sectors the greatest variations occur within business units. By contrast, changes between industries, but also between firms, are very small. The finding that shifts occur especially within firms therefore supports models that mainly explain the skill composition and the wage dynamic using a micro-level perspective.

Our results suggest that there was a restructuring process in terms of skill composition among Italian manufacturing firms during the early 2000s.<sup>3</sup> On average, firms substituted unskilled with skilled labor, providing evidence of a skill upgrading mechanism. Movements between sectors were instead observed from high- to low-skill sectors, which might reflect the Italy's peculiar specialization in the production of unskilled-intensive traditional goods. The restructuring process in terms of skill composition was not followed by a corresponding movement of wages. The relative price of the skilled factor was not adjusted positively as a consequence of the rise in the demand for skilled labor. The wage premium within firms fell, meaning that the wage gap narrowed. Although the data available do not allow us to test any theoretical explanation, the fact that the relative prices did not adjust to factor movements may be due, on the one hand, to the peculiarities of the Italian wage bargaining mechanism and, on the other, to the reforms implemented in Italy during the period examined in order to increase the labor market flexibility.

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<sup>3</sup>This finding is in line with those reported in Bugamelli, Schivardi, and Zizza, 2010.

The empirical exercise reveals that technical efficiency and trade activities are linked to this within-firm reallocation process between skilled and unskilled workers. The increase in the relative employment of skilled workers and the decrease in the wage gap between high- and low-skilled workers can be substantially attributed to changes in exporters and importers and in more productive firms. Although we cannot give any causal interpretation to our results, the findings are consistent with the hypothesis that both technical progress and the strong and sharp increase in competitive pressure following the international integration of markets<sup>4</sup> matched by the process of European integration, triggered a restructuring process that occurred within rather than across firms.

Finally, the decomposition of the hourly wage premium and skill intensity reveals that additional effects are detected when these unexplored margins are considered. The results suggest that the annual wage gap is pushed by a substantial fall in the hourly wage premium enjoyed by skilled workers. Not only has the hourly wage premium fallen, but on average firms have increased the numbers of hours worked by the skilled factor. This rise partially “offsets” the overall effect of the substantial fall in the hourly wage premium over the annual wage inequality. It follows that the fall in the annual wage premium would have been even larger without this adjustment in the number of hours worked.

The rest of the paper is structured as follows. Section 1.1 contextualizes the analysis in the literature. Section 2.2 describes the dataset and the construction of the variables used in the empirical analysis. Section 1.3 outlines the industry and firm-level decomposition framework and shows the results of this decomposition. Section 1.3.3 runs the decomposition analysis for different categories of firms depending on their technological efficiency and international involvement. Section 1.4 takes a closer look at the data, by extending the analysis to the further disaggregation of the annual wage into the price and quantity components. Section 1.5 concludes.

## 1.1 Trade, technology and labour market reforms

### 1.1.1 The Italian economy

In order to better understand the relationship between trade, technology and the labour market outcome, it is necessary to provide a broad picture of the macroeconomic context characterizing the Italian economy from the end of 1990s to the mid 2000s, the period under investigation in our empirical analysis.

As many other industrialized countries, the Italian economy in the last two decades has been under the pressure of important changes in the external context, some “exogenous shocks”, which influenced its economic trends. The process of international economic integration, known as “globalization”, together with the introduction of a

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<sup>4</sup>The period considered was characterized by large and rising imports from low-wage countries, especially from China, which joined the WTO at the end of 2001.

new technological paradigm, born from the spread of information and communication technology (ICT), have been recognized as the most important external changes which hit many advanced economies.

The impact of these shocks has been particularly strong in Italy due to its sectoral structure, based primarily on traditional medium/low-tech industries (textiles and clothing, leather products and footwear, and furniture), particularly exposed to price competition from the emerging countries and with a lower propensity to invest in ICT (Brandolini et al., 2009). These traditional products, that rely heavily on unskilled labor, have suffered particularly from the entry into the trade system of a sizable group of countries, such as China and India, endowed with less qualified workers and lower labour costs (Lanza and Quintieri, 2007; Felettigh et al., 2006; Sergio and Fabrizio, 1999). Italy's international competitiveness on international markets has shown signs of weakness: the share of Italian exports on the world market for goods has tended to decline since the mid-1990s (ICE, 2007). The low specialization in high-technology sectors represents an additional element of weakness of the Italian economic system which has further limited its competitive capacity. International comparisons show that Italy has lagged behind in technology investments: ITC sector accounted for 7.5% of the national value added in 2006, against the 12% registered in countries such as Finland and Ireland (OECD, 2008b).

Because of its structural characteristics, Italy was harder hit by the strong and sharp increase in the competitive pressure induced by these exogenous shocks.<sup>5</sup> The Italian macroeconomic performance has been characterized by weak output growth, especially compared with the main European countries and other leading industrial economies OECD, 2008b. Above all, the data has revealed a slowdown in the efficiency of the production system measured by both labour and total factor productivity (TFP). International comparison shows that Italy ranked last in terms of growth of GDP per hour worked over the period 1995-2006 (OECD, 2008a). In general, the Italian economy registered zero growth in the years 2001-2005 and average annual growth below 1% in the previous period, 1995-2000. Only Spain did worse in this subperiod. The evidence for the manufacturing sector is even more dramatic: indeed if we consider the 1995-2005 period, the average growth rate of value added per employee is negative. According to Bassanetti and Zollino, 2008, total factor productivity fell sharply in the period between 2001-2003 and it started to recover slightly starting from 2004.

The macroeconomic trend observed for Italy between the end of the 1990s and the mid 2000s show unsatisfactory results in terms of productivity, exports and ICT investments. However, additional micro-economic empirical analyses add insights to diagnosis of the state of Italian manufacturing industry and suggest that there exists a relatively small group of quite vital and dynamic firms able to adjust to the

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<sup>5</sup>As emphasized by Fund, 2005 and BarbaNavaretti et al., 2007, the lack of competitiveness of the Italian economy is not entirely driven by its sectoral specialization. Indeed, the drop in market share has been observed also in other sectors, less exposed to the international competition from emerging economies.

exogenous shocks, successfully changing their product mix and able to seize new market and investment opportunities (Dosi et al., 2012; Bugamelli, Schivardi, and Zizza, 2010; BarbaNavaretti et al., 2007).<sup>6</sup> In line with these recent empirical analyses, our paper takes a micro-economic perspective by disentangling the aggregate movements of employment and wages into shifts within each sector, between or within firms.

In addition to the exogenous shocks associated to the globalization and technological progress, in the last two decades Italy has undergone substantial reforms in the labor market. The collective bargaining structure enacted in the 1993, as a response to the recession and the rising unemployment, defined a two-tier bargaining structure: i) collective bargaining at the national (sectoral) level, determining the terms and conditions of employment and basic wage guarantees; and ii) bargaining at the second (regional or firm) level, allowing the bargaining partners to supplement national contracts. While the 1993 social pact designed a broad bargaining framework between the social partners, the Treu measure in 1997 (Law 197/1997) was the first reform addressing the employment issue by introducing temporary contracts and providing incentives for part-time work. Efforts to increase labor market flexibility were taken forward with the 2003 Biagi reform (Law 30/2003). This reform further deregulated the use of atypical work arrangements, such as temporary agency work (staff-leasing) and part-time work, and introduced new forms of atypical work arrangements such as on-call jobs (*lavoro intermittente*), job sharing and occasional work (*lavoro a progetto*).<sup>7</sup>

Several empirical and theoretical works have considered the effects of the reduction of employment protection legislation (EPL), through the liberalization of temporary contracts. A large literature has investigated the importance of temporary contracts in affecting job flows (Boeri and Garibaldi, 2007; Ichino, Mealli, and Nannicini, 2008; Blanchard and Landier, 2002), by increasing both the hiring and the firing of workers, and labour productivity (Autor, Kerr, and Kugler, 2007; Cingano et al., 2010; Bassanini, Nunziata, and Venn, 2009). As far as the Italian case is concerned, Rosolia and Torrini, 2007 show that the enhanced flexibility has mostly concerned younger workers entering the labour market who have suffered of a relative loss in entry wages with respect to the preceding generations. Lucidi, 2006 find that firms exhibiting a higher share of temporary workers among their workforce and a higher rate of labour turnover displayed a slower growth of value added per worker in the period 2001-2003. Cappellari, Dell'Aringa, and Leonardi, 2012 observe that while the reform of apprenticeship contracts had an overall positive effect on firms' productivity, mainly due to the substitution of external staff with firms' apprentices, the

<sup>6</sup>However, as stressed by Dosi et al., 2012, these firms coexists with a generally bigger ensemble of much less technologically progressive firms which nonetheless survive quite comfortably, possibly exploiting local market niches.

<sup>7</sup>See Cappellari, Dell'Aringa, and Leonardi, 2012 for a detailed description of the institutional changes in the Italian labour market due to the Treu measure and the Biagi reform.

reform of fixed-term contracts negatively affected job reallocation and favored the used of external collaborations, generating productivity losses.

### 1.1.2 Related literature

Beginning in the late 1980s, there was growing concern about the widening of the wage gap and the increase in relative demand for skilled workers, especially in developed countries. Several explanations were put forward to explain such trends, the most prominent one being skill-biased technological change (Katz and Murphy, 1992; Bound and Johnson, 1992; Machin and Reenen, 1998). The main reasons that induced economists to favor SBTC over trade-related alternative theories was the evidence, largely based on industry-level data, that skill upgrading occurred mainly within industries rather than between them, which contradicted the prediction of the standard Heckscher-Ohlin (HO) theory (Berman, Bound, and Griliches, 1994). Skill upgrading occurred not only in developed countries but also in developing ones, which also ran counter to the standard international trade theories. Moreover, despite the rise in the relative cost of skilled labor, the major US industries increased their ratio of skilled to unskilled labor (Lawrence and Slaughter, 1993). Finally, several empirical studies observed a positive correlation between sectoral indicators of technological change and the demand for skills (Bound and Johnson, 1992; Autor, Levy, and Murnane, 2003; Machin and Reenen, 1998; Bekman, Bound, and Machin, 1998).<sup>8</sup>

However, more recent developments in both theory and applied analyses, which have moved from an industry- to a firm-level perspective, have challenged this view. An emerging stream of studies has emphasized the importance of firm heterogeneity, suggesting that both trade and technology may induce within-firm skill upgrading. Put briefly, as far as technology is concerned, firms investing in information technology or adopting new production processes are more likely to substitute unskilled labor with skilled labor, leading to higher employment shares and wage premia for skilled workers.

As regards the role of trade, three main mechanisms whereby international competition may induce within-firm skill upgrading have been identified. First, some scholars have stressed the complementarity between trade and technology, suggesting that trade may induce a firm's technology upgrading which, in turn, increases the demand for more educated workers (Acemoglu, 2003; Ekholm and Midelfart, 2005; Bloom, Draca, and Reenen, 2016; Yeaple, 2005). Second, trade in tasks and offshoring can play a role (Feenstra and Hanson, 1995; Grossman and Rossi-Hansberg, 2008). If the low skill-intensive tasks are offshored, the skill intensity of firms located in developed countries rises.<sup>9</sup> Third, firms facing international competition are more

<sup>8</sup>See Vivarelli, 2014 for surveys of the literature on the relationship between innovation and skilled workers.

<sup>9</sup>Because the tasks offshored to developing countries tend to be more skill-intensive than those already performed there, the skill intensity rises also within firms in less advanced countries.

likely to be subject to a quality upgrading of their production because they compete on foreign markets, where consumers are willing to pay more for higher quality goods. This quality upgrading boosts the demand for labor quality, which in turn reflects on movements in wage premiums (Verhoogen, 2008; Kugler and Verhoogen, 2012; Brambilla, Lederman, and Porto, 2012).

From an empirical standpoint, several micro-level empirical analyses confirm the positive impact of investment in information technology on the volume of skilled labor (Haskel and Heden, 1999; Mairesse, Greenan, and Topiol-Bensaid, 2001; Duguet and Greenan, 1997; Casavola, Gavosto, and Sestito, 1996). Similarly, a large number of recent firm-level studies observe that both exports and imports play a role in within-firm skill upgrading.<sup>10</sup>

Further empirical micro-level studies look at the effects of technological changes and international competition on the employment and wage structure of Italian manufacturing firms', considering whether and to what extent the increased competition has induced a firm's restructuring process. Baccini and Cioni, 2010 show that, in the textile sector, technological change has mainly been concerned with labour saving, causing occupations related to labour intensive production phases to disappear. Bugamelli, Schivardi, and Zizza, 2010 suggest that the single market and the euro had the effect of triggering a restructuring process that occurred within rather than across firms. They observe a shift of business focus from production to upstream and downstream activities and a corresponding reduction in the share of blue collar workers within firms. Using a sample of 488 Italian manufacturing firms, Piva, Santarelli, and Vivarelli, 2005 jointly consider the impact of technological and organization change on the skill composition of manufacturing employment and observe that the upskilling trend is more related to the reorganisational strategy adopted by the companies than to the technological change alone (see also Piva and Vivarelli, 2002). Accetturo, Bugamelli, and Lamorgese, 2013, using Italian firm-level data for the 2000-06 period, show that international demand induces within-firm upgrading in favor of more skilled individuals.

Our paper more closely relates to the empirical analyses that apply a decomposition framework to disentangle the aggregate change in wages and employment structure between and within changes across sectors and firms. Bernard and Jensen, 1997 conducted a decomposition at both industry and firm-level that separately considered the movements in skill intensity and in the relative wage bill ratio. Using plant-level data for the US manufacturing sector from 1980 to 1987, they observed that employment share increases occurred within plants, especially among exporting establishments, while wage share increases occurred because of shifts across

<sup>10</sup>Mion and Zhu, 2013 find that import competition from China has been responsible for the observed increase in the share of non-production workers for Belgium firms. Bustos, 2011 establishes that the increase in exports due to trade liberalization in Argentina has impacted on firms' behavior generating a technology and skill upgrading. Other empirical studies confirming the causal impact of trade on labor market outcomes are Frias, Kaplan, and Verhoogen, 2012 and Verhoogen, 2008.

plants. Differently from our decomposition analysis, Bernard and Jensen, 1997 analyzed separately the movements in the skill intensity and in the relative wage bill ratio. Biscourp and Kramarz, 2007 developed a harmonized framework that integrated industry-level and firm-level analysis. However, they studied only the skill structure of the workforce, rather than dealing with movements in the relative wage ratio. Using data on French firm-level data from 1986 to 1992, they found that most skilled employment changes occurred within firms, and that most of the action took place in firms continuously present in foreign markets.

Our study is close to that of Manasse, Stanca, and Turrini, 2004, who conducted a decomposition that nested the wage bill with employment and wage movements, using data for Italian firms belonging to the metal-mechanical sector between 1995 and 1997.<sup>11</sup> They showed that within changes, correlated to technical progress, were offset by between movements related to demand changes associated with trade. By disaggregating non-manual workers into clerical workers and executives, their paper emphasized that the rise in the wage inequality and skill upgrading mainly occurred between these two classes rather than between manual and non-manual workers. Differently from Manasse, Stanca, and Turrini, 2004, we present evidence on skill upgrading and wage inequality in a representative sample of Italian firms belonging to all manufacturing sectors and for a different period. Similarly to Manasse and Stanca, 2006, we also provide evidence on an additional margin of adjustment; that is, we take account of the number of hours worked and the hourly wage. As in our paper, Manasse and Stanca, 2006 found for a sample of Italian firms in the 1990s, that annual wage skill-premia concealed a compositional effect. While the number of hour worked by skilled workers increased, the relative annual wages did not adjust. Our study considers a more recent period, and it conducts a decomposition analysis that consistently combines the industry-level analysis with the firm-level one.

Finally, our study marginally contributes to the very recent discussion about the evolution of wage distribution and the phenomena known as “polarization”, according to which the top of the wage distribution continues to become more unequal with the 90th percentile pulling further away from the median (Van Reenen, 2011). At the same time, the middle part of the wage distribution appears to be losing ground to the bottom as well as the top. Goos and Manning, 2007 examine polarization through the changing pattern of employment and show that in UK, since 1975, the low wage occupations (hairdressers, cleaners, supermarket shelf-stackers) have actually grown in importance alongside very high wage occupations (lawyers, bankers, management consultants, economists, etc.). Remarkably, this pattern has also been documented in the US (Autor, Katz, and Kearney, 2006) and many other OECD countries (Goos, Manning, and Salomons, 2009). The polarization in the labour market has been related to ICT technologies which have been replacing

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<sup>11</sup>See also Falzoni, Venturini, and Villosio, 2011 for an analysis of the wage dynamics of skilled and unskilled workers in Italy in the 1991-1998 period.

mainly “routine” tasks typically performed by middle-task jobs. New technologies have been revealed to be complementary to well-paid, high skill workers performing non-routine cognitive skills, as well as to low-paid least skilled jobs requiring non-routinized manual tasks. However, Naticchioni, Ragusa, and Massari, 2014 do not find evidence that wages have significantly responded in the same way to technological progress across many European countries, including Italy. This result is in line with the intuitions behind our results, according to which the wage bargaining rigidity prevents possible price adjustments following changes in the demand for jobs.

## 1.2 Data

The empirical analysis is based on the Micro.3 accounting dataset which includes census data on Italian firms with more than 20 employees operating in all sectors of the economy, over the period 2001-2006.<sup>12</sup> Although the data are almost 10 years old, they cover a particularly interesting period characterized by regulatory changes for temporary and permanent workers mainly driven by the need to increase the adaptability of the labour market in response to growing pressures from globalization and rapid technical change.<sup>13</sup> Moreover, the period under investigation guarantee continuity before the structural break and and the discontinuity induced by the financial and economic crisis from 2007 onward.

The census covers the population of firms with more than 99 employees, and it collects information for firms in the 20-99 employment range through a “rotating sample”. In order to complete the coverage of firms in that range, Micro.3 complements census data with data from the compulsory financial statements of limited liability companies.<sup>14</sup> From Micro.3 we select those firms belonging to the Manufacturing sector, according to their main activity, as identified by ISTAT’s standard codes for sectoral classification of business (ATECO).<sup>15</sup> A legitimate concern is whether the Micro.3 database is sufficiently representative of the Italian manufacturing industry. In order to ensure the representativeness of Micro.3 with respect to the national industrial structure, we compare the sectoral distribution of our sample with that of the universe for 2003 (but figures are comparable in the other years). The results are reported in Table A.1 in the Appendix. We compute a Wilcoxon-Mann-Whitney test for independence, a non-parametric test of the null hypothesis

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<sup>12</sup>The dataset was made available for work after careful screening to avoid disclosure of individual information. The data were accessed at the ISTAT facilities in Rome. The database was constructed through collaboration between ISTAT and a group of LEM researchers at the Scuola Superiore Sant’Anna, Pisa. See Grazzi et al., 2013 for more details.

<sup>13</sup>In particular, in Italy as in most OECD countries, most of the reforms focused on easing regulations governing temporary contracts. See OECD, 2011; Martin and Scarpetta, 2012 for a detailed discussion of the implementation of regulatory reforms in OECD countries during the 2000s.

<sup>14</sup>Limited liability companies (società di capitali) submit a copy of their financial statement to the Register of Firms at the local Chamber of Commerce.

<sup>15</sup>The ATECO classification is equivalent to the Statistical Classification of Economic Activities adopted by the European Community, commonly referred to as NACE.

TABLE 1.1: Variables codes and coverages

Variable Name	Notation	Source	Years covered
Total wage bill	$WB$	Micro.3	2001-2006
Wage bill for skilled labor	$WB_{sk}$	Micro.3	2001-2006
Wage bill for unskilled labor	$WB_{un}$	Micro.3	2001-2006
Number of employees	$L$	Micro.3	2001-2006
Skilled workers	$L_{sk}$	Micro.3	2001-2006
Unskilled workers	$L_{un}$	Micro.3	2001-2006
Total hours worked	$H$	Micro.3	2001-2006
Hours worked by skilled labor	$H_{sk}$	Micro.3	2001-2006
Hours worked by unskilled labor	$H_{un}$	Micro.3	2001-2006
Total Factor Productivity	$TFP$	Micro.3	2001-2006
Exports	$Exp$	Trade Statistics	2001-2006
Imports	$Imp$	Trade Statistics	2001-2006

*Note:* Table reports the variables used in the empirical analysis and their relative time availability

that two samples come from the same population against an alternative hypothesis, especially that a particular population tends to have larger values than the other. The results for the Wilcoxon-Mann-Whitney test indicate that the underlying distributions of the percentage of firms by sector is equal among the two groups, the universe of Italian manufacturing firms and those in Micro.3.<sup>16</sup>

Micro.3 contains information on a number of balance sheet items, and it also includes firms' export and import activities which are collected by ISTAT through the trade statistics dataset and matched by means of the Italian Register of Accounting firms coding system (ASIA). For the purpose of our analysis we utilize the following: number of employees and number of hours worked, wage bill and workforce composition, value added, material costs, tangible fixed assets, exports and imports.<sup>17</sup> Data on employment, wage bill and number of hours worked are available separately for manual workers (including blue collars, assistants, trainees and home-based workers<sup>18</sup>) and non-manual workers (executives and clerical workers<sup>19</sup>). We consider production and non-production workers as proxies for unskilled and skilled labor, respectively. Ideally, we would prefer to work with more specific information on the demographic components of the firm workforce in order further to investigate the skill structure and the wage skill premium. Although this categorization is rather imprecise, Goldberg and Pavcnik, 2007 note that cross tabulations of matched worker and employer surveys at the plant-level in the United States and the United Kingdom indicate a close relationship between the production/non-production status of workers and their educational level.

<sup>16</sup>The representativeness of Micro.3 has also been checked in relation to data from Eurostat: the coverage provided by Micro.3 for the overall Italian economy is fairly large: around 40% for employment and 50% when considering value added (Grazzi et al., 2013).

<sup>17</sup>Nominal variables are in millions of euros and are deflated using 2-digit industry-level production prices indices provided by ISTAT.

<sup>18</sup>Respectively, *operai*, *commessi*, *apprendisti* and *lavoratori a domicilio*.

<sup>19</sup>Respectively, *dirigenti* and *impiegati*.

TABLE 1.2: Number of active, continuous, exporting and importing firms

Year	Active firms	Continuous Firms	Exporters	Importers
2001	10,683		8,644	8,303
2002	9,966	4,472	7,598	7,128
2003	11,923	4,893	9,372	8,811
2004	11,461	6,683	9,076	8,652
2005	11,167	6,551	8,961	8,476
2006	11,187	6,588	8,978	8,608

*Note:* Active firms are those firms that are present in the sample in that specific year, continuous firms are those that are active in that year and in the next one.

As a measure of firms' international competitiveness we use the level of engagement in export and import activities. We distinguish between those firms with a value of exports (imports) above the median computed for each sector, which we term high-exporters *Hexp* (high-importers *Himp*), from those with a value below it, the low-exporters *Lexp* (low-importers *Limp*). Finally, as a proxy for technological efficiency we compute the Total Factor Productivity which can be taken as a measure of a firm's long-term technological change or technological dynamism.<sup>20</sup> We estimate the Total Factor Productivity (TFP) following the IV-GMM modified Levinsohn-Petrin procedure proposed by Wooldridge, 2009, in the value-added case. Material costs are used as a proxy for intermediate inputs while capital is proxied by tangible fixed assets at book value (net of depreciation). Again, we create two categories of firms based on the level of technological efficiency. We identify with *Htfp* those firms that exhibit a TFP larger than the median of the sector, while *Ltfp* denotes those with a smaller value.

Table 1.1 summarizes the main variables used in the empirical analysis and their relative sources.

As shown in Table 1.2, we obtain an unbalanced panel of active manufacturing firms over the period 2001-2006. The Table also reports the number of continuous firms, i.e. those firms active at time  $t$  and  $t + 1$ . The empirical analysis that follows is based on year by year first differences. It thus makes use of those firms that produce on a continuous basis for at least two years. In the Appendix we check whether we introduce any sample-selection bias when considering the continuous firms alone. Table 1.2 also distinguishes between the number of exporters and the number of importers. Approximately two-thirds of manufacturing firms were internationalized over the 2001-2006 period.<sup>21</sup>

Descriptive statistics are reported in Table 1.3, which shows the average value

<sup>20</sup>Unfortunately, the database does not provide information on the level of firms' investment in computers or in R&D activities.

<sup>21</sup>Note that the high percentage is partly explained by the fact that our sample comprises only firms with more than 20 employees. Since smaller firms are less likely to enter foreign markets, either by means of exports or imports, we end up with a larger fraction of internationalized firms compared with the universe of Italian active firms.

TABLE 1.3: Descriptive statistics: Employment and Wages

Sample	$\frac{WB_{sk}}{WB}$ (1)	WP (2)	SI (3)	W (4)	Wsk (5)	Wun (6)	L (7)	Lsk (8)	Lun (9)	Obs (10)
Overall	37.80	141.65	29.44	21.63	30.26	18.03	152	53	99	66,387
2001	36.59	140.33	28.29	20.76	28.59	17.68	167	56	111	10,683
2002	35.52	138.22	27.57	20.47	27.86	17.24	127	42	85	9,966
2003	37.37	143.36	28.94	21.42	30.25	17.90	146	50	96	11,923
2004	38.31	140.51	29.83	21.97	30.51	18.17	154	54	100	11,461
2005	39.34	147.06	30.66	22.34	32.71	18.40	158	57	101	11,167
2006	39.38	139.90	31.13	22.68	31.29	18.72	157	57	100	11,187
Small	32.92	136.42	25.84	18.96	25.49	16.03	31	8	23	26,816
Medium	39.57	143.58	30.71	22.76	32.25	18.84	114	36	78	32,142
Large	47.76	152.18	36.92	26.38	38.87	21.77	749	286	463	7,429
North	40.24	141.30	31.34	22.64	31.58	18.70	168	59	109	46,263
Centre	34.76	142.38	27.42	20.41	28.72	17.08	126	49	77	10,862
South	29.17	142.51	22.34	18.02	25.46	15.85	99	26	73	9,262
Hexp	41.87	143.86	32.33	23.60	33.62	19.57	238	86	152	33,184
Lexp	33.73	139.44	26.56	19.67	26.90	16.50	66	20	46	33,203
Himp	42.33	142.96	32.93	23.87	33.74	19.49	243	89	154	33,182
Limp	33.27	140.34	25.95	19.39	26.78	16.58	61	17	44	33,205
Htfp	43.88	142.61	34.40	25.32	35.66	20.56	247	92	155	30,127
Ltfp	33.16	140.40	25.60	18.85	26.15	16.25	74	20	54	30,193

Notes: Values are averages on active firms over the sample 2001-2006. Column 1: ratio between the wage bill for skilled workers and the total wage bill. Column 2: ratio of the annual wage rate of non production workers over the average wage, i.e. wage premium. Column 3: ratio of skilled workers in employment, i.e. skill intensity. Columns 4-6: average wage for all workers (*W*), for skilled (*Wsk*) and unskilled (*Wun*). Columns 7-9: average number of employees (*L*), of skilled workers (*Lsk*) and unskilled ones (*Lun*). *Hexp* (*Himp*): firms that export (import) more than the median value of their sector. *Lexp* (*Limp*): firms those that export (import) less than the median value. *Htfp* (*Ltfp*): firms with a level of TFP above (below) the median value of the sector.

for the main variables of interest computed over the set of manufacturing firms included in our sample. The table distinguishes among firms with high and low level of export/import intensity and technological efficiency, firms belonging to different geographical areas (north, center, south) and to different size classes (small, medium, large). *Large* firms are those that employ a number of workers larger than the 66th-percentile of the size distribution of the sector; *small* firms are those that employ a number of workers which is smaller than the 33rd-percentile; *medium* firms are those that employ a number of workers above the 33th-percentile and below the 66th-percentile.

Overall between 2001 and 2006, the wage bill ratio increases in almost each year, which reflects a fairly large increase in the skill intensity (*SI*). The Table confirms the large heterogeneity across firms in the sample, in terms of both wages and employment structure. Large firms and those located in the North of Italy pay substantially higher nominal wages than small and medium firms, and they employ the largest share of skilled workers. Marked heterogeneity is also detected among firms with different levels of participation in international markets and with different levels of

technological efficiency. More internationalized firms have a larger share of skilled workers in the wage bill compared with less internationalized ones. They also employ relatively more skills and have a larger wage premium. Moreover, they pay much higher wages to both types of workers than do firms less involved in trade activities. The same applies to firms with greater technological efficiency as proxied by their level of Total Factor Productivity.

### 1.3 Wage and employment movements

We start by decomposing the change in the relative wage bill into the respective contributions of skill intensity and wage premium. Each of these components is further disaggregated into the between and within contributions. While the former reflects reallocations of employment and wages that occur between different sectors/firms, the latter identifies changes that occur within individual sectors/firms. We contribute by providing a framework that consistently combines the industry-level analysis with the firm-level one.

#### 1.3.1 Industry and firm-level decomposition

Following the approach adopted by Biscourp and Kramarz, 2007, we run the decomposition analysis at both the industry- and firm-level. However, we extend their analysis by combining valuations on skill intensity and wage differentials as in Manasse and Stanca, 2006. We start with the industrial decomposition and consider the following equation

$$\underbrace{\Delta \frac{WB_{sk}}{WB}}_{WB_{tot}} = \Delta \sum_s \frac{W_{sk_s}}{W} \frac{L_{sk_s}}{L} = \underbrace{\sum_s \Delta \frac{W_{sk_s}}{W} \left( \frac{L_{sk_s}}{L} \right)}_{W_{tot}} + \underbrace{\sum_s \Delta \frac{L_{sk_s}}{L} \left( \frac{W_{sk_s}}{W} \right)}_{L_{tot}} \quad (1.1)$$

where the overall change in the wage bill ratio  $\Delta \frac{WB_{sk}}{WB}$  is given by the sum of the sectoral ( $s$ ) wage and employment contributions,  $W_{tot}$  and  $L_{tot}$ , respectively. The first term ( $W_{tot}$ ) is the sum of all changes in the wage premium, weighted by the time average share of skilled workers in the workforce. The second term ( $L_{tot}$ ) is the sum of all changes in skill intensities, weighted by the time average of the wage premium. In fact, changes in skill intensities and wage premium are gauged jointly by keeping the other variable constant at each stage. Both movements can be further disentangled into the within and the between sectoral components, which represent shifts within and between different sectors. Therefore, each component of equation 1.1 can be written as

$$\begin{aligned}
Wtot &= \sum_s \Delta \frac{W_{sk_s}}{W} \overline{\left( \frac{L_{sk_s}}{L} \right)} = \\
&= \left[ \underbrace{\sum_s \Delta \frac{W_{sk_s}}{W_s} \overline{\left( \frac{W_s}{W} \right)}}_{Wwit} + \underbrace{\sum_s \Delta \frac{W_s}{W} \overline{\left( \frac{W_{sk_s}}{W_s} \right)}}_{Wbet} \right] \overline{\left( \frac{L_{sk_s}}{L} \right)} \quad (1.2)
\end{aligned}$$

$$\begin{aligned}
Ltot &= \sum_s \Delta \frac{L_{sk_s}}{L} \overline{\left( \frac{W_{sk_s}}{W} \right)} = \\
&= \left[ \underbrace{\sum_s \Delta \frac{L_{sk_s}}{L_s} \overline{\left( \frac{L_s}{L} \right)}}_{Lwit} + \underbrace{\sum_s \Delta \frac{L_s}{L} \overline{\left( \frac{L_{sk_s}}{L_s} \right)}}_{Lbet} \right] \overline{\left( \frac{W_{sk_s}}{W} \right)} \quad (1.3)
\end{aligned}$$

where  $Wwit$  and  $Wbet$  represent the within and between sectoral components of the  $Wtot$  variable and, similarly,  $Lwit$  and  $Lbet$  represent within and between sectoral contributions of the  $Ltot$  variable.

Moving from sectoral to firm-level analysis, the wage bill ratio movement for each industry ( $\Delta \frac{WB_{sk_s}}{WB_s}$ ) can be written as the sum of the contributions by the firms belonging to the sector

$$\underbrace{\Delta \frac{WB_{sk_s}}{WB_s}}_{WBtot_s} = \Delta \sum_{i \in s} \frac{W_{sk_i}}{W_s} \frac{L_{sk_i}}{L_s} = \underbrace{\sum_{i \in s} \Delta \frac{W_{sk_i}}{W_s} \overline{\left( \frac{L_{sk_i}}{L_s} \right)}}_{Wtot_s} + \underbrace{\sum_{i \in s} \Delta \frac{L_{sk_i}}{L_s} \overline{\left( \frac{W_{sk_i}}{W_s} \right)}}_{Ltot_s}. \quad (1.4)$$

where the subscript  $i$  denotes a firm and  $Wtot_s$  and  $Ltot_s$  are, as previously, the wage and employment components, but for a single sector  $s$ . The two sectoral components can be further disentangled into the respective within and between firm-level movements for sector  $s$  as follows

$$\begin{aligned}
Wtot_s &= \sum_{i \in s} \Delta \frac{W_{sk_i}}{W_s} \overline{\left( \frac{L_{sk_i}}{L_s} \right)} = \\
&= \left[ \underbrace{\sum_{i \in s} \Delta \frac{W_{sk_i}}{W_i} \overline{\left( \frac{W_i}{W_s} \right)}}_{Wwit_s} + \underbrace{\sum_{i \in s} \Delta \frac{W_i}{W_s} \overline{\left( \frac{W_{sk_i}}{W_i} \right)}}_{Wbet_s} \right] \overline{\left( \frac{L_{sk_i}}{L_s} \right)} \quad (1.5)
\end{aligned}$$

$$\begin{aligned}
Ltot_s &= \sum_{i \in s} \Delta \frac{L_{sk_i}}{L_s} \overline{\left( \frac{W_{sk_i}}{W_s} \right)} = \\
&= \left[ \underbrace{\sum_{i \in s} \Delta \frac{L_{sk_i}}{L_i} \overline{\left( \frac{L_i}{L_s} \right)}}_{Lwit_s} + \underbrace{\sum_{i \in s} \Delta \frac{L_i}{L_s} \overline{\left( \frac{L_{sk_i}}{L_i} \right)}}_{Lbet_s} \right] \overline{\left( \frac{W_{sk_i}}{W_s} \right)}
\end{aligned} \tag{1.6}$$

where  $Wwit_s$  and  $Wbet_s$  represent the within and between firm-level components of the  $Wtot_s$  variable. Similarly,  $Lwit_s$  and  $Lbet_s$  represent within and between firm-level contributions of the  $Ltot_s$  variable.

We then aggregate all movements occurring within industries, i.e. between and within firms, as a weighted sum of all sectoral  $Ltot_s$  and  $Wtot_s$  contributions. Since  $Ltot_s$  and  $Wtot_s$  are the combination of between and within components, we can obtain the overall movement as a weighted sum of  $Lbet_s$ ,  $Lwit_s$ ,  $Wbet_s$  and  $Wwit_s$  as follows

$$\begin{aligned}
\underbrace{\left( \Delta \frac{WB_{sk}}{WB} \right)^{within}}_{WBtot^{wit}} &= \sum_s \underbrace{\overline{\left( \frac{L_s}{L} \right)}}_{Ltot_s} Ltot_s + \sum_s \underbrace{\overline{\left( \frac{WB_s}{WB} \right)}}_{Wtot_s} Wtot_s = \\
&= \sum_s \underbrace{\overline{\left( \frac{L_s}{L} \right)}}_{Lbet_s} Lbet_s + \sum_s \underbrace{\overline{\left( \frac{L_s}{L} \right)}}_{Lwit_s} Lwit_s + \sum_s \underbrace{\overline{\left( \frac{WB_s}{WB} \right)}}_{Wbet_s} Wbet_s + \sum_s \underbrace{\overline{\left( \frac{WB_s}{WB} \right)}}_{Wwit_s} Wwit_s
\end{aligned} \tag{1.7}$$

where we denote each weighted component with an upper bar. We use as weights the relative importance of each sector in the overall economy in terms of employment and wage bills, respectively.<sup>22</sup> The weighted aggregation of all these components gives the weighted wage bill variation that has occurred within industries. Note that the weighted average of all movements occurring between and within firms in each sector approximates the within movements computed at the industry-level, i.e.  $WBtot^{wit} \approx Lwit + Wwit$ .

### 1.3.2 Results

All wage and employment structure changes are computed on a yearly basis and then averaged over the span of interest. This approach has the advantage of increasing the number of observations because it requires balancing the panel over only

<sup>22</sup>Results are robust to the use of alternative weighting functions: for example if we apply as weights the relative importance of sectors in terms of wage bills to all types of contributions.

two consecutive years.<sup>23</sup> We start our analysis at the industry-level by distinguishing between movements of workers and wages across and within sectors. Industries are defined by means of the 2-digits NACE nomenclature, which defines 22 manufacturing sectors.<sup>24</sup> The overall wage bill ratio movement is first split into the  $Wtot$  and  $Ltot$  components as shown in equation 1.1. The two contributions are then further disentangled into the within and between parts as done in equations 1.2 and 1.3.

