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Essays On International Trade

PhD Thesis submitted by

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Abstract

This dissertation comprises three empirical essays on international trade.

Chapter One investigates how countries transition into non-traditional exports, a key driver of economic development. This study uses cross-country export data from 1990 to 2010 to examine how different Marshallian linkages—technology, labor, suppliers, and customers—affect the take-off and acceleration of export industries across sectors. The findings reveal that countries primarily diversify into technologically-related products, with developing nations expanding upstream rather than through downstream processing. This challenges the idea that developing countries should diversify by adding value to their raw materials. Instead, it supports Albert Hirschman's 60-year-old theory that upstream linkages are the key drivers behind the development of new competitive industries in the developing world.

Chapter Two examines how trade regulations shape firm-level export decisions in international markets. The analysis quantifies the effects of non-tariff measures (NTMs) on Colombian firms exporting to Latin America from 2007-2017. Panel evidence from a firm-level gravity model with difference-in-differences shows technical barriers to trade (TBT) and quantity control measures reduce trade overall, while other NTMs and tariffs have minimal impact. TBT measures shift trade from small to large firms and benefit global value chain participants. Conversely, quantity controls drive large firms from export markets, benefiting smaller ones. The results highlight that NTMs are more trade-restrictive than tariffs and that large firms benefit from protectionism, not globalization.

Chapter Three examines how trade policy shapes firm-level import decisions to source green technologies that are critical to mitigating climate change. Using firm-level import data from 35 emerging markets in a structural gravity model, this study analyzes how tariffs and trade regulations affect firms' imports of products associated with the green value chains of solar photovoltaic, wind power and electric vehicles. The panel estimates indicate that firms' import response to tariffs is particularly adverse for products associated with green value chains relative to average imports, driven by the solar value chain and downstream segments across all green value chains. Tariffs undermine not only the dollar value of firms' imports but also whether they import at all. Moreover, the effect is even more negative for undiversified firms. In contrast, trade regulations have a smaller and more varied impact on firms' imports of products associated with green value chains. The findings suggest that governments in emerging markets should avoid adopting protectionist policies that are increasingly used in high-income countries, as their local firms rely on imports for the short-term diffusion of green technologies.

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I had just arrived in Washington DC to start my new job at the World Bank when the pandemic hit. It allowed me to work from Rwanda for the next two years, with my wife Isabella and the opportunity to take the rest of my Ph.D. classes online. My work in East Africa also allowed me to observe and think deeply about the political economy of reform, neocolonialism, climate change, and the role of the private sector. This intellectual journey would not have been as complete without Faustin Nyangezi Rwamfizi in Kigali.

My next work assignment took me to Mexico City. Driven by nearshoring trends and accelerating climate change, my research expanded to examine strategies for diffusing decarbonization technologies beyond manufacturing centers, the focus of my final Ph.D. chapter. In Mexico, I was fortunate enough to reconnect with Ernesto Stein, my former supervisor at the Research Department of the Inter-American Development Bank. Ernesto, one of my co-authors in Chapter One, has been a role model and an unfailing source of advice, both academically and professionally.

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Introduction

How can trade promote pathways to development, understood as freedom or the ability of people have to realize their potential (Sen, 1999)? This question has guided my intellectual and professional journey as a development economist. It is also the guiding question of my dissertation.

My background offers a case study that highlights the implications of this question. Although I am originally from Berlin, Germany, once the proud world export champion, my interest in this field led me to Bolivia and Uganda. In these landlocked countries, I saw first-hand how limited access to markets puts producers at a disadvantage, preventing the deployment of modern technologies at a profitable scale. This experience challenged my views on development theory, which often emphasizes supply-side factors in poverty reduction and economic growth. I began to critically assess many of its policies, including those addressing market failures, enhancing institutions, investing in infrastructure and human capital. At the same time, I reinforced my belief in the importance of overcoming demand constraints, particularly for small-population countries, and in the value of solutions like expanding market access through greater integration with the global economy.

However, the increasing automation and the backlash against globalization are making this export-led model of industrialization less viable. While global market integration boosted demand for producers, it also intensified supply-side competition. China's entry into the global economy exemplified the competitive pressures faced by manufacturing firms in many low- and middle-income countries, often leading to reduced operations or closure. I witnessed these challenges firsthand during trade negotiations at the Council of the European Union and in Mexico, where trade liberalization has not led to improved firm performance. Instead, it has contributed to misallocation of resources and increased informality. These examples underscore that the benefits of market integration have been more uncertain than anticipated, fueling political retrenchment and economic nationalism.

New visions of how trade can further development have emerged. These include expanding trade in services, which has the potential to generate productivity gains and labor demand. Business and IT services in particular exhibit characteristics that could help emulate manufacturing-led development. Moreover, enhancing market access by focusing on regional supply chains provides an appealing alternative to waning multilateralism. Nearshoring and other de-risking strategies for trade with political allies attest to this trend. Finally, constraints to scale economies and hence market size highlight the need to complement demand by broadening the domestic middle class. Besides foreign sales, local consumers can help cover the initial fixed costs of new businesses and technologies, generate profits, and lay the foundation for trade to serve as a vehicle to development.

The range of topics in the three essays in this dissertation reflects my attempts to study how trade can provide pathways for development. In these essays, I have sought to be sensitive to the role played by this development discourse, including on climate change – the result of the greatest market failure the world has seen. Moreover, I highlight the importance of relatedness in capturing the dynamic process through which countries add new, related products to their exports. That aligns with long-held intuition that the structure of industries in an economy can predict future economic activities, helping to formalize path dependencies. Finally, underlying my dissertation is my belief that trade (policy) should facilitate scale economies, which is critical for supporting the growth of expanding industries.

Chapter One explores the channels that explain export competitiveness across countries and industries. Exploring what and to whom countries export has been a longstanding challenge for economists, dating back to David Ricardo's 19th-century concept of comparative advantage. This idea suggests that countries export what they are relatively good at to import what they are relatively bad at. Achieving export competitiveness, however, is a gradual and path-dependent process: a country's comparative advantage tomorrow depends on its advantage today. To unpack the channels behind the evolution of comparative advantage, we combine cross-country export data between 1990–2010 with measures of Marshallian linkages across industries related to technology, labor, suppliers, and customers. We find that countries tend to diversify toward technologically-related products. Moreover, developing countries tend to diversify upstream of current exports, not through downstream processing. This challenges the idea that developing countries should diversify by adding value to their raw materials.

As important as customer linkages are for export competitiveness in developing countries, firms increasingly have to contend with trade regulations to access foreign markets. Chapter Two studies how non-tariff measures (NTMs), a key instrument of government trade policy, shape firm-level export decisions. Focusing on specific types of NTMs, I quantify their relative importance and heterogeneous effects for Colombians firms exporting to Latin America between 2007 and 2017. Using panel evidence from a firm-level gravity model with a difference-in-differences identification strategy, technical barriers to trade (TBT) and quantity control measures both decrease trade on average. Other NTM types and tariffs play a minor role. At its core, TBT and quantity measures reallocate trade from small to big firms. The same mechanism benefits firms participating in global value chains. However, quantity controls make it more likely that big firms will leave export markets to the benefit of smaller ones. The results highlight that NTMs are more restrictive than tariffs and that big firms benefit from protectionism, not globalization.

While exports remain a key development pathway, the global shift to a low-carbon economy requires the adoption of green technologies beyond their production centers. For many developing countries, importing these technologies is the primary means of adoption, making trade policy a critical yet understudied lever in the green transition. Chapter Three examines how trade policies influence firms' decisions to import green technologies. Using firm-level import data from 35 emerging markets in a structural gravity model, this study analyzes how tariffs and trade regulations affect firms' imports of products associated with the green value chains of solar photovoltaic, wind power and electric vehicles. The study finds that firms' import response to tariffs is particularly adverse for products associated with green value chains relative to average imports, driven by the solar value chain and downstream segments across all green value chains. In contrast, trade regulations have a smaller, yet more varied impact.

The study reveals a tension between decarbonization goals and economic security that manifests differently across development levels. High-income economies, particularly the EU and US, are adopting protectionist policies to reduce dependence on China's dominance in green technologies. However, these policies risk raising adoption costs and hindering decarbonization efforts. In contrast, developing countries that rely heavily on imports for green technology adoption would find such protectionist policies counterproductive given their limited domestic manufacturing capacity. Instead, these countries should focus on preferential trade agreements and tariff reductions to accelerate green technology adoption, a strategy that better supports their decarbonization goals than prioritizing costly domestic production.

Chapter 1

Export Take-offs and Acceleration: Unpacking Cross-sector Linkages in the Evolution of Comparative Advantage[1]

1.1 Introduction

The transition to non-traditional export activities is attracting considerable policy and academic attention.[2] By and large, the classical literature on international trade tends to focus on studying country and industry specific characteristics as the main determinants of comparative advantage, perceived to be independent of the existence of other industries, beyond the obvious general equilibrium effects.[3] Yet, at

[1]Bahar, Dany, Samuel Rosenow, Ernesto Stein and Rodrigo Wagner (2019). "Export Take-Offs and Acceleration: Unpacking Cross-Sector Linkages in the Evolution of Comparative Advantage". *World Development* 117, pp. 48-60, 10.1016/j.worlddev.2018.12.01, licensed under © 2019 Elsevier Ltd. All rights reserved.

[2]In the academic literature, the diversification towards new export industries is commonly associated with economic development, macroeconomic stability as well as market access. For references on the relationship between diversification and economic development, see, for example, Imbs and Wacziarg (2003), Hausmann et al. (2007), and Cadot et al. (2011). Furthermore, Rodrik (2016) argues that reductions in diversification, such as those induced by premature deindustrialization, can jeopardize the process of economic development, for example because they prevent unconditional convergence in manufacturing (Rodrik, 2012). In this vein, Hartmann et al. (2017) show that export complexity can be associated with decreases in inequality. For important reviews of this policy debate, see Hirschman (1968) and Rodrik (2008). For effects on macroeconomic stability, see, for example, Krishna and Levchenko (2009), Koren and Tenreyro (2007), Caselli et al. (2020), and Hausmann et al. (2006). For links between diversification and market access see Nicita and Rollo (2015), Hoekman and Nicita (2011), and Fugazza and Nicita (2013).

[3]This literature focuses on studying changes in export baskets as a result of changes in the relative abundance of factor endowments (e.g. Heckscher and Ohlin, 1991; Romalis, 2004; Bernhofen et al., 2016) or changes in (mostly exogenous) productivity parameters (e.g., Ricardo, 1821; Eaton and Kortum, 2002; Melitz, 2003; Costinot et al., 2012). It typically takes the development of the comparative advantage of a single country industry as independent of other industries within the same country.

least since Hirschman (1958),[4] scholars have recognized that the evolution of competitive industries may evolve over time through *linkages* to other existing economic activities. Our paper contributes to this literature by empirically analyzing how alternative types of linkages can explain the dynamics in a country's export basket.

A large body of empirical literature shows that the emergence and growth of economic activities relates to the presence of incumbent industries in the same unit: a country (e.g., Hausmann and Klinger, 2006; Hausmann and Hidalgo, 2011; Hidalgo et al., 2007; Boschma and Capone, 2015), a sub-national region (e.g., Ellison and Glaeser, 1997; Neffke et al., 2011; Delgado et al., 2016; Balland et al., 2018) or even a firm (e.g., Breschi et al., 2003; Fan and Lang, 2000). Papers also explore linkages based on traditional channels discussed by Marshall (1920): similarity in technologies (e.g., Scherer, 1984; Boschma and Capone, 2015; Breschi et al., 2003), similarity in workers and labor skills (e.g., Farjoun, 1994; Neffke and Henning, 2013; Neffke et al., 2017), or input-output relations (e.g., Fan and Lang, 2000).[5] While this literature explores various measures of relatedness across industries, its contributions tend to focus on studying one channel at the time. Recently, a large group of multidisciplinary scholars working in this area highlighted the importance of unpacking the phenomenon of relatedness to understand the various channels behind it (Hidalgo et al., 2018). Our paper, precisely, fits into this call.