Column 1 of Panel *a* of Table 1.4 reports the components from the industry-level decomposition over the whole time span, from 2001 to 2006. Over the entire span the wage bill ratio component ( $WBtot$ ) increases on average by almost 0.26% per year, which means that the share of non-production workers in the wage bill rises. This increase is driven by a large quantity adjustment partially offset by a negative price one:  $Ltot$  grows by almost 0.45% annually, while  $Wtot$  falls by -0.19 % per year. In other words, we observe a rise in the demand for skilled labor not followed by a relative price adjustment in factors.

Most of the  $Ltot$  and  $Wtot$  movements occur within sectors.  $Lwit$  increases by 0.473% per year while  $Wwit$  drops by 0.219% annually. This reflects that within sectors unskilled labor is substituted with skilled labor, but that unskilled workers' wages rise relatively faster than those of skilled ones, i.e. the wage differential narrows. In regard to the between components, we note that the  $Lbet$  slightly falls by 0.023% per year, while  $Wbet$  rises by 0.028% annually. These movements suggest an expansion of skilled labor in unskilled-intensive industries, a result that can be interpreted as reflecting the Italian specialization in traditional sectors. At the same time, the positive  $Wbet$  component suggests that skilled-intensive sectors are those that most raise the average annual wage. The between changes, however, are very marginal compared with the within movements.

While the sectoral decomposition yields an overview of the employment and wage movements, it hides important elements of the changes in the demand for skilled labor and wages that take place within or between firms belonging to the same industry. Consequently, we investigate, within each sector, changes that are firm-level using equations 1.5 and 1.6. We then aggregate all sectoral contributions as in equation 1.7 in order to obtain the weighted wage bill variation that has occurred within industries, i.e. between and within firms. In fact,  $WBtot^{wit}$  approximates the sum of the two within components at the industry-level,  $Lwit$  and  $Wwit$ ,

<sup>23</sup>Taking a balance panel over a longer time period (e.g. 2001-2006) may also introduce a bias. Indeed, because small firms are more likely to exit (Geroski, 1995; Sutton, 1997b), using a larger interval increases the probability of selecting only large firms. However, using a longer interval might end up with selection of the more productive firms that extensively use skilled workers.

<sup>24</sup>We exclude from the analysis industry 16 (Manufacture of wood and wood and cork products, except furniture; manufacture of straw and plaiting material articles) because of the small number of firms active in this sector.

TABLE 1.4: Industry and firm-level wage bill share decomposition

	Panel a: Industry decomposition				Panel b: Firm decomposition				
	(1)	(2) B&J	(3) B&K	(4) M&S	(1)	(2) B&J	(3) B&K	(4) M&S	
$WBtot$	0.259	0.259	-	-	$WBtot^{wit}$	0.290	0.242	-	0.242
$Ltot$	0.450	0.326	0.326	-	$\overline{Ltot}_s$	0.638	0.348	0.341	0.608
$Lwit$	0.473	0.345	0.345	-	$\overline{Lwit}_s$	0.629	0.355	0.340	0.585
$Lbet$	-0.023	-0.019	-0.019	-	$\overline{Lbet}_s$	0.009	-0.007	0.001	0.023
$Wtot$	-0.191	-	-	-	$\overline{Wtot}_s$	-0.348	-	-	-0.367
$Wwit$	-0.219	-	-	-	$\overline{Wwit}_s$	-0.340	-	-	-0.381
$Wbet$	0.028	-	-	-	$\overline{Wbet}_s$	-0.008	-	-	0.015

Notes: All components are annual means averages for the period 2001-2006 (%). Panel a: Industry-level wage bill share decomposition. Panel b: Firm-level wage bill share decomposition. Column (1) our decomposition; Column (2) Bernard and Jensen, 1997's decomposition (B&J); Column (3) Biscourp and Kramarz, 2007's decomposition (B&K). Column (4) Manasse and Stanca, 2006's decomposition (M&S).

which are shown in panel *a* of Table 1.4.<sup>25</sup> The results of the firm-level decomposition are reported in column 1, panel *b*, of Table 1.4. The firm-level decomposition shows patterns in the nature of movements similar to those at the industry-level. Indeed, most of the directions (the signs) of the shifts match those obtained in the industry analysis. The magnitudes of these movements, however, are much larger at the firm-level.

First, the change in the weighted non-production share in the wage bill  $WBtot^{wit}$ , which approximates the movements within each industry, is mostly driven by a quantity adjustment, i.e. an increase in  $\overline{Ltot}_s$ . The share of skilled workers in employment rises, by around 0.64% per year. As observed at the industry-level, the relative wage share of non-production workers  $\overline{Wtot}_s$  does not adjust in response to an aggregate increase in the relative demand. The wage component is in fact negative and approximately -0.35% per year.

Second, most of the movements in the relative employment and wage shares are recorded within firms, suggesting that a large part of the action takes place within business units. By contrast, the contribution of the between firms components,  $Lbet_s$  and  $Wbet_s$ , is negligible and close to zero. The positive  $\overline{Lwit}_s$  component reflects that, on average, firms substitute unskilled with skilled labor. However, the within shift in the relative demand for skilled workers is not followed by an increase in their relative wage ( $\overline{Wwit}_s$ ). In fact, the wage premium drops over the entire period. Although surprising at first sight, this result is in line with the findings of Naticchioni and Ricci, 2010, who observed a decreasing trend of wage inequality using Italian household income and wealth data for the period 1993-2006. Although the available data do not allow us to test any theoretical explanation, the fact that the

<sup>25</sup>The scant difference between the two measures results from the approximation errors introduced when weighting the contribution from sectors.

relative prices have not adjusted to factor movements may be due to the Italian wage bargaining mechanism, which inhibits any wage-productivity link (Schindler, 2009). Indeed, as stressed by Manasse and Stanca, 2006, Italy is well-known for having a centralized and collective wage bargaining system, with strong unions, that prevents linking salaries to individuals' productivity.<sup>26</sup> At the same time, the fall in the wage premium may be related to the implementation in Italy during the period examined of reforms aimed at increasing labor market flexibility. Some scholars have argued that the enhanced flexibility has mostly concerned younger skilled workers entering the labor market. Despite a higher level of educational attainment, the workers have suffered a relative loss in entry wages compared with those of the previous generations (Rosolia and Torrini, 2007).<sup>27</sup>

To gauge the relative importance of the decomposition framework proposed in this paper, columns 2-4 of Table 1.4 replicate the analysis by adopting the methodologies implemented by Bernard and Jensen, 1997, Biscourp and Kramarz, 2007 and Manasse and Stanca, 2006, respectively.<sup>28</sup> This enables us to verify how sensitive the results are to the use of different methods.

Bernard and Jensen, 1997 ran their decomposition analysis at both industry and firm-level and separately analyzed the movements in the skill intensity and in the relative wage bill ratio. Their formulation did not directly address movements in the wage premia, i.e. in the dynamics of wage inequality. As reported in columns 2, panel *a* and *b*, on applying their decomposition to the Italian data, we obtain values different than that reported in column 1 for the employment components. This is because their methodology fails to discriminate between changes in the quantity and price of the relative factor, introducing a bias in the results driven by the effects of the wage components. Column 2 of the firm-level decomposition (panel *b*) suggests that failing to account for the negative variations in the wage components translates into lower values for both the within and between employment movements.<sup>29</sup> Biscourp and Kramarz, 2007 proposed a harmonized framework by integrating the decomposition analysis at the industry level with that at the firm level into a more complete framework. However, they studied only the skill structure of the workforce rather than dealing with both movements in relative employment and wage ratios. Similar to the findings obtained using the methodology of Bernard and Jensen, 1997, the

<sup>26</sup>Manasse and Manfredi, 2014, using sectoral-level data, suggest that in Italy in contrast with Germany wages do not substantially reflect sector productivity in the short run, while in the long-run, they tend to rise in sectors in which productivity falls.

<sup>27</sup>On splitting the sample into two distinct periods, 2001-2003 and 2003-2006, the decomposition analysis reveals that most of the employment and wage movements have taken place in the second half of the period examined, that is, after implementation of the Biagi reform (Las 30/2003). The law deregulated the use of atypical work arrangements, such as temporary agency work (staff-leasing) and part time work, and introduced new forms of atypical work arrangements such as on-call jobs (*lavoro intermittente*), job sharing and occasional work (*lavoro a progetto*). Results for the different sub-periods are available upon request.

<sup>28</sup>See the Appendix for further details on the decomposition formulas adopted by the previous empirical analyses.

<sup>29</sup>As regards as the  $WBtot^{wit}$  component (panel *b*), the difference between columns 1 and 2 is driven by the way in which we aggregate all the components, as indicated in equation (1.7).

results of column 3, panel *a* and *b*, show some biases in the employment components due to the effects on wages which are not properly taken into account. Finally, Manasse and Stanca, 2006 ran their decomposition analysis at only the firm level. Their formulation nested the wage bill with employment and wage decompositions instead of dealing separately with the relative wage bill and skill intensity. However, their methodology failed to account for industrial differences: between firms movements were not considered within the same industry but across all sectors. Indeed, column 4 of panel *b* reveals that while the within components are very similar to our results in column 1, the between effects show remarkable differences with an opposite sign for the between wage effect ( $Wbet_s$ ).

Some important conclusions can be drawn from the decomposition analysis. First, while the results from the industry and the firm-level analysis are consistent, changes at the firm-level are much greater in magnitude than those at the industry-level. The movements are reported within sectors; and within sectors the greatest variation in skill intensity and wage premium occurs inside firms. The finding that shifts occur especially within firms points to models that mainly explain the skill composition using a micro-level approach. Second, the share of skilled workers in the wage bill rises because of an increase in the relative demand for skilled labor. Firms, on average, substitute unskilled with skilled workers over the entire span, increasing the skill intensity of their workforces. However, the relative price of the skilled factor does not adjust positively as a consequence of the skilled upgrading. Indeed, the wage premium within firms falls. Third, comparison among the methodologies implemented in the literature emphasizes that a consistent empirical analysis should combine the industry-level analysis with the firm-level one and that, at the same time, it should take changes in the skill intensity and in wage gap into account.

### 1.3.3 Technical efficiency and international competitiveness

The finding that shifts occur especially within firms are consistent with models that explain the skill and wage movements using a micro-level theoretical framework, where both technology and trade can play a role. In what follows we adopt a very descriptive perspective and, in order to detect the role of technological efficiency and international competitiveness, we perform the decomposition for different categories of firms, according to their productivity level and to their commitment to exporting and importing activities. Of course, we do not attach any causal interpretation to our results given that our approach is purely descriptive. The aim is to pinpoint the firm characteristics associated with the movements observed in the firm-level decomposition. Following Manasse and Stanca, 2006, we distinguish between firms with high and low exports (imports) and high and low TFP. Thus, we calculate the different components of equation (1.7) by categories. The results are reported in Table 1.5.

The figures suggest that changes in the share of skilled workers in the wage bill can be attributed to changes in exporters and importers. The export status accounts

TABLE 1.5: Firm-level wage bill share decomposition: sub-samples averages by trade activities and productivity

Status	$\overline{WBtot_s^{wit}}$	$\overline{Ltot_s}$	$\overline{Wtot_s}$	$\overline{Lwit_s}$	$\overline{Lbet_s}$	$\overline{Wwit_s}$	$\overline{Wbet_s}$	Obs
All	0.290	0.638	-0.348	0.629	0.009	-0.340	-0.008	29187
Hexp	0.184	0.408	-0.224	0.461	-0.053	-0.239	0.015	14567
Lexp	0.103	0.193	-0.090	0.132	0.060	-0.068	-0.022	14620
Himp	0.075	0.256	-0.181	0.333	-0.078	-0.163	-0.018	14567
Limp	0.215	0.352	-0.137	0.266	0.085	-0.149	0.011	14620
Htfp	0.272	0.608	-0.336	0.441	0.167	-0.248	-0.088	15293
Ltfp	0.016	-0.006	0.022	0.153	-0.159	-0.059	0.081	13449

Notes: all components are annual means averages (%) over the period 2001-2006. *Hexp* (*Himp*): firms that export (import) more than the median value of their sector. *Lexp* (*Limp*): firms those that export (import) less than the median value. *Htfp* (*Ltfp*): firms with a level of TFP above (below) the median value of the sector.

for a substantial part of the skill intensity component. While we observe within-firm employment shifts also in firms that are low-intensive exporters, the principal contribution made by high-intensive exporting firms, which have a  $\overline{Lwit_s}$  component that is almost more than three times larger than that of less exporting ones.

One of the main findings of this decomposition analysis is that the smallness of the  $\overline{Lbet_s}$  component over the whole sample results from the aggregation of larger contributions with opposite signs by different categories, which almost offset each other. In particular,  $\overline{Lbet_s}$  is positive among low-intensive exporters, while it is negative for high-intensive exporters. This result is in line with what Manasse and Stanca, 2006 found on Italian data over the period 1989-1995. They claimed that the negative sign of the  $\overline{Lbet_s}$  component among exporters was indicative of Italy's peculiar trade specialization pattern. More precisely, they argued that Italy's comparative advantage favors those exporters that produce traditional goods, and therefore firms that are relatively more unskilled-intensive.

Concerning changes in the wage premium, we observe that export activity is discriminant with regard to both the within and between components. More precisely, intensive exporters are responsible for the drop in wage differentials (large and negative  $\overline{Wwit_s}$ ), but they are those that increase their average wage faster (positive  $\overline{Wbet_s}$ ). This suggests that, in these firms, wages rise overall with respect to the less intensive exporters, but faster for the unskilled workers than for the skilled ones.

Also import activities play a role in both within and between movements. In particular, firms more active in the import market reallocate workers to skilled labor within their firms much more rapidly than do the low-intensive importers. The  $\overline{Lwit_s}$  for high-intensive importers is, in fact, more than 25% larger than that for low-intensive ones. In addition, high-intensive importers account for the negative  $\overline{Lbet_s}$  component. In particular,  $\overline{Lbet_s}$  is positive among low-intensive importers, i.e. this category of firms gains market share in employment at the expense of high-intensive

importers, for which the  $\overline{Lbet}_s$  is negative. With respect to  $\overline{Wtot}_s$ , we observe that the import category discriminates only the between component. The negative  $\overline{Wbet}_s$  reported for these firms represents a drop in the ratio between the average wage paid by intensive importers and the average wage paid at the sectoral-level.

In regard to technological efficiency, we see that the decomposition by TFP level resembles that for the export category. In particular, more productive firms more rapidly reallocate labor to the more skilled factor (large and positive  $\overline{Lwit}_s$ ) and have gained shares in workforce (positive  $\overline{Lbet}_s$ ). Moreover, the productivity category discriminates wage inequality, with more productive firms contributing to the bulk of the fall in wage premia, as shown by the negative  $\overline{Wwit}_s$ , and reducing their share in the overall wage bill.

The decomposition analysis by firms' categories suggests that the largest contribution to the within-firm shifts of both skill intensity and wage premium is made by firms involved in international trade activities and the most productive ones. More intensive exporters and importers and more productive firms more rapidly modify their composition of skills in the workforce, substituting unskilled with skilled labor. At the same time they account for the bulk of the wage premium fall. Thus, those firms that undergo structural changes in the workforce are the ones responsible for the narrowing of the wage differential.

## 1.4 Hourly movements

While decomposition in equation (1.7) makes it possible to combine the industry-level analysis consistently with the firm-level one, it does not take into account the restructuring processes that can take place through the intensive margin, i.e. the number of hours worked and the hourly wages. Indeed, the labor market reforms in favor of labor flexibility introduced in Italy during the early 2000s may have induced firms to change the structure of their workforce by changing the relative number of hours worked and the hourly wages.

This section goes further in the decomposition of relative movements in wages to investigate whether the fall in the annual wage premium follows quantity rather than price adjustments. In particular, the drop in the wage premium may be driven by a reduction in the relative number of hours worked by the skilled factor or by a fall in the hourly wage premium enjoyed by non-manual workers. Considering annual rather than hourly wages - that is, by aggregating the number of hours worked with the hourly wage rate, as generally done in the literature - may lead to biased results. Changes in the average hours worked at the firm would eventually be accounted for in factor price (annual wages) rather than quantity movements (total hours employed). Thus, we disentangle the sectoral wage premium component ( $\overline{Wtot}_s$ ) of equation 1.4 into the quantity ( $\overline{Htot}_s$ ) and price ( $\overline{HWtot}_s$ ) movements. In turn, these shifts can be separated into between and within changes.

The sectoral wage premium component ( $Wtot_s$ ) of Equation 1.4 can be further disentangled into the quantity ( $Htot_s$ ) and price ( $HWtot_s$ ) movements, defined by summing shifts in the hourly skill intensity and in the hourly wage premium at the firm-level.

$$Wtot_s = \underbrace{\sum_{i \in s} \Delta \frac{h_{sk_i}}{h_s} \overline{\left( \frac{hw_{sk_i}}{hw_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)}}_{Htot_s} + \underbrace{\sum_{i \in s} \Delta \frac{hw_{sk_i}}{hw_s} \overline{\left( \frac{h_{sk_i}}{h_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)}}_{HWtot_s}. \quad (1.8)$$

Proceeding as before, we separate the between changes resulting from compositional effects from those occurring within firms. Thus, in equations 1.9 and 1.10 we calculate between and within effects for the two components of the wage premium that we derived above, i.e. the hourly skill intensity and the hourly wage premium.

$$\begin{aligned} Htot_s &= \sum_{i \in s} \Delta \frac{h_{sk_i}}{h_s} \overline{\left( \frac{hw_{sk_i}}{hw_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)} = \\ &= \underbrace{\sum_{i \in s} \Delta \left( \frac{h_{sk_i}}{h_s} \right) \overline{\left( \frac{h_i}{h_s} \right) \left( \frac{hw_{sk_i}}{hw_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)}}_{Hwit_s} + \underbrace{\sum_{i \in s} \Delta \left( \frac{h_i}{h_s} \right) \overline{\left( \frac{h_{sk_i}}{h_s} \right) \left( \frac{hw_{sk_i}}{hw_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)}}_{Hbet_s} \end{aligned} \quad (1.9)$$

$$\begin{aligned} HWtot_s &= \sum_{i \in s} \Delta \frac{hw_{sk_i}}{hw_s} \overline{\left( \frac{h_{sk_i}}{h_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)} = \\ &= \underbrace{\sum_{i \in s} \Delta \left( \frac{hw_{sk_i}}{hw_s} \right) \overline{\left( \frac{hw_i}{hw_s} \right) \left( \frac{h_{sk_i}}{h_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)}}_{HWwit_s} + \underbrace{\sum_{i \in s} \Delta \left( \frac{hw_i}{hw_s} \right) \overline{\left( \frac{hw_{sk_i}}{hw_s} \right) \left( \frac{h_{sk_i}}{h_s} \right) \left( \frac{L_{sk_i}}{L_s} \right)}}_{HWbet_s}. \end{aligned} \quad (1.10)$$

Finally, we want to aggregate over all sectors  $s$  the between and within decompositions for the three components of the relative wage bill, employment, hours worked and hourly wage. We do this in a similar way to what was done in equation 1.7. We in fact compute a weighted average whose weights are the relative importance of each sector in terms of employment and wage bill. Recalling equation 1.7, we apply the same weights attributed to the  $Wtot$  decompositions to the  $Htot$  and  $HWtot$  components. Equation 1.11 reports the weighted aggregation of all sectoral

TABLE 1.6: Hourly firm level wage bill share decomposition

Component	Annual means averages (%)
$\overline{WBtot}^{wit}$	0.291
$\overline{Ltot}_s$	0.640
$\overline{Lwit}_s$	0.628
$\overline{Lbet}_s$	0.012
$\overline{Htot}_s$	0.303
$\overline{Hwit}_s$	0.081
$\overline{Hbet}_s$	0.222
$\overline{HWtot}_s$	-0.652
$\overline{HWwit}_s$	-0.445
$\overline{HWbet}_s$	-0.206

Notes: All components are annual means averages (%).  
The decomposition is done for the period 2001-2006.

components,  $\overline{Lwit}_s$ ,  $\overline{Lbet}_s$ ,  $\overline{Hwit}_s$ ,  $\overline{Hbet}_s$ ,  $\overline{HWwit}_s$  and  $\overline{HWbet}_s$ .

$$\begin{aligned}
\underbrace{\left(\Delta \frac{WB_{sk}}{WB}\right)^{within}}_{\overline{WBtot}^{wit}} &= \sum_s \underbrace{\left(\frac{L_s}{L}\right) Ltot_s}_{\overline{Ltot}_s} + \sum_s \underbrace{\left(\frac{WB_s}{WB}\right) Htot_s}_{\overline{Htot}_s} + \sum_s \underbrace{\left(\frac{WB_s}{WB}\right) HWtot_s}_{\overline{HWtot}_s} = \\
&= \sum_s \underbrace{\left(\frac{L_s}{L}\right) Lwit_s}_{\overline{Lwit}_s} + \sum_s \underbrace{\left(\frac{L_s}{L}\right) Lbet_s}_{\overline{Lbet}_s} + \sum_s \underbrace{\left(\frac{WB_s}{WB}\right) Hwit_s}_{\overline{Hwit}_s} + \sum_s \underbrace{\left(\frac{WB_s}{WB}\right) Hbet_s}_{\overline{Hbet}_s} + \\
&+ \sum_s \underbrace{\left(\frac{WB_s}{WB}\right) HWwit_s}_{\overline{HWwit}_s} + \sum_s \underbrace{\left(\frac{WB_s}{WB}\right) HWbet_s}_{\overline{HWbet}_s}.
\end{aligned} \tag{1.11}$$

Here,  $\overline{WBtot}^{wit}$  is the weighted average wage bill variation that has occurred within industries, which is within and between firms. As before, we denote the weighted decomposition components with a bar.

As a final step, we further disentangle the relative wage movements into the between and within shifts in the hourly skill intensity and hourly wage premium. The drop in the annual wage premium observed in the firm-level analysis (panel *b* of Table 1.4) may be driven both by a fall in the hourly wage premium enjoyed by non-manual workers and by a reduction in the relative number of hours worked by the skilled factor.

Table 1.6, which reports the results for the hourly decomposition, reveals an interesting pattern. The fall between 2001 and 2006 in the annual wage premium within firms is driven by a strong reduction in the hourly wage premium,  $\overline{HWwit}_s$ .<sup>30</sup>

<sup>30</sup>Since data on hours worked by manual and non manual employees are not available for all the 29,187 observations of the previous decomposition, we have had to work with a slightly smaller sample of 29,167 firms. Note that overall  $\overline{WBtot}^{wit}$  (0.291%) is only marginally different from that computed over the whole sample (0.29%). Indeed, the reduced sample does not introduce any particular bias.

Moreover, we observe that the strong reduction in the hourly wage gap goes together with an increase rather than a decrease in the hourly skill intensity, the  $\overline{Hwit}_s$  component. The positive  $\overline{Hwit}_s$  component suggests that firms substitute unskilled with skilled workers not only in terms of jobs, at the extensive margin, but also in terms of hours, at the intensive margin. Thus, the drop in the annual wage gap is the result of a large fall in the hourly wage premium that goes together with an increase in the hourly skill intensity.

The between contributions,  $\overline{Hbet}_s$  and  $\overline{HWbet}_s$ , are very large and have the same signs as their relative within components. In particular, the number of hours worked per skilled worker grows faster across firms that have a larger hourly skill intensity (positive  $\overline{Hbet}_s$ ), while hourly average wages change greatly across firms that pay smaller hourly wage premia (negative  $\overline{HWbet}_s$ ). The between components, even if large, substantially offset each other.

## 1.5 Conclusion

This paper provides new evidence on the firm-level dynamics in labor market outcomes underlying the industry-level patterns. By using micro-level data, we have investigated the employment structure and the wage dynamic for Italian manufacturing firms in the early 2000s. To investigate such flows we have performed a decomposition analysis that breaks the variation in the skilled wage bill ratio down into employment and wage changes, within and between sectors and firms. We have innovated with respect to the existing literature by proposing a methodology that takes simultaneous account of variations in the skill intensity and the wage gap and that consistently combines the industry-level analysis with the firm-level one.

The analysis has reached a number of interesting results. It has confirmed the finding that the greatest variation in skill intensity and wage premium occurs within sectors, and mainly within firms. The within-firm movements point to theoretical frameworks that use a micro-level perspective and that take the intra-industry heterogeneity into account.

The changes in the wage bill ratios are mainly driven by a marked increase in the relative demand for skilled labor. At the same time the analysis reveals that the relative price of the skilled factor does not adjust positively. On the contrary, the annual wage premium falls, which means that the wage gap between skilled and unskilled labor narrows. This result highlights the peculiarity of the Italian labor market system.

The picture provided by the decomposition analysis has shaped our investigation of the factors behind changes in skill utilization and wage premium. The decomposition for different categories of firms, according to their level of commitment to exports and imports and their TFP, suggests that both trade activities and technological efficiency play a leading role in the reallocation process. In particular, we observe that trade activities and productivity discriminates most of the within changes

in skill intensity. More productive firms, along with more intensive exporters and importers, have more rapidly modified their composition of skills in the workforce, substituting unskilled with skilled labor.

Finally, we observe that the fall in the hourly wage premium exceeds the annual one. This is due to the fact that the number of hours worked by the average skilled employee rises with respect to those worked by the average unskilled worker. By performing the hourly decomposition, the paper has emphasized the importance of this additional margin when studying employment and wage movements. Indeed, understanding the changes in the number of hours worked and in the hourly wage is crucial, especially in light of the recent regulations requiring greater labor flexibility.

While we cannot definitely distinguish among the relative influences of institutions, market forces and technology on the evolution of labor force composition and wage inequality in Italy, our analysis of firm-level dynamics suggest that international demand, technological efficiency, and regulations have significantly influenced Italian employment and wage outcomes. In this regard, our analysis is a starting point for deeper investigation in search of a causal relationship among technology, trade, regulations, and labor market patterns.



## Chapter 2

# The granular origin of aggregate product diversification

The material of this chapter comes from a joint work with Lionel Fontagné and Angelo Secchi, which is still an unpublished manuscript.

What a country is able to sell internationally can reveal the level of technology and the nature of its productive capabilities.<sup>1</sup> The story of Korean electronics is an illustrative example of this phenomenon. Throughout the late 1980s and into the 1990s, this industry saw the flurry of several companies producing semiconductors, by pooling talents from the Korean Advanced Institute of Science and Technology (KAIST) while benefiting from public investments targeting the semiconductor technology (Okada, 2007).<sup>2</sup> In other cases, the success of a country in selling some products is instead the story of single firms. This is the case Costa Rica and Finland, whose outstanding export performances in electronics have been tightly linked to the story of two firms, Intel and Nokia.

In this work, we study the role of individual firms in defining the product diversification pattern of an industry in a certain origin country. We denote the product diversification in terms of the number of products exported towards a certain destination market, and we interpret this as the outcome of decisions made by a group of heterogeneous firms.<sup>3</sup> In doing this, we contribute to a recent literature which studies firms' idiosyncratic rather than shared forces in a country export performance (Freund and Pierola, 2015; Gaubert and Itskhoki, 2018).<sup>4</sup> While this literature has

<sup>1</sup>A stream of literature studies the movements of countries over the product space and finds that countries diversify by adding product categories that requires similar productive capabilities to what they already produce (Hidalgo and Hausmann, 2009). Tacchella et al., 2012 argue that the content of countries' product bundles, in terms of the complexity of the productive capabilities required to be produced, matters for growth.

<sup>2</sup>The semiconductor technology was populated by Daewoo since 1980, Samsung Electronics since 1983, Hyundai Electronics Industries since 1983 and Goldstar Electron from 1989.

<sup>3</sup>An alternative one is the concentration of market shares across products. In this spirit, Imbs and Wacziarg (2003) and Cadot et al. (2011) use an HHI defined at the sector or product level, respectively.

<sup>4</sup>In a recent work, Gaubert and Itskhoki, 2018 quantify the importance of the granular comparative advantage by featuring a model with a discrete number of firms as in Eaton, Kortum, and Sotelo, 2012 that combines a Ricardian comparative advantage with a firm heterogeneity. The authors show that the idiosyncratic firm dynamics account for a large share of the evolution of a country's comparative advantage over time, with a strong predictive ability for comparative advantage reversals observed in

been focusing on how individual firms shape the aggregate export sales, we here focus on how exporters, through their product choices, define the aggregate product bundle of an industry in a country, exported toward a certain market.

Decomposing the aggregate product set into firms' contributions is not as straightforward as splitting the aggregate sales into firms' market shares. Differently from what happens with the intensive margin, the aggregate product set is not generated by summation but by the union of the baskets of products exported by each firm. We formalize a conceptual framework that features a discrete number of firms that export potentially heterogeneous product sets towards a country and we study how firms product choices aggregates. We show that the relation between the aggregate and firm level diversification is mediated by the extent to which firms product sets overlap. In particular, we show that the average number of product overlaps per firm can be conveniently decomposed into three factors: the normalized number of firms exporting, the average product scope of firms - computed excluding the most diversified firm, and an index of product sets similarity.

We interpret firms' product set similarity as a measure of those characteristics that are common to all firms in a given industry, such as the availability of specific human capital, infrastructure, and technology versus those idiosyncratic features of individual firms, driven by their idiosyncratic knowhow and managerial talent. We show that indeed our index captures the extent to which aggregate performances, as captured by the Revealed Comparative Advantage of the industry, are driven by fundamental rather than firm-specific forces.

In the empirical part, we define an industry as a NACE 2 code, i.e. a classification of the firm core activity in the domestic market. To proxy the product diversification of an exporter towards a destination country, we use as the number of different HS6 product categories exported there. The definition of the industry is therefore not mechanically linked the product bundle of exports. We use a sample of French exporters between 1995-2011 and compute the number of overlaps of firms' product sets for each industry-destination pairs.

On average, the product sets of a firm operating in the food industry contains 4 products in common with other firms in the same industry. Considering that the average product scope is just above 5 this is a significant number. For basic metals, the average product set contains 4 items, half of which are in common with other firms in the industry. However, note that there are much more firms active in the food industry, 1080 against 349 in basic metals. To account for this, we quantify the importance of each component of our decomposition across destination markets and industries. We find that half of the variance in the number of product overlaps

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the data.<sup>5</sup> Freund and Pierola, 2015 shows that individual firms can transform sectoral patterns and alter comparative advantage. In a sample of developing countries, they observe that one out of five loses the Revealed Comparative Advantage. We build on the exercise by Freund and Pierola, 2015 to show that the revealed comparative advantage reversal is less dependent on single large firms, when firms are more similar in their product sets. This result reinforces the idea that the similarity of firms' product sets reflects the extent to which aggregate performances are driven by fundamental forces rather than granular.

per firm can be attributed to firms' product set similarity. We then decompose the variance of each single contribution of the decomposition into destination markets and industry characteristics. We find that destination characteristics, such as trade costs, are twice more important than industry characteristics in defining the normalized number of exporters. On the contrary, for the similarity index and the average product scope computed without the most diversified firm, this variability is evenly split between industry and destination factors.

In the spirit of Freund and Pierola, 2015, we estimate the revealed comparative advantage (RCA) in 24 industries and assess the contribution of export superstars using the Balassa index. In particular, we calculate the share of industries that would lose the RCA in the absence of the largest firm. We show that comparative advantage reversals is less likely when firms' product set similarity is higher. We also find that the probability of a RCA reversal increases with the normalized number of firms and the average product scope computed without the most diversified firm. We provide a statistical interpretation of these findings using distributional assumptions about the underlying heterogeneity in firms' product diversification.

## Set-up

We contribute to the recently growing literature in trade that investigates how micro behavior aggregates into macro patterns. The interest finds motivation in Arkolakis, Costinot, and Rodríguez-Clare, 2012, which proves a lack of implication of the recent literature for aggregate trade. Eaton, Kortum, and Sotelo, 2012 argues that a primary reason why models of heterogeneous producers deliver so little in the way of modification of how we think about aggregates is the device of treating the set of products as a continuum, which was initiated by Dornbusch, Fischer, and Samuelson, 1977. The feature of measure-zero varieties, embraced by the heterogeneous firm literature, is convenient for modelling. By invoking the law of large numbers, one can consider what affects the aggregate level to be driven by the parameters defining the distributions of the outcomes affecting individual units, but not on the realizations of those outcomes themselves. In presence of granularity instead - term coined by Gabaix, 2011 to represent the skewed nature of firm size distributions - shocks on big firms "carry on" to the aggregate.<sup>6</sup> To account for this, Eaton, Kortum, and Sotelo, 2012 and Gaubert and Itskhoki, 2018 propose to look at the number of firms that export to a destination as generated by Poisson stochastic mechanism, already proposed in Bernard et al., 2003, and therefore as a finite number. In these works, the realized market shares of firms can thus differ from those obtained in a continuum world. In a similar spirit, in our framework, we describe an industry (in an origin country) where an aggregate relationship, here the set of products exported towards

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<sup>6</sup>The skewed distribution of sales across firms was already subject of much attention in the industrial organization literature, e.g. Axtell, 2001; Sutton, 1997a. The effects of a granular economy has been studied in (Gabaix, 2011; Di Giovanni, Levchenko, and Mejean, 2014)

a destination country by the industry, is viewed as the outcome of decisions made by a finite group of heterogeneous firms.

Our object of interest is the product diversification of an industry towards a destination market, what is usually referred as the extensive margin of trade. As discussed in Armenter and Koren, 2014, many facts about the aggregate extensive margin of trade, for example how many firms and how many product categories are sent to how many destinations, can be consistent with a large class of trade models with firm heterogeneity. The authors suggests that this is due to the *sparse nature* of trade data, as firms are usually active only on a small subset of the overall number of product categories traded.<sup>7</sup> One consequence of this sparsity is that in computing the number of different varieties traded with a partner country, one needs to know the number of unique product categories, the number of firms but also the density of trade, which is the fraction of all possible firm-product combinations for which trade is positive. Bernard et al., 2009a shows that this density accounts approximately as much as the other components that generate the extensive margin of trade in the decomposition of country exports across destinations. In our framework, differences in this density are generated by the extent to which firms product sets overlaps.

We show that these overlaps can be conveniently decomposed into three factors: the normalized number of firms exporting, the average product scope of firms - computed excluding the most diversified one, and an index that we interpret as a measure of product sets similarity. In interpreting the first two components of decomposition - the normalized number of firms exporting and the average product scope of firms - we build on the comparative advantage literature. To interpret the third component, the similarity index of firms' product sets, we refer instead on early contributions on the theory of the firm (Marris, 1964; Penrose, 1955).

Comparative advantage literature has received new impetus starting from Eaton, Kortum, and Kramarz, 2004, whose model has been used to perform several counterfactual exercises.<sup>8</sup> In the multi-country, multi-sector version by Costinot, Donaldson, and Komunjer, 2011, countries draw a technology from a distribution whose parameters are country-industry specific and define their relative ability in producing some goods. Within each industry, a continuum of varieties is produced according to that technology. To generate a finite number of heterogeneous firms, one can instead resort to a Poisson-Pareto stochastic mechanism, as done in Bernard et al., 2003

<sup>7</sup>Variation in terms of the extensive margin, how many firms and how many product categories, explains the largest variation in exports across destination markets (Bernard et al., 2009a). Baldwin and Harrigan, 2011 has showed that evidence on the extensive margins is consistent with the heterogeneous-firms trade (HFT) model based on Melitz, 2003. Example of this can be the asymmetric country version (Helpman, Melitz, and Yona, 2008), fixed cost to export Chaney, 2008. To capture the extensive margin Baldwin and Harrigan, 2011 use the number of HS10 codes exported from the US. This is because in models with monopolistic competition, as most of the toolkit models in the recent trade literature, firms produce varieties rather than product categories. Instead, even at a highly disaggregated level, product codes do not correspond to a single product variety. For example, Bernard, Jensen, and Schott, 2009 shows that there are on average 30 firms per HS10 code.

<sup>8</sup>Among others, estimating the welfare gains from trade Caliendo and Parro, 2015 the impact of multilateral/unilateral tariff eliminations Arkolakis, Costinot, and Rodríguez-Clare, 2012 the effect of specialization on the volatility of GDP Caselli et al., 2019.

and Eaton, Kortum, and Sotelo, 2012. One can consider a pool of potential exporters belonging to an industry in an origin country and assume that their number is the realization of a random variable distributed Poisson. Each of these firms take, in turn, an iid productivity draw from a Pareto distribution and computes its marginal costs of supplying a foreign market, including a destination-specific iceberg trade cost. Next, by comparing its marginal cost with a cost cut-off the firm decides if it can serve that destination market. In this interpretation, the number of active firms in a market from a certain industry is the random variable representing the realization of this stochastic mechanism and it is industry-destination specific. Gaubert and Itskhoki, 2018 make clear that the parameters that governs the two distributions, the Poisson and the Pareto, determine the average productivity of the industry and when compared with those for the same industry in the rest of the world represent the “fundamental” source of a country comparative advantage.

We interpret the third component, firms’ product sets similarity index building on early contributions on the theory of the firm. These suggest that firms grows by diversifying across new activities (Marris, 1964) while gaining productive capabilities that can be used to produce new product varieties (Penrose, 1955). Different products require different knowhow or input capabilities, and firms differ in the capabilities they have. Capabilities are tied to the firm as they often cannot be bought ‘off the shelf’ (Teece, 1980; Teece et al., 1994; Sutton, 2012).<sup>9</sup> By comparing firms based on what they sell one can investigate the extent to which sectoral diversification reflects characteristics that are common to all firms in a given sector — such as the availability of specific human capital, infrastructure, and technology — versus idiosyncratic contribution of individual firms, driven by their idiosyncratic knowhow and managerial talent.

With these interpretations in mind we propose a different reading of the decomposition of the number of overlaps among product sets. The first term, can be seen as the size of a sample of random variables representing the product scopes. Their average, which represents itself a random variable, is the second component. The similarity index, captures the way in which individual product scopes relates to the aggregate normalizing with respect to the most diversified firm. In the next section we formalize a framework to rationalize what above.

## 2.1 Formal framework

This section sets up a formal framework to describe an industry (in an origin country) where an aggregate relationship, here the set of products exported towards a

<sup>9</sup>More recently, Bernard, Redding, and Schott, 2010 find that firms are much more likely to produce in certain pairs of industries suggesting complementarities exist across activities. Dosi, Grazzi, and Moschella, 2017 find firms are much more diversified in terms of products than in terms of technologies, with their main products more related to the exploitation of their innovative knowledge. Boehm, Dhingra, and Morrow, 2019 shows that input-output tables suggest firms co-produce in industries that share intermediate inputs, proposing input capabilities drive multiproduct production patterns.

FIGURE 2.1: Four illustrative arrays of product sets ( $ps_f$ ) for 3 firms.

		P <sub>1</sub>	P <sub>2</sub>	P <sub>3</sub>	P <sub>4</sub>
(a)	f <sub>1</sub>	1	1	1	1
	f <sub>2</sub>	1	1	1	1
	f <sub>3</sub>	1	1	1	1

		P <sub>1</sub>	P <sub>2</sub>	P <sub>3</sub>	P <sub>4</sub>
(b)	f <sub>1</sub>	1	1	1	1
	f <sub>2</sub>	1	1	1	0
	f <sub>3</sub>	1	1	0	0

		P <sub>1</sub>	P <sub>2</sub>	P <sub>3</sub>	P <sub>4</sub>	P <sub>5</sub>	P <sub>6</sub>
(c)	f <sub>1</sub>	1	1	1	1	0	0
	f <sub>2</sub>	0	1	1	0	1	0
	f <sub>3</sub>	1	0	0	0	0	1

		P <sub>1</sub>	P <sub>2</sub>	P <sub>3</sub>	P <sub>4</sub>	P <sub>5</sub>	P <sub>6</sub>	P <sub>7</sub>	P <sub>8</sub>	P <sub>9</sub>
(d)	f <sub>1</sub>	1	1	1	1	0	0	0	0	0
	f <sub>2</sub>	0	0	0	0	1	1	1	0	0
	f <sub>3</sub>	0	0	0	0	0	0	0	1	1

Notes: Firms are ranked from the most diversified (top) to the least diversified (bottom).

destination country by the industry, is viewed as the outcome of decisions made by a group of heterogeneous firms. In this framework there exists a finite number of products available for export. Each of them can be exported by more than one firm which, in defining its export strategy, is allowed to sell multiple products.<sup>10</sup> We formalize this situation by pairing each firm with a product set, i.e. with the list of products they are capable to export, and describing the set of products exported to a destination country by the entire industry as the union (in set-theoretic sense) of the sets of products of individual firms. We define the cardinality of these sets, as the aggregate and firm-level diversification, respectively. We show that the relation between the aggregate and firm level diversification is mediated by the extent to which firms product sets overlap. We then show that the average number of product overlaps per firm can be conveniently decomposed into three factors: the normalized number of firms exporting, the average product scope of firms - computed excluding the most diversified one, and an index that we interpret as a measure of product sets similarity. In the last section, we relate these three components to the statistical assumptions of recent works in the comparative advantage trade literature.

### 2.1.1 Definitions and notation

Let  $ps_{fdi}$  represents the set of products exported to destination  $d$  by a firm  $f$  from origin  $o$  active in industry  $i$ . We assume that each firm belongs to a single industry but can export diverse sets of products to different destinations. We fix the origin country and focus on the heterogeneity across product sets within a specific industry-destination country pair. Each firm belonging to that industry is represented by one single set of products containing the items it exports to that destination. In the rest of this section we drop the subscripts corresponding to industries and destinations for convenience.

We use  $|ps_f|$  to denote the cardinality of  $ps_f$ , that is the number of different products in the product set. We define the degree of product diversification at the

<sup>10</sup>This means that there may be different varieties of the same product. A variety is as usual identified as a firm-product pair.

firm level with  $|ps|_f$ , that is the firm product scope. To develop our argument it is sometimes convenient to rank firms according to their product scope. So, in line with a standard notation, we denote with  $|ps|_{(f)}$  the cardinality of the the product set of the  $f$ -th ranked firm in terms of increasing product scope.  $|ps|_{(1)}$  and  $|ps|_{(N)}$  represent then the product scopes of the least and most diversified firm respectively. Consistently PS represents the aggregate product set, that is the list of distinct products exported by the firms active in that industry-destination pair.  $|PS|$  is the corresponding aggregate measure of product diversification.<sup>11</sup> A useful way to think about the product sets of all the firms in an industry-destination is to organize them into a binary matrix. Different rows ( $f$ ) and columns ( $p$ ) represent different firms and products respectively and cells ( $f,p$ ) are switched to 1 if firm  $f$  exports product  $p$ . Table 2.1 reports different examples of  $ps_f$  for 3 firms. Consistently with our interest on the extensive margins note that firms (rows) are ordered from the most diversified (top) to the least diversified (bottom) and, conditional on this, products (columns) are ordered from the most to the least frequently exported.

Differently from what happens with the intensive margin the aggregate product set is not generated by summation but by the union of the baskets of products exported by each firm:  $PS = \bigcup_{f=1}^N ps_f$  with  $N$  representing the number of active exporters in a given industry-destination. As a consequence the cardinality of the aggregate product set, our measure of diversification at the industry level, is equal to the cardinality of union of the product sets of all firms,  $|PS| = |\bigcup_{f=1}^N ps_f|$ . A simple application of the inclusion-exclusion principle proves that

$$|PS| = \left( \sum_{f=1}^N |ps|_f \right) - OV, \quad (2.1)$$

where

$$OV = \sum_{1 \leq f < g \leq N} |ps_f \cap ps_g| - \sum_{1 \leq f < g < h \leq N} |ps_f \cap ps_g \cap ps_h| - \dots + (-1)^{N-1} |ps_1 \cap \dots \cap ps_N|,$$

represents the total number of products found in each pairwise intersection of product sets, adjusted for the cardinality of higher order intersections. Equation (2.1) formalizes the idea that, for a given number of firms, the aggregate diversification depends on the extent to which firms are diversified but also on the extent to which their product sets overlap.

Equation (2.1) summarizes how firms product sets contribute to generate the aggregate industry-country product diversification,  $|PS|$ . To clarify its content in light of the aims of the present paper we propose a different formulation of the same relation in terms of a simple recursive mechanism that, starting from an initial state, explicitly describes the construction of the aggregate industry-destination product scope. To set up the mechanism we first order the  $N$  firms by their product scope,

<sup>11</sup>Throughout the paper lower case letters are used to define variables at the firm level and upper case letters for variables at the industry-destination level.

from the most diversified to the least diversified. We then assume that only the most diversified firm is active in this industry-destination and that the other firms remain “shadow” firms in the background.<sup>12</sup> This assumption defines the initial state of the system: there is only one active firm, the most diversified, and by construction the aggregate industry diversification  $|PS|_t$  is determined by its product scope, i.e.  $|PS|_1 = |ps|_{(N)}$  where  $t=1$  denotes this initial state.

Then the mechanism works by activating one firm at a time following the (decreasing) product scope order, with  $t$  keeping track of iterations and running from 2 to  $N$ . At each time, the aggregate product set is updated to include the products of the newly activated firm according to the recursive rule

$$|PS|_t = |PS|_{t-1} + (1 - S)_{N-t+1} |ps|_{(N-t+1)} ,$$

where  $(1 - S)_{N-t+1}$ , denotes the fraction of the product set of the firm activated at  $t$  consisting of new items with respect to the aggregate industry product set at  $t - 1$ .<sup>13</sup> These fractions all depend on the position of the corresponding firm in the product scope ladder and they are not independent from each other since their sum is constrained to generate the aggregate product scope. Hence in solving this recurrence relation we assume that each of the  $N-1$  firm, excluding the first and most diversified, contributes to the same extent to generate the aggregate product scope, that is we assume  $(1 - S)$  to be constant across iteration. With this assumption

$$|PS|_N = |PS| = |ps|_{(N)} + (1 - S_{(N)}) \sum_{t=2}^N |ps|_{(N-t+1)} , \quad (2.2)$$

and  $(1 - S_{(N)})$  represents the weighted sum of firms shares of new products  $(1 - S)_{N-t+1}$  where the weights are given by the contribution of each firm in the number of firm-product pairs, that is  $|ps|_t / \sum_t |ps|_t$ .<sup>14</sup>

Equation (2.2) states that the aggregate level of diversification can be seen as composed by the diversification of the most diversified firm plus those of the remaining  $N-1$ , which contribute to the building of the aggregate diversification with only a fraction of their product scope. We interpret this second term as the result of the interplay of two simple mechanisms. The first mechanism is associated with the gradient in the loss of products when firms descend the product scope ladder, the

<sup>12</sup>The choice of starting with the most diversified firm here is arbitrary but turns out to be very convenient in the rest of the paper. While other choices, for example using the least diversified, might have changed the exact way we interpret our accounting exercise below, the mechanism generates the same aggregate product.

<sup>13</sup>Using product sets instead of with product scopes as in equation (2.1),  $(1 - S)_{N-t+1}$  can be written as  $\frac{|ps|_{(N-t+1)} - |PS_{t-1} \cap PS_{(N-t+1)}|}{|ps|_{(N-t+1)}}$  since at each iteration the aggregate product set is updated to include the newly activated firm according to  $PS_t = PS_{t-1} \cup ps_{(N-t+1)}$ .

<sup>14</sup>See Appendix B for details. Note also that the subscript  $-(N)$  formally means that a certain variable has been computed excluding the most diversified firm. In the case of  $S_{-(N)}$  this subscript refers to the fact that in the iterative procedure discussed above we started with the most diversified firm. In Appendix B we show that the two interpretations are perfectly consistent.

second to the intensity with which less diversified firms introduce items not yet exported (by more diversified firms) altering the degree of similarity of the content of the corresponding product sets. These forces in action shape the four arrays reported in Figure 2.1:

- case (a):  $PS = ps_f \forall f$ ,  $|PS| = |ps|_f \forall f$ ,  $OV = \sum_{f=1}^{N-1} |ps|_{(f)}$ ,  $(1 - S_{-(N)}) = 0$ . In this scenario all firms are identical with respect to their product set, hence also at the level of the entire industry one observes the same product set and correspondingly the same degree of diversification. This configuration is the output of an industry where firms are all equally diversified but they may or may not share a common pecking order across products.
- case (b):  $PS = ps_{(N)}$ ,  $|PS| = |ps|_{(N)}$ ,  $OV = \sum_{f=1}^{N-1} |ps|_{(f)}$ ,  $(1 - S_{-(N)}) = 0$ ; in this scenario firms with lower product scope are all subsets of the one hold by the most diversified firm. As a consequence the industry product set coincides with that of the most diversified firm. This configuration emerges when
  - within an industry - firms share a common pecking order of productivity across products but they differ in their degree of diversification.
- case (c):  $PS = \bigcup_{f=1}^N ps_f$ ,  $|PS| = \left( \sum_{f=1}^N |ps|_f \right) - OV$ ,  $OV = \left( \sum_{f=1}^N |ps|_f \right) - |PS|$ ,  $0 < (1 - S_{-(N)}) < 1$ ; this is the generic scenario where the diversification at the industry level depends on idiosyncratic product pecking orders of firms;
- case (d):  $PS = \bigcup_{f=1}^N ps_f$ ,  $|PS| = \sum_{f=1}^N |ps|_f$ ,  $OV = 0$ ,  $(1 - S_{-(N)}) = 1$ ; in this scenario firms have disjoint product sets and as a consequence the diversification at the industry level is nothing but the sum of the product scope of each firm.<sup>15</sup>

We next perform an accounting exercise and, combining equation (2.1) and (2.2), decompose the number of product overlaps among product sets,  $OV$ , along three different margins. These margins relates to diverse aspects of the firm-product arrays introduced in the previous section and will discipline our empirical investigations in the remaining of this paper. Formally, starting from the definition of  $OV$ , simple algebra shows that the average number of overlaps per firm reads<sup>16</sup>

$$\frac{OV}{N} = \tilde{N} \overline{|ps|}_{-(N)} S_{-(N)} , \quad (2.3)$$

where  $\tilde{N} = \frac{N-1}{N} \overline{|ps|}_{-(N)} = \frac{1}{(N-1)} \sum_{f=1}^{N-1} |ps|_{(f)}$  and  $S_{-(N)} = 1 - \frac{|PS| - |ps|_{(N)}}{\sum_{f=1}^{N-1} |ps|_{(f)}}$ .

The first term of the decomposition,  $\tilde{N}$ , is an index ranging from 0 and 1, representing the number of firms in an industry-destination: it is 0 when there is one firm only and go to 1 when the number of firms grows large. The second term is,

<sup>15</sup>This difference comes from consumers love for variety. Equally different is intended as having the same degree of substitutability with all the others.

<sup>16</sup>Details on how to obtain this decomposition in Appendix B.

$\overline{|\text{ps}|}_{-(N)}$ , represents the average product scope across firms computed excluding the most diversified firm. Intuitively how the average product scope differs from the one computed with all the firms including the most diversified depends on the shape of the product scope distribution typically found to be very skewed.

The interpretation of the third term is made simple in light of the recursive mechanism we described above. Indeed, we have seen that  $1 - S_{-(N)}$  represents the weighted average of the fraction of new products added to the existing aggregate product set across the  $N-1$  least diversified firms. Then  $S_{-(N)}$ , its complement to 1, can be seen a measure of similarity among the corresponding  $N-1$  product sets. It ranges, by construction, from 0 to 1. When  $S_{-(N)}=0$ , the product set of the most diversified firm in the industry contains as subsets those of all the other firms. This scenario rationalizes a situation where firms, potentially heterogeneous in terms of product scopes, select their products following one unique pecking order and the product set of the industry is then fully determined by one single firm, the most diversified and  $|\text{PS}| = |\text{ps}|_{(N)}$ .  $S_{-(N)}=1$  is, instead, associated with a situation where product sets of firms are entirely disjoint with no common elements. Also in this case firms may be heterogeneous in terms of product scopes but, here, in selecting products they follow individual non-overlapping product pecking orders. In this case, the product set of the industry is determined by all the firms' product sets and correspondingly  $|\text{PS}| = \sum_{f=1}^N |\text{ps}|_f$ . We associate to the first and the second scenario the label "maximal similarity" and "minimal similarity" respectively. As a consequence,  $S_{-(N)}$  can be read as the complement to 1 of the min-max normalization of the industry diversification  $|\text{PS}|$ .<sup>17</sup> Using again Figure 2.1,  $S_{-(N)}$  takes value 1, 3/5 and 0 in the case (b), (c) and (d) respectively.

An alternative interpretation of Equation (2.3) can be given in light of the set-up in 1.1. In this case, (2.3) describes a sample of  $N$  random variables  $|\text{ps}|_1, \dots, |\text{ps}|_N$ , the maximum of this sample  $|\text{ps}|_{(N)}$  and a random variable  $|\text{PS}|$ , the latter representing their aggregation - not a simple sum - as shown in Equation (2.2). The three components are clearly related. First the support of  $|\text{PS}|$  depends on the highest among the product scopes and on their sum since it ranges between  $|\text{ps}|_{(N)}$  and  $\sum_{f=1}^N |\text{ps}|_f$ . Second, the similarity index  $S_{-(N)}$  as the min-max normalization of  $|\text{PS}|$  measures the relative distance of the aggregate product scope from the value it would get in case of maximal diversity of the product sets.<sup>18</sup> Third, both the lower

<sup>17</sup>Measuring similarity is a classic problem in Ecology. Typically ecologists are interested in studying patterns of species diversity between habitats in a given landscape, the so called  $\beta$ -diversity. Diserud and Ødegaard, 2006 present a similarity index that in our notation reads  $C_S^N =$

$$\frac{\text{OV}}{\sum_{f=1}^N |\text{ps}|_{(f)}} \frac{\sum_{f=1}^N |\text{ps}|_{(f)}}{\sum_{f=1}^{N-1} |\text{ps}|_{(f)}}$$
 which can be easily shown to be equal to  $S_{-(N)}$ .

<sup>18</sup>The distribution of  $|\text{PS}|$  can be characterized by complementary CDF  $\Pr(|\text{PS}| > x)$ . This function measures how close  $x$  is to either of the two bounds of the support: the closer  $x$  is to 1 the closer  $|\text{PS}|$  is to  $|\text{ps}|_{(N)}$ , the closer  $x$  is to  $\sum_{f=1}^N |\text{ps}|_f$ . So the complementary CDF is a probabilistic measure capturing in an industry are close to the minimal versus maximal diversity benchmark. Were one agnostic about the shape of the distribution of  $|\text{PS}|$  and willing to assume it Uniform, then  $\Pr(|\text{PS}| > x)$  would be equal to  $S_{-(N)} = 1 - \frac{|\text{PS}| - |\text{ps}|_{(N)}}{\sum_{f=1}^{N-1} |\text{ps}|_{(f)}}$ , which is indeed our similarity index. In

and upper bounds of this support depend on the number of active firms,  $N$ , and their behavior can be characterized under different distributional assumptions on  $|\text{ps}|$ .

If we assume that the product scopes are Pareto distributed as frequently done in the international trade literature, and we denote the slope  $\alpha$  and set the minimum to one, i.e.  $|\text{ps}|_{(1)}=1$ , then  $E[|\text{ps}|_{(N)}] \sim N^{\frac{1}{\alpha-1}}$  and  $E[\sum_{f=1}^N |\text{ps}|_f] \sim N^{\frac{\alpha-1}{\alpha-2}}$ .<sup>19</sup> The expected value of the product scope of the most diversified and of the average product scopes of the  $N-1$  least diversified firms increases as a power function and linearly with the integer number of firms.

## 2.2 Data and definitions

In this section we describe our data sources and the data cleaning procedures implemented. We then operationalize the variables manipulated in the conceptual framework defining the empirical counterpart of the arrays used in Figure 2.1. We conclude with an illustrative example.

### 2.2.1 Data sources

Our analysis is based on firm-level and transaction-level data that comes from two different sources: the *Sirene Database*, which contains the list of French enterprises and their principal activity and the French custom database, which reports monthly firms' trade flows by destination country and type of commodity.<sup>20</sup>

*Sirene* data contain the list of firm identifiers for the universe of active and discontinued firms in France.<sup>21</sup> More importantly it contains information about their principal activity according to the "Nomenclature d'Activites Francaise" classification system (NAF) which is mostly equivalent to the NACE system, the statistical classification of economic activities in the European Community. Below we use principle activities to group firms in industries. Since the NAF system has undergone two revisions in the classification in 2003 and 2008 we have applied the conversion tables provided by INSEE to ensure consistency across years.<sup>22</sup>

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other words with a Uniform distribution the similarity index we propose is the complementary CDF of  $|\text{PS}|$ . In this case it is interesting to note that the  $\Pr(|\text{PS}| > x)$  is a linear function with a slope equal to  $-1/(\sum_{f=1}^N |\text{ps}|_f - |\text{ps}|_{(N)})$ . Hence, this slope is telling us how much extra diversity among products sets is implied by an additional product observed in the product set at the industry level.

<sup>19</sup>The properties of the largest value of a Pareto are discussed in Newman, 2005.

<sup>20</sup>Under the *Loi pour une Republique numerique* *Sirene* data have been available as Open Data since the beginning of January 2017. On the other hand, custom data is accessed through facilities provided by the INSEE (the French Statistical Institute) and were made available for analysis after careful screening to avoid disclosure of individual information.

<sup>21</sup>Our version has been downloaded on January 2020. While *Sirene* reports the years over which a firm is operative, it lacks information on the length of the accounting period. This prevent us to disentangle, in the event of a firm death, whether this has occurred before or after the end of the accounting year. We however prefer *Sirene* to other sources of data on firms, such as BRN used in Mayer, Melitz, and Ottaviano, 2014, for its coverage.

<sup>22</sup>Figure B.1 in the Appendix B.2 reports the the share of firms active in each NAF/NACE sector over the entire time window 1995-2010 and shows no significant discontinuities in correspondence of the NAF/NACE revisions.

Custom data report the universe of declared trade flows over the period 1995-2011 by firm, country of destination and commodity. Commodities are coded using the international Harmonized System (HS) classification at 6-digits. Over our period of interest there have been 3 revisions of the HS classification. Since differences in the granularity of the HS classification can induce mechanical changes in the number of HS codes traded by firms we convert the HS codes in different years using the correspondence tables provided by CEPIL.<sup>23</sup> We use as reference the one active between 1988-1995, because it is the least granular, with 5022 codes at 6-digit.

Another potential consistency problem with custom data is due to the fact that Custom declaration requirements have been slightly revised over our period of interest. Before 2010 there was a declaration threshold set at 1000€ for trade flows extra-EU only. We investigate consistency across destinations and time, building on Bergounhon, Lenoir, and Mejean, 2018, and imposing the 1000€ threshold for years where this limit was not in place. We do not observe significant changes in the number of firms and HS codes, and in share of intra EU trade.<sup>24</sup>

Finally we drop minor trade partners. We keep only those destinations that are at least once, over the period 1995-2010, within the smallest group of destinations needed to cover 95% or more of yearly total export. After filtering out these minor partners we end up with 69 countries.<sup>25</sup>

### 2.2.2 Empirical proxies

To pursue our investigation we need to define empirical proxies for industries and products. We define industries by grouping firms according to their principal economic activity as in Gaubert and Itskhoki, 2018. An economic activity takes place when resources such as capital goods, labor, manufacturing techniques or intermediary products are combined to produce specific goods or services and it is, then, characterized by an input of resources, a production process and an output of products (goods or services). The principal activity of a firm is the activity which contributes most to the total value added of that unit. An alternative typically used in the international trade literature is to use the international HS product classification. However using the principal activity to cluster firms seems more appropriated for our investigations since it is driven by commonalities such as the availability of specific human capital, of a similar technical knowledge or by tangible and intangible generic infrastructures. And therefore less by the content of their idiosyncratic product sets.

<sup>23</sup>Note that even in the case of a one-to-one reclassification, one would observe a jump in the probability to add a product in correspondence with a revision. Figure B.2 in the Appendix B.2 shows instead there are not significant changes in the probability of adding a product and in the share of added products after the harmonization across years is applied.

<sup>24</sup>As a further robustness check we also select only those firms that export at least 650K euro intra-EU. The latter is the most stringent threshold applied over our time horizon - in 2001 - for an exporter to be identified in the *regime* that requires declaring the type of products exported by a firm. Details on these cleaning procedures and their effects are reported in Appendix.

<sup>25</sup>The list is available upon request.

The *Sirene* database reports information on the principal activities for all firms. Principal activities are coded according to the NAF/NACE classification system that uses four hierarchical levels, of these, Divisions represent the second tier and consists in 88 different 2-digit codes. For our investigations we focus on the manufacturing industries selecting the 24 manufacturing industries with codes ranging from 10 to 33, excluding sector 12 (Manufacture of Tobacco products).

As mentioned above, custom data classifies commodities using the HS classification system. We use the classification at the most detailed level and identify a product with an HS6 code. Consistently, product diversification is defined in terms of the number of different HS6 codes exported. To provide an intuition of the level of detail that our definition of product captures consider the following example. Within motor cars for the transport of persons, one can distinguish, among others, those vehicles with spark ignition with an engine below 1000cc (HS code 870321) from those between 1000cc and 1500cc (870322). Likewise, one distinguishes those cars with a compression-ignition (diesel or semi-diesel) engine with cylinder capacity below 1500cc (870331) from those between 1500cc and 2500cc (870332).

A French company, owing its main activity in the domestic market to 'Manufacture of motor vehicles' (NAF/NACE 29), exports all the 4 products above. When looking on the web one discovers that among the products likely to be exported by the same firm one finds other components related to this main activity, such as "Safety glass for vehicles" (700721) and "Metal polishes" (340530). At the same time one also finds less obvious items, such as "Jerseys, pullovers and cardigans" (611030) "T-shirts of cotton knitted/crocheted" (610990).

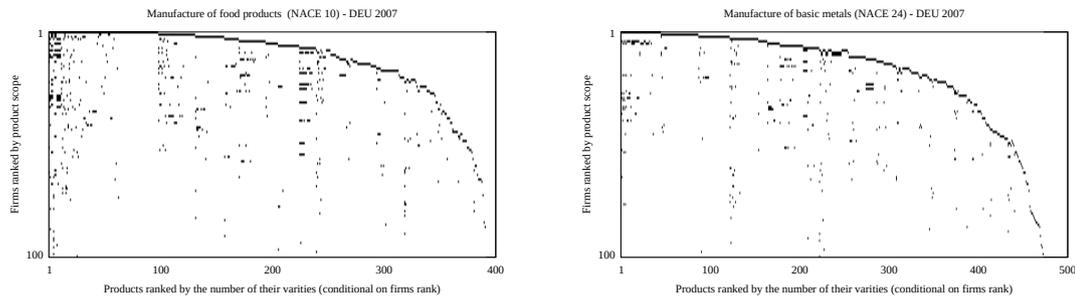
### 2.2.3 An illustrative example

In this section we present an example of an array of product sets and we provide an illustrative description of its structure and functioning through the lens of our conceptual framework.

As discussed above the arrays of product sets represent industry-destination specific objects, reporting on rows French exporters operating in an industry (defined as a NAF/NACE 2-digit code) and actively trading with a specific destination. On the columns they list products (defined as HS 6-digit codes) exported by at least one of these firms. Further, firm-product cells in the array record if that firm is declaring a positive trade flow for that product.<sup>26</sup> Hence the number of cells corresponds to the number of varieties exported to a given destination by firms active in a given industry. Producing a graphical representation of these arrays capable to highlight their salient properties is doable but somewhat challenging because typically the arrays are large and sparse objects. In 2007, the average number of active firms per industry-destination is about 158, their product set contains on average 3 items and all together these firms span about 245 unique products, which represents about 5%

<sup>26</sup>Positive here means above the thresholds imposed by the cleaning procedures detailed in the section 2.2.

FIGURE 2.2: Arrays of product sets for the top-100 French exporters

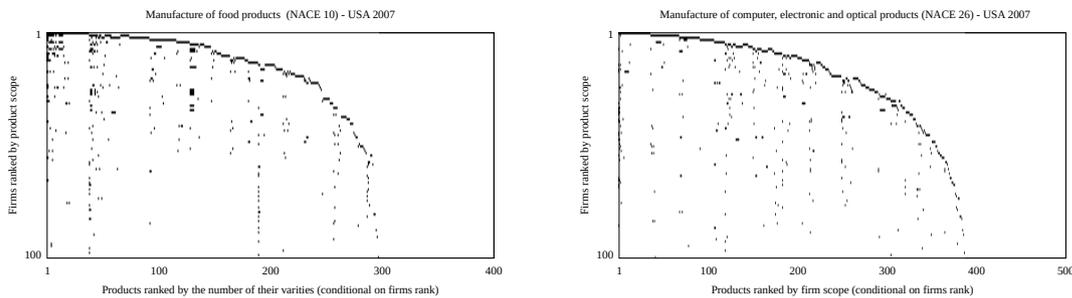


Notes: Arrays of product sets  $ps_f$  for the top-100 (export value) French exporters operating in “Manufacture of food products” (NAF/NACE 10, left-panels) and “Manufacture of computers, electronic and optical products” (NAF/NACE 24, right-panels) and active exporters in Germany (DEU) in 2007. Firms on the vertical axis are ranked according to their product scope  $|ps_f|$  (from top to bottom), and products on the horizontal axis according to the number of firms exporting them (from left to right).

of the entire set of HS6 codes. The average fill ratio, defined as the share of product-firm pairs with a positive trade flows, is about 5%. In order to overcome these difficulties we implement a visualization strategy that considers only the top-100 exporters in terms of their export value for each industry-destination pair. Moreover to improve their readability we order along the rows these 100 firms according to their product scope (from top to bottom) and, conditional on that, we order products in columns according to the number of existing varieties of each of them (from left to right). Figure 2.2 reports two of these arrays for the most important commercial partner of France, Germany, in two industries, “Manufacture of food products” (NAF/NACE 10) and “Manufacture of basic metals” (NAF/NACE 24). In the two panels black squares represent a variety with a positive export value and their size is, by construction, linked the dimensions of the entire array.<sup>27</sup>

Guided by our conceptual framework we first look at the extent to which product sets overlap among each other. Comparing with the basic metals industry the number of product overlaps per firm is about twice as large in food, being 4 against 2. This means that on average the product sets of a firm operating in the food industry contains 4 products that are shared with other firms in the same industry. Considering that the average product scope is just above 5 this is a significant number. For basic metals, the average product set contains 4 items half of which are in common

<sup>27</sup>Note that as expected both the arrays look and are very sparse confirming a fact well-known since researchers have access to finely disaggregated trade data cfr. Armenter and Koren, 2014, and the references therein. At the same time the level of heterogeneity among product scopes appears high in the two industries. even among the subset of the top-100 exporters. This comes as well with no surprise: a vast literature documents that trade is characterized by highly heterogeneous firms, with few big exporters dominating the market with large diversified product portfolios (Melitz, 2003; Bernard et al., 2007b; Bernard et al., 2018b). Gabaix, 2011 showed that this extreme skewness opens up the possibility of granular effects like those recently explored in Gaubert and Itshkhoki, 2018.

FIGURE 2.3: Arrays of product sets  $ps_f$  for the Top-100 French exporters

Notes: Arrays of product sets  $ps_f$  for the Top-100 French exporters operating in “Manufacture of food products” (NACE 10, left-panels) and in “Manufacture of basic metals” (NACE 24, right-panels) and active exporters in USA in 2007. Firms on the vertical axis are ranked according to their product scope  $|ps_f|$  (from top to bottom), and products on the horizontal axis according to the number of firms exporting them (from left to right).

with other firms in the industry.<sup>28</sup> The conceptual framework has also shown that the variability in the number of overlaps per firm is driven by three factors: the average product scope of firms computed excluding the most diversified one, the normalized number of active firms and an index that we interpret as a measure of product sets similarity. For the two industries in this example all the three components contribute to explain the difference in the number of overlaps per firm. There are much more firms active in the food industry, 1080 against 349. When we exclude the most diversified firm the average product scope remains for these two industries largely unchanged being just below 5 and above 4 for food and basic metals respectively. These two differences are, however, not enough to explain the variability of the number of overlaps between the two industries. Indeed, when we look at the similarity measure we get 0.85 for the former and 0.61 for the latter characterizing the product sets in the food industry as more similar than those in basic metals.

We conclude by illustrating what happens when we change the destination. Figure 2.3 reports the two firm-product arrays for the same industries but considering the US as destination. For the food industry the number of overlaps per firms drops significantly by almost 35%, that is to less than 3 overlaps per firm. Interestingly this results from the interplay of a reduction of the average product scope, computed without the most diversified firm, of about 25% from almost 5 to less than 4 products and a contemporaneous milder reduction of about 10% in the product set similarity. For basic metals changing the destination is associated with a completely different story. Indeed, we observe a milder drop in the number of overlaps per firm,

<sup>28</sup>An educated visual guess would have suggested the same thing, based on the number of black squares behind the convex hull of the product sets. In this case this turns out to be the correct guess. Note again that firms exporting alone one or two idiosyncratic products are not shown in Figure 2.2 because of the cut at the top-100 firms. Moreover note also blocks more dense are by construction more likely to appear in the top-left part of the arrays because of the ranking of firms and products.

about 7%, brought about by an increase of almost 15% in the average product scope, again computed excluding the most diversified exporter, and by a contemporaneous drop in the product set similarity of around 18%.

This variability across industries and destinations in the number of overlaps and in its components combines margins of trade typically investigated in the literature, the number of exporters and their product scopes, with a new margin associated with the similarity among product sets. This variability is systematically investigated in the next section.

## 2.3 Product sets across industries and destinations

To begin with, we consider the number of product overlaps per firm,  $(\frac{OV}{N})_{id}$ . We add the index 'id' to denote industries and destinations and to make explicit that this is the variability we explore in this section and we here assess to what extent this variability is associated with industry or destination factors. To assess the relative importance of sources of variability we regress  $(\frac{OV}{N})_{id}$  on industry and destination fixed effects.<sup>29</sup> Results show that industry and destination fixed effects account together for about 60% of the entire variability of the number of overlaps per firm and that this 60% is almost evenly shared by industry and destination specific factors.<sup>30</sup>

Next we exploit the decomposition defined in equation (2.3) showing that the number of product overlaps per firm can be factorized in 3 components: an index capturing the number of active firms  $\tilde{N}_{id}$ , the average product scope computed excluding the most diversified firm  $\overline{|\text{ps}|}_{-(N),id}$  and an index capturing the similarity across product sets  $S_{-(N),id}$ . Again the subscript id makes clear that they all vary across industry-destination.

### 2.3.1 Decomposition of the number of product overlaps per firm

We start assessing the relative importance of these three components in explaining the variability across industries and destinations in the number of product overlaps per firm. Borrowing the procedure proposed in Bernard et al., 2009b we run 3 distinct OLS regressions where the log of each of the three component is regressed on the log of  $(\frac{OV}{N})_{id}$ . As the OLS is a linear estimator and its residuals add to zero, each of the three estimated coefficients captures the component of the cross-sectional variation of  $(\frac{OV}{N})$  associated with each margin. Further their sum is, by construction, 1.<sup>31</sup>

<sup>29</sup>More precisely we compute semi-partial adjusted  $R^2$  for both sources of variability. They correspond to the difference between the adjusted  $R^2$  of a model with both the effects and that of the same model estimated with either of the two.

<sup>30</sup>More precisely industry fixed effects account for 31.9% of the variability while destination fixed effects 29.1%. Together explain 58.7%.

<sup>31</sup>For comparability in Appendix B.3 we use the same procedure to decompose the French export value across industry-destination pairs along traditional intensive and extensive margins precisely as done in Bernard et al., 2009b. We obtain results similar to those they got for the US in 2003.

TABLE 2.1: OLS regression decomposition of the number of product overlaps per firm across industry-destination pairs.

	all destinations	OECD	EU
Number of firms index $\tilde{N}$ -	0.023 (0.004)	0.011 (0.003)	0.010 (0.003)
Avg. product scope adj. - $\overline{ \text{ps} }_{-(N)}$	0.488 (0.033)	0.584 (0.046)	0.593 (0.052)
Similarity index - $S_{-(N)}$	0.489 (0.034)	0.406 (0.046)	0.397 (0.052)
obs	1,458	666	412

Notes: OLS decomposition of the variation across industry-destination in the number of product overlaps per firm, along three margins: the index capturing the number of firms  $\tilde{N}$ , the average product scope adjusted by omitting the most diversified firm  $\overline{|\text{ps}|}_{-(N)}$  and the similarity index  $S_{-(N)}$ . Each cell reports the coefficient and standard error of a distinct regression of the log of each margin on the logarithm of  $OV/N$ . The three coefficients sum to 1 because of the properties of the OLS estimator.

Table 2.1 reports the results of this variance decomposition. The estimated coefficients are 2.3%, 48.8% and 48.9% for the three components respectively when all the destinations are considered (first column). We read these results as showing that half of the variability in the number of product overlaps per firm is not explained by the traditional extensive margins considered in the existing literature, the number of firms and their average product scopes. Indeed, almost 49% of this variability is associated with the index capturing the extent to which product sets of firms active in the same industry-destination are. In the second and third column we perform the same decomposition on two sub-samples restricting the focus to the largest and more homogeneous destinations, the 34 members of the OECD and the 27 members of EU in 2007. While somewhat reduced with respect to the full sample the role of the similarity measure in explaining the variability of the number of overlaps per firm remains compelling. Indeed its variability is still associated with about 40% of the entire variability across industry-destination of the number of overlaps per firm.