Our contribution focuses on understanding the relative importance of cross-industry linkages through various channels in explaining take-offs and accelerations of export industries at a global scale. In particular, we simultaneously study three channels in the same setting: input-output relations, pooling of workers and the sharing of technology and knowledge. Our study is conceptually similar to that of Ellison et al. (2010) who explore the role of different Marshallian linkages to study industry agglomeration in US regions, and that of Delgado et al. (2016) who do so with the purpose of defining regional clusters.[6] Yet, the focus of our paper is neither on production nor co-agglomeration of industries or firms within a country. Rather, our focus is on understanding how these linkages explain the evolution of comparative advantage, as measured by export dynamics across nations.[7]

Several factors explain how the presence of related competitive industries can drive take-offs or accelerate the growth of export industries. First, technology generated by or for a specific sector could explain the emergence or growth of another

[4]The "old" empirical literature trying to measure these Hirschmanian linkages, including a full special issue of the *Quarterly Journal of Economics in 1976*, focused more on the effects on growth across countries (Jones, 1976). This literature typically included few controls to account for alternative hypotheses, beyond linkages.

[5]Recently, some of studies have looked at the role of workforce linkages on pioneer firms that enter new economic activities (e.g., Hausmann and Neffke, 2019; Jara-Figueroa et al., 2018).

[6]A related study is Farinha-Fernandes et al. (2018) who unpack relatedness between occupations to understand the evolution of the occupational structure of US urban areas.

[7]Our results are exclusively based on exports and not production data. Thus, when we refer to certain sectors as inexistent throughout the paper, unless otherwise noted, we refer to sectors that are not being exported competitively. That does not mean that such sector does not have domestic production. Conversely, when referring to sectors that do exist, they exhibit a RCA above 1 in the country's export basket, as described in section 1.3.1, and we refer to them as competitive sectors.

sector if the latter utilizes the knowledge created by the former. Second, the existence of competitive industries using a trained (and competitive) workforce similar to that required by a non-exported sector might play a role in explaining the take-off of the latter. Third, the existence of competitive industries producing goods that are intermediate inputs to sectors of a yet small or non-existent industry could help the latter to develop and become an exporter. Alternatively, the existence of a critical mass of firms in certain exporting industries could "pull" the development of a new upstream export sector.[8]

Our empirical analysis uses panel regressions of country-industry observations with multiple sets of interacted fixed effects. This allows us to control for particularities of a country in a sector, like natural advantages. It also controls for global trends in a sector as well as macroeconomic phenomena varying in each country every year, each industry every year, as well as country-industry time-invariant characteristics (such as fundamental comparative advantage determinants). Our measures of inter-industry linkages are taken from Ellison et al. (2010) and Greenstone et al. (2010), which are based on US data. Given the global character of our sample, which includes 114 countries, using US-specific data helps us to diminish concerns of biases due to endogeneity in our empirical approach.[9]

Our findings highlight the significance of certain channels and downplay others. Our most salient result is that customer linkages support the take-off and acceleration of upstream export industries. In particular, a one standard deviation increase in the density of customer linkages increases by more than six times the probability of an export take-off in upstream sectors during the next decade. Under that same shock, the growth of existing exports expands 5 percentage points faster per year than the baseline. For example, a country is more likely to increase exports of fabric if it already exports garments. We also find that technology linkages matter: A one standard deviation increase in technology linkages across sectors make a related new export take-off almost ten times more likely , and is also associated with a subsequent additional annual export growth of 15 extra percentage points over the next decade.

However, for the average country in our sample, we find no robust evidence that labor linkages explain the evolution of comparative advantage. Similarly, in the same sample, the existence of supplier linkages do not tend to predict the emergence of new downstream export sectors.

It is worth noting that developing countries drive our findings on the relevance

[8]Unlike specialized cross-industry demands, the effect of a sector-wide critical mass that shifts *all* other sectors (e.g., Krugman, 1991) is ultimately neutralized in our empirical approach, as we extract all country-year variation with our fixed effects.

[9]The identification assumption to interpret our findings as causal requires that the structure of the linkages in the US is related to the potential linkages in each country, but orthogonal to the unobserved heterogeneity. This is somewhat similar to the approach taken by Ellison et al. (2010), who use the linkages based on UK data to instrument for US ones. While we acknowledge that our identification strategy is not perfect, we believe that our findings –even if taken as suggestive evidence– add to this long literature.

of customer linkages. This is consistent with Hirschman (1958), who suggested that backward linkages tend to be an important and natural path for new economic activities in developing countries. Hirschman's argument was that a customer industry helps build a larger market size for supplier firms while offering specific know-how on how to produce more competitively. Intuitively, the existing downstream firm has incentives to help in the development of local competitive procurement as a way to reduce its costs. All these elements could reduce the risks for suppliers and encourage them to invest more in improving their competitiveness. A series of recent micro-level studies back up the evidence that firms "learn" from their customers. Javorcik (2004) finds evidence of productivity spillovers for firms selling to new foreign plants located in Eastern Europe.[10] Consistently, Blalock and Veloso (2007) find that Indonesian firms competing with foreign suppliers of local producers were more likely to experience productivity gains. Also, Pietrobelli and Saliola (2008) find that selling to a multinational firm enhances supplier productivity. More recently, Kee and Tang (2016) show that China gained comparative advantage in those intermediate inputs used by pre-existing Chinese exporters. Our work complements these and other micro-level studies on backward linkages by exploring this mechanism in a global sample.[11]

We acknowledge that our findings are not necessarily causal, but they do reveal systematic relationships across industries and countries in an area of research that has mostly been informed by case-by-case micro-evidence. Our paper contributes to a growing literature that explores the relative importance of alternative channels behind the evolution of related economic activity, with our focus being on the dynamics of comparative advantage –as measured through export performance– in a global setting. Beyond the literature on inter-industry linkages summarized above, our study also contributes to a literature that examines the broader role of the evolution of industry competitiveness at different stages of economic growth and development (e.g., Imbs and Wacziarg, 2003; Cadot et al., 2011).

The remainder of the paper is structured as follows. Section 1.2 explains the data sources and variable definitions, in particular the different measures of density around each sector. Section 1.3 is the core of our paper: it reports results based on regression analysis on how the various linkages predict the take-off and growth of export industries. Section 1.5 offers a series of robustness tests. Finally, section 1.6 concludes and discusses the implications of our results.

[10]One possibility is that they mitigate the risks related to self-discovery costs. For evidence on self-discovery costs in exports, see Hausmann and Rodrik (2003). Javorcik (2004) explores backward linkages from FDI, not in exports. Other recent articles have focused on how FDI can help change comparative advantage (Amighini and Sanfilippo, 2014; Lectard and Rougier, 2018). Our work complements the previous analysis by showing the type of industry network that is most robustly associated with export take-offs.

[11]It is important to clarify that our interest in exploring connections among sectors in the economy does not come from the transmission of aggregate fluctuations (e.g., Carvalho et al., 2012), but rather from structural changes in comparative advantage.

1.2 Data

Our empirical exercise requires combining international export data with measures of linkages across industries. Then we need a concordance to combine both datasets.

1.2.1 Export data

For bilateral exports, we use UN COMTRADE data between 1984-2014. These data cover 786 export sectors categorized under the 4-digit Standard International Trade Classification (SITC), revision 2.[12] Each 4 digit code represents a very specific export sector. Two examples of 4-digit SITC codes are "*Knitted/Crocheted Fabrics Elastic or Rubberized*" (SITC 6553), or "*Electrical Measuring, Checking, Analyzing Instruments*" (SITC 8748).

Following Hausmann et al. (2014), we exclude countries with less than 1 million citizens and total trade less than US $1 billion in 2010. We also exclude countries of the former Soviet Union from the analysis since their data do not exist prior to 1990 and remain sparse until 1995, and countries with no reported exports of any sector for a particular year. This leaves us with 114 countries to construct the total value of exports per sector and country to the rest of the world for each year. The sample represents more than 90% of world trade.

1.2.2 Linkages across industries

The channel-based linkages across industries come from Ellison et al. (2010), except for the labor flow measure taken from Greenstone et al. (2010). These measures are based on US manufacturing data from 1973-1998. We use these to extrapolate the technological relationship to other countries and years. We prefer using these off-the shelf measures, already validated in the literature. An advantage of using these measures is that we follow the standard practice of using US data only to compute relatedness, rather than data from each individual country, to be used in a global sample (e.g., Romalis, 2004; Rajan and Zingales, 1998). This has a number of advantages. First, it bypasses the impossibility of using input-output relations from countries in which some of the industries have not yet emerged. Second, our measures are not affected by potential distortions in each economy. Third, and related to the previous point, using relatedness in the US yields should alleviate concerns of endogeneity in our empirical approach.

The measure of technological relatedness used by Ellison et al. (2010) comes from citation patterns in the NBER patent database (for 1975 to 1997). It captures the fraction of patents developed in industry i that cite patents developed in each industry j, taking the average of the bi-directional fractions between i and j.

[12] We use product, good, sector and industry interchangeably throughout the paper. But given the level of granularity we use, they should be interpreted as sectors.

The measures for supplier and customer linkages, also used by Ellison et al. (2010), came from the Bureau of Economic Analysis's benchmark table of input-output accounts of 1987. That is, the fraction of each industry i's inputs purchased from industry j (a.k.a. supplier linkages); as well as the fraction of i's output that is sold to industry j (a.k.a. customer linkages). These relations were aggregated at the SIC3 digit level.

The measure of labor relatedness comes from Greenstone et al. 2010. It is based on the US Current Population Survey's, an outgoing rotation file published by the Bureau of Labor Statistics. It captures the fraction of workers who leave industry i and transition to firms in industry j within a 15-month period.[13]

We normalize all these channel-specific measures to represent percentiles in the distribution of relatedness.[14] This normalization ensures that the channel-specific relatedness measures have the same range as the geographic-based (agnostic) relatedness measures, as explained below. Higher relatedness scores indicate a stronger relationship between sectors for all measures. See Appendix A.5 for a list of the top 15 sector pairs, based on each measure discussed.

The data on technological and input-output relatedness use the SIC 3-digit industry classification, while the data on labor relatedness use the 2-digit SIC classification. To align our analysis with the aggregation level of our trade data, we adapt the measures of cross-industry relatedness to match SITC sectors. This approach follows the methodology outlined by Cuñat and Melitz (2012) in footnote 24 and their subsequent documentation.[15]

Note that linkage data are only available for manufacturing industries. Therefore, our analysis is restricted to these industries and does not cover all SITC 4-digit sectors, as in Ellison et al. (2010). This makes us "lose" about 15 percent of the export sectors from the SITC export data.

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[13]Note that the initial year of our regressions would be 1990. Thus, the time period upon which these relatedness measures are constructed are appropriate as baseline for our exercise.

[14]For example, a relatedness of 0.3 implies that those two sectors are in the 30th percentile of relatedness.