Moreover, when checking for these three components how much of their variability is due to industry rather than destination factors, as done above for the number of product overlaps per firm, two main results emerge. First, while industry-destination fixed effects account for a large part of the variability for all the three components, for the similarity index this is significantly higher raising up to 66.3%. These variability is evenly split between industry and destination factors for the similarity index and the average product scope computed without the most diversified firm. On the contrary for the number of active firms, as measured by  $\tilde{N}$ , destination factors explain are more important than industry factors accounting for more than 70% of the entire variance.<sup>32</sup>

<sup>32</sup>Complete results are reported in Table B.3 in Appendix B.3.

### 2.3.2 Product scope and the role of the most diversified firm

The number of products sold by firms in international markets has been largely investigated in the empirical literature on multi-product exporters. Again guided by the decomposition in equation (2.3) here we are interested in a specific feature of this extensive margin. Indeed, we want to describe the effect on the average product scope in a given industry-destination of the removal, when computing it, of the most diversified firm.

Figure 2.4 (left-panel) show the complementary cumulative distribution function estimated using the average product scopes of the 1,509 industry-destination pairs available in 2007 and computed excluding in each of them the most diversified firm. Also this distribution is skewed with half of the observations displaying an average product scope of less than 3 products among which 41 have only 1 product.<sup>33</sup>

On the other tail of the distribution there are almost 30 industry-destination pairs with an average product scope higher or equal than 10; they cover all the most important French trade partners and span four industries: “Manufacture of motor vehicles, trailers and semi-trailers” (NAF-29), “Manufacture of chemicals and chemical products” (NAF-20), “Manufacture of other transport equipment” (NAF-30) and (NAF-14) “Manufacture of wearing apparel”.<sup>34</sup>

The right-panel of Figure 2.4 displays the complementary cumulative distribution function of the product scope of the most diversified firm in each industry-destination pairs. This distribution appears very skewed ranging from 1 to 557 and with an average of about 55 products.<sup>35</sup> It is worth to recall that if, in line with the existing empirical evidence, one assumes that in each industry-destination the distribution of product scopes is Pareto then each of the 1,509 observations in this distribution can be interpreted as the largest value in a sample of  $N$  measurements where  $N$  represents the number of active firms observed in each industry-destination. It follows the product scope of the most diversified firm is expected to grow as  $N^{1/(\alpha-1)}$  where  $\alpha$  is the exponent of the Pareto. In the case  $\alpha=2$  (Zipf) the product scope of the most diversified firm is expected to growth linearly with  $N$ .<sup>36</sup>

Next we turn to one feature of this distribution, that is the main interest for this work. The mean of this distribution is 3.5; not surprisingly if we compute, in each industry-destination, the average product scope including in the computation also

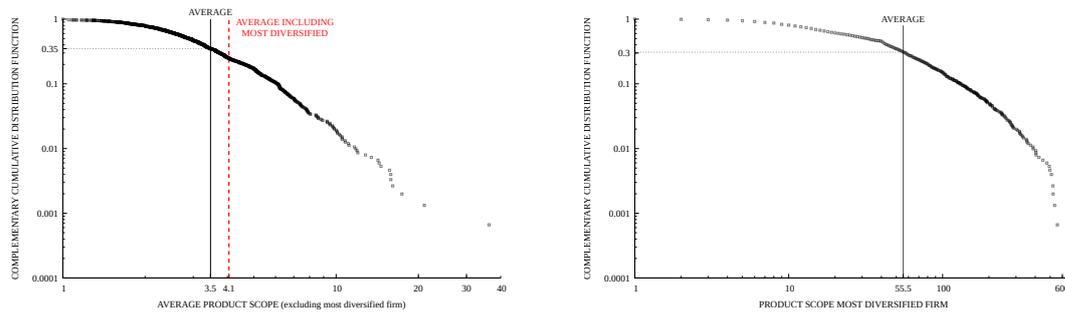
<sup>33</sup>Observations with an average product scope equal to 1 span several industries but are typically associated to destinations of secondary importance for France. Here the complete list (“ARG” “BHS” “CHL” “COL” “IDN” “IRN” “KAZ” “KWT” “LBR” [10] “LBY” “MLT” “NGA” “OMN” “PAN” “PHL” “TWN” “UKR” “VNM”).

<sup>34</sup>The complete list of destinations displaying an average product scope higher or equal than 10 is (“AUT” “BEL” “CZE” “DEU” “ESP” “GBR” “GRC” “HUN” “IRL” “ITA” “LBY” “MLT” “NLD” “POL” “PRT” “ROM” “SGP” “SVK” “SVN” “SWE” “USA”).

<sup>35</sup>The product scope of the most diversified firm is 1 in 9 industry-destination pairs NAF-14, NAF-18, NAF-19, NAF-21, NAF-31 and NAF-32 and 7 small commercial partners. The 10 highest values are instead all recorded in NAF-29 and span several of the most important export destinations for France.

<sup>36</sup>More precisely if  $|ps|$  is assumed to be Pareto distributed with lower bound 1 and exponent  $\alpha$  then the expected value of the largest realization in a sample of  $N$  measurements is equal to  $NB(N, (\alpha - 2)/(\alpha - 1))$  where  $B$  is the Legendre’s Beta function Newman, 2005.

FIGURE 2.4: CCDF of the average adjusted product scope



Notes: Complementary cumulative distribution function together with its average (solid vertical bar) of the average product scope computed excluding the most diversified firm (left-panel) and of the product scope of the most diversified firm (right-panel). Vertical dashed bar in the left-panel represent the average product scope computed including the most diversified firm. Note the log scale on both axis.

the most diversified firm the same average raises to 4.1.<sup>37</sup> We check, with a t-test, that these two averages are statistically different obtaining a t-statistics that allows to reject the null of equal means at any reasonable level. Note that this result is not driven by few industry-destination observations for which the removal of the most diversified substantially influences the product scope distribution and its average. Indeed, a Fligner-Policello test of stochastic dominance provides strong evidence that the distribution of the average product scope computed excluding the most diversified firm reported in Figure 2.4 is dominated by the one computed considering it. More qualitatively the top 100 industry-destination pairs in terms of the average product scope without the most diversified span 11 industries and 44 destinations while including the most diversified these figures are 9 and 51 respectively. 4 industries and 14 destinations are not common between the two groups of top-100 observations. The rank correlation across industry-destination between the average product scope with and without the most diversified firms while still high decreases to 0.946 and 0.843 with the Spearman's Rho and Kendall's Tau respectively. Hence we conclude that removing the single most diversified firm seems to affect how the average product scope is distributed and how it varies across industry-destination.

### 2.3.3 Similarity across product sets

Figure 2.5 displays the complementary cumulative distribution of the similarity index computed for the 1,509 industry-destination pairs. The distribution is mildly left skewed with an average similarity of about 0.52 and a median of 0.55. Further the observed values of the similarity measure span the entire theoretical support ranging from 0 to 1.<sup>38</sup> At these two extremes we have 51 and 6 industry-destination

<sup>37</sup>

<sup>38</sup>The corresponding frequency histogram is reported in Figure B.3 in Appendix B.3.

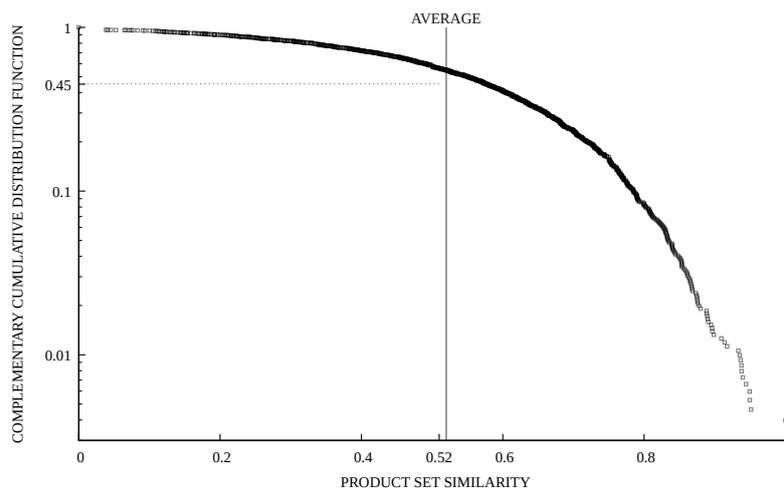


FIGURE 2.5: Complementary cumulative distribution of the similarity index

*Notes:* Complementary cumulative distribution together with its average (solid vertical bar) of the similarity index across product sets. Note the log scale on the y-axis only.

typically associated with minor French trade partners but still covering 20 out of 23 industries and 19 destinations.<sup>39</sup>

Above we already mentioned that the similarity varies significantly across industry and destinations (see Table B.3 in Appendix B.3). Here we can dig further in this variability. The observations belonging to bottom ( $S_{-(N)} \leq 0.38$ ) and top ( $S_{-(N)} \geq 0.69$ ) quartile of the distribution both cover the entire list of industries and the vast majority of the destinations (57 and 67 out of 67 destinations respectively). With the notable difference that the destinations associated with observations in the lower quartile do not include some of the most important French trade partners.<sup>40</sup> A simple correlation analysis confirms that the similarity index  $S_{-(N)}$  significantly correlates with industry and destination basic characteristics. Regression results suggest that a 10% increases in the distance from France and in GDP of a destination is associated with a 1.65% reduction and almost 1% increase in similarity respectively.<sup>41</sup>

## 2.4 Comparative advantages and product set similarity

In the above sections we have defined and empirically characterized an index of similarity of firms product set. We have interpreted this index to capture the extent to which performance of exporters in an industry-destination emerges from idiosyncratic rather than shared capabilities of firms. This section tests the relation between

<sup>39</sup>Industries include NAF-11 NAF-13 NAF-14 NAF-15 NAF-16 NAF-17 NAF-18 NAF-19 NAF-20 NAF-21 NAF-22 NAF-23 NAF-24 NAF-25 NAF-27 NAF-28 NAF-31 NAF-32 NAF-33 and destinations ("BHR" "BHS" "BRA" "CHL" "COL" "IRN" "KAZ" "KWT" "LBR" "LBY" "LKA" "MLT" "NGA" "OMN" "PAN" "PHL" "QAT" "UKR" "VNM").

<sup>40</sup>These destinations are ("BEL" "CHE" "DEU" "ESP" "GBR" "ITA" "NLD" "POL" "PRT" "USA").

<sup>41</sup>Details and complete estimation results are reported in Appendix B.3.

the product set similarity in an industry and the role of individual firms in defining the revealed comparative advantage of that industry.

There is a growing literature that has documented the pervasiveness and the role of large firms in defining aggregate trade patterns (Gabaix, 2011; Di Giovanni, Levchenko, and Mejean, 2014). Freund and Pierola, 2015 shows that individual firms can transform sectoral patterns and alter comparative advantage. In a sample of developing countries, they observe that one out of five loses the Revealed Comparative Advantage in a sector when the top exporter is dropped. In the spirit of Freund and Pierola, 2018, we estimate revealed comparative advantage (RCA) in the 24 manufacturing industries using the Balassa index and we calculate the share of industries that would lose RCA in the absence of the largest firm of the industry. We augment their exercise to investigate whether product set similarity helps explaining the role of single firms in defining the export capability of a country.

#### 2.4.1 Estimating the role of individual firms for the Revealed Comparative Advantage

According to Balassa, 1965, a country has a revealed comparative advantage in an industry if it exports more than its "fair" share, that is, the share that the industry represents in total world trade. This is if

$$RCA_{oi} = \frac{\frac{X_{oi}}{X_o}}{\frac{X_i}{X}} > 1 \quad (2.4)$$

where  $X_{oi}$  is the exports from country  $o$  in industry  $i$ ,  $X_o$  is total exports from country  $o$ ,  $X_i$  is the export of that industry worldwide and  $X$  is the world exports. For example, in 1999 "Manufacture of beverages" represented 3.3% of French exports, but accounted only for 0.7% of total world trade. Hence, French RCA in "Manufacture of beverages" (NAF/NACE 11) for that year was 4.57, indicating that beverages are 4.57 times more prevalent in France's export basket than in that of the world. Similarly, in 1999, goods related to the "Manufacture of motor vehicles" (NAF/NACE 29) were 1.34 times more prevalent in France's export basket than in the rest of the world.

We fix the origin to France and drop the subscript  $o$ , and compute the  $RCA_i$  for French industries over different samples. First, over the full sample. Then, over 24 samples, corresponding to the number of manufacturing industries, by dropping at each time only the largest firm of that industry in France. The largest firm is defined as the top exporter in terms of export share. In this way for each industry in France we have two information,  $RCA_i$  and  $RCA_i^{-TOP}$ .<sup>42</sup> We then define a reversal in RCA a situation in which the industry would lose the RCA if there were no top exporter, which is

$$RCA_i^{REV} = [RCA_i > 1 \ \& \ RCA_i^{-TOP} < 1]. \quad (2.5)$$

<sup>42</sup>Note that we have information on the largest firms only for France through micro-data.

year	$RCA^{REV}$			
	RCA >1 (1)	reversals (2)	industries list (3)	
1995	11	1	29	
1996	11	1	33	
1997	10	1	27	
1998	9	1	29	
1999	10	2	25,29	
2000	10	1	25	
2001	9	0	NA	
2002	9	0	NA	
2003	11	2	17,25	
2004	12	1	33	
2005	12	1	33	
2006	12	1	33	
2007	11	1	33	
	all observations		only reversals	
	avg. RCA>1	1.75	avg. RCA	1.10
	avg. RCA<1	0.73	avg. RCA no Top 1	0.91
	t-test	11.72***	t-test	4.21***

Notes: Columns (1) to (3) report the number of industries with Balassa RCA index greater than 1, the number of reversals observed when the Top 1 firm is removed and the list of industries in which reversal are observed. In the bottom part of the table we compare the average value of the RCA index between industry-year pairs where it is greater than 1 and those where it is lower than 1 and between industry-year pairs where the reversal of RCA is observed with and without the Top 1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

TABLE 2.2: Export capabilities and comparative advantage

The second column of Table 2.2 shows the number of industries that have a RCA in France out of the 24 possible manufacturing industries, using Balassa RCA as metric. On average, France holds a RCA in 11 industries and this number is quite stable over time. The next column of the Table shows the number of industries that loose a RCA when exports from the top firm in the industry is removed. Overall, we observe up to 18 percent of RCA reversals within a year. Among the industries with more frequent reversals across time, one finds “Manufacture of fabricated metal products”(naf code 25), “Manufacture of motor vehicles” (naf code 29) and “Repair and installation of machinery and equipment” (naf code 33). Note that, on average, these reversal are not due to tiny jump in the value of the  $RCA_i$  below the 1 threshold. The t-test on the difference in RCA before and after removing the top exporter for these industry-year pairs is significant at 1%.

To test the role of firms product set similarity on the probability that an industry has a RCA created by a single firm, we estimate the following model

$$Pr[RCA_{idt}^{REV}] = \delta_{dt} + \beta_1 \tilde{N}_{idt} + \beta_2 \overline{|\text{ps}|}_{-(N),idt} + \beta_3 S_{-(N),idt} + \epsilon_{idt}. \quad (2.6)$$

We include a time-destination fixed effect  $\delta_{dt}$  to exploit the variability within a country-year across industries of our variables.<sup>43</sup> We also control for the other components that determine the number of overlaps per firm, that is the number of active firms in an industry-destination  $\tilde{N}$  and the average product scope across firms computed excluding the most diversified firm,  $\overline{\text{ps}}_{-(N)}$ . Our coefficient of interest is  $\beta_3$  as it captures

All level variables  $\tilde{N}_{idt}$ ,  $\overline{\text{ps}}_{-(N),idt}$  and  $S_{-(N),idt}$  are transformed using the inverse hyperbolic sine (MacKinnon and Magee, 1990). This linear monotonic transformation behaves similarly to a log-transformation, except for the fact that it is defined at zero. The interpretation of regression estimators in the form of the inverse hyperbolic sine is similar to the interpretation of a log-transformed variable.<sup>44</sup> Results are robust to using a regular log-transformation (after the proper correction to allow for zero values).

We estimate equation 2.6 with a LPM, in order to include the fixed effects. The standard errors of the coefficients are clustered at the  $(d, t)$ , i.e. at the level of the fixed effect. Our standard errors, therefore, account for the possibility that a shock in France will affect the structure of RCAs across industries.<sup>45</sup>

## 2.4.2 Results on Firms Product Set Similarity

Table 2.3 reports the estimations of model in 2.6.

The coefficient on the similarity index is negative and statistically significant. In terms of magnitude, an increase by 10% in the similarity index is associated to an expected fall by 13.8% in the probability of reversal of the RCA Balassa, conditional on the adjusted number of firms and the average product scope in the industry-destination pair. The negative sign suggests that the RCA of a industry is less dependent on single large firms, when firms have more similar product sets. RCAs are therefore more resilient to granular forces in those industries with higher similarity index. This result reinforces the idea that the similarity of firms' product sets reflects the extent to which the aggregate performance of the industry are driven by fundamental rather than granular forces.

The coefficient on the adjusted number of firms and the adjusted average product scope is instead positive. We interpret the positive sign in the following way. Following the discussion in Section 2.1, an increase in the number of firms rises in expectation the product scope of the largest firm. This is because the number of firms can be seen as the size of a random sample of firms' product scope. In case the underlying generating process of firms' heterogeneity is distributed as a Pareto, then in expectation, the product scope of the largest firm grows with the sample size.

<sup>43</sup>Note however that the RCA varies only across industries and year, and we have expanded our variable to exploit our sample.

<sup>44</sup>The inverse hyperbolic sine (asinh) is defined as  $\log(y_i + \sqrt{(y_i^2 + 1)})$ , approximately  $\text{asinh}(y_i) = \log(2) + \log(y_i)$ .

<sup>45</sup>We should argue better this point. However significance are stable on different type of clustering.

TABLE 2.3: Probability of RCA reversal in dropping the top exporter

Dep. var.	RCA Balassa (1)
$\text{asinh}(\tilde{N})$	0.121*** (0.002)
$\text{asinh}(\overline{ \text{ps} }_{-(N)})$	0.066*** (0.004)
$\text{asinh}(S_{-(N)})$	-0.138*** (0.009)
Observations	19,526
Adjusted R <sup>2</sup>	0.032
Residual Std. Error (df = 18652)	0.206

Notes: OLS estimates of the probability of observing the RCA index to fall below 1 following the removal of the TOP 1 exporter in a industry. All specifications include destination-year fixed effects. Standard errors are clustered at destination-year level. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

If one assumes that the extensive and intensive margins of trade are correlated as in Bernard et al., 2018b, then an increase in the number of firms rises in expectation also the market share of the most diversified. This means that this firm becomes in expectation relatively more relevant for the industry, and that is why we expect the industry to loose the RCA if we drop the superstar. On another note, in Section 2.1 we have shown that the product scope of the most diversified firm grows at a rate that depends on the skewness of the underlying distribution.<sup>46</sup> We can interpret the positive coefficient on the adjusted product scope following this observation. Under the same assumptions, an increase in the average scope, given a certain sample size, can be associated to a fall the slope of the Pareto  $\alpha$ . This in turn, makes the distribution that governs firms' heterogeneity more skewed and therefore in expectation the product scope of the most diversified larger. We expect therefore the most diversified firm to count more in defining the RCA of the industry when the adjusted average product scope increases, given a certain adjusted number of firms.

<sup>46</sup>This follows from the fact that  $E[|\text{ps}|] = \left(\frac{\alpha-1}{\alpha-2}\right) |\text{ps}|_{\min}$ . Where  $|\text{ps}|_{\min}$  is the minimum possible value of the product scope, which in our case is set to 1.

## 2.5 Conclusion

This chapter argues that the aggregation of exporters decisions on their product baskets at the industry-destination level can not be reduced to the simple sum of product scopes. The way this aggregation emerges from exporters behaviors depends also on which products they decide to sell. We show that this aggregation can be conveniently decomposed into three factors: the normalized number of firms exporting, the average product scope of firms - computed excluding the most diversified firm, and an index of product sets similarity.

We first provide evidence that the similarity component plays an important role in explaining the differences across industry-destination in the way individual product sets of French exporters aggregate. We also find that similarity displays a significant variation across industry-destination with both dimensions playing an equally important role. Moreover the distribution of the average product scope across industry-destination is found to be significantly affected by the removal of the most diversified firm in line with the idea that the success of individual companies may have implication for the economy as a whole.

Finally we show that similarity among product sets is important to quantify the resilience of the RCAs of French industries when they experiment the loss of their champion. We interpret this evidence suggesting that the similarity of firms' product sets reflects the extent to which the aggregate performance of the industry are driven by fundamental rather than firm-specific forces.



## Chapter 3

# Non transparent Technical Regulations as obstacle to trades

The material of this chapter is an unpublished manuscript: Iodice, I. "The Sound of Silence. Non-transparent Technical Regulations as Obstacles to Trade".

Understanding how to comply with foreign technical regulations is not an easy task for exporters. The procedure of collecting information on the details of a technical requirement, on the goods it targets, and on how to prove conformity with it can be very costly. If the access to this information is made particularly complicated for foreign firms, domestic regulations can affect the export behavior of firms. While there is consent in the literature that countries can misuse technical regulations to protect domestic industries (Beverelli, Boffa, and Keck, 2014; Orefice, 2017), little is known about the role of transparency in the protective nature of these policies. This is surprising given that, over the last decades, technical regulations have gained relevance, becoming among the most reported trade barriers by exporters (OECD, 2005).<sup>1</sup> But this is all the more surprising given that exporters complain even more about procedural obstacles related to foreign regulations than about the regulations themselves (International Trade Center, 2016).

This chapter aims to fill this gap by providing a framework to investigate the nature of these trade barriers. We first document the relevance of procedural obstacles among technical regulations. We then estimate the impact of newly introduced regulations that have not been properly disclosed internationally on the exporting behavior of firms. To interpret our results and guide additional understanding of the phenomenon we make use of a theoretical baseline model of investment under uncertainty using the intuitions of the real options literature developed in Dixit and Pindyck, 1994.

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<sup>1</sup>In his farewell statement to the General Council in 2013 Pascal Lamy, former Director-General of the World Trade Organization (WTO), stressed the key role of non-tariff barriers in new trade policies. In particular, surveys of exporting firms across OECD countries document that "technical measures and customs rules and procedures . . . are [consistently] among the five most reported categories of non tariff [trade] barriers" (OECD 2005, p. 24).

The object of this study are technical regulations that are trade restrictive. We consider those regulations, namely Technical Barriers to Trade (TBTs), that have been contested by exporting countries at the WTO through a soft law mechanism called Specific Trade Concern (STC).<sup>2</sup> Raising a STC against another WTO member is costly: trade representatives must allocate their resources in preparing the case among a potentially large arena of misbehaviors. Therefore, this set of TBTs should identify the most trade restrictive regulations. We use the timeline recommended by the WTO to characterize transparency in the introduction of a new TBT. Essentially, countries should announce the draft measure through a document called "Notification" at least eight months before the enforcement. We define as non transparent the case in which governments fully elude this timeline and enforce the TBT without previously announcing it to the other WTO members. We refer to these TBTs as *Surprise Measures*. The database on Specific Trade Concern, as coded by the WTO, does not, at least directly, report when and how contested TBTs have been introduced. To fill this gap, we construct a novel database by using information from the content of the STCs and from Notifications, which have been parsed while detecting the dates of implementation of TBTs.<sup>3</sup> This procedure allows us to identify when a measure has been introduced and whether it has been previously announced. We then match this data with a panel of French exporters covering the period 1995-2007 to estimate the differential effects of Surprise Measures on firms' trade margins. Our identification relies on the common trend assumption across products that are exported to a certain destination within a certain sector. We compare goods that are similar except for the fact that some have been object of the new regulation and others have not. In addition, the fact that our sample includes TBTs that are not Surprise, which we call *Announced Measures*, provide us with a benchmark to evaluate the effect of the lack of transparency itself.

In the first part of this work, we document the pervasiveness of transparency-related obstacles using the content of STCs. To do so we use the motivation provided by countries to rise a case at the TBT Committee.<sup>4</sup> Consistently, we find that almost 40% of the TBTs rised as STCs are Surprise Measures, they have been enforced without being previously announced.<sup>5</sup> The importance of transparency emerges also by looking at the dynamics of French product level exports around the adoption of a restrictive TBT. While measures that have been announced do not have a significant impact, Surprise Measures cause a substantial fall, of around 20%, in the

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<sup>2</sup>STCs may be brought by any WTO member considering to be negatively affected by an SPS/TBT measure imposed by a WTO trading partner. They represent 'soft law' mechanisms to deal with NTMs, as they are based on diplomatic relations, rather than adjudication.

<sup>3</sup>This procedure is able to identify the history for more than 70% of the measures touched by a STC.

<sup>4</sup>This result is coherent with the evidence from International Trade Center's 2016 survey on EU exporters. Indeed, "information and transparency issues" are among the most reported procedural obstacles by European firms. These includes inaccuracy or information on the licensing and certification process.

<sup>5</sup>These issues are prevalent also recently. For example, in 2017, 56% of STCs raised for the first time concerned unnotified measures. See Note by the Secretariat, 'Twenty-Third Annual Review of the Implementation and Operation of the Agreement', G/TBT/40, at 24.

export value of those products covered by the new regulation. We test further the distinction between Announced and Surprise measures while accounting for firm heterogeneity.

We identify two regimes for the effects of TBTs on firms' behavior, depending on how the regulation has been implemented. Announced TBTs cause exit of firms in the period before the TBT is introduced and an increase in the export value for those who stay. Surprise TBTs are instead associated to a substantial decrease, ranging between 20 and 30%, of the average export value in the semester in which the measure is enforced. On the other hand, they do not determine substantial exit. We interpret these differences in terms of the different timing in which firms evaluate whether to adopt the new technical requirement as well as the information at disposal when taking this decision. Timing is crucial whenever the choice to comply with the new regulation implies an investment that is at least partly irreversible. In case of Announced measures, the announcement of the change in regulation affects firms' expected payoff before entering the market, when the per period sunk cost of exporting there has not yet been paid. This allows the firm to take into consideration the additional cost of adapting the new regulation in the decision to serve the market in that period. On the other hand, Surprise measures affect the instantaneous payoff once the firm has entered and already paid the per period sunk cost to serve the market. The different timing in which firms consider whether to implement the new requirement explains why exit of firms is significant only when the change in regulation is announced. Information are also crucial to decide when to invest, if firms are uncertain about their future payoffs and they have an option to wait. In the case of Surprise TBTs, the lack of Notification about the new regulation rises the uncertainty on the costs of serving the market. This in turn rise the value of the real option of waiting to collect more information before adapting the new standard.

In support of this interpretation, we observe that the average exporter reduces its export activity with the market covered by a Surprise TBTs, by cutting on the frequency -the extensive margin- rather than on the average value per shipment. This reinforces the idea that firms undergo a temporary halt of their activity, which is observed as a reduction in the number of months in which exporters serve the market. The adverse effect of these TBTs is short-lasting, firms recover their export activity in a couple of semesters. However, not all firms are equally able to survive this period. Small and medium size firms tend to exit definitely the market, while only large firms can afford to wait. We investigate further whether the temporary halt can be interpreted as due to an increase in the real option of waiting to invest. We exploit the presence of delayed Notifications to investigate their role in reducing the uncertainty of the trading environment. We find that delayed Notifications, which provide late formal information on how to adopt the new requirement, reduce the persistence of the export halt. This finding further strengthens the idea that by eluding transparency, countries effectively hinder the investment decisions of firms.

Previous empirical literature has found transparency in trade policy to boost

trade and investment flows (Francois, 2001; Helble, Shepherd, and Wilson, 2009; Lejarraga and Shepherd, 2013). Metrics used in these type of works are very broad in scope – they are built on perception-based indices or on general transparency provisions within regional trade agreements. An exception, is a recent work by Ing, Cadot, and Walz, 2018 which proposes an index based on what governments actually do in the area of Non Tariff Measures (NTMs). Their index includes the number of NTMs that are notified by a country. We share with this work the focus on Non Tariff Measures, since NTMs, and TBTs in particular, are complex legal instruments which can impose substantial procedural obstacles. In our work we use the procedure of implementation of these regulations, to capture not only whether, as in the case of Ing, Cadot, and Walz, 2018, but also *how* countries announce and disclose these type of regulations. In doing so we provide transparency with a definition along one fundamental attribute: predictability.<sup>6</sup>

Our work thus refers to the literature that studies the role of trade policy uncertainty on investment decisions of international firms. Recent theoretical contributions (Handley and Limao, 2015; Coelli, 2018) have combined intuitions from trade models with firm heterogeneity (Melitz, 2003) with those from the real options literature (Dixit and Pindyck, 1994). In presence of an irreversible investment and the possibility to wait, uncertainty on the trade environment incentives firms to delay the investment decision on whether to enter a market (Handley and Limao, 2015) or to undergo technology upgrading (Handley and Limão, 2017; Coelli, 2018). These studies test their predictions by exploiting the enforcement of trade Agreements as episodes of changes in policy uncertainty and using variation in the gap between applied and bounds tariffs (similarly also (Carballo, Handley, and Limão, 2018)). Instead, little is known on the sources of uncertainty about NTMs. In this chapter we propose to look at the presence of formal Notification about the implementation of a TBT. We then use episodes of changes in TBTs, with and without formal Notification, to estimate the effect of reduced uncertainty on the export investment decision of foreign firms.

We also contribute to the literature that has studied NTMs to restrict trade. Previous literature has found that NTMs have been used to compensate reductions in applied tariffs.<sup>7</sup> However, while ‘There is little question that governments sometimes do deploy regulations to favor domestic producers over foreign ones’, how they succeed is still mostly un-answered (Rodrik, 2018). The complex and heterogeneous nature of NTMs makes it indeed very challenging to distinguish whether a

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<sup>6</sup>Helble, Shepherd, and Wilson, 2009 identify two dimensions of transparency: predictability (reducing the cost of uncertainty) and simplification (reducing information costs). As acknowledged by the authors, their indexes are not able to disentangle the two but instead try to account for both sources together.

<sup>7</sup>A non exhaustive sample of the literature that has studied the trade policy substitution between tariff and Non Tariff Measures includes Moore and Zanardi, 2011 Beverelli, Boffa, and Keck, 2014 and Orefice, 2017. The last two works have dealt specifically with TBTs. In particular, Beverelli, Boffa, and Keck, 2014 show that policy substitution between tariffs and TBTs prevails in developed countries. Orefice, 2017 that TBTs (and also SPSs) become effective barriers to trade as a consequence of reductions in tariffs.

measure pursues a legitimate policy objective rather than a disguised protectionist motive.<sup>8</sup> In addition, database on NTMs are usually silent with respect to the time series of the underlying regulations.<sup>9</sup> Recent literature have therefore used NTMs contested at the WTO through STCs to identify those regulations that restrict trade, and the time of the concern to proxy the one of the underlying regulation.<sup>10</sup> To investigate the nature of the obstacles behind these NTMs, some works use firm level data to distinguish the effects on the intensive (average export value) and extensive (number of exporters) margins of trade (Fontagné et al., 2015). This distinction is then used to infer whether these barriers impose mostly a variable rather than a fixed costs.<sup>11</sup> Our contribution to this literature is twofold. First, we investigate the nature of these trade barriers. We do this by looking at a recently added information on the database about STC, i.e. the reasons why WTO members complain about other members' use of TBTs. Second, we propose an algorithm which cross-references data on STC with external documents, to collect information on the history of these regulations. This allows to identify whether the effect manifests as a consequence of the policy change.

This paper refers also to the literature that has studied the effects of TBTs on trade. An example is the work by Bao and Qiu (2012), which uses all the TBTs notified at the WTO, and finds that the presence of a notified TBT decreases other countries' extensive margins, while increases their intensive margin. They explain this as to be due to a rise in the fixed cost, which pushes out of the market some firms. When considering, instead, only those TBTs that entail product standard harmonization, Schmidt and Steingress, 2018 observe that these measures rise trade both through an increase in the sales volume of existing exporters as well as through entry of new exporters. They explain this as a market size effects: harmonization works as a demand shifter, raising firms' incentives to produce those varieties. On the other hand, Fontagné and Orefice, 2018 focuses on TBTs that have been risen as STC by the EU to identify stringent TBTs and finds that they induce exit of exporters. The authors do not find however a significant effect on the intensive margin of firms. Our work reconciles this peculiar result. Within TBTs raised as STCs there are two regimes: when announced, restrictive TBTs produce effects that are similar to the ones observed by Bao and Qiu (2012) for the sample of notified measures. This effect is then offset by

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<sup>8</sup>An example is the different thresholds set by the US and EU regulation on the speed below which all hybrids and electric vehicles have to emit artificial warning sounds for pedestrians. The US National Highway Traffic Safety Administration issued in December 2010 this to be below the 30kph. The European Union issued in 2014 set, instead, a lower threshold, of 20 kph, motivating this as to be due to differential risk for noise pollution. However, engineer studies are far from unanimous on which is the best threshold that trades off noise pollution with efficacy of the sound in preventing injuries. [Regulation (EU) No 540/2014 of the European Parliament]

<sup>9</sup>For an exhaustive overview of this issues refer to Ederington and Ruta, 2016.

<sup>10</sup>For an exhaustive overview of this literature refer to Ederington and Ruta, 2016. For example, Herghelegiu, 2018 use a sample of developing countries and finds that only TBTs and SPSs that have been object to a concern are used to substitute tariffs.

<sup>11</sup>This is because, in a model with firm heterogeneity à la Chaney, 2008 the aggregate trade elasticity to fixed trade costs is predicted to be driven by the extensive margin, with a negligible role of the intensive margin. A sample of this literature includes Fontagné et al., 2015.

the negative effect of the surprise measures. Our work confirms that depending on the reasons that lie behind the adoption and design of TBTs, trade effects of exporters may be very different. In another interpretation, Maggi, Mrázová, and Neary, 2018 prove that Red Tape Barriers might impose different firms' behaviors depending on whether the import demand is sufficiently concave.

The remainder of the chapter proceeds as follows. Section 3.1 provides background on the institutional setting and explain how we measure lack of transparency. Section 3.2 and 3.3 describe the data the event-study framework we employ to evaluate the effects of non transparent TBTs. Section 3.4 describes the main results and section 3.5 discusses their interpretation. Section 3.6 discusses the results on the heterogeneity of the effect along firm characteristics while 3.7 the persistence of the effects of uncertainty. Section 3.8 concludes.

### 3.1 Institutional Framework

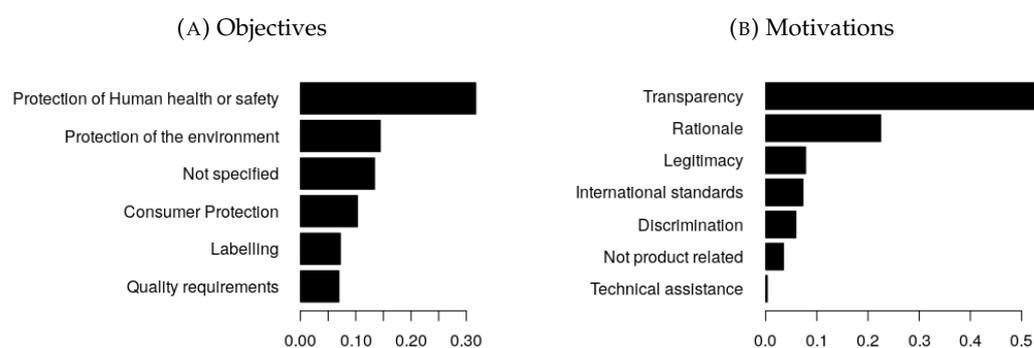
According to the TBT Agreement, WTO members can introduce in their domestic market, technical standards that differ from international ones to pursue legitimate policy objectives. Countries might aim, for example, to guarantee the quality of the imports, to protect human health or the environment, its national security, or to prevent deceptive practices. On the other hand, these measure should not create any arbitrary or unjustifiable discrimination between domestic and foreign competition. To do so, along with providing a legitimate rationale, governments must implement a TBT in the least trade-restrictive way.<sup>12</sup> For example, countries must announce the new measure to international partners enough in advance and disclose all relevant information to guarantee the transition within a predictable market environment. Whenever a WTO member believes that these principles have not been respected, she can contest the TBT by raising a Specific Trade Concern to the WTO and identifying the nature of the issue.<sup>13</sup> When looking at the objectives proposed by governments for those TBTs that have been contested to the WTO, the majority are legitimate ones. The most frequent being related to the protection of human health and safety, or of the environment (panel (a) of Figure 3.1).

The Mexican ban of the chlorofluorocarbon compounds (CFCs) for the manufacture and import of household refrigerators and air conditioners is an example of a TBT which has been contested despite a seemingly legitimate rationale. Indeed, the use of CFCs might have serious environmental consequences as their long lifetimes in the atmosphere can deplete the ozone layer. Raising concerns about the effects of CFCs started back in the end of the 80s, when countries came together to the signature of the Montreal Protocol. In the 90s, this Protocol was further strengthened by calling for the complete elimination of CFCs by the year 2010. In Mexico, the ban has

<sup>12</sup>The TBT Agreement states that "Members shall ensure that technical regulations are not prepared, adopted or applied with a view to or with the effect of creating unnecessary obstacles to international trade." (Art. 2.2)

<sup>13</sup>These are discussed within the TBT Committee that meets every four months.

FIGURE 3.1: Most frequent Objectives and Motivations of STCs



Sample of TBTs contained in the STC database. Each STC has one or more objectives (motivations). One occurrence is thus the combination STC-objective (motivations). The total number of occurrences in the dataset is 598 (478).<sup>16</sup>

been adopted and enforced in the same day, under a status of emergency, on the 22th September 1998. Interestingly, the Mexican standard has been formally announced to international partners only on the 12th of October 1998, once the measure have already been implemented.<sup>14</sup> When the TBT Committee met in November 1998, the representative of the United States drew attention to the new Mexican standard through a STC, raising an issue on “transparency”. In particular, the US delegate questioned the nature of emergency with which the measure has been implemented and claimed that exporters were uncertain on how to comply with the new regulation. For example, international partners were not provided with a list of accredited laboratory that perform conformity assessment tests.<sup>15</sup>

Interestingly, issues related to the procedure of how a TBT has been disclosed and implemented are the most pervasive. Indeed, the majority of the concerns are raised because of issues of transparency (panel (b) of Figure 3.1).<sup>17</sup> This is surprising in light of the fact that international disciplines codifies explicitly how countries should introduce a new TBT. This procedure is summarized in the timeline shown in Figure 3.2. Essentially, governments are required to announce other members about proposed measures which might have a significant effect on trade and which are not based on international standards. They do so by providing a Notification, which is a formal document which discloses, among others, information on how to implement the new regulation.<sup>18</sup> This formal announcement must take place at an early stage so

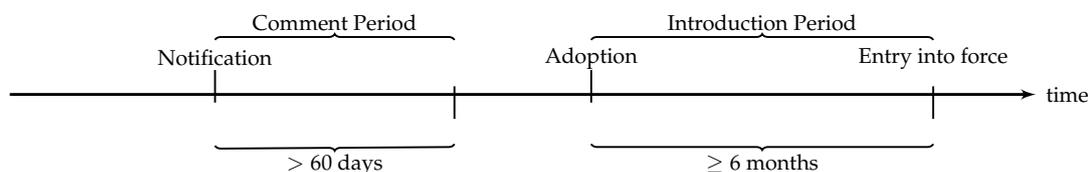
<sup>14</sup>One can find the full text of the formal announcement on the ITM database under the Symbol G/TBT/Notif.98.485

<sup>15</sup>“She questioned the nature of the emergency and indicated that, in order to comply with the Mexican regulations, products had to be tested by an accredited laboratories. Until today, however, not a single laboratory had been accredited to perform the required tests. Therefore, US exporters were uncertain about how to comply with the regulation.” (G/TBT/M/14, par 35)

<sup>17</sup>We group, similarly to what done in the ITC survey (2016), “transparency” with “missing information” and “unreasonable time”.

<sup>18</sup>A notification is “a transparency obligation requiring member governments to report trade measures to the relevant WTO body if the measures might have an effect on other Members” (World Trade Organization, 2017).

FIGURE 3.2: Ideal timeline of introduction of a new technical regulation



Notes: Elaboration from the The WTO Agreements Series on TBTs.

that to allow exporters to adapt in time to the changing requirement. Then, a 60-day comment period begins, during which other members can look into the details of the draft, ask for further information and then provide written comments. Afterwards, countries can introduce the measure, leaving (at least) 6 months before it becomes compulsory. Thus, between notification and entry into force no less than 8 months should pass.

### 3.1.1 Surprise Measures

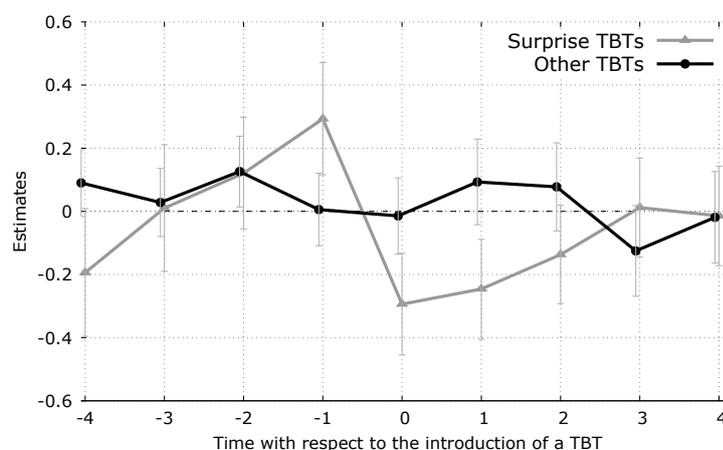
The fact that the procedure of introduction of a new TBT is codified and agreed among WTO members help us in defining the lack of transparency. In particular, we define as non-transparent the avoidance of this procedure – the case in which a country enforces a TBT without previously announcing it. In such cases, we call the underlying TBT a Surprise measure. The Mexican case above represents therefore an example of these measures.

When measures are instead notified before being enforced we call them *Announced Measures*. This distinction becomes relevant for policymakers as far as it is informative of the source of trade obstacles.<sup>19</sup> Essentially, this is the case if it is the lack of transparency itself, which imposes idiosyncratic costs to exporters. For example, the introduction of a Surprise measure might be associated to delays in customs clearing or might increase the probability of a shipment to be rejected at the customs. In addition, the lack of transparency might also impose to exporters a cost of searching and screening the documentation since they have to inform autonomously about the new requirement. With respect to Announced TBTs, Surprise Measures can rise the uncertainty on the profitability to serve the market. Surprise TBTs then can also increase the opportunity cost to invest before the uncertainty is solved, which in turn incentives firms to wait until formal information will be are provided.

Figure 3.3 plots the log change in French exports for those products that are subject of a trade restrictive TBT, conditional on destination and product time-invariant

<sup>19</sup>Based on interviews with trade representatives from various WTO member countries, Holzer, 2019 distinguishes STCs that contest how the measure has been implemented from STCs that challenge the content of the measure.

FIGURE 3.3: French exports dynamics around the introduction of a TBT



*Notes:* Time is a semester. The image plot the estimated coefficients, and relative 95% confidence bar, of a model where we regress the (log) value of French export in a (product, destination country, time) market over semestral dummies around the introduction of the TBT, for two type, Surprise and Other TBTs. The model includes (product, destination country) fixed effects and therefore exploits the time variability within markets TBTs. All TBTs information come from WTO STC database. In Appendix C the regression table.

characteristics. French exports are substantially hit by unexpected changes in foreign technical regulation. Interestingly, these type of regulations are enforced in presence of a positive trend in French exporting activity, suggesting that countries may have used these regulations as a shelter from import penetration. On the other hand, this adverse effects seems to be temporary, lasting on average no longer than a year. Similar patterns are not observed for other TBTs, where the aggregate export activity seems not to be substantially altered.

### 3.2 Data and Stylized facts

In order to study the role of the lack of transparency for TBTs which impede trade, we face two types of empirical problem. First, given the extremely large number of regulations and their heterogeneous nature, it is difficult to classify which type of regulations are indeed trade restrictive. For example, the same HS6 product might be touched by several regulations, that cover different aspects of it. Some of them might even be aiming at boosting trade, as episodes of harmonization to international standards.<sup>20</sup> Second, database on TBTs and NTMs in general, usually lacks identification codes of the underlying regulation and therefore it is hard to trace back the timeline of introduction of the measure.<sup>21</sup>

To identify the set of potentially trade restrictive TBTs we use the WTO database on TBT Specific Trade Concerns. This database records all the concerns raised to

<sup>20</sup>This kind of measures are studied in Schmidt and Steingress, 2018.

<sup>21</sup>For example, Trains and Perinorm provide information which are snapshot of the existing regulations at the time the data were collected.

the WTO, but it provides only the period in which a STC is active over a proposed or adopted regulation, while does not directly report the timeline of the underlying regulation.<sup>22</sup> Previous literature has proxied the time of introduction of a TBT with a window around the period in which the concern is ongoing. However, recently, the WTO STC database on TBTs has been updated and now contains identification keys for the regulations. We use these keys to retrieve external documentation by web-crawling the WTO repository on TBTs (the Information Management System repository). We fill the gap in the data and create a new database with the timestamps of the regulation by parsing the aforementioned documentation. This database is meant to be merged with both firm-product level data as well as with information on products' tariff rates. This database

### 3.2.1 STC Database

The database is managed by the WTO and contains information about all the concerns raised between 1995 and 2011, for a total of 318 STCs.<sup>23</sup> These concerns regard 403 different TBTs, since within the same STC countries might complain about one or more measures, proposed or adopted by another WTO member. Interestingly, concerns might also be raised over TBTs that have never been formally notified by countries, a circumstance that is not envisaged under the TBT Agreement.

For each concern, the database reports the country that has introduced the measure (maintaining country), the HS product codes affected by the measure, the objective of the regulation provided by the maintaining country, the date of initiation (and further dates if prolonged), the country(-ies) that has complained about the measure (raising country) and the motivation of its complaint (the issue).<sup>24</sup>

### 3.2.2 New Database about Timelines of TBTs

We capture the timeline of a TBT through three dates: notification, adoption and entry into force. The latter two are used to identify the period over which the TBT is introduced in a market: after the adoption, firms may start to implement the measure, and they will have to comply to it by the date of enforcement. The notification date will be used to identify when the country informs the WTO about the new regulation. Note that there are some contested TBTs that have never been notified.

To collect these dates we use two sources of information: i) the documents provided by the country introducing the TBT, including possibly the Notification and ii) the content of the STC from the records of the Meetings of the TBT Committee

<sup>22</sup>A STC is active from the moment in which is raised at the TBT committee until when the case is no longer discussed. Within the WTO an STC is considered to be no longer active if it is not raised in WTO committee for two years or more. The date of the last raising at the TBT committee is assumed to be the date of the resolution of the STCs.

<sup>23</sup>The dataset is freely available at [https://www.wto.org/english/res\\_e/publications\\_e/wtr12\\_dataset\\_e.htm](https://www.wto.org/english/res_e/publications_e/wtr12_dataset_e.htm)

<sup>24</sup>While there is no official information on the specific HS product concerned by each STC on TBT, the WTO computes an HS mapping through text documentation.

also called Minutes. We access the first type of information through an identification code provided in the STC database.<sup>25</sup> For each code, we download the documentation available by web scraping the WTO online repository on TBTs.<sup>26</sup> There are two main types of document: the Notification and the Revision.<sup>27</sup> We process these as follows:

1. from the Notification we retain i) the date of notification, ii) the proposed date of adoption and iii) the proposed date of entry into force. The format of this document is standard and therefore we could automatize its reading.<sup>28</sup>
2. From the Revisions we collect information on whether a TBD date has been added afterwards, or whether the initial proposed dates have been modified.<sup>29</sup> Unfortunately, these documents are not standardized and we had to collect information manually.

We then text parse the information of the Minutes, which are the documents recorded by the Secretariat during the meetings, to see whether further dates are provided by the concerned country.<sup>30</sup> The Minutes are particularly useful to collect information for those cases in which the country has not notified the measure or has later updated them.<sup>31</sup>

Figure 3.4 shows how the final sample is obtained. Note that revised dates are those that have been modified with respect to the proposed ones, because, for example, they have been updated in a Revision. Added dates are those that have been found, either in Minutes or in later Revisions, in case the notification misses these information.<sup>32</sup> On overall, we identify the timeline for 301 out of the 403 measures, almost the 75%.

A concern with this methodology might be the selection bias introduced in our sample due to the fact that the timeline of less transparent measures, by their nature,

<sup>25</sup>This is called “Document Symbol”. In most of the cases, it has a standard format, which includes “G/TBT/N/” followed by the country isocode at 3 digit plus the number of the notification. For example, on December 11<sup>th</sup> 2018 Turkey has reported a notification, whose “Document Symbol” is “G/TBT/N/TUR/142”.

<sup>26</sup>This is accessed through the TBT Trade-Information Management System at “<http://tbtims.wto.org/en/Notifications/Search>” through the “requests” package from Python libraries. Note that the same program might also be used to download documentation for other NTMs, e.g. the SPSs, by providing a list of identification keys. We will soon make it available on my website at <https://ioire.github.io>

<sup>27</sup>Potentially, there is also the Addendum and the Corrigendum, but these two sources of information are less relevant to us, since they provide information such as the availability of translated documents or the correction of typos.

<sup>28</sup>An example of this document is provided in the Appendix Figure C.1, Soon I will upload on my web page all the program written in Python 3.6 to replicate the database. The same code can be used for different type of notifications, as well as SPS documents. Note also that, while the date of notification is always present, the other two may be left “To be decided”.

<sup>29</sup>In two cases, this document informs about the withdrawal of the measure.

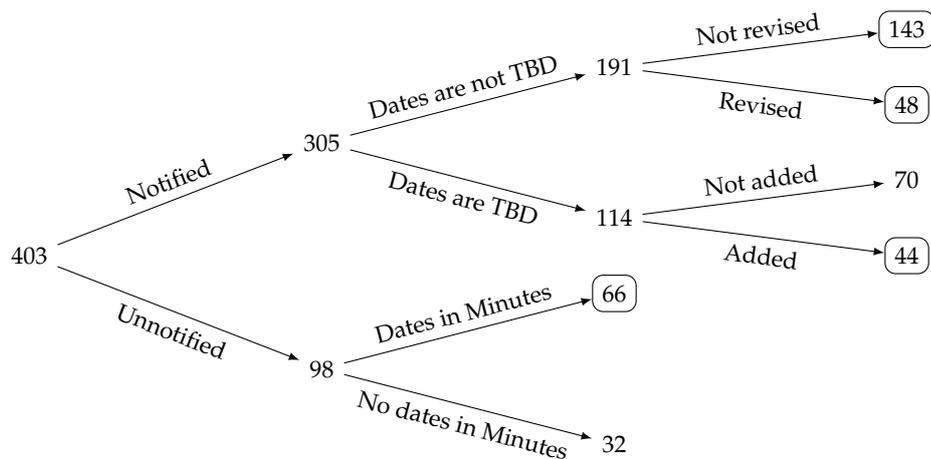
<sup>30</sup>Appendix provides details on how information from the Minutes are treated.

<sup>31</sup>In case divergent dates are found from the various sources, we apply the following ranking: we first pick the dates in the minute, then the ones in the revision and lastly the proposed dates in the notification. The information of the minute is the preferred one because countries might modify the proposed date of adoption or enforcement without providing documentation that formalize this.

<sup>32</sup>For further details please refers to C.1

are more difficult to identify.<sup>33</sup> However, this possibility is mitigated by the fact that the sources of documentation from which we retrieve the dates are heterogeneous. In particular, the fact that we can collect information from the Minutes, which are produced by a third country, reduces issues of this selection. Moreover, the share of notified measure for which we can identify the timeline is 77%, while is 67% for unnotified ones. Therefore our ability to retrieve dates between notified and unnotified TBTs is not substantially different.

FIGURE 3.4: Data sources for the database on TBT timelines



*Notes:* Frequency of TBTs by the source from which their timeline information is retrieved. The edges of the tree represent attributes that identify whether a certain source of information can be used. Final nodes with rectangular frames highlight those cases in which we could identify the timeline.

### 3.2.3 Stylized Facts about Timelines of TBTs

Using these new database we are able to identify those technical regulations that have been introduced as Surprise Measures. These are almost 40% of the sample for which we have identified the underlying timeline of introduction. Table 3.1 shows the frequency of Surprise TBTs by country and number of HS4 products within HS2 categories. Surprise measures are common in developed countries and they are also relatively very frequent in the two giant developing economies, China and India. China has introduced unattended regulations very frequently, given the fact that she is a more recent member of the WTO. In the case of India, Surprise TBTs are even more frequent than Announced ones. Surprise TBTs are mostly common among food products, with wine and spirits being by large the most touched category.

Among Surprise Measures we distinguish two cases, illustrated in Figure 3.5, (a) Never Notified and (b) Notified in delay. The former are measures for which the

<sup>33</sup>A sampling bias could be due to the varying probability of being included in the sample due to the transparency with which the measure has been introduced.

FIGURE 3.5: Types of Surprise measures

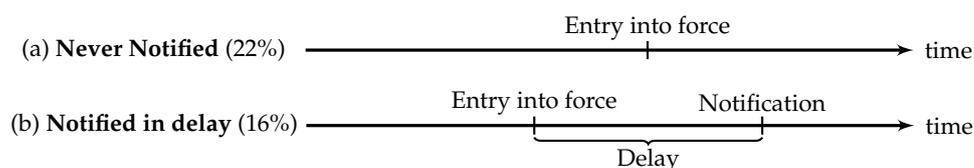


TABLE 3.1: Top 5 countries and products by surprise TBTs

Country	#(Surprise TBTs)	Share (%)	Sector (HS2)	#(Surprise TBTs)	Share (%)
EU	17	26	Beverages & Spirits (22)	29	40
Korea	10	48	Meat (02)	18	50
China	10	27	Edible Preparations (21)	17	35
India	7	70	Fish (03)	15	47
USA	7	50	Electrical Machinery (85)	13	33

*Notes:* The share of Surprise is the ratio between the number of contested TBTs introduced by a country (within an HS2 category) as Surprise measures over the total number of contested TBTs introduced by the same country. Results are shown for the first ten countries in terms of Surprise share and only for those countries with at least 3 contested TBTs.

Notification will never be provided. This means that WTO members will not receive any formal documents with the details of the new requirement. For example, this is the case of a measure introduced by Mexico in 1997, regarding the the labelling of spirits. The requirement has not be formally disclosed to the WTO through a Notification even after the enforcement. The European Union has therefore re-raised a STC on this measure in a following meeting of the TBT Commission in an attempt to receive clarifications on it.<sup>34</sup> In other cases, the regulation is enforced and notified thereafter - this is the case instead, of the Mexican ban on CFCs, where the notification occurred with a delay of one month from the enforcement. On average, the Notification occurs within three months, and in almost all the cases the measure is eventually notified within a year.

### 3.2.4 French Firm Level Data

The firm-level data comes from two different sources: (i) the French customs, which reports exports for each firm by destination, product and month for the period between 1995 and 2007 and (ii) BRN (*Régime du bénéfice réel normal*), the French firm level administrative database which provides information on firms' balance-sheets, over the same period.<sup>35</sup> We aggregate the monthly trade data at the semestral level so that our panel includes 26 periods. The choice of using a semestral panel comes from a trade off between the possibility to exploit at most our data on timelines and

<sup>34</sup>Details on this example can be found in the WTO Database on STCs, item 20.

<sup>35</sup>Firms are obliged to comply with BRN status if they earn annual revenues larger than 763K €. The dataset is accessed through facilities provided by the INSEE (the French Statistical Institute) and were made available for analysis after careful screening to avoid disclosure of individual information.

TABLE 3.2: Summary statistics for STC database

	Mean	Median	Min	Max
#(TBT) by Country	4	5.2	1	27
#(HS4 categories) by TBT	32	3	1	314
#(months) in the Introduction Period by TBT	1.3	1	1	6

*Notes:* Each STC can cover more TBTs when the rising country refers to more Notified measures.

the fact that there is a lot of seasonality and lumpiness in the monthly data, that is that most companies do not sell the same product to a given market in every month. Instead, the median exporter ship a certain HS4 product in a destination twice a semester.

The link to BRN, while it reduces the sample to relatively larger firms, allows us to identify the principal activity of enterprises. In this way, we can select the manufacturing industries, which are the ones directly interested by changes in technical requirements of production. Note that this dataset has been used in several trade related papers dealing with French data (Eaton, Kortum, and Kramarz, 2011b; Mayer, Melitz, and Ottaviano, 2014). In addition it allows us to have access to information on the domestic sales of the firm, which is used identify class sizes independently from the exporting activity.

### 3.2.5 Construction of the Estimating Sample

Since we have detailed data on French firm exports in the period 1995-2007, we use a sample of 123 TBTs that have been object of a STC by the European Union and that have been introduced in the same period.<sup>36</sup> These 123 contested TBTs have been raised against a total of 31 different countries, with China being the largest target. Table 3.2 shows that there is a large variability in terms of HS4 categories covered by each TBT. The one that covers the largest number of HS4 products the Mexican “Mandatory standard on Labelling of Industrial Products”, which interests several products across a large number of different HS2 sections from textile to food. The length of the introduction period is instead rather homogeneous across regulations, with the majority having been introduced within just one semester. The longest introduction period regards the Korean “Mandatory Emission standard for Automobiles”, which was adopted in April 2000 and enforced 3 semester thereafter, in June 2002.<sup>37</sup>

<sup>36</sup>Ideally, one would want to identify those TBTs that are trade restrictive specifically to French exporters, however, European countries participate as a single entity within the TBT Committee. On the other hand, technical regulation are homogeneous across EU countries and TBT measures are applied in a non-discriminatory way to all trading partners. Therefore, we can plausibly assume that a TBT contested by the EU proxies an obstacle for French firms.

<sup>37</sup>G/TBT/N/KOR/4

TABLE 3.3: Summary statistics of the estimation sample

	SEMESTRAL AVERAGE	
	Full sample	Touched by TBT
#(HS4, country)	35964	1122
#(exporters)	17131	2580
Total Export	3.26e+10	2.44e+09

We restrict the firm-level sample to export flows towards extra EU-27 destinations since concerns might be rise by the EU against extra-EU countries. Concerning the products, the WTO STC database records them at the 4-digit Harmonized System, therefore we aggregate at this level the export data, which is originally at the Combined Nomenclature at 8 digits.<sup>38</sup> We calculate total export flows by destination market, retaining markets with above-10 percentile exports. Destinations in the bottom 10 percentile of total French exports can be considered less relevant for French exporters.<sup>39</sup> Then, this data has been joined with tariff data from TRAINS, which contains information on the effectively applied tariffs (defined as the lowest available tariff between preferential and MFN) at the HS 4-digit.<sup>40</sup>

Table 3.3 reports the average number of exporters, of HS4-country pairs and of the value of exports for the full sample as well as for those markets touched at least once by one TBT in our sample. Interestingly, these markets are the 3% of all the possible (destination-HS4) pairs, still, their value represent around the 7.5% of the total export value.

### 3.3 Research Design

This Section describes how we estimate the effects of the introduction of a new regulation on the exporting activity of firms. We first present the variables of interest, we then illustrate the empirical strategy and finally we discuss how we tackle potential issues to our identification.

<sup>38</sup>Actually, the STC database contains 6% of HS2s products, 62% HS4s and the remaining 32% are HS6 goods. We keep the level of the analysis at 4-digit HS and we therefore drop the concerns that refers to HS2 goods, to avoid imputing to all HS4 subcategories, while we aggregate the HS6 at the HS4 level.

<sup>39</sup>A similar cleaning procedure is applied in Fontagné and Orefice, 2018. This makes our work comparable with theirs. Note that the number of countries in the sample is reduced from 168 Non-EU countries to 151.

<sup>40</sup>HS 4-digit tariff data is a simple average tariff within HS-4 headings of the HS-6 tariff level data, this aggregation is directly provided by TRAINS. Unfortunately, the database has many empty entries, in the literature there are various algorithm that have been used proposed to increase the number of observations. In this chapter, we apply the interpolation procedure suggested in Beverelli, Boffa, and Keck, 2014. In addition, since TRAINS provides tariffs in percentage points (i.e. 10% ad-valorem tariff listed as 10), we divide tariff by 100 and then compute the price equivalent transformation.

### 3.3.1 Definition of Variables

Let  $A_{HS4,d}$  and  $E_{HS4,d}$  be the date of adoption and entry into force of the TBT regulations, respectively; with  $HS4,d$  denoting 4-digit HS product category and destination country. These dates contain the day, month and semester of the event. We call introduction period ( $I_{HS4,d}$ ) the semester(-s) from the one in which the measure is adopted to the one in which it is eventually enforced. We use this to identify an indicator which takes value 1 when a restrictive TBT is introduced in the  $(HS4,d)$  market, i.e.  $TBT_{HS4,d,t} = \mathbb{1}[\text{if } s \in I_{HS4,d}]$ . Note that  $A_{HS4,d}$  and  $E_{HS4,d}$  are not available in those markets where a restrictive TBT has never been introduced, thus the indicator TBT is zero over the full time span. We then call  $N_{HS4,d}$  the notification date and use this to define Surprise measures as:

$$\text{SurpriseTBT}_{HS4,d,t} = \mathbb{1}[\text{if } (N_{HS4,d} = NA \text{ or } N_{HS4,d} > E_{HS4,d}) \text{ and } TBT_{HS4,d,t} = 1]. \quad (3.1)$$

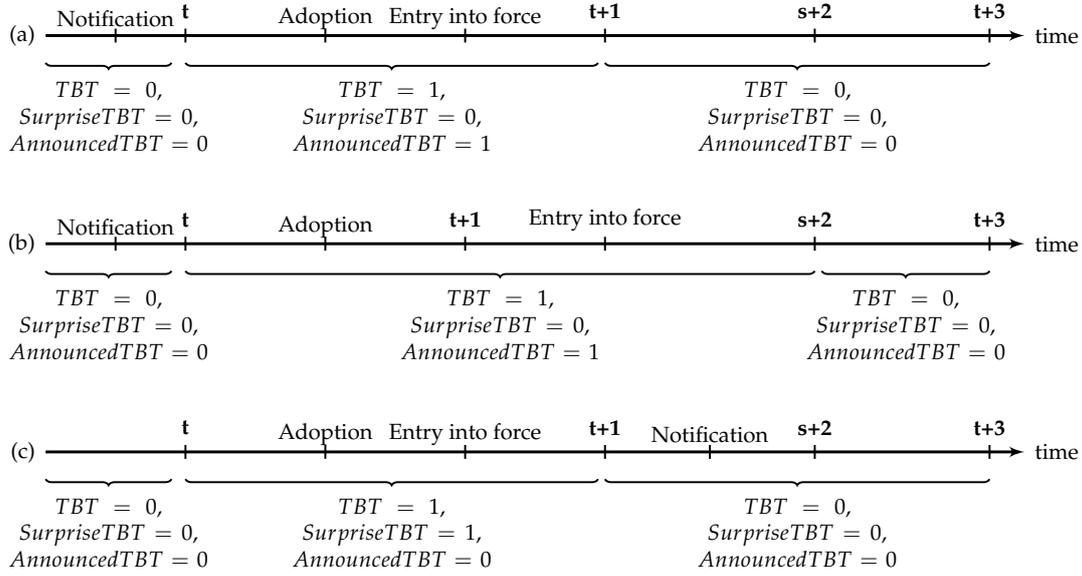
$\text{SurpriseTBT}_{HS4,d,t}$  take value 1 during the period in which the measure is introduced, if by the time of enforcement there is no previous notification. This includes both the cases in which the TBT will never been notified, and therefore  $N_{HS4,d}$  is Not Available, as well as those cases in which the notification occurs later than the enforcement. Similarly, we define Announced measures as

$$\text{AnnouncedTBT}_{HS4,d,t} = \mathbb{1}[\text{if } N_{HS4,d} \leq E_{HS4,d} \text{ and } TBT_{HS4,d,t} = 1]. \quad (3.2)$$

Figure 3.6 illustrates the behaviors of our indicator functions for some ideal timelines. Each timeline is (HS4-country) specific, but the index  $(HS4,d)$  is dropped from the notations. Panel (a) shows a case in which adoption and entry into force occur in the same semester  $s$ . Therefore, the TBT indicator takes value one in that period while zero in the others. In the meantime, since the notification occurs before the enforcement, Surprise is zero while Announced is one. Panel (b) shows a case in which adoption and entry into force occur in two consequent semesters. Also in this case, the notification precedes the introduction, so in the two periods  $\text{AnnouncedTBT} = 1$ . On the contrary, Panel (c), depicts a case in which the notification occurs after the enforcement, therefore when  $TBT = 1$  also  $\text{SurpriseTBT} = 1$ .

In conclusion, note that there are some  $(HS4,d)$  that have been touched by more than one TBTs over time. For these markets the introduction period contains multiple windows over which the TBT switch on and off. For example, Korea has introduced three regulations on passenger cars that has been contested by EU, in 1998, 2002 and 2006 respectively. Each episode might me either Surprise or Announced, depending of whether the underlying measure has been notified before the relative enforcement.

FIGURE 3.6: Illustration of the indicator functions for three ideal time-lines



Notes: Illustration of three ideal timelines. Each timeline is (HS4-country) specific, but we drop the index  $HS4, d$ . Timeline (a):  $TBT = 1$  in one period since and the measure is adopted and enforced in the same semester;  $Surprise = 0$  because the notification is before the enforcement. Timeline (b):  $TBT = 1$  in two periods since the TBT is enforced the semester after the one of the adoption;  $Surprise = 0$  since notification is before the enforcement. Timeline (c):  $TBT = 1$  in one period since and the measure is adopted and enforced in the same semester;  $Surprise = 1$  because the notification is after the enforcement.

### 3.3.2 Empirical Strategy for Firm Level Estimation

To quantify the average effect of a trade restrictive TBT on firms' trade margins one can estimate the following linear regression model:

$$y_{i,HS4,d,t} = \alpha + \beta_0 TBT_{HS4,d,t} + \epsilon_{i,HS4,d,t}, \quad (3.3)$$

where  $\alpha$  is the intercept and  $y_{i,HS4,d,t}$  denotes the trade margins of firms, with  $i$  being the firm identifier.

A concern with this identification strategy is the possible endogeneity of the imposition of a regulation. Endogeneity might stem from an omitted variable. This is the case if an external shock induces correlation between the probability of imposing a new technical regulation on certain goods and variations in firms' margin of trade over the same goods. For example, if countries couple TBTs with other policies that target the same goods. Existing literature has found evidence of the use of TBTs as a policy substitute of tariffs cut (Orefice, 2017). Then, in our preferred specification we add the applied tariff rate at the HS4 product level, in order to avoid confounding

the effects of changes in regulation with those of changes in tariffs.<sup>41</sup> In addition to changes in tariff, there might other policies that are however unobserved. To circumvent this instance, we add a set of three-way fixed effects HS2-destination country-semester ( $\mu_{HS2,d,t}$ ). These fixed effects controls for varying factors such as business cycles, import-demand shocks and multilateral trade resistance (Head and Mayer, 2014). We also add firm dummies ( $\mu_i$ ) to control for firm unobserved, time invariant characteristics that are likely to shape idiosyncratic exporters' behavior. Our preferred specification is therefore as follows

$$y_{i,HS4,d,t} = \beta_0 TBT_{HS4,d,t} + \delta asinh(\text{tariff}_{HS4,d,t}) + \mu_{HS2,d,t} + \mu_i + \epsilon_{i,HS4,d,t}. \quad (3.4)$$

The identification strategy consists of comparing changes in trade margins across HS4 products sold by similar firms, operating in initially similar market conditions except for the introduction of a restrictive TBT.<sup>42</sup>

The standard errors of the coefficients for all estimations are clustered at the ( $HS4, d, s$ ), i.e. at the level of assignment of the treatment in our research design.<sup>43</sup> Our standard errors, therefore, account for the possibility that firms' trade margins may be correlated between units that are shocked by the same regulation.

A similar specification and identification strategy is used to investigate the differential impacts of Announced and Surprise TBTs. In this case, we distinguish the two treatments, as defined in equations 3.1 and 3.2, and include them both in our specification:

$$y_{i,HS4,d,t} = \alpha_0 \text{AnnouncedTBT}_{HS4,d,t} + \beta_0 \text{SurpriseTBT}_{HS4,d,t} + \delta asinh(\text{tariff}_{HS4,d,t}) + \mu_{HS2,d,t} + \mu_i + \epsilon_{i,HS4,d,t}. \quad (3.5)$$

To capture firms' trade margins we use as dependent variables (i) the firm's export value (in logs) to capture the intensive margin of trade and (ii) a dummy variable for a firm exiting a certain market to proxy the extensive margin, which we define as follows:

$$\text{exit}_{i,HS4,d,t} = \begin{cases} = 1 & \text{if } i \text{ exports HS4 in } d \text{ in } s \text{ and } s-1 \text{ but never in } s+1 \text{ and } s+2 \\ = 0 & \text{if } i \text{ exports HS4 in } d \text{ in } s \text{ and } s-1, \text{ and at least once in } s+1 \text{ and } s+2. \end{cases} \quad (3.6)$$

An exiting firm has therefore sold product *HS4* in destination *d* in this period as well as in the last one but will not export it in the following two.<sup>44</sup> We use two lags because of semestral data, to avoid confounding the effect of exit with the absence

<sup>41</sup>The tariff level is transformed through the hyperbolic arcsine (*asinh*). This is because the *asinh* function is close to the logarithm while still allowing to include observations with zero tariff in the analysis.

<sup>42</sup>A similar identification strategy has been used in Fontagné and Orefice, 2018, where, however, the time of the effect of a TBT is proxied by the period in which a concern is risen.

<sup>43</sup>In Abadie et al., 2017, the authors discuss this experimental design reason for clustering, which is when clusters of units, rather than individual units, are assigned to a treatment.

<sup>44</sup>In the Appendix we discuss alternative definitions of exit.

of the market due to seasonality.<sup>45</sup> Note that the probability of exit a market is a lagged proxy of the extensive margin there. This means that, if *ceteris paribus* a firm exits a market today, one records a reduction in the number of firms in the market tomorrow.

### 3.3.3 Validation of the research design

We here discuss two potential issues with our identification strategy, namely underidentification and the validity of the parallel trend assumption, and how we handle them.

#### Underidentification

A potential issue associated with 3.4 and 3.5 regards the underidentification associated to the structure of the fixed effects as well as the potential non convexity of the weights in computing  $\alpha_0, \beta_0$  as weighted averages of different TBTs events (Borusyak and Jaravel, 2017; Chaisemartin and D’Haultfœuille, 2018; Goodman-Bacon, 2018; Abraham and Sun, 2018). In our estimation, underidentification arise if a restrictive TBT touches all HS4 products within an HS2 category. Then, within a treatment unit one can not disentangle the market characteristics from the effects of the treatment event.<sup>46</sup> Table 3.2 shows that the average TBTs touches indeed several HS4 products, making underidentification plausible. We test this scenario in the robustness checks. Other concerns about the underidentification are mitigated because our sample has a very large group of untreated observations, which means a rich set of potential good comparison. We show for example, that our results are robust to the use of alternative set of fixed effects aimed to detect a idiosyncratic behavior in markets touched by TBTs. In addition, we show that our results are stable to reductions in the variance of the length of the introduction window of TBTs. Large variability in the treatment length might cause the estimators to be weighting the event by event estimates in an implausible way.<sup>47</sup>

#### Parallel trend assumption

Another source of endogeneity, in addition to omitted variables as discussed above, might stem from reverse causality. For instance, if the government of a certain destination market introduces a TBT in response to import penetration from French firms, or if a STC is raised by the EU against a regulation in a market because French

<sup>45</sup>We also control that the firm still exports something or somewhere else to rule out the possibility to confound a firms’ exit with the complete termination of her export activity, for example in case of her death.