[15]Cuñat and Melitz (2012) argue that "*[s]ince publicly available concordances from SITC rev.2 to US SIC do not indicate proportions on how individual SITC codes should be allocated to separate SIC codes, we construct our own concordance. We use export data for the United States, which is recorded at the Harmonized System (HS) level (roughly 15,000 product codes). Each HS code has both a SITC and a SIC code. We aggregate up the value of US exports over all HS codes for the last ten available data years (1991–2000) across distinct SITC and SIC pairs. For each SITC code, we record the percentage of US exports across distinct SIC codes. We then concord exports for all countries from SITC to SIC codes using these percentage allocations. In most cases, this percentage is very high, so our use of US trade as a benchmark cannot induce any serious biases. For 50% of SITC codes, the percentage assigned to one SIC code is above 98%. For 75% of SITC codes, this percentage is above 76%.*" For the purposes of our work it is important to mention that, despite the differences in the aggregation levels of the export data (4-digit) and the relatedness data (3-digit), we maintain sufficient variation across industries when converting the latter to the 4-digit level. Using a coarser granularity of trade data like 2-digit, on the other hand, would make us lose a lot of the variation. In theory, we could aggregate export data to the 3-digit level. However, we would still suffer from an imperfect match. Therefore, in line with other studies, we have chosen to use 4-digit disaggregation levels in our study.

1.3 Methodology

1.3.1 Variable definition

Dependent variables: take-off and acceleration of export sectors

We construct two dependent variables to explore the take-off and growth of export sectors. Generically labeled $Y_{c,p,t\rightarrow T}$, these quantify the *evolution* of exports and comparative advantage of a country in an industry between years t and T.

First, we use the Revealed Comparative Advantage (RCA) of Balassa (1965) as a main input to many of our measures, including the *take-off* of exports. RCA captures the share of a given industry in the country's total exports, divided by the share of the same sector in world's exports:

$$RCA_{c,p,t} \equiv \frac{x_{c,p,t}/\sum_p x_{c,p,t}}{\sum_c x_{c,p,t}/\sum_c\sum_p x_{c,p,t}}$$

where $x_{c,p,t}$ is total export value of industry p from country c to the world in year t. [16]

We define the *take-off* of an export sector with a dummy variable that takes the value one if the sector started with $RCA < 0.1$ in the initial year and ended with RCA >1 in the final year T. Formally,

$$Y_{c,p,t\rightarrow T} = 1[RCA_{c,p,T} \geq 1 | RCA_{c,p,t} \leq 0.1\,] \quad (1.1)$$

While the choice of 0.1 is somewhat arbitrary, we choose it to include industries that are significantly small (in relative terms).[17] Thus, when studying take-offs we exclude from the regression all the sectors in which the country already had $RCA \geq 0.1$ in the initial year. We do this to avoid that export take-offs result from small improvements in the competitiveness of a given country's sector over the decade, which could be explained by idiosyncratic reasons. Moreover, our definition of take-offs adds two extra conditions to address noise in the data. First, we ensure that the initial RCA is not transitorily low: we require $RCA \leq 0.1$ from $t-2$ to t. Second, we also define that the $RCA \geq 1$ condition is sustained for at least two years after the end of the decade (i.e., from T to $T+2$). These conditions are designed to avoid confusion arising from intermittent exports (Bernini et al., 2016).

[16] Thus, for instance, in the year 2000, soybeans represented 4% of Brazil's exports, but accounted only for 0.2% of total world trade. Hence, Brazil's RCA in soybeans for that year was $RCA_{Brazil,Soybeans} = 4/0.2 = 20$, indicating that soybeans are 20 times more prevalent in Brazil's export basket than in the world.

[17] However, note that more than 60% of take-off events correspond to cases in which exports started the period with zero or almost zero (i.e, below USD $10,000) exports. While we cannot claim that this measures the emergence of a new sectors (given that it includes many sectors that, albeit small, already existed), we perform some robustness tests in section 1.5 that use smaller initial thresholds and the main results remains robust.

When examining the acceleration of exports, we define our dependent variable $Y_{c,p,t\to T}$ as the compound annual growth rate (CAGR) in the export value, conditional on having positive exports initially $x_{c,p,t} > 0$.[18] That is:

$$Y_{c,p,t\to T} = \left(\frac{x_{c,p,T}}{x_{c,p,t}}\right)^{1/T-t} - 1 \text{ if } x_{c,p,t} > 0 \tag{1.2}$$

Clarifying our two dependent variables may simplify the interpretation of the results. An export take-off event is implicitly related to export diversification, as its occurrence potentially leads to a larger share of a previously under-represented export sector in the country's export basket.[19] When it comes to export growth, since our estimations always use country-year, product-year and country-industry fixed effects, the results could also be understood as reflecting changes in competitiveness of that export sector.

To ensure that our results are not coming from overlapping observations, our analysis uses decade-long changes: from 1990 to 2000 and from 2000 to 2010. We prefer to use ten-year periods to assess the impact of medium- to long-term processes, as structural change does not happen overnight.

Independent variables

To construct variables that measure the extent to which an industry is exposed to other existing ones through cross-industry linkages, we construct "density" measures. We explain them step by step.

Co-location relatedness based on co-location of exports

On top of the Marshallian linkages explained above, we also construct a now standard cross-sector linkage based on co-location patterns. For this channel-agnostic measure we follow Hausmann and Klinger (2006), HK here onwards. It computes the probability that two sectors are co-exported competitively from the same country.[20] We follow HK, so the proximity variable $\varphi^{HK}_{i,j}$ uses the minimum of the two conditional probabilities between pairs of industries.

$$\varphi^{HK}_{i,j} = \min\left\{ \Pr(RCA_i \geq 1 | RCA_j \geq 1) \quad ; \quad \Pr(RCA_j \geq 1 | RCA_i \geq 1) \right\} \tag{1.3}$$

[18] We note that the two measures are not completely mutually exclusive. There is a potential overlap in the support $0 < RCA_t < 0.1$. This is not a problem for our central point. While we want to distinguish between the take-off and growth of a new export industry, the reality is more continuous. In any case, most of the variation did not come from the overlapping part; otherwise, otherwise we would always have the same results using both dependent variables, which is not the case. Overall, more than 60% of export take-off events correspond to cases where exports started the period with a value of zero or close to zero (i.e., below USD $10,000).

[19] We carefully use the word *potentially* because this will, of course, depend on the final distribution of all the shares of export sectors within the export basket of the country. If the rise of one sector is completely outweighed by the fall of another, we would not see diversification as measured by traditional concentration indices.

[20] The measure was also used in the seminal work of Hidalgo et al. (2007)

Like Hidalgo et al. (2007), $\varphi_{i,j}^{HK}$ considers $RCA \geq 1$ as the threshold to define whether a sector is competitively exported in a particular country and year. The proximity variable $\varphi_{i,j}^{HK}$ is always distributed between 0 and 1. As an alternative index of co-location, we adapt the co-agglomeration index of Ellison and Glaeser (1997) –EG hence onwards– to export data. We label it $\varphi_{i,j}^{EG}$. See Appendix A.1 for a definition of the EG approach.

Both measures of relatedness are geography-based. Yet, we refer to them as "agnostic" measures: while they respond to co-location patterns within the same geographic unit (a country, in our case), they provide no understanding on *how or why* these two industries tend to be co-located in the same country.

Correlation of various relatedness measures

Table 1.1 displays the correlation matrix between all the relatedness measures we have described. These relatedness measures are symmetrical and defined for each pair of industries. The correlations between all relatedness measures are positive and statistically different from zero. The correlation between the agnostic co-location measure, φ^{HK} and φ^{EG}, is 0.49. The correlations of the agnostic relatedness measures with the channel-defined relatedness measures range between 0.10 to 0.19.

TABLE 1.1: Correlations of relatedness measures

Variables	HK	EG	Patents	Consumer	Supplier	Labor
HK	1.000					
EG	0.498	1.000				
Patents	0.158	0.137	1.000			
Consumer	0.102	0.101	0.289	1.000		
Supplier	0.120	0.113	0.364	0.457	1.000	
Labor	0.168	0.191	0.573	0.391	0.377	1.000

This table displays bivariate correlation coefficients for all proximity measures. It includes the two agnostic measures HK and EG, as well as the proximities of Marshallian channels.

Density around a sector

Next, we use these agnostic and Marshallian relatedness measures among industries to define densities, following previous work (e.g., Hausmann and Klinger, 2006; Hidalgo et al., 2007). Density quantifies the extent to which a particular sector p is related to other already existing competitive sectors in a given country and year. Formally, density is defined as:

$$\Phi_{c,p,t} = \frac{\sum_{j \neq p} \varphi_{p,j} \times R_{c,j,t}}{\sum_{j \neq p} \varphi_{p,j}} \tag{1.4}$$

where $R_{c,j,t} = 1$ is a dummy variable indicating whether a neighboring industry is present (i.e. $RCA_{c,j,t} \geq 1$) , and 0 otherwise. The neighborhood proximities $\varphi_{p,j}$

correspond to the relatedness measures discussed before. $\Phi_{c,p,t}$ distributes between 0 and 1.

Depending on the proximity $\varphi_{p,j}$ used, the interpretation of density $\Phi_{c,p,t}$ would vary. Using any of the Marshallian proximity measures $\varphi^{m}_{p,j}$ would yield a different density $\Phi^{m}_{c,p,t}$. For example, using proximity $\varphi^{Labor}_{p,j}$ yields the *density* of Marshallian labor flows $\Phi^{Labor}_{c,p,t}$. A high value of $\Phi^{Labor}_{c,p,t}$ implies that country c in the initial year t was competitive in a large number of sectors which relate to sector p in terms of labor similarities. An analogous interpretation applies for all other density measures, including the agnostic ones.

1.3.2 Empirical framework

Our basic specification regresses a *change* in comparative advantage on different channel-based densities, namely:

$$Y_{c,p,t\to T} = \beta\Phi^{channel}_{c,p,t} + Controls_{p,c,t} + \eta_{c,t} + \delta_{p,t} + \alpha_{c,p} + \varepsilon_{c,p,t} \tag{1.5}$$

The outcome variable $Y_{c,p,t\to T}$ alternates between our two measures defined in section 1.3.1: the binary take-off event and the continuous growth among existing exports. The right-hand-side densities $\Phi^{channel}_{c,p,t}$ measure the intensity with which industry p relates to the current export basket of the country. Thus, the main parameter of interest is the vector β, with one coefficient for each channel. The estimation method is a linear probability model for the binary variable and panel ordinary least squares (OLS) for growth of existing exports.

Importantly, we exploit the granularity of our data to control for all three feasible types of interacted fixed effects. This strongly reduces concerns about alternative explanations. First, $\eta_{c,t}$ represents country-by-decade effects capturing changes in income, institutions, exchange rates and population, among others. Second, $\delta_{p,t}$ represent industry-by-decade fixed effects, capturing variables like changes in global demand for industry p, common technological changes in an industry, among others. Importantly, we also include $\alpha_{c,p}$. These fixed effects control for all possible country-industry interactions that might explain intrinsic comparative advantage driven by initial time invariant effects. For example, this controls for all the various alternative explanations taking the form of (industry intensity) $\times$ (country endowment), as in Romalis (2004) or Nunn (2007). It also captures most of the natural comparative advantage of a location in an industry.

Specification (1.5) includes additional controls that may vary by decade-long interval. These controls vary depending on whether we estimate the binary export take-off or export growth. For the take-off of exports, we include the beginning of period $RCA_{c,p,t}$. For acceleration of exports, we control for the baseline level of exports. Both control for the convergence effect: growth is faster when starting from a lower base. For the binary take-off of exports, this relationship may be the other way around, since some exports, even if low, are predictive of more future exports as opposedm to zero. Given the fat-tailed nature of these level-variables, we perform on them a log-like monotonic transformation: the inverse hyperbolic sine transformation.[21]

Furthermore, to estimate acceleration of exports, we also control for pre-existing "momentum": export growth (CAGR) in the previous period. We also include a dummy of zero exports at the beginning of the previous period to control for possible distortions when computing the momentum variable.[22]

1.4 Results

This section presents findings on which Marshallian linkages are more strongly associated with changes in comparative advantage.[23]

1.4.1 Summary statistics

Table 1.2 displays the summary statistics of our variables for the two ten-year changes. Panel A displays the take-off events sample (i.e., for all observations in a country, sector and year combination for which $RCA_{c,p,t} < 0.1$), while panel B does so for the subgroup starts the period with positive exports ($x_{c,p,t} > 0$).

In our sample, a take-off event only occurs in 0.6% of possible cases. That is, from all country-sector combinations that exhibit RCA below 0.1, on average, approximately one in 150 takes off within a decade. This means take-offs are unlikely events, on average. Existing export industries in a country grow at an average of 8 percent per year, in nominal US dollars. As a benchmark, US inflation in the 1990s and 2000s was 3 and 2.5 percent, respectively; suggesting that average real growth was around 5%.[24] Growth had massive heterogeneity, since the standard deviation was 22%; at least three times larger than average growth of exports.

Importantly, the relation between density and new exports is already apparent in the raw data, when we compare panels A and B in table 1.2. Exported sectors, with an average density of about 0.19 (panel B), are twice as densely connected to

[21] The inverse hyperbolic sine is defined at zero and behaves similarly to a log-transformation. The interpretation of regression estimators in the form of the inverse hyperbolic sine is similar to the interpretation of a log-transformed variable.

[22] We use the previous period CAGR during 1985-1990 for the 1990-2000 period, and 1990-2000 for the 2000-2010 period. In order to correct for undefined growth rates caused by zeros in the denominator, we compute the CAGR following the above equation using $exports_{c,p,t} + 1$ for all observations. Note that when studying the growth rates the CAGR of export value in the dependent variable will always be defined, given that we limit the sample only to sectors which are being exported at the beginning of the period (that is, $x_{c,p,t} > 0$). However, the CAGR in the previous period included as a control may have an undefined growth rate; therefore, to control for our own correction, we also add as an additional control a binary variable indicating whether $exports_{c,p,t-1} = 0$ (at the beginning of the previous period, i.e. 1985 or 1990), which correspond to the observations most likely to be distorted. We tried alternative specifications and the results remained robust.

[23] To check the consistency with the existing literature, Appendix section A.2 confirms that the agnostic co-location densities predict changes in comparative advantage (Hausmann and Klinger, 2006; Hidalgo et al., 2007), even with our own strict set of fixed effects.

[24] However, note that our regressions in the rest of the paper have country-year fixed effects (plus others), so the estimators can be interpreted in real, not nominal, terms.

other sectors than those of small and nonexistent exports in the sample for potential take-offs (average density is about 0.08 in panel A). This is true for all density measures we use, and even considering that the definition of density in Equation (1.4) excludes the exporting of the own industry. This is a natural starting point to attempt to unpack the channels behind co-location. Note, as explained above, that the Marshallian linkages are available only for manufacturing industries.

TABLE 1.2: Summary statistics

Variable	N	Mean	Std. Dev.	Min	Max
Panel A - Export Take-Offs					
Export take-offs	63,232	0.006	0.08	0.0	1.0
$\Phi_{c,p,t}(HK)$	63,232	0.079	0.07	0.0	0.5
$\Phi_{c,p,t}(EG)$	63,232	0.087	0.07	0.0	0.5
$\Phi^{Patents}_{c,p,t}$	63,232	0.087	0.07	0.0	0.5
$\Phi^{Supplier\ Linkages}_{c,p,t}$	63,232	0.087	0.07	0.0	0.6
$\Phi^{Customer\ Linkages}_{c,p,t}$	63,232	0.085	0.07	0.0	0.5
$\Phi^{Labor\ Linkages}_{c,p,t}$	63,232	0.085	0.07	0.0	0.5
Initial RCA	63,232	0.011	0.02	0.0	0.1
Panel B - Export Growth					
10-year export growth	90,798	0.080	0.22	-0.9	2.7
$\Phi_{c,p,t}(HK)$	90,798	0.201	0.13	0.0	0.8
$\Phi_{c,p,t}(EG)$	90,798	0.195	0.12	0.0	0.8
$\Phi^{Patents}_{c,p,t}$	90,798	0.194	0.11	0.0	0.5
$\Phi^{Supplier\ Linkages}_{c,p,t}$	90,798	0.193	0.11	0.0	0.6
$\Phi^{Customer\ Linkages}_{c,p,t}$	90,798	0.193	0.12	0.0	0.6
$\Phi^{Labor\ Linkages}_{c,p,t}$	90,798	0.193	0.12	0.0	0.6
Initial Exports	90,798	14.956	3.30	7.6	25.4
Pre-period CAGR	90,798	0.791	2.46	-0.8	48.9
Pre-period zero exp	90,798	0.079	0.27	0.0	1.0

This table presents descriptive statistics for our key dependent variables: export take-offs and growth. It also includes statistics for agnostic and channel-specific density measures ($\Phi_{c,p,t}$) as well as control variables. The upper panel presents the sample used in the estimations of the export take offs, where we limit the sample to those country-industry observations that have RCA below 0.1 in the beginning of the 1990-2000 and 2000-2010 periods. The lower panel presents results used in the estimations of export growth rates, where we limit our observations to those country-industry pairs with exports above zero at the beginning of the 1990-2000 and 2000-2010 periods. Note that the sample used resembles the one used in the estimation of Specification (1.5) shown in table 1.3.

The table also includes summary statistics for the two agnostic density measures ($\Phi_{c,p,t}$, using $\varphi_{i,j}$ for both HK and EG relatedness measures) as well as the four channel-specific ones. While the proximities of different channels were normalized, so their averages are uninteresting, the densities are also bound to be between zero and one, but they are not normalized. The density of a sector proxies for the existence of other sectors that share similar technologies, workers, customers or inputs. For example, values of $\Phi^{HK}_{c,p,t}$ closer to 1 indicate that a given sector is highly related to the composition of its country's export basket. Conversely, values closer to 0 mean that there is little relatedness between the sector under consideration and the rest of the country's export basket. The same logic applies to the channel-specific density measures, where relatedness is defined through characteristics common to industry pairs.

1.4.2 Channels mediating take-off and growth of exports

Table 1.3 displays the estimates of Equation (1.5). Columns 1 to 4 consider the different channels $\Phi_{c,p,t}$ separately while column 5 does it jointly. For comparison purposes, we report standardized coefficients by normalizing the regressors to have mean zero and unit standard deviation.

Panel A shows that patent citations and customer linkages are relevant predictors of the take-off of an export industry, with a point estimate of roughly 0.05 (p-value < 0.01). The estimates and significance for these two channels remain largely unchanged when all mechanisms are tested together. The interpretation of the coefficients in column 5 is as follows. A small or inexistent export industry that has a one standard deviation higher density of customer linkages to the current basket is roughly 4 percentage points more likely to take off in the next decade. More precisely, the point estimate of 4.1 for customer linkages (column 5), represents more than a sixfold increase vis-a-vis the unconditional probability of a take-off, which was 0.6% (see section 1.4.1). For patent citations the additional effect is ninefold increase of the unconditional take-off probability. To a much lesser extent, labor flows also predict take-offs. But the magnitude is weaker and it becomes insignificant when all channels are tested jointly.[25]

The results for export growth are shown in panel B of table 1.3. All channels are individually statistically significant in columns 1 to 4. Together, however, only the patent linkages and the customer linkages remain statistically significant at standard levels, as seen in column 5. In particular, an increase of one standard deviation in a product's patent linkages based density is associated with 14.8 percentage points of additional export growth. This additional effect is almost twice the unconditional growth rate.

Discussion

Our results highlight the critical role of technology in facilitating cross-industry spillovers for the take-off of new exports. In addition, we find that customer linkages are also important: exports are more likely to take off if the sector supplies inputs to an already competitive sector within the country.

We emphasize this particular finding because it is consistent with a long-held view first put forward by Hirschman (1958). It is also consistent with more recent

[25] An interesting benchmarking would be to compare these channel-based estimates with those of the agnostic co-location density, similar to the regressions in Hidalgo et al. (2007), using only the agnostic co-location HK. The estimation provided in Appendix A.2 yields a coefficient $\Phi^{HK}_{c,p,t}$ of 0.028. This means that the estimators of the customer and patent-based densities shown in table 1.3 are roughly twice as powerful as the agnostic density.

TABLE 1.3: Take offs and growth of related industries

Panel A - Dependent variable: Export Take-Offs					
	(1)	(2)	(3)	(4)	(5)
$\Phi^{Patents}_{c,p,t}$	0.0547				0.0590
	(0.019)***				(0.026)**
$\Phi^{Labor}_{c,p,t}$		0.0265			-0.0158
		(0.013)*			(0.017)
$\Phi^{Supplier\ Linkages}_{c,p,t}$			0.0085		-0.0152
			(0.009)		(0.009)
$\Phi^{Customer\ Linkages}_{c,p,t}$				0.0539	0.0414
				(0.014)***	(0.013)***
Initial RCA	0.1215	0.1245	0.1266	0.1235	0.1215
	(0.036)***	(0.036)***	(0.037)***	(0.037)***	(0.036)***
N	63232	63232	63232	63232	63232
R^2	0.53	0.53	0.53	0.53	0.53
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p
Panel B - Dependent variable: Export Growth					
	(1)	(2)	(3)	(4)	(5)
$\Phi^{Patents}_{c,p,t}$	0.2057				0.1479
	(0.036)***				(0.042)***
$\Phi^{Labor}_{c,p,t}$		0.1538			0.0479
		(0.029)***			(0.036)
$\Phi^{Supplier\ Linkages}_{c,p,t}$			0.0773		-0.0193
			(0.023)***		(0.020)
$\Phi^{Customer\ Linkages}_{c,p,t}$				0.1520	0.0499
				(0.033)***	(0.029)*
Initial Exports	-0.1390	-0.1389	-0.1386	-0.1387	-0.1390
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Pre-period CAGR	0.0064	0.0064	0.0062	0.0063	0.0065
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Pre-period zero exp	-0.0270	-0.0267	-0.0254	-0.0260	-0.0273
	(0.010)***	(0.010)***	(0.010)**	(0.010)***	(0.010)***
N	90798	90798	90798	90798	90798
R^2	0.82	0.82	0.82	0.82	0.82
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p

This table estimates specification (1.5) with the channel-specific density measures. The upper panel estimates the specification for export sectors take-offs and the lower panel does so for the export growth. Columns 1 to 4 evaluate the impact of each channel-specific density measure separately, while column 5 includes all channel-based measures jointly. All specifications include country-by-decade, product-by-decade and product-by-country fixed effects. All coefficients are standardized with zero mean and unit standard deviation. Standard errors are clustered at the country level and presented in parenthesis.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

work. For example, Javorcik (2004), using firm-level data for Lithuania, finds that FDI productivity spillovers from customers to suppliers are more frequent. Pietrobelli and Saliola (2008) also find that selling to a competitive customer, in their case a multinational, increases supplier productivity. More recently, Kee and Tang (2016) show that China gained comparative advantage in sectors that were upstream of Chinese exporters, again implying that the pre-existence of a downstream sector leads to spillovers to the upstream supplier. Amendolagine et al. (2019) argue that this effect might be stronger if the multinational is connected to global value chains. Taken together, these studies suggest that the existence of a competitive downstream industry could act both as a source of spillovers and as a risk mitigation mechanism for entrepreneurs and investors to start a new upstream sector, which then leads to new exports. This is consistent with the idea that the emergence of a new sector is subject to fixed costs associated with market uncertainty (e.g., Wagner and Zahler, 2015).

Customer linkages may also influence the future growth of existing exports, though their impact is comparatively smaller. One standard deviation increase in the value of the customer linkages density is associated with 5 percentage points higher export growth over the next decade. This is a 60% increase over the unconditional mean, but smaller than the effect of patent citations.