<sup>46</sup>Underidentification is an issue discussed in the literature about the staggered treatment setting, where the presence of unit and time fixed effects arise a problem of multicollinearity (Borusyak and Jaravel, 2017)

<sup>47</sup>In settings with treatment effect heterogeneity and variation in treatment timing, these weights can be negative, see e.g. Chaisemartin and D’Haultfœuille, 2018 for a discussion on how the negative weights arise.

firms are loosing market shares there. Regarding the latter case, this issue should be mitigated by the fact that we use concerns raised by the EU as a whole and not raised specifically by France. In addition, Figure 3.3 suggests this not to be our case. Instead, given the positive trend before the introduction of a Surprise measure, the former is a more plausible threat to our identification. The inclusion of the set of fixed effects plays here again a crucial role: our research design treats the variability in the introduction of restrictive TBTs as good as random conditional on market and firm characteristics. In other words, the parallel trend assumption of the difference in difference design is here imposed conditional on being an HS4 products sold by a similar firm in the same period, to the same country of destination within the same HS2 sector. In order to inspect the validity of this assumption, we run a specification analogous to 3.4 but introducing additional dummies to select a larger window:

$$y_{i,HS4,d,t} = \sum_{l=-B}^{-1} (\alpha_l \mathbb{1}[L_{HS4,d,t}^{AnnouncedTBT} = l] + \beta_l \mathbb{1}[L_{HS4,d,t}^{SurpriseTBT} = l]) + \sum_{k=0}^{A+1} (\alpha_k \mathbb{1}[K_{HS4,d,t}^{AnnouncedTBT} = k] + \beta_k \mathbb{1}[K_{HS4,d,t}^{SurpriseTBT} = k]) + \delta \operatorname{asinh}(\operatorname{tariff}_{HS4,d,t}) + \mu_{HS2,t,d} + \mu_i + \epsilon_{i,HS4,d,t}, \quad (3.7)$$

where  $L_{HS4,d,t}$  represents the number of periods before the introduction of the TBT while  $K_{HS4,d,t}$  the one after, while the superscripts *AnnouncedTBT* and *SurpriseTBT* are used to distinguish windows around Announced versus Surprise TBTs. Therefore these two variables represent the relative time around the introduction of a TBT. More specifically  $L_{HS4,d,t} = s - \min\{I_{HS4,d}\}$  is the number of periods before the first semester of introduction of the TBT, while  $K_{HS4,d,t} = s - \max\{I_{HS4,d}\}$  is the number of periods after the last semester of introduction. For example,  $L_{HS4,d} = -1$  identifies the period before the introduction of the TBT. Then,  $B \geq 0$  are the number of time lags from the treatment included in the model, while  $A \geq 0$  are the specific short run effects. If the introduction of a TBT is randomly assigned and unpredictable conditionally on the tariff level and on the market and firm fixed effects, there are no pre-trends,  $\beta_l = 0$  for  $l < 0$ . This assumption will be tested graphically and statistically. In addition, an event study design, by focusing on trade margins around the event window, allows us also to investigate the dynamics and persistence of the effect.

### 3.4 Estimating Firms' Reaction to Surprise TBTs

In this Section we discuss our estimates of the effects of changes of regulations on firms' trade margins. The second part of this Section is devoted to test their quality. We then look at the estimates of the dynamics of the effects. These estimates are used to both verify the validity of the parallel trend assumption and to investigate the persistence of the effects due to a change in regulation.

### 3.4.1 Baseline Results

Table 3.6 reports the estimates of the two baseline specifications described in model 3.3 and 3.4. The table has 6 columns: in columns 1-2, the dependent variable is the export value in log, followed by the probability of exit in columns 3-4, and the lagged probability of exit in 5-6.

Estimates of model 3.3 in columns 1,3,5 show that the introduction of a restrictive TBT increases the probability of exiting the market in the period before the introduction (around 4.5%), while does not affect significantly the intensive margin. These results are similar to the ones found in Fontagné and Orefice, 2018.<sup>48</sup> The null effect on the intensive margin of the average firms, coupled with the evidence of a strong negative effect of TBTs on aggregate export, has motivated the authors to argue that restrictive TBTs mostly increases the fixed (rather than variable) trade costs which push some firms out of the market.<sup>49</sup>

However, when we estimate model (3.4) and disentangle Announced from Surprise measures, a very different picture emerges. Announced measures are associated to a rise in the average export value of firms (around 23%) and a positive effect (almost 6%) on the probability of exit in the period before the introduction. Surprise measures cause instead a substantial fall, of around 30%, in the average export value of exporters, while they do not significantly impact the probability of exit. This set of results unveils two different regimes within restrictive TBTs. When Announced, a TBT produces a positive effect on the intensive margin, which is then offset on the average restrictive TBT by the negative effect of Surprise measures.

What we find for Announced measures is in line with Bao and Qiu, 2012. The authors have indeed estimated the effects of TBTs by using a sample of notified measures. The authors interpret these results in terms of the evolution of competition as well as of exporters' demand in the market. In particular, they suggest that, in addition to the reallocation of market shares due to selection, the rise in the aggregate export is coherent with the idea that, when TBTs pursue legitimate objectives, they work as an information revelation or quality assurance feature. This raises consumers confidence over foreign goods and hence boosts demand for imports. In our case, instead, we do not observe an aggregate increase in French exports following the introduction of a TBT (Figure 3.3). Thus the average increase in firms' intensive margin is here more coherent with a story of reallocation of market shares across French exporters, following a rise in the cost to serve the market, rather than an information-revealing aspect of these TBT.

On the other hand, results on Surprise measures are new to the literature. In this case we observe a fall in the intensive margin, while not a significant exit of firms.

<sup>48</sup>Note that the estimate of  $\beta_0$  on exit is higher both because we use higher frequency data, as well as because we use a more precise definition of a TBT which considers the actual dates of the TBT rather than the ones of the STC.

<sup>49</sup>In Chaney (2008) the aggregate trade elasticity to fixed trade costs is predicted to be driven by the extensive margin, with a negligible role of the intensive margin.

TABLE 3.4: Announced vs Surprise measures - Baseline Model

DEPENDENT VARIABLE	Export <sub>t</sub>		Exit <sub>t</sub>		Exit <sub>t-1</sub>	
	(1)	(2)	(3)	(4)	(5)	(6)
TBT	0.11 (0.09)		0.01 (0.017)		0.045 <sup>c</sup> (0.01)	
SurpriseTBT		-0.27 <sup>b</sup> (0.13)		0.04 (0.03)		0.00 (0.02)
AnnouncedTBT		0.23 <sup>b</sup> (0.11)		0.00 (0.01)		0.055 <sup>a</sup> (0.02)
asinh(tariff)	-0.05 <sup>a</sup> (0.00)	-0.05 <sup>a</sup> (0.00)	0.00 <sup>a</sup> (0.00)	0.00 <sup>a</sup> (0.00)	0.00 (0.00)	0.00 (0.00)
Obs.	4,214,856	4,214,856	2,522,245	2,522,245	2,418,685	2,418,685
Adj. R2	0.26	0.26	0.11	0.11	0.11	0.11
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
HS2-Country-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

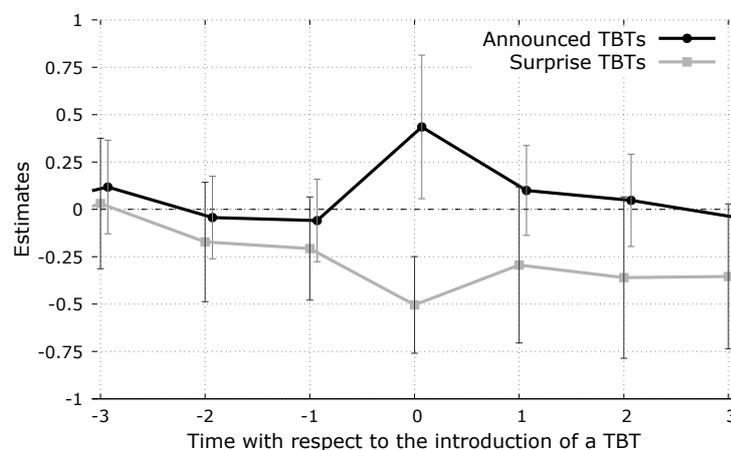
Notes: Export is in log, so the marginal effect of a dummy reads  $100(e^\beta - 1)\%$ , with  $\beta$  being the coefficient on the dummy. Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 since who exits does not export in the period. Significance levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

### 3.4.2 Underidentification

Often TBTs touch a large set of products within or even across HS2 sectors. When this happens, there are fewer candidates to be included in the counterfactual group of untreated units. To check that our results do not suffer of this underidentification we test whether our estimates are robust to drop those TBTs that cover a large share of HS4 products within the same HS2 sector. Point estimates of  $\alpha_0$  and  $\beta_0$  do not almost change when we exclude those TBTs which cover more than 90%, 80%, 70% and 60% of units within an  $HS2, d, t$  group (see Tables C.7 and C.8 in the Appendix).

We test whether our results are stable to the exclusion of those TBTs where the introduction period extends over several semesters. This is because, in case of heterogeneous treatment length, the Difference in Difference estimator is a variance weighted average of treatment effects, where the weights depends on both sample size and the variance of the treatment status (Goodman-Bacon, 2018). Implausible negative weights may arise if there is a large variance in the duration of the treatment. Long introduction period might occur only for Announced TBTs, since Surprise ones by construction, are introduced in one semester, the one in which they are enforced. Then, apart from the the quality of the estimation, the fact that Announced TBTs have introduction periods which might last longer than those of Surprise TBTs can generate differences in the interpretation of the effects. Interestingly, when we sub-sample those TBTs whose introduction period last no more than 3 ( cols 1 and 2 of Table C.10), 2 (cols 3 and 4), and 1 (cols 5 and 6) semesters, the average effect does not change dramatically and, if anything, decrease on both the intensive and

FIGURE 3.7: Dynamic model for Export, regression coefficients and 95% CI



Notes: The image plot the estimated coefficients of equation 3.5 with lags and leads around the treatment, for two type of treatments, Surprise and Announced TBTs. The dependent variable is here the (log) value of export.

(coherently) the extensive margin. In other words, the shorter the period of introduction of the measure, the lower the exit of firms from the market, the lower the gain in market shares from surviving firms. This can be explained by the fact that longer introduction are usually granted in case of more complicated requirements, for which longer adaptation is needed and plausibly a larger investment.

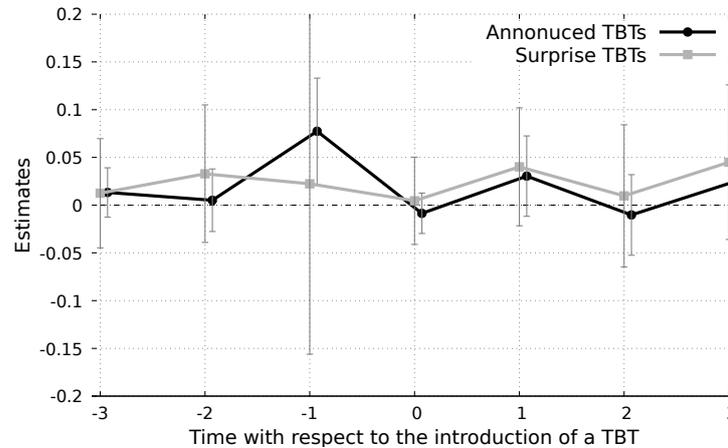
### 3.4.3 Dynamic Effects

We are interested in the dynamic effects of Surprise and Announced TBTs for two reasons. First, it permits us to test the parallel trend assumption, and therefore the quality of our identification. Second, it allows to investigate the persistence of the effects and to validate and enrich the interpretation of the phenomenon. Figures 3.7 and 3.8 plot the regression estimates of Equation 3.7 for a time window around the introduction period of a TBT, for the export and the exit probability.<sup>50</sup> Each Figure display 2 panels, representing the coefficients for the sample of Surprise and Announced measures, respectively.

Figure 3.7 shows that, for both Surprise and Announced measures the effect on the value of export is significant only during the period of introduction of the TBT. In both cases, no substantial pre-trend is detected. This means that before the introduction of a TBT, the HS4 product lines touched by the new regulation are not statistically different from the others within the same HS2 produce category, that we use as counterfactual group. This is mostly important for the Surprise measures, for which we have observed a positive trend that precedes the introduction of the TBT

<sup>50</sup>We choose three lags, i.e. one year and an half, since at the earliest a Notification occurred 21 months before the introduction, while at the latest, a late Notification is provided 19 months later.

FIGURE 3.8: Dynamic model for Exit, regression coefficients and 95% CI



Notes: The image plot the estimated coefficients of equation 3.5 with lags and leads around the treatment, for two type of treatments, Surprise and Announced TBTs. The dependent variable is here the probability of exit.

relative to the average performance of French exports. In contrast, during the introduction of a new requirement we detect an idiosyncratic behavior in the export of targeted products. However, this appears to vanish quickly, even if the estimates are quite imprecise, mostly in the case of Surprise measures.

Figure 3.8 shows that the effect of Announced measures on the probability of exit is significant just in the period before the regulation is enforced. This is coherent with the timing of the announcement: almost the entirety of the Announced measures are notified between 3 and 6 months before the introduction period. This suggest that in case of Announced measures firms know there will be negative shock in the next period and will there exit before incurring the per period cost. On the other hand, there is no significant exit on the average firm following a Surprise TBT. Yet in this case too estimates of Surprise TBTs are more imprecise.

### 3.4.4 Robustness Checks

**Alternative counterfactual groups** The choice of including  $(HS2, d, t)$  set of fixed effects allows us to compare products that are, except for being subject to the new regulation, otherwise similar in their characteristics. We have indeed shown that these groups of products are on a parallel trend before the advent of the TBT. Then, if the country target through a Surprise TBT those imports that are performing relatively well in the country, we expect their effect to be particularly negative with respect to otherwise similar goods than relative to the average product sold in the destination. Indeed, Table C.5 shows that the estimates of a model where we include just (destination,time) pair fixed effect is lower, around 17%. Interestingly, when we instead exclude the firm fixed effect, estimates do not change dramatically. This suggests that firms are hit by Surprise TBTs despite their destination, product, time invariant

characteristics, such as the time invariant component of differences in firms overall ability and exporting performance.

**Full sample of French exporters** As discussed in Section 3.2.4, the estimating sample includes those firms that are under the BRN regimes, which is those that earn annual revenues larger than 763€. Matching trade data with administrative data allows us to resort information on both domestic and export activity which will be used to identify size classes in a way less dependent from the exporting activity of a firm. This database is the standard for works that French data but might however potentially introduces a severe selection bias towards larger firms. We show this not to be the case in Appendix C.4. While observations almost double in size the results remains qualitatively similar. Differences are in the direction that one would expect. In case of Announced measure, the estimated coefficient on exit is slightly larger in the full sample, while the estimate on the the intensive margin became non significant. The coefficients associated to Surprise Measure do not change substantially, it decreases but in a not significant way. An explanation of this can be found in the next section.

### 3.5 Interpreting the effects of Surprise measures

By distinguishing the effects on firms' trade activity, our estimates uncover differences between Announced and Surprise TBTs. While Announced measures cause exit of firms before the introduction of the new measure, Surprise measures affect adversely firms' trade activity by causing a simultaneous drop in their export value.

We interpret this evidence within a framework of investment under uncertainty using the intuitions of the real options literature developed in Dixit and Pindyck, 1994. This framework builds on two main elements: (i) the irreversibility of investments and (ii) the possibility to wait to invest. Most of the investment are partly irreversible, they generate assets that can not be fully appropriated to an alternative use of a firm. In other words, these investments, once complete, become sunk costs. The choice of exporting in a market is modelled as an irreversible investment in Limão and Maggi, 2015 and Hanson, Lind, and Muendler, 2016. Also the choice of staying in a market can include the evaluation of some irreversible costs. These are associated for example to updating the distributional networks, tailoring production to changing regulation and filling in periodic declarations and other forms. The role of future conditions is particularly important when firms must decide on costly irreversible investments such as adopting a new product requirement, producing a new good or selling in a market. The reason is that a firm with an opportunity to invest is holding an option similar to a financial call option, which gives the right but not the obligation to buy an asset at some future time. When a firm makes an irreversible investment expenditure, it loses this option to invest. For example, it gives up the

possibility of waiting for new information to arrive that might impact on the profitability or timing of the investment. This lost option value is an opportunity cost that must be considered as part of the cost of the investment.

We can think of a change in technical regulation as a change in the sunk cost to serve that market. In case of Announced measures, this change affects firms' expected payoff before entering the market, when the per period sunk cost of exporting there has not yet been incurred. This allows the firm to take into consideration the additional cost of adapting to the new regulation in the decision to serve the market in that period. On the other hand, Surprise measures affect the instantaneous payoff once the firm has entered and already paid the per period sunk cost. The different timing in which firms consider whether to implement the new requirement explain why we observe a significant exit of firms in the case the change in regulation is anticipated by firms, while we do not in the case the measure is unexpected.

In case of surprise TBTs, we can explain the fall in the export value, along with no significant exit, as to be due to a temporary halt in the exporting activity of firms within the semester. We interpret this halt to be caused by a rise in the uncertainty of serving the market. We think of this as to be due to the fact that when countries avoid to codify the regulation through a notification they rise the uncertainty on the profitability of the market. This interpretation finds support in the words of the US representative bringing the case of the Mexican ban to the TBT Committee. The lack of information on the list of licence providers, he argued, raised the uncertainty on the cost of proving conformity of its own products. The increase in uncertainty rise in turn the value of the real option of waiting to collect new information before implementing the investment to adapt to the new standard. In other words, by rising the uncertainty, Surprise measure incentives firms to delay their investment decision about remaining in the market. We therefore think of this temporary halt as the output of firms decision to wait for new information to come.

### **3.5.1 A temporary halt of export**

While we interpret the drop in the export value as due to a temporary halt of the activity of exporters, another possibility is that firms continue to export but at a reduced intensity. If firms halt their exporting activity, we should observe a reduction in the frequency with which a firm operate in a market. On the other hand, if firms keep the same shipment rate but reduce their size we expect to see a fall in the average export value per shipment. As shipment unit we use data on monthly export activity. We decompose the semestral export value into (i) the number of months in which a firm exports and (ii) the average export value per active month. We then use these two margins as the new dependent variables in our baseline model in equation (3.5). The estimates in table 3.5 shows that the average number of months in which a firm serve a market with a product falls substantially when an unexpected TBT is introduced on it. The average shipment instead does not. This evidence support our interpretation that when firms are caught by Surprise TBTs they stop, at least

TABLE 3.5: Announced vs Surprise measures - Shipment margin

DEPENDENT VARIABLE	#(Shipments)	Export per Shipment
	(1)	(2)
SurpriseTBT	-0.201 <sup>b</sup> (0.083)	-0.195 (0.145)
AnnouncedTBT	-0.044 (0.035)	0.253 <sup>b</sup> (0.113)
asinh(tariff)	-0.007 <sup>a</sup> (0.001)	-0.051 <sup>a</sup> (0.002)
Obs.	4,214,856	4,214,856
Adj. R2	0.26	0.26
Firm FE	Yes	Yes
HS2-Country-Time FE	Yes	Yes

*Notes:* The number of shipments is the number of months in which a firm is active. The export per shipment is the average export value per active month. Export is in log, so the marginal effect of a dummy reads  $100(e^{\beta} - 1)\%$ , with  $\beta$  being the coefficient on the dummy. Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 since who exits does not export in the period. Significance levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

for a while, to serve the market. The fact that simultaneously we do not record a significant exit suggests this to be only a temporary halt.

### 3.6 Firm heterogeneity and the ability to wait

With firm heterogeneity not all firms are equally likely to survive the same negative shock. Those firms that were close to the surviving cutoff before the shock will be forced to exit. This is the case for both Announced and Surprise measures, if the new regulation impose additional costs to serve the market whatever the source of the cost is. In both cases, we expect the least productive firms to struggle the most in surviving the change in the regulation. In this section we look at the differential effects of Announced and Surprise measures for different classes of firms' size.<sup>51</sup>

#### 3.6.1 Estimating the role of size

We proxy the size of a firm with its total sales in the domestic market. This choice is made to reduce potential concerns of simultaneity in case we were to use the export value. We classify the size of the firms in three groups. We do this by using the 40th and 80th percentile of the size distribution in each period  $s$ . We define three dummy variables for each group  $Size_{c,i,t}$  with  $c$  indexing  $\{S, M, L\}$ , which takes value one

<sup>51</sup>In the standard framework a' la Melitz, differences in terms of productivity maps into the differences in performances of firms, such as their size.

when the total sales of a firm is respectively below or equal the 40th, above the 40th but below the 80th, above or equal the 80th percentile. We augment our specification in 3.5 with size classes and their interaction with Announced and Surprise TBTs:

$$\begin{aligned}
y_{i,HS4,d,t} = & \sum_{c \in \{L,M\}} \gamma_{0,c} \text{Size}_{c,i,s} + \sum_{c \in \{L,M,S\}} \alpha_{0,c} \text{Size}_{c,i,t} \times \text{AnnouncedTBT}_{HS4,d,t} \\
& \sum_{c \in \{L,M,S\}} \beta_{0,c} \text{Size}_{c,i,t} \times \text{SurpriseTBT}_{HS4,d,t} + \\
& + \delta_1 \text{asinh}(\text{tariff}_{HS4,d,t}) + \mu_{HS2,d,t} + \mu_i + \epsilon_{i,HS4,d,t} \quad (3.8)
\end{aligned}$$

We drop  $\text{Size}_{S,i,s}$  in order to have our estimates as deviation from small firms in markets where the regulation does not change. We are interested in decomposing the effect of a regulation into the marginal contribution of each size class. We will therefore be looking at the estimates of  $\beta_{0,c} + \gamma_{0,c}$  for Surprise TBTs and  $\alpha_{0,c} + \gamma_{0,c}$  for Announced TBTs. For the marginal effect of being treated by a regulation, given a certain size, we will be looking at  $\beta_{0,c}$  and  $\alpha_{0,c}$  across size classes  $c$ .

### 3.6.2 Results and discussion

Table 3.6 reports the estimates of the specifications described in model 3.5 and 3.8. The table has 6 columns: in columns 1-2, the dependent variable is the export value in log, followed by the probability of exit in columns 3-4, and the lagged probability of exit in 5-6.

In markets with no change of regulation, the medium (large) size firm exports on average 22% (46%) more of a small firm counterpart and she is around 7% (12%) less likely to exit the market.

Conversely, in markets touched by a Surprise TBT, the medium size firm exports even less than the small firm counterpart in a market with no regulation, on average 21% less, and is around 6% more likely to exit the market. Large firms touched by a Surprise TBT export instead only 21% more than a small firm counterpart in a market with no regulation and are always 12% less likely to exit the market. Small firms export instead 34% less than their counterpart in markets with no TBT and their probability to exit the market is 13% larger. By comparing each class size with its own counterpart in a market not touched by a regulation, we see that the expected export value is substantially lower for all the three size classes. The drop in export value is more substantial for small and medium size firms, who lose 29% and 34%, respectively, against the 17% loss for large firms. On the other hand, the probability of exit increase significantly only for small and medium firms, by 12% and 13% respectively. On the contrary, in the period before the introduction of a Surprise TBT we do not record any significant change in the probability of exit for any size class.

In markets touched by an Announced measures, the medium size firm exports again on average 22% more of the small firm counterpart in a market with no TBT. Large firms export around 91% more, while small firms get larger - they export 27%

more than the small firm counterpart in a market with no TBT. In the period before the introduction of the Announced TBT small firms exit with a probability that is 10% bigger, medium firms with no substantial difference, while large firms are only 4% less likely, than the small counterpart in a market with no TBT. Then, by comparing each class size with its own counterpart in a market not touched by a regulation, we see that the expected export value is substantially larger for small and large firms. In the period before the introduction of a announced TBT, the probability of exit increase for all class sizes, but in particular for small firms.

This set of results reinforces our interpretation of the estimates of the baseline model. In case of Announced measures, mostly small firms exit before the TBT is implemented to avoid to pay the sunk cost to serve the market and adopt the new regulation. In case of Surprise TBTs, firms did not expect the change and exit within the same period in which the measure is enforced. Only large firms do not exit substantially, while the record a significant reduction in the export value pointing to the fact that this firms undergo a temporary stop. We interpret this evidence as suggesting that large firms wait and delay their investment decision on serving the market. One possible reason of why large firms are more prone to wait is that they find it easier to divert their sales somewhere else. This channel has been investigated in Fontagné et al., 2015, who finds that multi-destination firms, are able to switch destination countries more easily than other firm when they are hit by a new TBT. They explain this by benefiting from a wide portfolio of alternatives, multi-destination firms are more able than other firms in diverting trade towards TBT-free destinations for which fixed-costs of market access have already been paid.

### **3.7 Persistence of Uncertainty and the role of formal Information**

Our argument builds on the assumption that Surprise measure rise the uncertainty on the cost to serve the market. Our theoretical framework predicts that when uncertainty rises firms will postpone their investment decision on whether to stay. This is because the uncertainty over the profitability of the investment creates a value to waiting for new information. In this section we investigate weather the arrival of new information, through late notification, erodes the value of the wait option. To do so we distinguish the dynamic effects between those Surprise measures for which a notification is provided with delay and those that are left unnotified. For this purpose, we modify our baseline specification to include the distinction between late notified and never notified ones.

#### **3.7.1 Estimating the role of late notifications**

We define a k-periods far from a Surprise measure to be Late Notified in semester  $t$ , if in  $s$  it is k-period apart from the introduction and a notification has been provided

TABLE 3.6: Effects of Announced vs Surprise measures for different size classes

DEPENDENT VARIABLE	Export <sub>t</sub>		Exit <sub>t</sub>		Exit <sub>t-1</sub>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Size</i> <sub>MED,t</sub>	0.195 <sup>a</sup> (0.006)	0.196 <sup>a</sup> (0.006)	-0.072 <sup>a</sup> (0.003)	-0.072 <sup>a</sup> (0.003)	-0.077 <sup>a</sup> (0.003)	-0.077 <sup>a</sup> (0.003)
<i>Size</i> <sub>BIG,t</sub>	0.378 <sup>a</sup> (0.008)	0.378 <sup>a</sup> (0.008)	-0.122 <sup>a</sup> (0.003)	-0.122 <sup>a</sup> (0.003)	-0.130 <sup>a</sup> (0.003)	-0.130 <sup>a</sup> (0.003)
SurpriseTBT × <i>Size</i> <sub>SMALL</sub>		-0.339 <sup>a</sup> (0.151)		0.125 <sup>b</sup> (0.072)		-0.019 (0.121)
SurpriseTBT × <i>Size</i> <sub>MED</sub>		-0.429 <sup>a</sup> (0.094)		0.132 <sup>a</sup> (0.036)		-0.006 (0.092)
SurpriseTBT × <i>Size</i> <sub>BIG</sub>		-0.192 <sup>b</sup> (0.106)		0.004 (0.021)		0.020 (0.084)
AnnouncedTBT × <i>Size</i> <sub>SMALL</sub>		0.246 <sup>b</sup> (0.140)		-0.0003 (0.037)		0.103 <sup>a</sup> (0.046)
AnnouncedTBT × <i>Size</i> <sub>MED</sub>		0.078 (0.117)		0.003 (0.023)		0.073 <sup>a</sup> (0.035)
AnnouncedTBT × <i>Size</i> <sub>BIG</sub>		0.273 <sup>a</sup> (0.137)		-0.013 (0.013)		0.095 <sup>a</sup> (0.036)
asinh(tariff)	-0.05 <sup>a</sup> (0.002)	-0.053 <sup>a</sup> (0.002)	0.001 <sup>a</sup> (0.0005)	0.001 <sup>a</sup> (0.001)	0.001 <sup>a</sup> (0.0005)	0.001 <sup>a</sup> (0.001)
Obs.	4,214,856	4,214,856	2,522,245	2,522,245	2,418,685	2,418,685
Adj. R2	0.26	0.26	0.11	0.11	0.11	0.11
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
HS2-Country-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Export is in log, so the marginal effect of a dummy reads  $100(e^{\beta} - 1)\%$ , with  $\beta$  being the coefficient on the dummy. Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 since who exits does not export in the period. Significance levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

by the start of the semester:

$$SurpriseTBT_{HS4,d,t,k}^{UN} = \mathbb{1}[\text{if } K_{HS4,d,t}^{SurpriseTBT} = k] \times \mathbb{1}[\text{if semester}(N_{HS4,d}) < s].$$

We then distinguish unnotified measures as those that after k-periods from the introduction have no notification. This might occur either because it will be provided afterwards or because it will never be notified:

$$SurpriseTBT_{HS4,d,t,k}^{LN} = \mathbb{1}[\text{if } K_{HS4,d,t}^{SurpriseTBT} = k] \times \mathbb{1}[\text{if semester}(N_{HS4,d}) \geq s \text{ or } N_{HS4,d} = NA].$$

We estimate a semi-dynamic model with short run effects after the introduction of the Surprise TBTs, which distinguishes the two groups:

$$\begin{aligned} y_{i,HS4,d,t} = & \beta_0 SurpriseTBT_{HS4,d,t} + \sum_{k=1}^{A-1} \beta_k^{LN} SurpriseTBT_{HS4,d,t,k}^{LN} + \\ & \sum_{k=1}^{A-1} \beta_k^{UN} SurpriseTBT_{HS4,d,t,k}^{UN} + \sum_{k=0}^{A-1} \alpha_k \mathbb{1}[\text{if } K_{HS4,d,t}^{AnnouncedTBT} = k] + \\ & + \delta asinh(\text{tariff}_{HS4,d,t}) + \mu_{HS2,t,d} + \mu_i + \epsilon_{i,HS4,d,t} \quad (3.9) \end{aligned}$$

We are here interested in comparing  $\beta_k^{UN}$  and  $\beta_k^{LN}$ , to see whether the average effect of Unnotified TBT is more persistent – significant for a longer k – than the case of Late Notified TBTs.

### 3.7.2 Results and discussion

Columns 1 to 3 of Table 3.7 reports the estimates of the coefficients of model 3.9 when we increase at each stage by one the number of forward periods (A). For those measures that are notified, the drop in the export value lasts just one semester, the one in which the Surprise TBT occurs. On the other hand, the effects of unnotified measures last longer, also during the subsequent period. This suggests that indeed notifications play a role in reducing the value of the wait option. An alternative explanation could be that the group of Unnotified and Late Notified measures have different effects already at the moment of their enforcement. Table C.10 in Appendix shows this not to be the case: the estimate of the lagged variables is almost the same (-0.28 versus -0.26) and indeed the p-value of the equality of coefficients is around 90%. In other words, while Surprise measures hit firms in an equivalent way, independently of whether they will be or not notified in the following months, the fact of being disclosed within the semester makes the effects to not persist to the successive one.

TABLE 3.7: Export, semi-dynamic for Unnotified and Late Notified

	(1) Export	(2) Export	(3) Export
$SurpriseTBT_{HS4,d,t,k=0}$	-0.269 <sup>c</sup> (0.14)	-0.268 <sup>c</sup> (0.14)	-0.267 <sup>c</sup> (0.14)
$SurpriseTBT_{HS4,d,t,k=1}^{UN}$	-0.310 <sup>a</sup> (0.119)	-0.320 <sup>a</sup> (0.135)	-0.321 <sup>a</sup> (0.135)
$SurpriseTBT_{HS4,d,t,k=1}^{LN}$	0.0936 (0.193)	0.0951 (0.194)	0.0924 (0.194)
$SurpriseTBT_{HS4,d,t,k=2}^{UN}$		-0.186 (0.173)	-0.294 (0.255)
$SurpriseTBT_{HS4,d,t,k=2}^{LN}$		0.0192 (0.177)	0.0152 (0.177)
asinh(tariff)	-0.0520 <sup>a</sup> (0.00204)	-0.0514 <sup>a</sup> (0.00206)	-0.0508 <sup>a</sup> (0.00210)
$N$	3965137	3819196	3666606
adj. $R^2$	0.261	0.262	0.262
Firm FE	Yes	Yes	Yes
HS2-Country-Time FE	Yes	Yes	Yes

*Notes:*  $K$  are the number of semesters after the introduction of a TBT. The superscript  $UN$  and  $LN$  are used to distinguish the two types of Surprise TBT, Unnotified and Late Notified ones. Estimates for Announced TBT and the relative forward window are not shown. The definition of the sample is described in Appendix. Export is in log. Standard errors in parenthesis are clustered at (HS4,country,Time). Significance levels: <sup>c</sup>  $< 0.1$ , <sup>b</sup>  $< 0.05$ , <sup>a</sup>  $< 0.01$ .

### 3.8 Conclusion

The findings of this paper support the view that, depending on how changes in technical regulations are promoted internationally, trade effects on exporters may be very different. When TBTs are introduced in a less transparent way, they cause a temporary stop of the exporting activity of firms. Only large firms are able to wait. Small and medium firms tend instead to exit permanently the export market. In accordance with the temporary nature of this lack of information, the adverse effects are only short-lasting, encompassing at most two semesters. The provision of formal documentation from the introducing country, solves the uncertainty and allow firms to restore their exporting activity. We interpret this temporary halt as due to the fact that, in face of a rise in uncertainty, firms postpone their export decision to the time in which they have access to more information.

# Conclusions

Research in international trade has changed substantially over the last twenty years, as attention has shifted from countries and industries towards firms. This shift has brought new understanding of economic phenomena while identifying new channels through which micro properties transmit to the aggregate.

In the first chapter of this thesis we argue that one has to take a micro-prospective to understand why we observe a skill upgrading in the Italian workforce. Movements of workers across industries have favored less skilled intense sectors, fact that is consistent with the Italian specialization in more traditional manufacturing sectors. However, we find that most of the changes in the Italian skill composition have occurred within firms, where one observes a skill-upgrading effect with a negative adjustment of the wage premium. The fall in the annual wage premium is at odds with what have been observed in other OECD countries, including Germany and UK. A similar pattern has been instead observed for France, which has been explained as to be due to a composition effect related to the increase in the educational attainment of the labour force. The interplay of the supply and demand characteristics of the Italian labor market is left for future research.

A recent stream of the literature has moved attention towards the pivotal role of few large firms in driving aggregate patterns. This literature tries to go beyond the feature of traditional trade models that assume a continuum of measure-zero firms. New challenges are posed in the understanding of the granular features of the global economy and in the development of tools to analyze them.

In the second chapter, we show that the relation between the aggregate and firm level diversification is mediated by the extent to which firms product bundles overlap. In particular, we show that the average number of product overlaps per firm can be conveniently decomposed into three factors: the normalized number of firms exporting, the average diversification of firms - computed excluding the most diversified firm, and an index of product sets similarity. We interpret firms' product set similarity as a measure of those characteristics that are common to all firms in a given industry, such as the availability of specific human capital, infrastructure, and technology versus those idiosyncratic features of individual firms, driven by their idiosyncratic know how and managerial talent. We show that indeed our index captures the extent to which aggregate performances, as captured by the Revealed Comparative Advantage of the industry, are driven by fundamental rather than firm-specific forces. We also believe the similarity of firms' product sets might be a vehicle of the transmission of trade shocks. We leave this channel for future

investigations.

Over the last twenty years, the trade environment in which firms operate has changed substantially. The reduction in tariff protection has been accompanied by a surge of Non Tariff Measures. These policies are often complex and qualitative instruments, making it difficult to detect their discriminatory application against trade partners.

In the third chapter of this thesis, we argue that the lack of transparency can be used by countries to transform technical regulations - which give access to serve a market to both domestic and foreign sellers - into unnecessary obstacles to trade. By avoiding to inform in time other WTO members about changes in regulations, governments can effectively hinder import penetration. The lack of relevant information on how to implement the foreign regulation, rise exporters' real option to wait and postpone their export investment decision in time. While for large firms this is a temporary halt of the exporting activity, small and medium firms tends to permanently exit the market. The political economy that motivates countries to impose unnecessary, while temporary, obstacles to trade is left for future research.

## Résumé

Dans l'UE, seulement environ 4,5% des entreprises exportent. Parmi les grandes entreprises, ce chiffre est dix fois plus élevé. Même au sein des entreprises exportatrices, une grande hétérogénéité persiste, la majeure partie des ventes se concentrant dans une poignée d'entreprises. Les dix premiers exportateurs européens comptent à eux seuls pour un montant compris entre le 10 et 20% de la part totale des exportations. Alors que les économistes ont généralement lu les faits stylisés sur le commerce à travers la lentille de l'avantage comparatif des pays, des rendements d'échelle croissants et de *love for variety*, ce n'est que récemment que l'attention s'est portée sur le moteur fondamental des flux commerciaux - l'entreprise. Ce changement a permis de mieux comprendre les implications des divers épisodes de libéralisation tarifaire qui ont caractérisé la seconde moitié du siècle dernier ainsi que le début des années 2000. L'environnement commercial dans lequel les entreprises opèrent a toutefois rapidement changé. Les accords commerciaux contemporains vont désormais bien au-delà des traditionnelles restrictions commerciales à la frontière. Ils couvrent les normes réglementaires, les règles de santé et de sécurité, l'investissement, la banque et la finance, la propriété intellectuelle, le travail, l'environnement et bien d'autres sujets. La compréhension de l'interaction entre cet environnement commercial et les caractéristiques des entreprises pose de nouveaux défis aux spécialistes du commerce international.

**L'apport d'une micro-perspective** Depuis le milieu des années 90, la disponibilité croissante de micro-données avec des flux commerciaux désagrégés a mis en lumière un ensemble de faits sur la façon dont les entreprises servent de médiateurs pour le commerce d'un pays (Bernard and Jensen, 1995). Ces études ont montré que les entreprises commerciales diffèrent sensiblement des entreprises qui opèrent uniquement sur le marché national. Dans un large éventail de pays et de secteurs, les exportateurs sont plus grands, plus diversifiés, plus productifs, plus exigeants en termes de compétences et de capital, et ils versent des salaires plus élevés que les entreprises non exportatrices.<sup>52</sup> Ces faits ont remis en question les théories traditionnelles du commerce basées sur les avantages comparatifs et les produits différenciés, qui prédisent que toutes les entreprises d'un secteur seraient soit exportatrices soit non exportatrices. Ils ont également permis de jeter un nouvel éclairage sur des

<sup>52</sup>Pour des enquêtes complètes sur cette littérature théorique et empirique, voir Bernard et al., 2007a; Melitz and Trefler, 2012; Melitz and Redding, 2014; Bernard et al., 2018a.

phénomènes globaux, tels que l'évolution de la composition de la main-d'œuvre et des salaires, ce qui a motivé et soutenu de nouvelles théories.

Dans le premier chapitre de cette thèse, dans un travail conjoint avec Chiara Tomasi, nous montrons qu'il faut une micro-perspective pour trouver une explication à la raison pour laquelle l'Italie, un pays avec un avantage comparatif dans les industries peu qualifiées, a connu une augmentation de la composition en compétences de sa main-d'œuvre pendant la période d'intégration commerciale du début des années 2000.<sup>53</sup> Les théories classiques prédisent que les pays disposant d'une main-d'œuvre non qualifiée se spécialisent dans les industries qui utilisent ce facteur de manière plus intensive. En raison de l'expansion du commerce, les travailleurs devraient passer des industries en contraction à celles en expansion, ce qui modifierait le ratio global entre les travailleurs qualifiés et non qualifiés et leurs salaires relatifs. Notre exercice, tout en confirmant les mouvements de travailleurs des industries manufacturières qualifiées vers les industries non qualifiées, souligne le fait que la plupart des changements dans la composition de la main-d'œuvre italienne se sont produits au sein des industries, et principalement des entreprises, où l'on observe un *skill upgrade*. Cette situation est similaire à celle observée pour les États-Unis en Bernard et al., 2007a et soutient les modèles qui tiennent compte de l'hétérogénéité intra-industrielle et des ajustements au niveau des entreprises. Par exemple, Bustos, 2011 prédit que l'ouverture commerciale, en augmentant l'accès au marché, incite les entreprises les plus compétitives à subir dans la mise à niveau technologique.<sup>54</sup> Dans notre échantillon d'entreprises italiennes, les entreprises les plus productives et les plus grandes sont en effet celles qui contribuent le plus à l'augmentation de l'intensité de compétences. D'autre part, nous constatons que le prix de la main-d'œuvre qualifiée ne s'est pas ajusté positivement. Au contraire, la prime salariale annuelle a diminué, ce qui signifie que l'écart salarial entre la main-d'œuvre qualifiée et non qualifiée se réduit. Ceci est en contradiction avec ce qui a été observé au Royaume-Uni, aux États-Unis et en Allemagne sur la même période, tout en étant conforme à ce qui a été rapporté pour la France (Naticchioni, Ragusa, and Massari, 2014). Concernant ce dernier cas, Verdugo, 2014 a expliqué la diminution de l'écart de salaire comme étant due à des changements dans la composition au niveau de l'éducation et de l'expérience au sein de la population active.<sup>55</sup> Bien que nous n'ayons pas pu tester cet argument, nous avons épuisé la possibilité que la baisse de la prime salariale annuelle soit due à un ajustement à la marge intensive,

<sup>53</sup>Ce travail est publié dans Iodice and Tomasi, 2016.

<sup>54</sup>Bustos, 2011 observe en effet que l'augmentation des exportations due la libéralisation du commerce en Argentine a eu un impact sur le comportement des entreprises générer une technologie et une mise à niveau des compétences. Autres études empiriques confirmant l'impact causal du commerce sur les résultats du marché du travail sont Frias, Kaplan, and Verhoogen, 2012 et Verhoogen, 2008. Sur la base de données au niveau des entreprises françaises, Harrigan, Reshef, and Toubal, 2016 a constaté que l'exportation entraînait une polarisation au sein de l'entreprise : croissance plus rapide de la part des cadres et déclassement des compétences au sein des travailleurs de la production.

<sup>55</sup>Verdugo, 2014 a en effet constaté une forte co-variation négative entre les changements de la prime de compétence et l'offre relative de compétences au sein des groupes d'expérience. Un examen de l'évolution des écarts salariaux français est présenté dans Charnoz, Coudin, and Gaini, 2013.

sur les heures travaillées par le salarié. Cela aurait pu avoir été une conséquence de la flexibilité accrue du travail introduite au début des années 2000. L'interaction des caractéristiques de l'offre et de la demande sur le marché du travail italien est laissée à l'étude future.

**Les caractéristiques de l'hétérogénéité des entreprises** Le déplacement de l'attention des pays et des industries vers les entreprises introduit de nouveaux mécanismes pour le commerce international afin de façonner des modèles globaux par l'interaction des caractéristiques des entreprises et de leur orientation vers l'exportation. Les travaux fondateurs de Melitz, 2003 prédisent que même avec une hétérogénéité fixe dans la productivité des entreprises, l'ouverture au commerce stimule la productivité globale, via un mécanisme qui sélectionne les meilleures entreprises .<sup>56</sup> Des recherches ultérieures ont introduit un lien entre la productivité et la capacité des entreprises à se développer dans différentes marges commerciales, comme le nombre de marchés d'exportation à desservir (Eaton, Kortum, and Kramarz, 2011a), le nombre de produits à fournir à chaque marché d'exportation (Bernard, Redding, and Schott, 2010; Bernard, Redding, and Schott, 2011; Hottman, Redding, and Weinstein, 2016), le nombre de pays à partir desquels s'approvisionner en intrants intermédiaires et quels intrants importer de chaque pays source (Antras, Fort, and Tintelnot, 2017; Berman, Rebeyrol, and Vicard, 2019). Si les décisions des entreprises concernant ces marges de participation sont interdépendantes, les différences exogènes initiales entre les entreprises peuvent être amplifiées dans l'économie internationale (Bernard et al., 2018a). Ce mécanisme pourrait expliquer pourquoi nous observons de très grands exportateurs qui dominent les échanges dans un large éventail de pays et de secteurs. Par exemple, Freund and Pierola, 2015 indique que parmi 32 pays, la première entreprise représente en moyenne 14% du total des exportations (non pétrolières) d'un pays et les cinq premières entreprises représentent 30%.

Dans le deuxième chapitre, nous contribuons à la littérature récemment croissante sur le commerce qui étudie la façon dont le micro-comportement s'agrège en macro-modèles. L'intérêt pour ce sujet trouve sa motivation dans Arkolakis, Costinot, and Rodríguez-Clare, 2012, qui prouve un manque d'implication de la littérature récente pour l'agrégat. Eaton, Kortum, and Sotelo, 2012 fait valoir qu'une des raisons principales pour lesquelles les modèles de producteurs hétérogènes fournissent si peu de modifications de la façon dont nous pensons aux agrégats est le dispositif de traitement de l'ensemble comme un continuum, qui a été initié par Dornbusch, Fischer, and Samuelson, 1977. La caractéristique des variétés à mesure zéro, de la littérature hétérogène sur les entreprises, convient la modélisation. En invoquant la loi des grands nombres, on peut considérer ce que affecte

<sup>56</sup>Le même cadre peut être étendu pour tenir compte de plusieurs décisions endogènes qui affectent la productivité des entreprises, notamment l'adoption de technologies (Bustos, 2011; Lileeva and Trefler, 2010), l'innovation (Atkeson and Burstein, 2010; Perla, Tonetti, and Waugh, 2015; Sampson, 2016), les changements endogènes dans la composition de la main-d'œuvre (Helpman, Itskhoki, and Redding, 2010; Helpman et al., 2017) et les changements endogènes dans la gamme de produits (Bernard, Redding, and Schott, 2010; Bernard, Redding, and Schott, 2011).

le niveau agrégé qui doit être déterminé par les paramètres définissant la répartition des résultats affectant les unités individuelles, mais pas sur la réalisation eux-mêmes. En présence de granularité au lieu de cela - terme inventé par Gabaix, 2011 pour représenter la nature asymétrique de la distribution de la taille des entreprises - les chocs sur les grandes entreprises "portent on" à l'agrégat.<sup>57</sup> Pour expliquer cela, Eaton, Kortum, and Sotelo, 2012 et Gaubert and Itskhoki, 2018 propose d'examiner le nombre d'entreprises qui exportent vers une destination comme généré par un processus de Poisson déjà proposé dans la Bernard et al., 2003, et donc comme un nombre fini. Dans ces travaux, les parts de marché réalisées par les entreprises peuvent diffèrent donc de celles obtenues dans un monde continu.

Dans un travail conjoint avec Lionel Fontagné et Angelo Secchi, nous décrivons une industrie (dans un pays) où une relation agrégée, ici l'ensemble des produits exporté vers un pays de destination par l'industrie, est considéré comme le résultat de décisions prises par un groupe fini de personnes hétérogènes entreprises. Nous montrons qu'à la différence de ce qui se passe avec la marge intensive, l'ensemble des produits agrégés n'est pas généré par sommation mais par l'union des paniers de produits exportés par chaque entreprise. Nous formalisons un cadre conceptuel qui présente un nombre discret d'entreprises qui exportent des ensembles de produits potentiellement hétérogènes vers un pays et nous étudions la façon dont les entreprises agrègent leurs choix de produits. Nous montrons que la relation entre la diversification au niveau de l'agrégat et au niveau de l'entreprise dépend de la mesure dans laquelle les ensembles de produits des entreprises se chevauchent. En particulier, nous montrons que le nombre moyen de chevauchements de produits par entreprise peut être décomposé en trois facteurs: le nombre normalisé d'entreprises l'exportation, la gamme de produits moyenne des entreprises - calculée en excluant les entreprise la plus diversifiée, et un indice de produits établit la similitude. Nous interprétons la similarité des ensembles de produits des entreprises en nous appuyant sur les premières contributions à la théorie de l'entreprise. Celles-ci suggèrent que les entreprises se développent en se diversifiant dans de nouvelles activités (Marris, 1964) tout en acquérant des capacités productives qui peuvent être utilisées pour produire de nouvelles variétés de produits (Penrose, 1955). Des produits différents nécessitent un savoir-faire ou des capacités d'intrants différents, et les entreprises diffèrent dans les capacités dont elles disposent. Les capacités sont liées à l'entreprise car elles ne peuvent souvent pas être achetées "sur étagère" (Teece, 1980; Teece et al., 1994; Sutton, 2012).<sup>58</sup> En comparant les entreprises sur la

<sup>57</sup>La nature hautement asymétrique était déjà l'objet d'une grande attention dans le secteur industriel la littérature d'organisation, par exemple Axtell, 2001; Sutton, 1997a Les effets d'une économie granulaire ont été étudiés dans (Gabaix, 2011; Di Giovanni, Levchenko, and Mejean, 2014)

<sup>58</sup>Plus récemment, Bernard, Redding, and Schott, 2010 a constaté que les entreprises sont beaucoup plus susceptibles de produire dans certaines paires d'industries, ce qui suggère que des complémentarités existent entre les activités. Dosi, Grazzi, and Moschella, 2017 constatent que les entreprises sont beaucoup plus diversifiées en termes de produits qu'en termes de technologies, leurs principaux produits étant davantage liés à l'exploitation de leurs connaissances innovantes. Boehm, Dhingra, and Morrow, 2019 montre que les tableaux d'entrées-sorties suggèrent que les entreprises coproduisent

base de ce qu'elles vendent, on peut déterminer dans quelle mesure la diversification sectorielle reflète des caractéristiques communes à toutes les entreprises d'un secteur donné - telles que la disponibilité d'un capital humain, d'infrastructures et de technologies spécifiques - par opposition à la contribution idiosyncrasique des entreprises individuelles, déterminée par leur savoir-faire et leur talent de gestionnaire.

Nous montrons qu'en effet, notre indice saisit la mesure dans laquelle les performances globales, telles que saisies par l'avantage comparatif révélé (ACR) de l'industrie, sont motivées par des forces fondamentales plutôt que spécifiques à l'entreprise. Nous calculons les ACR des industries françaises avec et sans le premier exportateur et nous constatons qu'une augmentation de 10% de l'indice de similarité de l'ensemble des produits est associée à une réduction de 3,4% de la probabilité de perdre l'ACR en raison de la suppression du premier exportateur. Nous interprétons ces données comme suggérant que la similarité des ensembles de produits des entreprises reflète la mesure dans laquelle la performance globale de l'industrie est déterminée par des forces fondamentales plutôt que par des forces spécifiques à l'entreprise. Nous pensons également que la similarité des ensembles de produits des entreprises pourrait être un vecteur de transmission des chocs commerciaux. Nous laissons ce canal pour les enquêtes futures.

**Un nouvel environnement commercial** La redistribution de l'activité économique entre les entreprises, comme dans Melitz, 2003, et au sein des entreprises entre les variétés de produits, comme dans Mayer, Melitz, and Ottaviano, 2014, stimule la productivité globale et offre une source non traditionnelle de gains de bien-être grâce au commerce. Lorsque les barrières commerciales tombent ou que les coûts de transport diminuent, les entreprises les plus performantes en termes de productivité (variétés des produits de haute qualité) survivent et se développent, tandis que les entreprises non exportatrices à faible productivité (variétés de produits de faible qualité) sont plus susceptibles d'échouer (d'être abandonnées). Cette tendance à considérer les accords commerciaux comme exemple d'une politique qui améliore la productivité a occupé une place importante dans la littérature commerciale et a été utilisée pour promouvoir plusieurs épisodes de réduction des droits de douane et des quotas. Cependant, "Nous ne négocions plus seulement la réduction des droits de douane, mais aussi la réduction des barrières non tarifaires, qui ont pris une importance énorme".<sup>59</sup> Les accords commerciaux contemporains vont désormais bien

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dans des industries qui partagent des intrants intermédiaires, proposant que les capacités d'intrants conduisent à des modèles de production multiproduits.

<sup>59</sup>Citant Pascal Lamy, ancien directeur de l'OMC, lors de son discours d'adieu le 24 juillet 2013.

au-delà des restrictions commerciales traditionnelles.<sup>60</sup> Ils recherchent une intégration profonde entre les nations plutôt qu'une intégration superficielle, pour reprendre la distinction proposée par Lawrence, 2000. Ils comprennent par exemple les normes réglementaires, les règles de santé et de sécurité, l'investissement, le système bancaire et la finance, la propriété intellectuelle, le travail, l'environnement, et bien d'autres sujets. Différents types de mesures existent et, grâce au récent système de codification de la CNUCED, les mesures non tarifaires (MNT) peuvent être classées en fonction de l'objectif qu'elles visent (Cadot, Malouche, and Sáez, 2012). Parmi celles-ci, les obstacles techniques au commerce (OTC) constituent la majeure partie des MNT, s'appliquant à une large gamme de produits. Ces instruments peuvent concerner les caractéristiques ou la qualité d'un produit ou les procédures d'essai, la certification, l'étiquetage, etc. Ils doivent être conçus pour atteindre des objectifs de politique publique, tels que la protection de la sécurité et de la santé humaines, de l'environnement et de la sécurité nationale. Toutefois, ce sont des outils politiques complexes et, malgré leur statut officiel, ils peuvent également être utilisés pour des raisons d'économie politique, devenant ainsi des obstacles inutiles au commerce (OMC, 2012). La faible disponibilité des données et la difficile quantification de ces politiques rendent particulièrement difficile la détection de leur application discriminatoire à l'égard des partenaires commerciaux. Les enquêtes menées auprès des exportateurs dans les pays de l'OCDE indiquent que les réglementations techniques figurent parmi les obstacles non tarifaires les plus signalés (Rapport de l'OCDE p.24, 2005). Il est intéressant de noter que, plus que la réglementation technique elle-même, les exportateurs de l'UE se plaignent surtout de la les obstacles procéduraux pour se conformer à ces règlements (Rapport ITC 2016, tableau B5). Bien qu'il soit admis dans la littérature que les pays peuvent abuser des réglementations visant à protéger les industries nationales (Beverelli, Boffa, and Keck, 2014; Orefice, 2017), peu est connu sur le rôle des obstacles procéduraux dans le caractère protecteur de ces politiques.

Le troisième chapitre examine les obstacles procéduraux et leurs effets sur l'activité d'exportation des entreprises. À cette fin, nous utilisons des règlements techniques nouvellement introduits qui ont été contestée par les pays exportateurs à l'OMC par le biais d'un mécanisme de droit souple appelé "Specific Trade Concern" (STC). Nous construisons une nouvelle base de données en utilisant le contenu des STCs qui est disponible sous forme de documentation textuelle sur le portail de l'OMC. Ces documents ont été automatiquement analysés tout en détectant les dates de mise en œuvre des règlements qui ont été contestés. Cette procédure nous permet d'identifier quand et comment un règlement technique contesté a été introduit dans un pays.

<sup>60</sup>Rodrik, 2018 compare l'accord de libre-échange États-Unis-Israël, entré en vigueur en 1985, avec l'accord de libre-échange États-Unis- L'accord de libre-échange de Singapour est entré en vigueur en 2004. Le premier contient 22 articles et trois annexes, dont la majeure partie est consacrée aux questions de libre-échange telles que les tarifs douaniers, les restrictions agricoles, les licences d'importation et les règles d'origine. La seconde est près de dix fois aussi longtemps. Sur ses 20 chapitres, seuls sept couvrent des sujets commerciaux classiques. D'autres chapitres traitent de les obstacles transfrontaliers.

Selon que le nouveau règlement a été correctement divulgué, nous introduisons le concept de mesures "surprises" ou "annoncées". Nous interprétons ces différences en fonction du moment où les entreprises évaluent si elles doivent adopter la nouvelle exigence technique ainsi que des informations dont elles disposent pour prendre cette décision.

La littérature empirique précédente a constaté que la transparence de la politique commerciale permettait de stimuler les échanges et les flux d'investissement (François, 2001; Helble, Shepherd, and Wilson, 2009; Lejarraga and Shepherd, 2013). Les mesures utilisées dans ce type de travaux sont fondées sur des indices basés sur la perception ou sur des dispositions générales de transparence dans le cadre d'accords commerciaux régionaux. Une exception est un travail récent de Ing, Cadot, and Walz, 2018 qui propose un indice basé sur ce que les gouvernements font réellement dans le domaine des mesures non tarifaires (NTM). Cet indice comprend le nombre de NTMs notifiées par un pays. Nous partageons avec ce travail l'accent mis sur les mesures non tarifaires, car les NTM, et les OTC en particulier, sont des instruments juridiques complexes qui peuvent imposer des obstacles procéduraux importants. Dans notre travail, nous utilisons la procédure de mise en œuvre de ces réglementations, pour déterminer non seulement si, comme dans le cas de Ing, Cadot, and Walz, 2018, mais aussi *comme* les pays annoncent et divulguent ce type de réglementations. Ce faisant, nous fournissons une définition de la transparence selon un attribut fondamental : la prévisibilité.<sup>61</sup>

Notre travail fait donc référence à la littérature qui étudie le rôle de l'incertitude de la politique commerciale sur les décisions d'investissement des entreprises internationales. Des contributions théoriques récentes (Handley and Limao, 2015; Coelli, 2018) ont combiné les intuitions des modèles commerciaux avec l'hétérogénéité des entreprises (Melitz, 2003) avec celles de la littérature sur les options réelles (Dixit and Pindyck, 1994). En présence d'un investissement irréversible et de la possibilité d'attendre, l'incertitude sur l'environnement commercial incite les entreprises à retarder la décision d'investissement sur l'opportunité d'entrer sur un marché (Handley and Limao, 2015) ou de se soumettre à une mise à niveau technologique (Handley and Limão, 2017; Coelli, 2018). Ces études testent leurs prévisions en exploitant l'application des accords commerciaux comme des épisodes de changements dans l'incertitude politique et en utilisant la variation de l'écart entre les tarifs appliqués et les tarifs consolidés (de même que Carballo, Handley, and Limão, 2018). Nous utilisons plutôt des épisodes de changements dans les OTC, avec et sans notification formelle, pour identifier l'effet de l'incertitude sur la décision d'investissement des entreprises étrangères en matière d'exportation.

Nous trouvons que le manque de transparence peut être utilisé par les pays pour transformer les règlements techniques - qui donnent accès à le marché domestique

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<sup>61</sup>Helble, Shepherd, and Wilson, 2009 identifie deux dimensions de la transparence : la prévisibilité (réduction du coût de l'incertitude) et la simplification (réduction des coûts d'information). Comme le reconnaissent les auteurs, leurs indices ne sont pas en mesure de démêler les deux mais tentent plutôt de rendre compte des deux sources ensemble.

aux vendeurs nationaux et étrangers - en obstacles inutiles au commerce. En évitant d'informer à temps les autres membres de l'OMC des changements de réglementation, les gouvernements peuvent effectivement entraver les importations. Le manque d'informations pertinentes sur la manière de mettre en œuvre la réglementation étrangère, augmente la possibilité réelle pour les exportateurs d'attendre et de reporter à temps leur décision d'investissement à l'exportation. Alors que pour les grandes entreprises, il s'agit d'un arrêt temporaire de l'activité d'exportation, les petites et moyennes entreprises ont tendance à quitter le marché de façon permanente. L'économie politique qui motive les pays à imposer des obstacles au commerce inutiles, bien que temporaires, est laissée à la recherche future.

## Resume of the Three Essays

### Chapitre 1

Le premier chapitre de la thèse est une extension de Iodice and Tomasi, 2016. Ce travail étudie l'évolution de l'emploi et la structure des salaires des entreprises manufacturières italiennes au début des années 2000. En particulier, nous décomposons la variation du ratio de la facture salariale qualifiée en mouvements de l'emploi et des salaires. Notre technique permet de démêler la structure susmentionnée en les transferts intersectoriels et intrasectoriels, et entre ou au sein des entreprises. Nous fournissons un cadre méthodologique qui prend simultanément en compte l'évolution de l'intensité des compétences et du fossé salarial. Les résultats suggèrent que la plupart des changements sont signalés au sein des entreprises, où l'on observe un effet de mise à niveau des compétences non suivi d'un ajustement des prix. Le site l'augmentation de l'emploi relatif des travailleurs qualifiés et la la réduction de l'écart salarial entre les travailleurs hautement qualifiés et les travailleurs peu qualifiés peut être attribuée en grande partie aux changements survenus au sein des exportateurs et importateurs, et dans des entreprises plus productives. Enfin, le document poursuit tient compte de l'évolution de la prime de salaire horaire et de l'intensité des compétences, et il montre que l'écart salarial annuel est induit par une baisse substantielle de la prime de salaire horaire et par une augmentation du nombre d'heures travaillé par le facteur qualifié.

### Chapitre 2

Le deuxième chapitre s'appuie sur le travail commun avec Lionel Fontagné et Angelo Secchi. Nous décrivons une industrie (dans un pays d'origine) où une relation globale, l'ensemble des produits exportés vers un pays de destination par une industrie, est considérée comme le résultat de décisions prises par un groupe fini d'entreprises hétérogènes. Nous montrons que la relation entre la diversification au niveau de l'agrégat et de l'entreprise est influencée par la mesure dans laquelle les

ensembles de produits des entreprises se chevauchent. En particulier, nous montrons que le nombre moyen de chevauchements de produits par entreprise peut être facilement décomposé en trois facteurs : le nombre normalisé d'entreprises exportatrices, le nombre moyen de produits des entreprises - calculé en excluant l'entreprise la plus diversifiée - et un indice de similarité des ensembles de produits. Nous utilisons un échantillon d'exportateurs français entre 1995 et 2011 et calculons la contribution de ces trois composantes à la variation du nombre de chevauchements par entreprise selon les destinations et les industries. La similarité des ensembles de produits représente la moitié de la variation. La distribution de l'étendue moyenne des produits dans les différentes industries-destinations s'avère être significativement affectée par la suppression de l'entreprise la plus diversifiée. Nous calculons les ACR des industries françaises avec et sans le premier exportateur et nous constatons qu'une augmentation de 10% de l'indice de similarité de l'ensemble des produits est associée à une réduction de 3,4% de la probabilité de perdre l'ACR en raison de la suppression du premier exportateur. Nous interprétons ces données comme suggérant que la similarité des ensembles de produits des entreprises reflète la mesure dans laquelle la performance globale de l'industrie est déterminée par des forces fondamentales plutôt que par des forces spécifiques à l'entreprise.

### Chapitre 3

Le troisième chapitre examine en détail le document de travail (non publié) Iodice, 2019. Ce chapitre examine la nature protectrice des réglementations techniques nouvellement introduites qui ne sont pas correctement divulguées au niveau international. Nous commençons par créer une nouvelle base de données qui identifie le processus d'adoption des obstacles techniques au commerce (OTC) qui ont été contestés à l'OMC par le biais d'une préoccupation commerciale spécifique (STC). Nous croisons ensuite cette base de données avec un panel d'exportateurs français au niveau de l'entreprise et nous réalisons une étude des événements. Nous constatons que dans plus d'un tiers des cas étudiés, les pays ont adopté les réglementations sous-jacentes sans avoir préalablement annoncé le changement aux autres membres. Dans ces cas, la nouvelle réglementation entrave les exportateurs en provoquant un arrêt temporaire de leur activité. Cet arrêt dure d'un à deux semestres, et il est plus court dans le cas où le contenu du nouvel OTC est finalement divulgué par les gouvernements. Alors que les grandes entreprises peuvent attendre que davantage d'informations soient disponibles, les petites entreprises quittent le marché. Nous interprétons ces éléments comme suggérant que les pays peuvent effectivement entraver les concurrents étrangers en augmentant l'incertitude sur la rentabilité du marché. Les entreprises ont alors la possibilité de retarder leur décision d'investir ou d'exporter sur ce marché.



## Appendix A

# Appendix 1

### A.1 Checking the consistency of the database

In this appendix we check the representativeness of our dataset with respect to the universe of Italian manufacturing firms. In particular, we check whether the sectoral distribution of Micro.3 is representative of the overall population by using ASIA (Archivio Statistico Imprese Attive) which is the registry of active firms in Italy. In ASIA, firms are classified according to their main activity, as identified by ISTAT's standard codes for sectoral classification of business (5-digit ATECO).

TABLE A.1: Coverage of the dataset: number of firms and percentage by sector (2003)

Sector (Ateco)	Universe		Micro.3	
	Number	(%)	Number	%
Food products and beverages (15)	71,345	13.17	30,843	6.91
Manufacture of textiles (17)	27,762	5.12	35,492	7.96
Wearing apparel (18)	41,615	7.68	26,051	5.84
Tanning & dressing of leather (19)	21,985	4.06	21,891	4.91
Manuf. of wood & cork products (20)	46,584	8.6	11,853	2.66
Manuf. of pulp & paper products (21)	4,566	0.84	10,105	2.27
Recorded media (22)	27,344	5.05	15,181	3.4
Manuf. of coke, petroleum prod (23)	443	0.08	1,499	0.34
Manuf. of chemicals products (24)	6,127	1.13	17,281	3.87
Rubber and plastic products (25)	13,084	2.41	25,933	5.81
Other non-metallic mineral prod. (26)	27,230	5.03	26,840	6.02
Basic metals (27)	3,814	0.7	13,376	3
Fabricated metal products (28)	99,519	18.37	64,938	14.56
Machinery and equipment (29)	42,391	7.82	61,422	13.77
Office machinery and computers (30)	1,976	0.36	1,445	0.32
Electrical machinery (31)	18,316	3.38	20,081	4.5
Radio, tv & communication equip. (32)	8,671	1.6	6,064	1.36
Medical, precision, optical inst. (33)	22,399	4.13	9,738	2.18
Motor vehicles, trailers (34)	1,962	0.36	8,905	2
Other transport equipment (35)	4,684	0.86	5,602	1.26
Manufacturing (36)	50,018	9.23	31,503	7.06
Total	541,835	100	446,043	100
	Two-sample Wilcoxon rank-sum (Mann-Whitney) test			
$z$				-0.340
$Prob >  z $				0.7341

Notes: The Table reports, for 2003, the number and the percentage of firms for the entire population of Italian manufacturing firms and our dataset (Micro.3).

We compute a Wilcoxon-Mann-Whitney test for independence, which is a non-parametric analog to the independent samples t-test and can be used when you do not assume that the dependent variable is a normally distributed interval variable (one has only to assume that the variable is at least ordinal). A large value of the test statistic for the Wilcoxon-Mann-Whitney, indicates that the frequencies observed in the sample is very different from the one observed in the population. Indeed, the distributions of both groups are equal under the null hypothesis. In Table A.1 we report the share of each manufacturing sector in terms of number of firms for the universe of Italian manufacturing firms (ASIA) and the population contained in Micro.3 for 2003. According to the values reported in the table we accept the null hypothesis, that is the distribution of the number of firms in each sector in the sample does not differ from that of the entire population. Indeed, the small values for the Wilcoxon-Mann-Whitney tests confirm that there is a correspondence between the frequencies of the Micro.3 database and the one of the entire population of firms.

### A.1.1 Checking the consistency of the balanced database

In this appendix we check whether we introduce any sample-selection bias when considering the balanced dataset. Table 1.2 shows the number of firms which are sampled each year and those that are active over two consecutive years. On using a balance panel the number of firms in the sample diminishes from 66,387 to 29,173. In Table A.2 we investigate whether the smaller sample, consisting of firms present in both 2003 and 2004, is representative of the whole number of firms operating in 2003.<sup>1</sup> One expects those firms active on a continuous basis to be on average larger: this is because the probability of being sampled for a firm with fewer than 100 employees is lower, and also because larger firms are more likely to survive (Geroski, 1995; Sutton, 1997b). Indeed, the average value of sales, exports and imports is marginally higher in firms that produce in both 2003 and 2004. However, the shares of skilled workers in employment as well as the ratios of the wage rate of skilled workers to the average wage are similar between the two samples. Thus, since our analysis will focus on the wage and skill structure of firms, we should not incur any large selection bias.

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<sup>1</sup>We report here 2003-2004 but figures are comparable in other years.

TABLE A.2: Variables statistics for active and continuous firms

	<i>Active firms</i>			<i>Continuous firms</i>		
	Mean	Sd	Observations	Mean	Sd	Observations
$\ln(\text{Sales})$	9.31	1.36	11,923	9.85	1.32	6,683
$\ln(\text{Export})$	6.13	3.65	11,923	7.07	3.52	6,683
$\ln(\text{Import})$	5.30	3.38	11,923	6.34	3.17	6,683
$\frac{L_{sk}}{L}$	0.29	0.20	11,923	0.31	0.21	6,683
$\frac{\bar{W}_{sk}}{\bar{W}}$	1.43	1.47	11,921	1.46	1.87	6,683

Notes: The Table reports the statistics of some variables' distributions for active firms in 2003 and continuous firms between 2003 and 2004.

### Alternative approaches to the decomposition analysis

This section presents the formula for the decompositions provided by Bernard and Jensen, 1997, Biscourp and Kramarz, 2007 and Manasse and Stanca, 2006. Equations A.1 and A.2 show the decompositions proposed by Bernard and Jensen, 1997, respectively for the skill intensity and the wage bill ratio variations.

$$\Delta \frac{L_{sk}}{L} = \underbrace{\sum_j \Delta \frac{L_{skj}}{L_j} \left( \frac{\bar{L}_j}{\bar{L}} \right)}_{\text{within}} + \underbrace{\sum_j \Delta \frac{L_j}{L} \left( \frac{\bar{L}_{skj}}{\bar{L}_j} \right)}_{\text{between}} \quad (\text{A.1})$$

$$\Delta \frac{WB_{sk}}{WB} = \underbrace{\sum_j \Delta \frac{WB_{skj}}{WB_j} \left( \frac{\bar{WB}_j}{\bar{WB}} \right)}_{\text{within}} + \underbrace{\sum_j \Delta \frac{WB_j}{WB} \left( \frac{\bar{WB}_{skj}}{\bar{WB}_j} \right)}_{\text{between}} \quad (\text{A.2})$$

where  $j$  stays for sector or firm.

Biscourp and Kramarz, 2007 present the decomposition as in equation A.3 where the between and within firms movements are run over each single industry  $s$

$$\Delta \frac{L_{sk_s}}{L_s} = \underbrace{\sum_{i \in s} \Delta \frac{L_{sk_i}}{L_i} \left( \frac{\bar{L}_i}{\bar{L}_s} \right)}_{\text{within}} + \underbrace{\sum_{i \in s} \Delta \frac{L_i}{L_s} \left( \frac{\bar{L}_{sk_i}}{\bar{L}_i} \right)}_{\text{between}} \quad (\text{A.3})$$

The contributions from each industry  $s$  are then aggregated together to obtain an aggregate weighted within component

$$\left( \Delta \frac{L_{sk}}{L} \right)^{wit} = \sum_s \left( \frac{\bar{L}_s}{\bar{L}} \right) \sum_{i \in s} \Delta \frac{L_i}{L_s} \left( \frac{\bar{L}_{sk_i}}{\bar{L}_i} \right) + \sum_s \left( \frac{\bar{L}_s}{\bar{L}} \right) \sum_{i \in s} \Delta \frac{L_{sk_i}}{L_i} \left( \frac{\bar{L}_i}{\bar{L}_s} \right) \quad (\text{A.4})$$

where each industry contribution is weighted according to the industry share in total workforce.

Finally, Manasse and Stanca, 2006 run their decomposition analysis only at the firm level but they nest together the wage bill with employment and wage decompositions as follows

$$\Delta \frac{WB_{sk}}{WB} = \Delta \sum_i \frac{W_{sk_i}}{W} \frac{L_{sk_i}}{L} = \underbrace{\sum_i \Delta \frac{W_{sk_i}}{W} \left( \frac{L_{sk_i}}{L} \right)}_{W_{tot}} + \underbrace{\sum_i \Delta \frac{L_{sk_i}}{L} \left( \frac{W_{sk_i}}{W} \right)}_{L_{tot}} \quad (A.5)$$

where the subscript  $i = 1, \dots, I$  identifies only the firms sampled. They further decompose equation A.5 into the corresponding *within* and *between* components as follows

$$\begin{aligned} W_{tot} &= \sum_i \Delta \frac{W_{sk_i}}{W} \left( \frac{L_{sk_i}}{L} \right) = \\ &= \left[ \underbrace{\sum_i \Delta \frac{W_{sk_i}}{W_i} \left( \frac{W_i}{W} \right)}_{W_{wit}} + \underbrace{\sum_i \Delta \frac{W_i}{W} \left( \frac{W_{sk_i}}{W_i} \right)}_{W_{bet}} \right] \left( \frac{L_{sk_i}}{L} \right) \end{aligned} \quad (A.6)$$

$$\begin{aligned} L_{tot} &= \sum_i \Delta \frac{L_{sk_i}}{L} \left( \frac{W_{sk_i}}{W} \right) = \\ &= \left[ \underbrace{\sum_i \Delta \frac{L_{sk_i}}{L_i} \left( \frac{L_i}{L} \right)}_{L_{wit}} + \underbrace{\sum_i \Delta \frac{L_i}{L} \left( \frac{L_{sk_i}}{L_i} \right)}_{L_{bet}} \right] \left( \frac{W_{sk_i}}{W} \right) \end{aligned} \quad (A.7)$$

### Hourly decomposition by different categories

This section presents the hourly decomposition by categories. Results are in line with what emerges from the annual decomposition. Table A.3 shows that intensive exporters, importers and more productive firms, while rising fast their skill intensity, experience a drop in the hourly wage premium. This fall is even larger than the annual one as in these firms the relative number of hours worked by the skilled factor rise.

TABLE A.3: Hourly decomposition: sub-samples averages by trade activities and productivity

Status	$\overline{WBtot_s^{wit}}$	$\overline{Ltot_s}$	$\overline{Lwit_s}$	$\overline{Lbet_s}$	$\overline{HWtot_s}$	$\overline{HWwit_s}$	$\overline{HWbet_s}$	$\overline{Htot_s}$	$\overline{Hwit_s}$	$\overline{Hbet_s}$	Obs
Hexp	0.187	0.390	0.447	-0.058	-0.562	-0.358	-0.203	0.359	0.098	0.262	14588
Lexp	0.101	0.213	0.145	0.068	-0.063	-0.055	-0.008	-0.050	-0.016	-0.033	14580
Himp	0.048	0.214	0.294	-0.079	-0.506	-0.280	-0.227	0.340	0.105	0.234	14584
Limp	0.243	0.395	0.305	0.090	-0.121	-0.138	0.017	-0.031	-0.024	-0.007	14584
Htfp	0.275	0.611	0.441	0.170	-0.641	-0.351	-0.290	0.305	0.080	0.225	15281
Ltfp	0.014	-0.008	0.152	-0.159	0.017	-0.063	0.079	0.005	0.001	0.004	13887

Notes: all components are annual means averages (%) over the period 2001-2006. *Hexp* (*Himp*): firms that export (import) more than the median value of their sector. *Lexp* (*Limp*): firms those that export (import) less than the median value. *Htfp* (*Ltfp*): firms with a level of TFP above (below) the median value of the sector.