1.4.3 Effect in industrialized vs. developing countries

We now turn to explore the extent to which the economic channels exhibit differential impact across levels of development. Hirschman (1958) hypothesized that developing countries have fewer linkages between their activities and therefore the effects of linkages might be different from those in developed countries, at least for the emergence of a new competitive sector. Table 1.4 shows the results for subsamples, split according to OECD membership. As expected, our findings indicate important heterogeneity in the effect, supporting Hirschman's hypothesis.

The results highlight three findings. First, column 1 shows that none of the channels are statistically significant in the OECD subsample. This does not mean that channels are irrelevant. What it says is that, on average, we cannot tell apart which channel systematically predicts take-offs relatively more than the others. Note that part of this lack of significance may be due to the small sample of potential take-offs: for OECD economies, only 16% of the country-sector observations enter the take-off regression, because OECD economies already export more sectors in the first place with RCA above 0.1.[26]

Second, column 2 shows that for developing countries patents and customer linkages are important to explain export take-offs. This is consistent with our baseline results in table 1.3. Importantly, here we confirm that customer linkages

[26] In contrast to OECD economies, the sample of non-OECD countries splits roughly 50-50 between the potential take-off sample and the growth sample, because they have much fewer exports with RCA above 0.1.

TABLE 1.4: Export take-offs and growth of related industries, OECD vs. non-OECD exporters

Dependent variable	**Export Take-Off**		**Export Growth**	
	(1)	(2)	(3)	(4)
	OECD	non-OECD	OECD	non-OECD
$\Phi^{Patents}_{c,p,t}$	-0.0092	0.0804	0.0234	0.2354
	(0.031)	(0.032)**	(0.047)	(0.068)***
$\Phi^{Labor}_{c,p,t}$	0.0157	-0.0224	0.0683	0.0727
	(0.030)	(0.020)	(0.040)*	(0.053)
$\Phi^{Supplier\ Linkages}_{c,p,t}$	0.0174	-0.0250	0.0439	-0.0632
	(0.016)	(0.010)**	(0.018)**	(0.036)*
$\Phi^{Customer\ Linkages}_{c,p,t}$	0.0224	0.0460	0.0389	0.0399
	(0.026)	(0.015)***	(0.027)	(0.052)
Initial RCA	0.1071	0.1314		
	(0.089)	(0.040)***		
Initial Exports			-0.1323	-0.1425
			(0.002)***	(0.002)***
Pre-period CAGR			0.0040	0.0083
			(0.001)**	(0.001)***
Pre-period zero exp			-0.0349	-0.0429
			(0.020)*	(0.012)***
N	6356	56706	37528	53268
R^2	0.59	0.54	0.86	0.81
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p

This table estimates specification (1.5) using all channel-specific density measures, separating the sample between OECD and non-OECD exporters. Columns 1 and 2 estimates the specification for export sectors take-offs while columns 3 and 4 do so for export growth. The specifications resemble column 5 of table 1.3. All specifications include country-by-decade, product-by-decade and product-by-country fixed effects. All coefficients are standardized with zero mean and unit standard deviation. Standard errors are clustered at the country level and presented in parenthesis.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

with existing activities tend to predict take-off, but not necessarily subsequent growth, in developing economies, as shown in column 4. This, again, coincides with Hirschman's view that a domestic buyer helps achieve a critical mass of demand for upstream sectors.

Third, we also find some evidence for the divergent role of forward and backward linkages across development levels. On the one hand, supplier linkages do not contribute to explaining new exports in developing countries. They even exhibit statistically significant negative coefficients in columns 2 and 4. This, again, was argued by Hirschman: For developing countries, it is likely that the final activity is performed in a richer country. For example, cocoa powder exported from an African economy to Switzerland may reduce the probability that chocolate exports emerge in the same African economy in the subsequent decade. On the other hand, we find that supplier linkages do matter for the growth of exports from existing sectors for developed countries, as seen in column 3.

Furthermore, our results confirm Hirschman's observation that for developing countries the effect of forward linkages is much less pronounced than that of backward linkages (Hirschman, 1958, p. 116). The difference in coefficients between supplier and customer densities in column 2 supports this hypothesis (p-value <0.01). One way to think about these findings in the context of developing countries is the role that an existing competitive sector can have on its potential suppliers. It helps these emerging upstream sectors to get critical mass and reduce the costs of taking risks in a context of incomplete markets. In the presence of frictions in credit markets, for example, the mere existence of a local market for a sector can reduce uncertainty both for the creditor and the investor. In contrast, in OECD countries with more complete markets, customer linkages are less relevant to the development of new sectors. Beyond market incompleteness, we interpret having connections to local buyers as providing know-how about what and how to produce. Note that this is not just about having competitive customers *anywhere* -meaning, non locally- given that this effect is captured by our strict set of fixed effects, which would capture, for example, (static) transportation costs of inputs for a given country-industry pair.

Our findings for the acceleration of exports confirm the importance of patent linkages for developing countries (column 4) and the lack thereof in developed economies (column 3).[27] To interpret this finding, we should again avoid a narrow view of what the patent citation network means. At least since the seminal work by Jaffe et al. (1993), it is the conventional view that the spread of knowledge is highly localized. This reflects the short-term nature of the mobility of inventors and knowledge creators (Breschi and Lissoni, 2009). In this context, it makes sense that the technology-based effect we document might be more predictive in developing countries, which generally lack this inventive expertise and/or have poorer infrastructure to enable mobility. In OECD economies, the specific skills from other

[27] Similar sized standard errors suggest that the lack of significance is not due to the smaller number of observations in the sample across the different cuts.

TABLE 1.5: Correlations of density measures, controlling for fixed effects

Variables	Φ^{HK}	Φ^{EG}	$\Phi^{Patents}$	Φ^{Labor}	$\Phi^{Slinkages}$	$\Phi^{CLinkages}$
Φ^{HK}	1.000					
Φ^{EG}	0.634	1.000				
$\Phi^{Patents}$	0.249	0.260	1.000			
Φ^{Labor}	0.285	0.302	0.754	1.000		
$\Phi^{SLinkages}$	0.204	0.225	0.556	0.523	1.000	
$\Phi^{CLinkages}$	0.200	0.221	0.545	0.547	0.330	1.000

This table presents correlations between density measures after conditioning on country-by-decade, product-by-decade and country-by-product fixed effects.

industries nearby may be less of a binding constraint, and therefore harder to produce a systematic prediction in the emergence and growth of export sectors. Overall, columns 3 and 4 show that the factors that predict growth of exports in OECD economies are different from those in developing economies.

1.5 Robustness and additional tests

This section offers alternative tests to support our main results. In particular, we focus on the early stages of take-offs and on the possible biases arising from the estimation of linear probability models. We also present results aiming to to tell apart specific mechanisms from co-location based measures.

1.5.1 Addressing concerns about collinearity

We know that all densities Φ are based on the same matrix $R_{c,t}$, which contains the structure of existing exports with RCA above one. Although we multiply densities with different channel-based industrial proximities, there is still the potential concern of collinearity among Φ. This may complicate the interpretation of significance in the joint specification presented in column 5 of table 1.3. However, even if the raw density measures are highly correlated, the β parameters in column 5 already correct for all feasible combinations of fixed effects. Thus, the empirical question becomes how much do the densities Φ correlate *after* controlling for fixed effects. Table 1.5 shows these correlations conditional on country-by-decade, product-by-decade and product-by-country fixed effects. The resulting correlations are positive but not strikingly large. This is consistent with the proximities in table 1.1, which showed significant variation between channels. Additionally, we computed the Variance Inflation Factor (VIF), used to assess the availability of enough independent variation among correlated variables. The VIF value was 1.9; which is in the acceptable range. Therefore, multi-collinearity seems a less relevant concern for our empirical strategy. There is enough variation to empirically distinguish the different channels.

1.5.2 The birth of new competitive export sectors

Our baseline definition of binary export take-offs was based on country sector pairs with a low initial RCA of 0.1. This condition, hence, includes country-sectors that were already existent. In this section, we explore whether our results are robust to the birth or emergence of new exports. To do so, we limit our sample used to those country-sector pairs that not only have an initial RCA below 0.1 but also exhibit an initial export value below USD $10,000.[28] Using this subset (corresponding to about 60 per cent of the original sample of export take-offs), we explore the mechanisms that can explain the export take-offs of these country sectors over a decade. Although Hirschman (1958) focused primarily on industries reaching critical mass rather than their initial emergence, the study of entirely new export sectors provides valuable insights into our baseline effects. The joint specification of table 1.6 in column 5 indicates that our main results remain robust to considering the birth of new exports. Both technology and customer linkages are significant and of similar magnitude. The coefficients are between one half and two-thirds of those reported in our baseline estimation in table 1.3. An important difference appears when we look at the various channels individually in specifications 1 to 4: in that comparison only the existence of competitive buyers is significant. This, and other robustness of customer linkages, is why we highlight this channel in our conclusions.

1.5.3 Alternative estimation for the binary take-off and its evolution over time

Our baseline model for export take-offs of table 1.3 follows recent contributions, such as that of Boschma and Capone (2015), and sticks to the linear probability model for the binary outcome. There were many reasons to do so. First, non-linear models suffer from the so-called incidental parameter problem with many fixed effects, as described by Greene (2004). In these models, the maximum likelihood estimator tends to be inconsistent when T, the length of the panel, is fixed, as in our case with two time intervals. Second, non-linear fixed effects models are not the most commensurate estimation technique, given that Angrist and Pischke (2009) argue that average effects from the linear probability resemble marginal effects of non-linear models. Third, and crucial for our case, non-linear fixed effects models impose a challenging computational complexity. Estimating three large groups of interacted fixed effects in our application proved untenable. Despite all these reasons, we ran additional specifications for robustness tests in table 1.7.

For the nonlinear models of columns 1 and 2 we use the complementary log-log specification. Although it is also restricted to the unit interval, it is a more advisable option than logit or probit when the following conditions hold on to (i) when the probability of take-off is small, as in our case; (ii) when the sample is restricted

[28] Given that there many sectors that are re-exported from third countries without having local production, and also considering that small amounts of trade have noise due to misclassification, we choose this threshold, which is, de facto, equivalent to zero exports, as in Wagner and Zahler (2015).

TABLE 1.6: Birth of new export sectors

Dependent variable: Export Take-offs if initial $RCA_{c,p,t} \leq 0.1$ **and** $exp_{c,p,t} \leq 10K$					
	(1)	(2)	(3)	(4)	(5)
$\Phi_{c,p,t}^{Patents}$	0.0196				0.0329
	(0.013)				(0.019)*
$\Phi_{c,p,t}^{Labor}$		0.0030			-0.0191
		(0.012)			(0.015)
$\Phi_{c,p,t}^{Supplier\ linkages}$			-0.0021		-0.0122
			(0.008)		(0.009)
$\Phi_{c,p,t}^{Customer\ Linkages}$				0.0268	0.0267
				(0.012)**	(0.013)**
Initial RCA	-0.0692	-0.0667	-0.0661	-0.0732	-0.0737
	(0.126)	(0.127)	(0.126)	(0.126)	(0.126)
N	32954	32954	32954	32954	32954
R^2	0.54	0.54	0.54	0.54	0.54
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p

This table estimates specification (1.5) with the channel-specific density measures. It estimates export sectors emergence, defined by country-sectors having RCA below 0.1 and export value below USD 10,000 at the beginning of the period, and achieving an RCA above 1 in a decade time. Columns 1 to 4 evaluate the impact of each channel-specific density measure separately, while column 5 include all channel-based measures jointly. All specifications include country-by-decade, product-by-decade and product-by-country fixed effects. All coefficients are standardized with zero mean and unit standard deviation. Standard errors are clustered at the country level and presented in parenthesis.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

to only observations that are eligible to take-off (i.e., the sample excludes country-industry pairs that have already taken-off); and (iii) when the take-off event is associated to repeated exposure to a risk - as every year in a decade - but one observes data only at the end and changes are persistent. In that context, our decade-long propensity might not be symmetric as assumed in logit or probit models. As a result, the clog–log is preferred because it behaves like a hazard rate (Singer et al., 2003). For computational reasons, we needed to limit the number of simultaneous fixed effects. Therefore, we estimate this clog-log model for each of the two sub-periods separately. One for 1990 to 2000 and another for 2000 to 2010. The table lists the initial year of each sample. The results of both time periods highlight the robustness of having customer linkages with competitive sectors. These were positive and statistically significant. The patent linkages are positive and significant for the first decade, but not for the second.[29]

Alternatively, we also consider the trimmed approach of Horrace and Oaxaca (2006) for binary data. The proposed method involves initially estimating a linear probability model. After this initial estimation, observations where the predicted probability does not lie between 0 and 1 are excluded from the sample. The linear probability model is then re-estimated using this refined subset of data. This approach aims to improve model accuracy by focusing on predictions that fall within the plausible range of probabilities. Horrace and Oaxaca (2006) show that this approach may reduce the potential biases of the linear probability models. Column 3 reports the results of this approach. Despite having fewer observations, the point estimate for customer linkages is very similar to our baseline in table 1.2, suggesting that the potential bias from linear probability models may not have been large. Importantly, customer linkages was the only variable that survived as significant in all this binary regression, reinforcing our emphasis in this channel.

1.5.4 Unpacking the effect of co-location in its various channels

A central goal of our paper was to distinguish between the channels. Acknowledging that these channels are neither orthogonal to each other nor orthogonal to the agnostic co-location density, here we complement our findings of section 1.3 by building additional support for the results.

There are at least two additional ways to explore whether our channel-based measures add meaningful information beyond co-location. First, one standard way is to re-estimate the baseline table 1.3, but this time adding the *co-location or agnostic* density $\Phi_{c,p,t}$ as an additional control to explore whether the channel measures lose significance. We do this in the Appendix section A.4, and our findings remain robust.

Second, to unpack the effect of co-location, we employ a two-step approach in which we systematically exclude one correlated channel at a time. The first step is to estimate a linear regression of $\Phi^{agnostic}_{c,p,t}$ on a single $\Phi^{channel}_{c,p,t}$. Then we compute the

[29] Coefficients signs are comparable, but the magnitudes are not comparable to other models in this paper.

TABLE 1.7: Non-linear estimation of take-off events

Dependent variable: Export Take-offs			
Estimation	Non-linear		Linear
Cross-section	1990	2000	1990 and 2000
	(1)	(2)	(3)
$\Phi^{Patents}_{c,p,t}$	23.0454	15.8771	0.0543
	(13.730)*	(10.954)	(0.036)
$\Phi^{Labor}_{c,p,t}$	1.0126	5.8811	0.0141
	(9.453)	(8.880)	(0.024)
$\Phi^{Supplier\ linkages}_{c,p,t}$	-3.4025	-3.8452	-0.0158
	(6.374)	(4.813)	(0.017)
$\Phi^{Customer\ Linkages}_{c,p,t}$	16.8617	20.2757	0.0512
	(8.228)**	(8.731)**	(0.021)**
Initial RCA	12.2341	11.5037	0.1598
	(1.599)***	(1.995)***	(0.054)***
N	23416	15524	22194
Pseudo-R^2	.05	.05	.
R^2			0.56
Fixed Effects	c, p	c, p	c-t, p-t,c-p

This table re-estimates our main specification of Eq. (1.5) for the binary outcome of export take-off. But instead of using a standard linear probability model, it uses alternative approaches that deal with the binary nature of the dependent variable. Columns 1 and 2 display the coefficients of a complementary log-log model (cloglog) for decades starting in 1990 and 2000, respectively, adding both country and sector fixed effects. Column 3 uses the trimmed methodology for linear probability models of Horrace and Oaxaca, 2006, excluding observations for which the predicted values are outside of the unit interval. Column 3 includes country-by-decade, product-by-decade and product-by-country fixed effects. Coefficients in column 3 are standardized to have mean zero and unit standard deviation. Standard errors are clustered at the country level and presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

TABLE 1.8: Take offs and growth, unpacking agnostic density

Panel A - Dependent Variable: Export Take-offs					
	(1)	(2)	(3)	(4)	(5)
	Baseline	Patents	Labor	Supplier	Customer
$\widetilde{\Phi cpt}$	0.4028	0.3063	0.3377	0.3321	0.2861
	(0.103)***	(0.090)***	(0.096)***	(0.083)***	(0.096)***
N	63232	63232	63232	63232	63232
R^2	0.53	0.53	0.53	0.53	0.53
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p
Panel B - Dependent Variable: Export Growth					
	(1)	(2)	(3)	(4)	(5)
	Baseline	Patents	Labor	Supplier	Customer
$\widetilde{\Phi cpt}$	0.5029	0.3127	0.2970	0.3590	0.3456
	(0.100)***	(0.093)***	(0.089)***	(0.088)***	(0.094)***
N	90798	90798	90798	90798	90798
R^2	0.82	0.82	0.82	0.82	0.82
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p

This table estimates specification (1.6) with the agnostic (HK) relatedness measure orthogonal to every channel specific based density. The upper panel estimates the specification for take-off events and the lower panel does so for export growth. Column 1 is the benchmark: it reports results using the coefficient for the agnostic density HK, without extracting the effect of any channel. Columns 2 to 5 evaluate the impact of the agnostic density cleaned from each channel specific based densities. All specifications include country-by-year, product-by-year and country-by-product fixed effects. Control variables are not shown for expositional purposes. Standard errors are clustered at the country level and presented in parenthesis. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

residual, which we label $\widetilde{\Phi^{channel}_{c,p,t}}$. We then extract all joint variance from the agnostic measure. Then, we examine how strongly the residual $\widetilde{\Phi^{channel}_{c,p,t}}$ explains export take-offs and growth, using an approach similar to specification (1.5) but with a modified first term. Specifically, we estimate:

$$Y_{c,p,t\rightarrow T} = \beta_d \widetilde{\Phi^{channel}_{c,p,t}} + Controls_{p,c,t} + \eta_{c,t} + \delta_{p,t} + \alpha_{c,p} + \varepsilon_{c,p,t} \quad (1.6)$$

Table 1.8 shows the results when unpacking the HK agnostic co-location. The first column reports the results for the coefficient of the agnostic density without "extracting" the portion correlated to any other measure (hence, the title of the column is "-"). We report it to serve as benchmark.[30] As expected, this agnostic channel is a strong predictor of both take-off and growth of exports.

Column 2 reports the coefficient of the agnostic or co-location density “cleaned”

[30]It replicates the estimates of table A.1 in the Appendix, except that the number of observations is limited to those for which the channel-defined densities are not missing. That is, in the case where $\widetilde{\Phi_{c,p,t}} = \Phi_{c,p,t}$.

from patent-based density. Columns 3 to 5 follow the trend, cleaning all other channels.

Overall, the cleaned coefficients in columns 2 to 5 are 20 to 40% smaller than the one in column 1 (with the "full" agnostic measure), depending on the channel and the outcome. For take-offs, the coefficient for the density orthogonal to customer linkages is the smallest (panel A, column 5), which confirms our findings so far. That is, the agnostic measure matters less once the role of customer linkages is stripped from it. When it comes to explaining future growth of already existing exports (panel B), labor force and patent citation densities may matter more, as stripping these linkages from the agnostic measure result in lower coefficients. Appendix table A.2 uses the alternative agnostic EG instead of the HK density, finding similar results.

In summary, the robustness tests in this section highlight the importance of customer linkages, over and above other channels, in facilitating the take-off of upstream exports. However, it is important to recognize that the explanatory power of agnostic co-location is strong and relevant even when specific correlated channels are excluded. This is an appeal not to over-interpret a single channel as the sole cause of the evolution of the export basket. In an unreported regression similar to table 1.8, we controlled for all channels simultaneously and co-location was still significant and strong. Co-location in one benchmark country (the US) still contains additional information for new exports in the rest of the countries, although part is accounted by our measures of Marshallian channels.

1.6 Conclusion

New exports do not emerge randomly. They tend to be related to pre-existing exports in the same country, as reviewed in Hidalgo et al. (2018). In this paper, we contribute to unpacking this relationship by shedding light on the channels that mediate the take-off and growth of exports across industries and countries. To that end, we *simultaneously* explore the role of the alternative cross-sectoral linkages suggested by Marshall (1920): technology, labor and input-output relationships.

On average, we find that take-offs and export growth tend to increase if the country was already competitive in related sectors, the latter measured by patent citations and customer links. Other channels tend to be less robust. Our findings on patent citations underscore how technological capacity drives export competitiveness. In this sense, patent linkages reflect the existence of knowledge and technology which, because they are local, facilitate their diffusion among economic actors (e.g., Jaffe et al., 1993; Breschi and Lissoni, 2009; Boschma, 2005; Bahar et al., 2014).

With respect to customer linkages, our findings imply that, for example, a country is more likely to become a competitive exporter of semiconductors (an upstream product) if it already exports computer memory chips. Moreover, our global stylized fact generalizes microeconometric evidence showing that spillovers are more likely in upstream linkages (e.g., Javorcik, 2004; Pietrobelli and Saliola, 2008; Kee and Tang, 2016; Amendolagine et al., 2019). Overall, we believe that the role of upstream linkages reflects not only a pure flow of materials, but also a source of know-how, critical mass and lower risks (Hirschman, 1958).

Consistent with Albert Hirschman's view, the impact of linkages between sectors can vary greatly depending on the level of development. For example, our results on customer linkages are driven by developing countries. In contrast, our results for developed countries suggest that supplier linkages explain export growth.

Finally, our findings provide some insights for the development policy debate. First, in many low-income countries people like to think about "adding value" through the "vertical diversification into processing of primary commodities" (see Cramer 1999; McMillan et al. 2003). That implies promoting diversification downstream from current competitive sectors. In contrast, our evidence for developing countries is that new export sectors tend to appear upstream, not downstream of current industries. Second, scholars have argued that distortions accumulate in supply chains, providing a rationale for subsidizing the most upstream sector, which would otherwise accumulate most of these distortions (Liu, 2019). However, our estimations suggest that even if a subsidy were to create that new upstream sector, this may not necessarily lead to the take-off of new downstream exports.

To be clear, our findings do not necessarily translate into a single normative advice. Under some circumstances, countries may decide to enrich the productive ecosystem against the revealed forces of comparative advantage within each market with particular characteristics. Clarifying these decisions is a matter for further discussion, as in Lin and Chang (2009). In any case, these interventions should respond to concrete and contextual market failures, instead of simply following the potential for agglomeration, as if clustering were a goal by itself (Rodriguez-Clare, 2007).

Chapter 2

Barrier or Opportunity? How Trade Regulations Shape Colombian Firms' Export Strategies[1]

2.1 Introduction

Market access conditions attract policy and academic attention.[2] While tariffs have declined over time, trade regulations matter increasingly for firms wishing to access international markets (UNCTAD, 2019b). Governments impose these regulations to establish the standards and procedures a product must comply with to be sold in their market. Labeling requirements or safety certification are telling examples, assuring safety and product quality for consumers and encouraging trade. However, trade regulations can also increase exporters' compliance and thus production costs since additional investment in technology and processes may be required. This implies that trade regulations may both reduce supply and increase demand for tradables.

Firms also face uneven compliance costs of trade regulations, mostly due to market entry costs (Bernard et al., 2012; Melitz and Redding, 2015).[3] Fixed market entry costs imply that the most productive companies are most likely to enter and thrive

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[2]In the academic literature, market access is commonly associated with export diversification and firm competitiveness, important precursors to economic development. For references regarding the relationship between market access and export diversification, see, for example, Fugazza and Nicita (2013). For effects of market access for firm capabilities, see Falciola et al. (2020). For important reviews of this policy debate see Nicita and Melo (2018).