## Appendix B

# Appendix 2

### B.1 Formal Framework

#### A1. Heuristic mechanism

The heuristic mechanism can be written allowing for firm specific share of new products with respect to the existing aggregate product set in the recursive relation, that is

$$|PS|_f = |PS|_{t-1} + (1 - S)_{N-t+1} |ps|_{(N-t+1)} ,$$

where the term  $(1 - S)_{N-t+1}$  is firm specific. Then

$$\begin{aligned} |PS|_N &= |PS|_{N-1} + (1 - S)_1 |ps|_{(1)} \\ &= |ps|_{(N)} + \sum_{t=2}^N (1 - S_{-(N)})_{N-t+1} |ps|_{(t)} . \end{aligned}$$

Comparing this expression with equation (2.2) gives

$$(1 - S) = \sum_{t=2}^N \left( \frac{|ps|_{(f)}}{\sum_t |ps|_{(f)}} \right) (1 - S_{-(N)})_{N-t+1} ,$$

which states that  $(1 - S)$  is the weighted average of the individual firm specific  $(1 - S_{-(N)})_{N-t+1}$  with weights their relative share of varieties among the  $N-1$  least diversified firms.

## A2. Prof of the decomposition in equation (2.3)

Starting from  $OV = \sum_{f=1}^N |ps|_f - |PS|$  simple algebra gives:

$$\begin{aligned}
 OV &= \sum_{f=1}^N |ps|_f - |PS| = |ps|_{(N)} + (N-1) \left( \frac{\sum_{f=1}^{N-1} |ps|_{(f)}}{N-1} \right) - |PS| \\
 &= (N-1) \overline{|ps|}_{-(N)} \left( 1 - \frac{|PS| - |ps|_{(N)}}{(N-1) \text{Avg}(|ps|_{-(N)})} \right) \\
 &= (N-1) \overline{|ps|}_{-(N)} \left( 1 - \frac{|PS| - |ps|_{(N)}}{\sum_{f=1}^{N-1} |ps|_{(f)} + |ps|_{(N)} - |ps|_{(N)}} \right) \\
 &= (N-1) \overline{|ps|}_{-(N)} \left( 1 - \frac{|PS| - |ps|_{(N)}}{\sum_{f=1}^N |ps|_f - |ps|_{(N)}} \right),
 \end{aligned}$$

where  $\overline{|ps|}_{-(N)} = \frac{1}{(N-1)} \sum_{f=1}^{N-1} |ps|_{(f)}$ . Combining this results with the fact that, from equation 2.2,  $(1 - S_{-(N)}) = \left( \frac{|PS| - |ps|_{(N)}}{\sum_{f=1}^N |ps|_f - |ps|_{(N)}} \right)$  gives (2.3).

### Link OV/N with fill ratio

In the following, we derive the relation between the fill ratio of an array and the value of  $OV/N$  of that array. The fill ratio is defined as  $\text{fill ratio} = \frac{\sum |ps|_f}{N|PS|}$ . Then recalling from Equation 2.3 that  $OV = (\sum |ps|_f) - |PS|$ , one obtains:

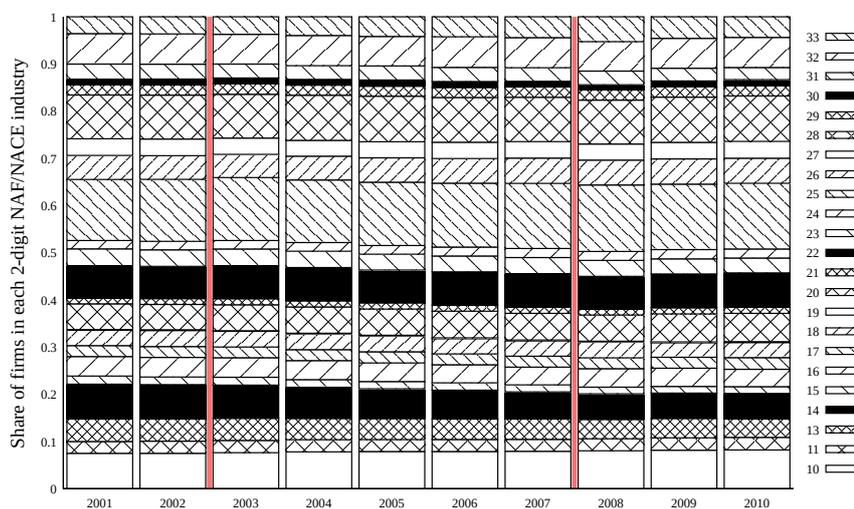
$$\frac{OV}{N} = |PS| \left[ \text{fill ratio} - \frac{1}{N} \right]. \quad (\text{B.1})$$

The larger the fill ratio, the larger the number of products shared by the average firm with all the others. In particular, given a number of active firms and the sum of their product scopes, the maximum (minimum) fill is obtained when  $OV$  is max (minimal), which is also when  $1 - |PS|^* = 1$  ( $1 - |PS|^* = 0$ ). Thus, there is a simple relation that links the concepts of fill ratio with respect to our similarity index.

## B.2 Appendix - Data and definitions

### Effects of revisions in NAF/NACE and HS classifications

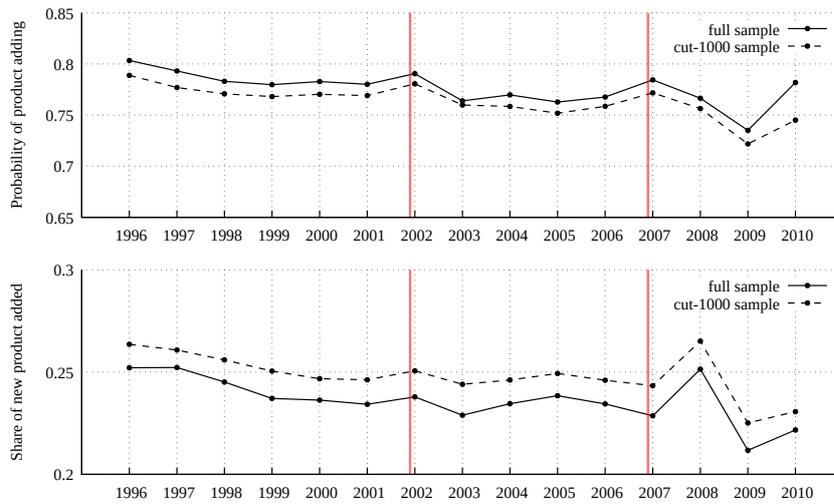
FIGURE B.1: Share of firms active in each NAF/NACE industry over the period 1995-2010



Share of firms active in each NAF/NACE industry over the period 1995-2010. Vertical bars between 2002-2003 and 2007-2008 represent revisions in the classification.

In Figure B.1 we report the time-evolution of the share of firms active in each 2-digit NAF/NACE industry in Manufacturing in France. Red vertical bars signal revisions in the NAF/NACE classification effective from 1 January 2003 and 1 January 2008 respectively. We do not observe any clear discontinuity after either of the two revisions.

FIGURE B.2: Time evolution of the probability of product addin



Time evolution of the probability of product adding and of the share of new product added after harmonizing the HS classifications over the period 1995-2010. Vertical bars in 2002 and 2007 represent revisions in the classification.

In Figure B.2 we report the time-evolution of the probability of adding a new product and the share of new products added by the manufacturing firms in our sample. Red vertical bars signal revisions in the HS classification effective from 1 January 2002 and 1 January 2007 respectively. We do not observe any clear discontinuity after either of the two revisions.

## B.3 Product sets across industries and destinations

### Export value decomposition

TABLE B.2: OLS regression decomposition of French export across industry-destination pairs.

	all destinations	OECD destinations	EU destinations
Firms	0.452 (0.035)	0.387 (0.043)	0.379 (0.043)
Products	0.458 (0.022)	0.383 (0.027)	0.337 (0.031)
Density	-0.338 (0.025)	-0.272 (0.031)	-0.257 (0.030)
Intensive	0.427 (0.032)	0.502 (0.039)	0.541 (0.045)
obs	1,509	667	391

*Notes:* OLS regression decomposition of the variation across industry-destination of French exports along four margins: the unique number of firms, the unique number of products, the density of trade and the intensive margin represented by the average value per observation. Each cell reports the coefficient and standard error of a distinct regression of the log of each margin on the logarithm of the export value. The four coefficients sum to 1 because of the properties of the OLS estimator.

For comparisons with previous works Table B.2 reports results of an OLS regression decomposition of aggregate French trade across industries-destination pairs in 2007. As in Bernard et al., 2009b the margins considered are the number of unique exporters, the number of unique products, the density of trade and the intensive margin measured as the average value per observation. In line with the results found for the US trade in 2003 the three extensive margins account for a significant part (almost 60%) of the variation in overall exports. This result does not change if we restrict the sample covering larger and more homogeneous markets.

### Variability across industries and destinations of $\tilde{N}$ , $\overline{|\text{ps}|}_{-(N)}$ and $S_{-(N)}$

	industry FE	destination FE	industry-destination FE
number of firms index - $\tilde{N}$	19.3%	41.5%	56.8%
Avg. product scope excluding most diversified - $\overline{ \text{ps} }_{-(N)}$	31.7%	25.0%	54.6%
Similarity index - $S_{-(N)}$	34.5%	35.0%	66.3%
obs	1,509	1,509	1,509

Notes: Explanatory power of industry and destination factors for the three components defining the number of product overlaps per firm.

### Histogram of $S_{-(N)}$

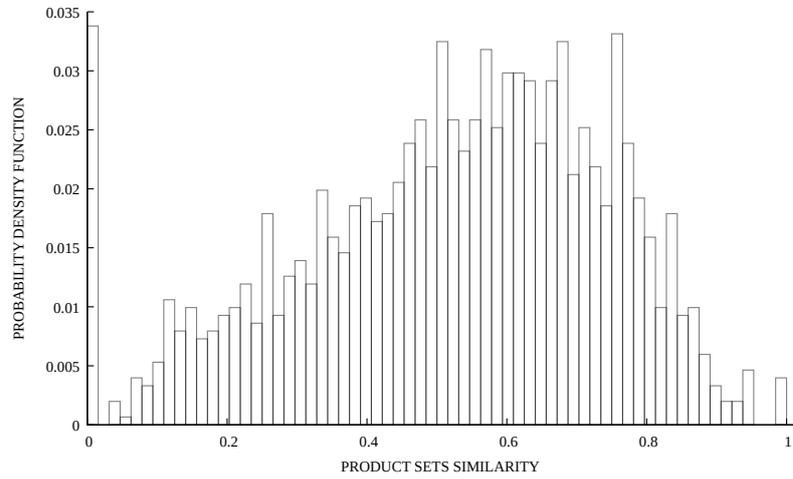


FIGURE B.3: Frequency histogram of the similarity index.

Correlation analysis of  $S_{-(N)}$ 

Dependent variable: $S_{-(N)}$	
	(1)
log(distance)	-0.086*** (0.006)
log(gdp)	0.051*** (0.008)
industry-fe	yes
destination-fe	no
Observations	1,463
Adjusted R <sup>2</sup>	0.546

*Notes:* Standard errors are clustered at the fixed-effects level. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

TABLE B.3: Correlations of the similarity index  $S_{-(N)}$  with industry and destination characteristics.

Table B.3 reports results of two separate regressions. In column (1) we regress the similarity index  $S_{-(N)}$  on the (log) distance and the (log) GDP of a destination country including industry fixed-effects. In column (2) we regress the same dependent variable on the (log) total French export value in an industry including country fixed-effects. Standard errors are clustered at the fixed-effects level.



## Appendix C

# Appendix 3

### C.1 Construction of the Database

#### C.1.1 Procedure to search timestamps in the content of the concern.

The content of the Minutes that we use is a text variable provided in the STC database.<sup>1</sup> The algorithm that parse them look at all possible timestamps contained in the text. We then had to go over them manually to decide whether those dates where indeed the one of interests. In case no relevant dates are provided we label the measures based on the content of the Minutes in 3 ways: (i) 'Y' if the measure is already in force (ii) 'NY' not yet in force and (iii) 'NA' not available. The first case labels those measure that are declared to be in force in the text of the Minutes, even if no specific dates are provided. The second case, labels those measure that are declared to still be under a process of drafting. The third case labels those measure that do not provide sufficient information to distinguish between the above cases. For those measures that are declared in force yet, we assume that the enforcement has occurred in the semester in which the concern has been raised for the first time, since it is plausible that, as no draft is provided, the country is complaining about the entry into force of a new measure.

#### C.1.2 Estimation sample for the (semi)dynamic models

Due to the leads of lags of the treatment indicator in an event study framework, information on the treatment needs to be observed for a longer observation window than for the dependent variable. To identify the window of estimation we follow the guidelines on Data Requirement in Schmidheiny and Siegloch, 2019 "For a given balanced panel of the dependent variable from  $[\underline{s}, \bar{s}]$  and an effect window  $[L, \bar{L}]$ , we need to observe events from  $\underline{s} - \bar{L} + 1$  to  $\bar{s} + |L| - 1$ . If events are derived from changes in policy variables, i.e. treatment status, we need to observe treatment status from  $\underline{s} - \bar{L}$  to  $\bar{s} + |L| - 1$ ". The intuition behind this requirement is the following. Imagine that a technical regulation is introduced in October 1994. When we estimate a (semi)-dynamic model with, for example, three leads after the event ( $l = 3$ ), we are

<sup>1</sup>In Figure C.1 you can find an example of the extracted text associated to a concern.

assuming that there are short term effects up to three semesters from the introduction. This means that we follow those market up to the first semester of 1996, including them in the treated group. If we do not have information on regulation before 1995, then, we can not distinguish, at the beginning of our sample, those market that are still experiencing short term effects from those that are not. To avoid this, we will estimate our model on the window starting from  $s = 3$ , after all unobservable post effects have faded away."

## C.2 Baseline Tables

TABLE C.1: Dynamic and semi-dynamic model estimates

	(1) Export	(2) Export	(3) Export	(4) Exit	(5) Exit	(6) Exit
$L_{HS4,d,t}^{AnnouncedTBT} = 3$	0.104 (0.126)		0.118 (0.126)	0.0156 (0.0159)		0.0132 (0.0158)
$L_{HS4,d,t}^{AnnouncedTBT} = 2$	-0.0463 (0.112)		-0.0430 (0.111)	0.00950 (0.0210)		0.00950 (0.0209)
$L_{HS4,d,t}^{AnnouncedTBT} = 1$	-0.0616 (0.111)		-0.0589 (0.111)	0.0876 <sup>a</sup> (0.0310)		0.0883 <sup>a</sup> (0.0308)
$L_{HS4,d,t}^{AnnouncedTBT} = 0$	0.431 <sup>b</sup> (0.193)	0.232 <sup>b</sup> (0.111)	0.435 <sup>b</sup> (0.193)	-0.0163 (0.0145)	-0.00933 (0.0123)	-0.0158 (0.0145)
$L_{HS4,d,t}^{SurpriseTBT} = 3$	0.0300 (0.161)		0.0308 (0.176)	0.000337 (0.0271)		0.0131 (0.0296)
$L_{HS4,d,t}^{SurpriseTBT} = 2$	-0.173 (0.146)		-0.172 (0.161)	0.0493 (0.0423)		0.0756 (0.0490)
$L_{HS4,d,t}^{SurpriseTBT} = 1$	-0.204 (0.133)		-0.207 (0.139)	0.0201 (0.0986)		0.0171 (0.106)
$L_{HS4,d,t}^{SurpriseTBT} = 0$	-0.366 <sup>b</sup> (0.150)	-0.271 <sup>c</sup> (0.147)	-0.504 <sup>a</sup> (0.130)	0.00388 (0.0323)	0.0393 (0.0315)	-0.00491 (0.0334)
$K_{HS4,d,t}^{AnnouncedTBT} = 3$		-0.0374 (0.124)	-0.0421 (0.136)		0.0386 (0.0291)	0.0530 (0.0303)
$K_{HS4,d,t}^{AnnouncedTBT} = 2$		-0.0222 (0.115)	0.0475 (0.124)		-0.0112 (0.0178)	-0.0176 (0.0283)
$K_{HS4,d,t}^{AnnouncedTBT} = 1$		0.111 (0.127)	0.100 (0.121)		0.0227 (0.0153)	0.0402 (0.0267)
$K_{HS4,d,t}^{SurpriseTBT} = 3$		-0.218 (0.117)	-0.354 (0.195)		0.0399 <sup>b</sup> (0.0190)	0.0634 (0.0525)
$K_{HS4,d,t}^{SurpriseTBT} = 2$		-0.0576 (0.151)	-0.360 (0.217)		-0.0793 <sup>b</sup> (0.0333)	0.00273 (0.0568)
$K_{HS4,d,t}^{SurpriseTBT} = 1$		-0.175 (0.120)	-0.294 (0.210)		0.0181 (0.0167)	0.0260 (0.0288)
asinh(tariff)	-0.0554 <sup>a</sup> (0.00220)	-0.0502 <sup>a</sup> (0.00214)	-0.0528 <sup>a</sup> (0.00237)	0.00148 <sup>a</sup> (0.000508)	0.000767 (0.000493)	0.00120 <sup>b</sup> (0.000542)
Obs.	3617360	3666606	3069085	2231765	2262662	1972190
adj. R <sup>2</sup>	0.260	0.262	0.261	0.116	0.116	0.116
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
HS2-Country-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes:  $L$  represents the lags, while  $K$  the leads, before and after the introduction of a TBT, respectively. The superscript *Antic* and *Surp* are used to distinguish the two types of TBT. Model (1) and (4) are semi dynamic backward models, (2) and (5) are semi dynamic forward model while (3) and (6) are dynamic models. Cols (3) and (6) are the estimates of Fig. 3.7 and 3.8. Export is in log. Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 since exit is defined for firms that have exported at least two subsequent periods. levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

### C.3 Motivation Table

Data is aggregated at the  $HS4, d, t$  level, which is summing exports value across firms. We then run the following specification:

$$y_{HS4,d,t} = \sum_{l=-B}^{-1} (\alpha_l \mathbb{1}[L_{HS4,d,t}^{AnnouncedTBT} = l] + \beta_l \mathbb{1}[L_{HS4,d,t}^{SurpriseTBT} = l]) + \sum_{k=0}^{A+1} (\alpha_k \mathbb{1}[K_{HS4,d,t}^{AnnouncedTBT} = k] + \beta_k \mathbb{1}[K_{HS4,d,t}^{SurpriseTBT} = k]) + \delta \text{asinh}(\text{tariff}_{HS4,d,t}) + \mu_{HS4,t} + \epsilon_{HS4,d,t}, \quad (C.1)$$

where the variables are as defined for the full dynamic specification of 3.4. Note that here the model includes ( $HS4, d$ ) fixed effects and therefore exploits time variability within markets.

TABLE C.2: Coefficients plotted in 3.7 Dynamic specification

$L_{HS4,d,t}^{AnnouncedTBT} = -4$	0.0877 (0.0545)	$L_{HS4,d,t}^{SurpriseTBT} = -4$	-0.205* (0.104)
$L_{HS4,d,t}^{AnnouncedTBT} = -3$	0.0247 (0.0554)	$L_{HS4,d,t}^{SurpriseTBT} = -3$	-0.000434 (0.103)
$L_{HS4,d,t}^{AnnouncedTBT} = -2$	0.125* (0.0575)	$L_{HS4,d,t}^{SurpriseTBT} = -2$	0.0859 (0.0917)
$L_{HS4,d,t}^{AnnouncedTBT} = -1$	0.00353 (0.0591)	$L_{HS4,d,t}^{SurpriseTBT} = 1$	0.275** (0.0920)
$L_{HS4,d,t}^{AnnouncedTBT} = 0$	-0.0149 (0.0618)	$L_{HS4,d,t}^{SurpriseTBT} = 0$	-0.295*** (0.0841)
$L_{HS4,d,t}^{AnnouncedTBT} = 1$	0.0918 (0.0695)	$L_{HS4,d,t}^{SurpriseTBT} = 1$	-0.250** (0.0819)
$L_{HS4,d,t}^{AnnouncedTBT} = 2$	0.0776 (0.0716)	$L_{HS4,d,t}^{SurpriseTBT} = 2$	-0.112 (0.0807)
$L_{HS4,d,t}^{AnnouncedTBT} = 3$	-0.127 (0.0738)	$L_{HS4,d,t}^{SurpriseTBT} = 3$	0.0127 (0.0820)
$L_{HS4,d,t}^{AnnouncedTBT} = 4$	-0.0232 (0.0745)	$L_{HS4,d,t}^{SurpriseTBT} = 4$	-0.0185 (0.0818)
N			593490
adj. $R^2$		0.771	

Notes: Estimates are shown in two columns but all coefficients are estimated within the same specification as in eq C.1. HS4-Country FE and Tariff level are included.  $L$  represents the lags, while  $K$  the leads, before and after the introduction of a TBT, respectively. The superscript *Antic* and *Surp* are used to distinguish the two types of TBT. Significance levels:  $c < 0.1$ ,  $b < 0.05$ ,  $a < 0.01$ .

TABLE C.3: Effects of Announced vs Surprise measures - Population of French exporters

DEPENDENT VARIABLE	Export <sub>t</sub>		Exit <sub>t</sub>		Exit <sub>s-1</sub>	
	(1)	(2)	(3)	(4)	(5)	(6)
TBT	0.08 (0.09)		0.02 (0.02)		0.05 <sup>b</sup> (0.02)	
SurpriseTBT		-0.24 <sup>a</sup> (0.09)		0.02 (0.01)		-0.01 (0.02)
AnnouncedTBT		0.13 (0.08)		-0.00 (0.01)		0.06 <sup>b</sup> (0.03)
asinh(tariff)	-0.05 <sup>a</sup> (0.00)	-0.05 <sup>a</sup> (0.00)	0.00 <sup>a</sup> (0.00)	0.00 <sup>a</sup> (0.00)	0.00 (0.00)	0.00 (0.00)
Obs.	8,167,539	8,167,539	4,560,835	4,560,835	4,378,804	4,378,804
Adj. R2	0.32	0.32	0.28	0.28	0.28	0.28
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
HS2-Country-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Export is in log, so the marginal effect of a dummy reads  $100(e^\beta - 1)\%$ , with  $\beta$  being the coefficient on the dummy. Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 since who exits does not export in the period. Significance levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

TABLE C.4: Effects of Announced vs Surprise measures - Excluding Regulations on HS6

DEPENDENT VARIABLE	Export <sub>t</sub>	Exit <sub>t</sub>	Exit <sub>s-1</sub>
	(1)	(2)	(3)
SurpriseTBT	-0.25 <sup>a</sup> (0.10)	0.49 <sup>a</sup> (0.02)	-0.01 (0.02)
AnnouncedTBT	0.20 (0.14)	-0.00 (0.01)	0.10 <sup>a</sup> (0.04)
asinh(tariff)	-0.05 <sup>a</sup> (0.00)	0.00 (0.00)	0.00 (0.00)
Obs.	4,017,721	8,167,539	4,560,835
Adj. R2	0.29	0.30	0.18
Firm FE	Yes	Yes	Yes
HS2-Country-Time FE	Yes	Yes	Yes

Notes: Export is in log, so the marginal effect of a dummy reads  $100(e^\beta - 1)\%$ , with  $\beta$  being the coefficient on the dummy. Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 since who exits does not export in the period. Significance levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

## C.4 Robustness checks Tables

**Alternative definition of exit** In our exercise, the time dimension is crucial, since we aim at capturing short term effects. Our definition of exit, instead, collapse past, present and future choices of firms into a single value. An exiting firm is one who chooses to exit today, as well as chooses to stay out of the  $HS4, d$  market in the next 2 semesters. We here test alternatives definition of exit. To investigate the possibility of a short halt we define a "short exit" by looking only one period ahead: firms exit a market if they are present today but not in the next semester. We then investigate a "long exit": firms exit a market if they are not present for the next 3 semesters. Moreover, according to our definition of exit, an active exporter is one that has exported in the market consecutively in the last two semesters. In very seasonal markets, such as the air conditioning in Mexico discussed above, we have less active firms. We then define a "Seasonal Exit" if the firm had exported at least once between today and the last semester (once in the full year) while not in the full next one (short seasonal exit) or two (long seasonal exit). Across the board of Table C.11 we observe that the only variable which is highly significant for all four alternative definitions of exit is the dummy that identifies one period before the introduction of an Announced TBT. The estimates become even larger when defining longer exit, up to around 9%, suggesting that once a firm decide not to comply with a certain regulation it will stay out from that market for long.

TABLE C.5: Export, alternative set of fixed effects

	(1) Export	(2) Export	(3) Export
SurpriseTBT	-0.267 <sup>b</sup> (0.137)	-0.299 <sup>a</sup> (0.142)	-0.178 <sup>a</sup> (0.0687)
AnnouncedTBT	0.230 <sup>b</sup> (0.111)	0.216 (0.131)	0.188 <sup>a</sup> (0.0713)
asinh(tariff)	-0.0527 <sup>a</sup> (0.00201)	-0.108 <sup>a</sup> (0.00232)	-0.0179 <sup>a</sup> (0.00176)
<i>N</i>	4214856	4215092	4249924
adj. $R^2$	0.261	0.094	0.221
Firm FE	Yes	No	Yes
HS2-Country-Time	Yes	Yes	No
Country-Time FE	No	No	Yes

*Notes:* Export is in log. Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 since exit is defined for firms that have exported at least two subsequent periods. levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

TABLE C.6: Exit, alternative set of fixed effects

	(1) Exit <sub>s-1</sub>	(2) Exit <sub>s-1</sub>	(3) Exit <sub>s-1</sub>
SurpriseTBT	0.00356 (0.0615)	0.00674 (0.0639)	-0.0121 (0.0221)
AnnouncedTBT	0.0542 <sup>a</sup> (0.0198)	0.0550 <sup>a</sup> (0.0191)	0.0396 <sup>a</sup> (0.0114)
asinh(tariff)	0.00143 <sup>a</sup> (0.000484)	0.00143 <sup>a</sup> (0.000459)	-0.000388 (0.000333)
<i>N</i>	2424981	2429888	2456379
adj. <i>R</i> <sup>2</sup>	0.114	0.034	0.097
Firm FE	Yes	No	Yes
HS2-Country-Time	Yes	Yes	No
Country-Time FE	No	No	Yes

*Notes:* Standard errors in parenthesis are clustered at (HS4,country,time). The observations in cols 3 and 4 are larger than in 1 and 2 because of automatic drop of singletons. levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

#### C.4.1 Negative weighing

TABLE C.7: Export, exclusion of TBTs by the coverage share of the fixed effect

	(1)	(2)	(3)	(4)
	Export	Export	Export	Export
SurpriseTBT	-0.273 <sup>b</sup> (0.137)	-0.256 <sup>c</sup> (0.139)	-0.268 <sup>c</sup> (0.140)	-0.256 <sup>c</sup> (0.147)
AnnouncedTBT	0.241 <sup>b</sup> (0.113)	0.246 <sup>b</sup> (0.114)	0.267 <sup>b</sup> (0.116)	0.290 <sup>b</sup> (0.123)
asinh(tariff)	-0.053 <sup>a</sup> (0.002)	-0.053 <sup>a</sup> (0.002)	-0.053 <sup>a</sup> (0.002)	-0.053 <sup>a</sup> (0.002)
<i>N</i>	4212139	4211987	4211893	4211524
adj. <i>R</i> <sup>2</sup>	0.261	0.261	0.261	0.261

*Notes:* Cols represents estimation of the static specification over a sample of TBTs that cover no more than 90% (1), 80% (2), 70% (3) and 60% (4) observations within the *HS2, d, t* category. Export is in log. Standard errors in parenthesis are clustered at (HS4, country, time). Significance level: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

TABLE C.8: Exit, exclusion of TBTs by the coverage share of the fixed effect

	(1)	(2)	(3)	(4)
	Exit <sub>s-1</sub>	Exit <sub>s-1</sub>	Exit <sub>s-1</sub>	Exit <sub>s-1</sub>
SurpriseTBT	0.003 (0.061)	0.002 (0.062)	0.005 (0.063)	0.003 (0.065)
AnnouncedTBT	0.055 <sup>a</sup> (0.0200)	0.056 <sup>a</sup> (0.0202)	0.055 <sup>a</sup> (0.0204)	0.058 <sup>a</sup> (0.0213)
asinh(tariff)	0.00141 <sup>a</sup> (0.0005)	0.00141 <sup>a</sup> (0.0005)	0.00141 <sup>a</sup> (0.0005)	0.00141 <sup>a</sup> (0.0005)
<i>N</i>	2,423,222	2,423,120	2,423,059	2,422,839
adj. <i>R</i> <sup>2</sup>	0.114	0.114	0.114	0.114

*Notes:* Cols represents estimation of the static specification over a sample of TBTs that cover no more than 90% (1), 80% (2), 70% (3) and 60% (4) observations within the *HS2, d, t* category. Export is in log. Standard errors in parenthesis are clustered at (HS4, country, time). Significance level: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

FIGURE C.1: Example of the format of the Notification

<b>WORLD TRADE ORGANIZATION</b>	G/TBT/N/ARG/101 23 May 2003 (03-2765)
Committee on Technical Barriers to Trade	Original: Spanish
<b>NOTIFICATION</b>	
The following notification is being circulated in accordance with Article 10.6.	
<b>1.</b>	<b>Member to Agreement notifying:</b> ARGENTINA <b>If applicable, name of local government involved (Articles 3.2 and 7.2):</b>
<b>2.</b>	<b>Agency responsible:</b> National Institute of Vitiviniculture <b>Name and address (including telephone and fax numbers and E-mail and Web site addresses, if available) of agency or authority designated to handle comments regarding the notification shall be indicated if different from above:</b> <i>Idem</i> National Enquiry Point
<b>3.</b>	<b>Notified under Article 2.9.2 [ X ], 2.10.1 [ ], 5.6.2 [ ], 5.7.1 [ ], other:</b>
<b>4.</b>	<b>Products covered (HS or CCCN where applicable, otherwise national tariff heading, ICS numbers may be provided in addition, where applicable):</b> Wine
<b>5.</b>	<b>Title, number of pages and language(s) of the notified document:</b> Wine – Sulphate Content (2 pages, in Spanish)
<b>6.</b>	<b>Description of content:</b> Establishes the maximum limits for sulphate content, expressed as potassium sulphate, both in wine that is in circulation and in wineries.
<b>7.</b>	<b>Objective and rationale, including the nature of urgent problems where applicable:</b> The need to establish, as an exporting country, the appropriate limits for these products through essential production and conservation techniques, as laid down by the International Organization of Vine and Wine (OIV).
<b>8.</b>	<b>Relevant documents:</b> INV Resolution No. 14/2003
<b>9.</b>	<b>Proposed date of adoption:</b> 30 April 2003 (Official Journal) <b>Proposed date of entry into force:</b> 8 May 2003
<b>10.</b>	<b>Final date for comments:</b> -
<b>11.</b>	<b>Texts available from: National enquiry point [X], or address, telephone and fax numbers and E-mail and Web site addresses, if available, of other body:</b> Punto Focal de la República Argentina Dirección Nacional de Comercio Interior (DNCI) Avda. J. A. Roca 651, Piso 4º, Sector 22 (1322) Buenos Aires Fax: 54 11 4349 4072 Tel.: 54 11 4349 4067 E-mail: <a href="mailto:focalote@mecon.gov.ar">focalote@mecon.gov.ar</a> Web site: <a href="http://www.puntofocal.gov.ar">http://www.puntofocal.gov.ar</a>

TABLE C.10: Testing equality of coefficient between unnotified and late notified at the enforcement time

	Export
$SurpriseTBT_{HS4,d,t-1,k=1}^{LN}$	-0.279 <sup>a</sup> (0.0617)
$SurpriseTBT_{HS4,d,t-1,k=1}^{UN}$	-0.263 <sup>c</sup> (0.127)
asinh(tariff)	-0.0527 <sup>a</sup> (0.00225)
Obs.	4,214,856
adj. $R^2$	0.261
Firm FE	Yes
HS2-Country-Time FE	Yes

*Notes:* P-value under the equality of the coefficients for  $SurpriseTBT_{s-1,k=1}^{LN}$  and  $SurpriseTBT_{s-1,k=1}^{UN}$  is 0.8983.  $K$  represents the leads, with  $k = 1$  being one period ahead. Since the variables of interest are lagged ( $s - 1$ ), they estimates the effect of a SurpriseTBT in the period of enforcement, distinguishing between those TBTs that will be notified by the next semester, denoted with subscript  $LN$  and those that will not, denoted with subscript  $UN$ . Significance levels: <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

TABLE C.11: Alternative definitions of exit

	(1) Short	(2) Long	(3) Short Seasonal	(4) Long Seasonal
$L_{HS4,d,t}^{AnnouncedTBT} = 3$	0.0185 (0.0171)	0.0172 (0.0171)	0.0219 (0.0158)	0.0218 (0.0165)
$L_{HS4,d,t}^{AnnouncedTBT} = 2$	-0.0249 (0.0167)	0.0280 (0.0223)	0.0253 (0.0172)	0.0331 <sup>b</sup> (0.0168)
$L_{HS4,d,t}^{AnnouncedTBT} = 1$	0.0571 <sup>b</sup> (0.0222)	0.0886 <sup>a</sup> (0.0328)	0.0691 <sup>a</sup> (0.0253)	0.0700 <sup>a</sup> (0.0264)
$L_{HS4,d,t}^{AnnouncedTBT} = 0$	-0.0148 (0.0168)	-0.0234 (0.0149)	0.0314 (0.0191)	0.0199 (0.0196)
$K_{HS4,d,t}^{AnnouncedTBT} = 1$	-0.00918 (0.0243)	-0.000682 (0.0281)	0.0118 (0.0199)	0.00527 (0.0199)
$K_{HS4,d,t}^{AnnouncedTBT} = 2$	0.0255 (0.0269)	-0.0169 (0.0276)	0.0280 (0.0213)	0.0325 (0.0180)
$K_{HS4,d,t}^{AnnouncedTBT} = 3$	0.0401 (0.0243)	0.00903 (0.0267)	0.0545 <sup>b</sup> (0.0227)	0.0547 <sup>b</sup> (0.0243)
$L_{HS4,d,t}^{SurpriseTBT} = 3$	-0.0566 (0.0338)	0.0603 <sup>b</sup> (0.0265)	-0.0463 (0.0370)	-0.0229 (0.0342)
$L_{HS4,d,t}^{SurpriseTBT} = 2$	0.0153 (0.0336)	0.0494 (0.0306)	0.00433 (0.0297)	0.00398 (0.0336)
$L_{HS4,d,t}^{SurpriseTBT} = 1$	-0.00702 (0.0707)	0.0284 (0.115)	0.0179 (0.0645)	0.0430 (0.0479)
$L_{HS4,d,t}^{SurpriseTBT} = 0$	0.0107 (0.0225)	0.0296 (0.0309)	0.0491 (0.0382)	0.0234 (0.0436)
$K_{HS4,d,t}^{SurpriseTBT} = 1$	-0.0242 (0.0378)	0.0415 (0.0423)	-0.0207 (0.0313)	-0.0199 (0.0358)
$K_{HS4,d,t}^{SurpriseTBT} = 2$	-0.0327 (0.0603)	0.0399 (0.0540)	0.0562 (0.0386)	0.0231 (0.0324)
$K_{HS4,d,t}^{SurpriseTBT} = 3$	0.0283 (0.0389)	0.0388 (0.0260)	0.0310 (0.0243)	0.0364 (0.0230)
asinh(tariff)	0.00289 <sup>a</sup> (0.0005)	0.00111 <sup>a</sup> (0.0005)	0.00183 <sup>a</sup> (0.0004)	0.00155 <sup>a</sup> (0.0005)
N	3370080	1523284	4673742	4673742
adj. R <sup>2</sup>	0.101	0.121	0.090	0.091
Firm FE	Yes	Yes	Yes	Yes
HS2-Country-Time FE	Yes	Yes	Yes	Yes

Notes: *L* represents the lags, while *K* the leads, before and after the introduction of a TBT, where the subscript *Antic* and *Surp* are used to distinguish the two types of TBT. Short Exit is defined Standard errors in parenthesis are clustered at (HS4,country,time). The number of observations in cols change depending on the definition of exit, since . Significance level is <sup>c</sup> < 0.1, <sup>b</sup> < 0.05, <sup>a</sup> < 0.01.

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