[3]In general, firms face three types of costs. First, firms incur product-specific production costs that reflect their capabilities. Second, firms incur variable trade costs: shipping costs in the form of iceberg trade costs and ad-valorem tariffs. These costs vary with sales, but do not depend on the exporter's scope. Both production costs and variable trade costs deter exports at all margins. Third,

in export markets (Melitz, 2003; Bernard et al., 2011). They are best equipped to deal with diverse regulations, standards, testing, and certification procedures across sales markets. Taken together, the overall impact of trade regulations on trade and its distribution across firms is uncertain.

This paper quantifies the heterogeneous effects of Latin America's trade regulations for Colombia's exporting firms, concentrating on specific types and channels through which they operate: firms' value of exports and their probability of participating in and exit from export markets. There is a focus on Latin America and the Caribbean (LAC) as the region has become Colombia's most important export market. This, coupled with the unique data of trade regulations and other non-tariff measures (NTMs) in LAC, provides an ideal setup.

We use a firm-level gravity model with a difference-in-differences research design that identifies heterogeneity in treatments across NTM types and channels. Our econometric approach accounts for selection and omitted variable bias as well as endogeneity in the timing of NTMs with respect to trade flows into destination markets. Moreover, we test the robustness of the results with stringent fixed effects, different measures of firm size and alternative samples to rule out endogeneity concerns.

The impact of trade regulations varies greatly by type and channel. Of all the types of NTM considered, only technical barriers to trade (TBTs) — a standard-like measure — and quantity controls explain changes in Colombian firm-level exports. On average, TBTs undermine Colombia's firm-level exports behavior across all three channels considered. These results are consistent with a model in which trade regulations increase firms' compliance costs relative to consumer benefits. The effect is even more pronounced for quantity control measures which undermine Colombian firms' exports and their likelihood of remaining in markets. Intriguingly, new quantity controls in product-destination markets *lower,* on average, firms' exit rates.

Looking at the heterogeneous effects of NTMs, we show that this effect is driven by small firms that benefit from quantity controls. Conversely, big firms are more likely to leave export markets when faced with new quantity controls. We argue that quantity control measures constrain big firms more than small firms and we help explain this outcome. However, a regressive effect is at play for TBTs for all three channels; big firms benefit from a dampened effect, whereas small firms see their exports and likelihood of remaining in markets significantly reduced. Similarly, firms participating in global value chains (GVC) benefit from a muted trade impact when TBTs or quantity controls are introduced in the sales market. In contrast, non-GVC firms suffer from reduced exports and likelihood of participating in markets.

Our paper improves the understanding of the role of NTMs for firm-level trade along three dimensions. First, we quantify the relative importance of NTM types for firm-level export decisions. Some NTM types are by definition trade restrictive, such

firms incur fixed exporting costs by product and destination market, reflecting the compliance costs of trade regulations. Thus, the market access cost schedule varies by firm-product-destination.

as import prohibitions and quotas. In contrast, the effect of standard-like measures such as sanitary and phytosanitary (SPS) or TBTs on export dynamics depends on compliance costs relative to information benefits and is, in theory, ambiguous.[4] We demonstrate that TBTs and quantity control measures, on average, deter Colombian exports. Our findings are consistent with Adarov and Ghodsi (2023), Disdier et al. (2008), Yousefi and Liu (2013), and Li and Beghin (2012) who find negative TBT effects on trade flows.

Second, we explore the channels through which NTM effects operate. To that end, we distinguish three firm-level export decisions: the value of exports to product-destination markets (intensive margin); the probability of participating in them (extensive margin I) and exit from them (extensive margin II). While we document that TBTs and quantity control measures undermine all three margins, firms mostly respond by reducing existing exports. This finding challenges Bao and Qiu (2012) who highlight positive firm-level responses at the intensive margin.

At the same time, we find that firms respond to additional types of trade regulation at the extensive margin. In addition to TBTs and quantity controls, increases in tariffs and SPS measures in product-destinations make it less likely that Colombian firms participate in these markets. This pattern could reflect exporters' inability to pay the additional compliance costs and trade diversion to less costly product-destination markets. Our findings are consistent with firm-level evidence from France (Fontagné et al., 2015; Fontagné and Orefice, 2018).

Third, we extend the analysis of heterogeneity in the effects of NTM types across firm characteristics. Our results align with the predominant finding of the empirical literature that small firms suffer disproportionate impacts of TBTs (e.g., Arkolakis, 2010; Curzi, 2020; Asprilla et al., 2019; Macedoni and Weinberger, 2022). Moreover, we show that GVC firms, defined as those that both import and export, benefit from the same muted trade effects of TBTs as big firms, even though the two firm characteristics differ substantially in definition. However, we also marshal novel evidence that quantity control measures make it less likely small firms will exit export markets, with the opposite effect occurring for big firms. We argue that the quantity controls are more binding for big firms, increasing their likelihood to leave markets and, conversely, helping small firms take over their space.

Superior data and methods underpin these three contributions. We combine a panel of Colombian firm-level trade data from 2007 to 2017 with time-varying information on NTMs in regional export markets. Employing a firm-level gravity model with a difference-in-differences research design, we estimate the relative importance of NTM types controlling for unobserved confounders at the firm-product-destination level. In doing so, we address empirical limitations in the literature. This concerns, on the one hand, the use of cross-sectional data to estimate NTM impacts (e.g., Bratt, 2017; Fugazza et al., 2018). On the other hand, many studies evaluate

[4] See Ronen (2017) for the intuition on trade-promoting effects of NTMs. Beghin et al. (2015) find that almost 40% of product lines affected by TBT measures yield negative NTM advalorem equivalents (AVEs), suggesting a net trade-promoting effect of these measures.

NTMs in isolation or bundled (Disdier and Marette, 2010 or Fontagné et al., 2015), not their joint or relative effects. Moreover, drawing from Kee and Nicita (2022), we also account for the endogeneity of NTMs by predicting NTM selection based on that in neighboring countries. This approach is suitable in our context, given the cultural and legal proximity of Colombia's regional destination markets and their similarity in introducing trade regulations.

The paper is structured as follows. Section 3.3 explains our data sources and procedures to clean them. Section 3.4 documents stylized facts about Colombia's exporting firms and the market access conditions they face. Section 3.5 explains our empirical identification strategy, defines key variables, and addresses concerns to identify how market access conditions affect Colombian firms trading with the region. The results and robustness tests are presented in section 3.6. Sections 2.5.5 and 2.5.6 explore heterogeneous NTM effects based on firms' size and participation in global value chains, respectively. Finally, section 3.7 concludes and discusses the implications of our results.

2.2 Data

The empirical investigation is based on three distinct datasets, all covering the period 2007–2017. The first dataset contains information on export and import transactions collected by Colombian customs. The second provides data on NTM types applied by Latin American importing countries. The third contains bilateral applied ad-valorem tariffs of Latin American importing countries.

2.2.1 Colombian firm-level exports

We use transaction-level export and import data from Colombia's customs agency DIAN. The data is part of the expansion to the Exporter Dynamics Database, as described in Fernandes et al. (2016). The data cover the universe of exporting firms in all sectors at the exporter-HS 6-digit product-destination-year level and includes seven variables: country of origin, exporting firm identifier, country of destination, HS 6-digit product, export value, export quantity, and year. Information on export and import values is expressed in US dollars and is FOB (free on board). We processed the raw dataset to a series of cleaning procedures, as detailed in Cebeci and Fernandes (2015).

To merge with the tariff variable described below, we convert the HS product nomenclatures of 2007, 2012, and 2017 to the HS combined version.

Moreover, we exclude all firm observations from the mining sector (HS chapter 25–27). That helps to avoid potential bias from Latin America's commodity price cycles during 2007–2017. Thus, our sample frame contains all Colombian exporting firms between 2007 and 2017, except those from the mining sector.

2.2.2 Non-tariff measures

We use NTM data from UNCTAD and the Latin American Integration Association (LAIA) for its 18 core members in LAC between 2007 and 2017.[5] The raw data are recorded at the level of the reporter-national tariff line-destination country-NTM 4-digit and year level. Our two-step data processing method creates a comprehensive dataset that captures all trade regulations across Latin America from 2007 to 2017, offering a new perspective on regional trade policy.

First, given a change in the classification of NTMs in 2012 we reconcile two NTM classifications pertaining to the period 2007–2011 and 2012–2017. To that end, we derive a correspondence table between the pre-2012 and post-2012 classification at the 1-digit NTM chapter level using LAIA's data collection in both classifications in 2011 and 2012. We reclassified NTMs from 2007 to 2011 according to the chapter-level categories defined in the MAST Classification M5 (UNCTAD, 2019a). As a result, we observe the number of NTMs of each type (e.g., SPS, TBT, PSI, quantity control) for all Latin American reporter-destination-product continuously in each year between 2007 and 2017.

Second, we aggregate NTM data from the national tariff line level to the HS 6-digit product level. The background is that NTM data are collected at the national tariff line at 10 digits. However, since we take into account exports to various destinations countries that do not harmonize national tariff line classifications, our two datasets cannot be satisfactorily merged at that level. Aggregation results in little attrition. Moving from 10 to 6-digit product classification implies a reduction of about 6% in the number of observations included in our reference sample.

2.2.3 Tariff data

Ad-valorem tariffs for Colombia's 17 regional trading partners come from UNCTAD TRAINS. Measured at the importer-HS 6-digit product level between 2007 and 2017, tariffs reflect the effectively applied rate, which is defined as the lowest available tariff. If a preferential tariff exists, it is used as the effectively applied tariff. Otherwise, the Most-Favored-Nation (MFN) applied tariff is used.

Thus, while we measure tariffs in terms of ad valorem price effects, NTMs are measured in count terms. The reason is that bilateral, product-specific ad valorem equivalents (AVEs) of NTMs remain scarce, despite recent progress for standard-like NTMs (Adarov and Ghodsi, 2023).

2.3 Stylized facts

Before diving into our empirical exercise, we present a series of stylized facts on Colombian exporting firms as well as the tariffs and NTMs they face in their regional

[5] Argentina, Bolivia, Brazil, Chile, Costa Rica, Colombia, Cuba, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Peru, Paraguay, Uruguay and Venezuela.

sales markets.

2.3.1 Colombian firm-level exports

Table 2.1 shows the evolution of Colombian exports between 2007 and 2017 and their geographical composition in eight major regions, following the World Bank classification. Three results stand out. First, Colombian exports reached a peak in 2012 (first row) and declined from then on until 2016. This decline was driven by the collapse of oil prices, which matter for 35% of Colombian exports related to minerals. Second, Latin American and Caribbean (LAC) countries have become the most important destination market for Colombian exports, surpassing North America, and, in particular, the USA, since 2012. Given the importance of regional exports for Colombian firms, this provides us with sufficient external validity to explore their trade response to market access conditions in LAC. Third, the importance of East Asian and Pacific destination markets for Colombian exporters has doubled between 2007 and 2017 to 10% of total exports now.

TABLE 2.1: Colombian exports, by region and year

Destination	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
World	1.00	1.25	1.10	1.36	1.97	2.08	2.00	1.85	1.22	1.04	1.27
East Asia & Pacific	0.05	0.04	0.05	0.08	0.06	0.09	0.11	0.13	0.11	0.08	0.10
Eastern Europe	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01
Latin America & Caribbean	0.37	0.39	0.31	0.29	0.33	0.32	0.32	0.31	0.36	0.34	0.37
Middle East & N. Africa	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
North America	0.37	0.40	0.41	0.44	0.40	0.37	0.33	0.28	0.29	0.35	0.30
South Asia	0.00	0.00	0.02	0.02	0.01	0.02	0.05	0.05	0.02	0.01	0.01
Sub-Saharan Africa	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.00
Western Europe	0.19	0.16	0.19	0.15	0.18	0.17	0.18	0.20	0.20	0.20	0.19

Source: Author's calculation is based on the original Colombian customs data.
Note: This table displays Colombian exports as a share of total exports and has been normalized to 100 in 2007.

Since NTM data are only available for LAC countries, the focus of the paper is on Colombian exports to LAC countries. Thus, the following tables explore how export margins have evolved, taking LAC countries as the destination. Table 2.2 reveals that the number of firms exporting to LAC countries followed a U-shaped pattern over the period under investigation. The number of firms decreased by about 10% during the global financial crisis of 2007–2010 and then steadily increased to reach a new peak in 2017. In relative terms, however, the importance of LAC firms remained stable at around 68% of all exporting firms over the whole period. Moreover, the importance of firms only exporting to LAC destination markets remained stable between 2007–17. Indeed, both the number and the corresponding share of firms exporting to LAC countries exclusively wavered at around 3,500 firms or 44% of all exporting firms in Colombia during the whole period, respectively.

Looking at the product diversification of Colombian firms yields three insights. First, multi-product firms dominate Colombian exporters. They make up 91% of all exporting firms, a share which remained remarkably stable between 2007–17. Second, table 2.3 reveals that Colombian exporters increased the diversification of their

TABLE 2.2: Number of Colombian exporting firms and destination markets

Destination	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Number of exporting firms to LAC	5,615	5,815	5,696	5,098	5,255	5,520	5,508	5,450	5,604	5,612	5,738
Number of exporting firms to LAC only	3,383	3,713	3,669	3,114	3,286	3,526	3,535	3,462	3,518	3,523	3,621
Share of LAC firms in total firms	0.68	0.69	0.70	0.69	0.71	0.73	0.71	0.70	0.69	0.68	0.68
Share of LAC only firms in total firms	0.41	0.44	0.45	0.42	0.44	0.46	0.46	0.45	0.43	0.43	0.43

Source: Author's calculation is based on Colombian customs data.
Note: This table displays Colombian firm-level export dynamics to Latin America and the Caribbean (LAC), measured in absolute (number of firms) and relative terms (share in total number of exporting firms). The third and fourth rows report the number and the share of firms among those exporting to some LAC country that exports exclusively to the region.

product portfolio from an average of 19 HS 6-digit products in 2007 to 26 products in 2017. Third, the increase in product diversification is driven by the expansion of regional export relationships, rather than extraregional ones. Put in perspective, Colombian exporting firms show a relatively high level of product diversification; Peruvian firms, for example, only export, on average, 8.5 HS 6-digit products (Fugazza et al., 2018).

TABLE 2.3: Number of exported products per Colombian firm

	Mean		Median		Maximum	
	LAC	All	LAC	All	LAC	All
2007	19.5	17.4	10.0	9.0	128	131
2008	20.5	18.3	10.0	9.0	133	133
2009	22.8	20.1	11.0	10.0	180	181
2010	23.3	20.8	11.0	10.0	175	175
2011	26.0	22.9	12.0	11.0	193	195
2012	27.0	23.7	13.0	11.0	202	204
2013	29.0	25.7	13.0	11.0	207	209
2014	29.4	26.1	13.0	12.0	202	204
2015	29.6	26.0	13.0	11.0	207	208
2016	28.6	25.4	13.0	11.0	182	186
2017	26.6	23.6	12.0	11.0	153	155

Source: Author's calculation is based on Colombian customs data.
Note: This table reports the number of exported HS 6-digits products by Colombian firms over time and by LAC and world destination markets.

Colombian exporting firms are increasingly diversified in their sales markets. Table 2.4 shows that the average share of the sales market grew from 6.4 in 2007 to 7 in 2017. In addition, Colombian firms export to an additional five destination markets beyond the region, resulting in a total of 12 destination markets globally (columns 2 and 3).

2.3.2 Tariffs in Latin America and the Caribbean

In the period between 2007 and 2017, Colombian exporters observed a decline in tariffs in their regional destination markets. The applied tariff decreased steadily from 6.7% in 2007 to only 4.1% in 2017, as seen in table 2.5, as Colombia ratified numerous preferential trade agreements with regional partners during the period

TABLE 2.4: Number of destination markets per Colombian firm, by year

	Mean		Median		Maximum	
	LAC	All	LAC	All	LAC	All
2007	6.4	10.1	6.0	8.0	16	45
2008	6.5	10.3	6.0	8.0	16	48
2009	6.6	10.7	6.0	9.0	16	48
2010	6.7	11.2	7.0	9.0	17	51
2011	6.8	11.5	7.0	9.0	17	51
2012	6.9	11.6	7.0	9.0	17	49
2013	7.0	12.0	7.0	9.0	17	51
2014	7.0	12.3	7.0	9.0	17	61
2015	7.0	11.9	7.0	9.0	17	61
2016	7.0	11.9	7.0	9.0	17	58
2017	6.9	11.5	7.0	9.0	16	60

Source: Author's calculation is based on Colombian customs data.
Note: This table reports the number of destination markets by Colombian exporters over time.

under investigation.[6] This is most evident for 2017 when tariff reductions of the Pacific Alliance between Colombia and Mexico, Peru and Chile, came into effect. At the same time, Most-Favored-Nation (MFN) tariffs negotiated at the World Trade Organization (WTO) saw only a slight decline from 9.1% in 2007 to 8.7% in 2017, reflecting the ongoing impasse in multilateral trade negotiations.

2.3.3 Non-tariff measures in Latin America and the Caribbean

The NTM dataset contains 6,211 regulations for Colombia's 17 destination markets in LAC between 2007 and 2017. To study the variation of regulations over time, we document the share of all regulations entered before vs. after 2007, the first year of data collection, and the share remained active vs. abolished in 2017, the last year of data collection. This leaves us with four margins of variation, of which all but one – regulations entered prior to 2007 that remained active in 2017 – can be exploited in our empirical strategy. Of the 6,211 regulations, 17 (0.3%) were implemented prior to 2007 and abolished before 2017; 2,367 (38.1%) regulations were implemented before 2007 and we still in place in 2017; 84 (1.4%) regulations were introduced and then abolished between 2007 and 2017; and 3,743 (60.3%) regulations were introduced between 2007 and 2017 and remained active in 2017. Table 2.6 reports the corresponding figures for each LAC member. Ecuador and Panama stand out in the region as they introduced more than 83% of regulations between 2007 and 2017, far above the region's average. In sum, this means that the majority of applicable regulations in

[6]The Pacific Alliance, signed in 2013 between Colombia and Mexico, Peru and Chile, reduced 92% of tariffs between members in 2016. Moreover, the free trade agreement (FTA) between Colombia and Costa Rica entered into force on August 1, 2016. As a result, 74% of industrial products became duty-free.

TABLE 2.5: Average tariffs facing Colombian exports, by LAC destination market between 2007–2017

Applying country	Tariff	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
ARG	Applied	4.5	3.6	3.4	2.5	2.0	1.4	0.8	1.2	1.1	1.1	1.0
	MFN	11.1	11.0	12.3	12.3	12.3	12.3	13.2	13.4	13.4	13.4	13.5
BOL	Applied	7.9	7.9	9.6	10.3	10.3	10.3	10.6	10.6	10.6	10.6	10.5
	MFN	8.7	8.7	10.4	11.1	11.1	11.1	11.5	11.4	11.4	11.5	11.7
BRA	Applied	4.0	3.0	2.3	1.5	0.7	2.5	13.0	2.0	2.0	2.1	2.1
	MFN	12.1	13.0	13.3	13.4	13.4	13.4	13.4	13.5	13.5	13.5	13.5
CHL	Applied	5.5	5.4	5.5	5.4	5.3	5.3	5.9	5.9	0.6	5.9	0.7
	MFN	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
CRI	Applied	6.1	6.6	5.7	5.7	5.6	5.7	5.7	5.7	5.7	5.7	5.7
	MFN	6.1	6.6	5.7	5.7	5.6	5.7	5.7	5.7	5.7	5.7	5.7
CUB	Applied	10.6	10.6	10.6	10.6	10.6	10.6	10.2	10.2	10.2	10.2	10.2
	MFN	10.6	10.6	10.6	10.6	10.6	10.6	10.2	10.2	10.2	10.2	10.2
ECU	Applied	11.4	11.2	11.2	11.7	10.2	10.2	10.2	10.5	10.7	11.0	11.0
	MFN	12.2	11.9	11.8	11.8	10.8	10.8	10.8	11.1	11.4	11.8	11.8
GTM	Applied	5.5	5.5	5.5	4.5	4.2	4.0	3.7	3.4	3.3	3.3	3.3
	MFN	5.8	5.8	5.8	5.8	5.8	5.8	5.7	5.7	5.7	5.7	5.7
HND	Applied	5.9	5.8	5.9	5.9	5.9	5.8	5.8	5.8	2.1	2.1	2.1
	MFN	5.9	5.9	5.9	5.9	5.9	5.8	5.8	5.8	5.8	5.8	5.8
MEX	Applied	2.6	2.4	2.3	8.9	8.2	7.8	7.5	1.6	6.9	6.8	0.8
	MFN	12.9	12.8	11.8	9.8	9.1	8.7	8.3	8.1	7.8	7.7	7.6
NIC	Applied	5.9	5.8	5.8	5.9	5.8	5.8	5.8	5.8	5.8	5.8	5.8
	MFN	5.9	5.8	5.8	5.9	5.8	5.8	5.8	5.8	5.8	5.8	5.8
PAN	Applied	7.5	7.5	7.4	7.2	7.1	7.1	7.0	7.0	7.0	7.0	7.0
	MFN	7.5	7.5	7.4	7.2	7.1	7.1	7.0	7.0	7.0	7.0	7.0
PER	Applied	9.3	6.1	5.5	5.5	4.0	4.0	3.8	3.8	3.0	3.0	0.9
	MFN	9.4	6.1	5.5	5.5	4.1	4.1	3.9	3.9	3.0	3.0	3.0
PRY	Applied	6.3	9.5	4.8	4.2	3.6	3.0	2.2	1.7	1.1	1.0	0.9
	MFN	10.3	10.3	10.3	10.3	10.3	10.3	10.2	10.1	10.1	10.1	10.0
SLV	Applied	5.7	5.8	5.7	5.8	5.8	4.5	4.2	3.9	3.8	3.8	3.4
	MFN	6.1	6.2	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1
URY	Applied	4.8	4.2	3.6	3.0	2.5	2.0	1.5	1.1	0.8	0.7	0.7
	MFN	10.5	10.5	10.5	10.5	10.5	10.5	10.6	10.6	10.6	10.5	10.5
VEN	Applied	10.8	10.9	10.9	10.7	10.9	10.9	10.9	7.5	4.1	3.9	4.0
	MFN	13.3	13.4	13.4	13.2	13.4	13.4	13.4	13.0	13.1	12.8	13.9
LAC average	Applied	6.7	6.6	6.2	6.4	6.0	5.9	6.4	5.2	4.6	4.9	4.1
	MFN	9.1	8.9	9.0	8.9	8.7	8.7	8.7	8.7	8.6	8.6	8.7

Source: Author's calculation based on UNCTAD TRAINS tariff data.
Note: This table displays Colombia's most-favored nation (MFN) and applied tariffs over time in its LAC destinations markets. MFN tariffs measure the normal non-discriminatory tariffs charged on imports from Colombia. Applied refers to the effectively applied tariff, which is defined as the lowest available tariff. If a preferential tariff exists, it will be used as the effectively applied tariff. Otherwise, the MFN applied tariff will be used. The LAC average reports Colombia's simple average of MFN and applied import tariff rates across the 17 LAC destination markets, respectively.

2017 were implemented after 2007. This provides us with sufficient variation to estimate the impact of NTMs on Colombian exports using an identification strategy based on the introduction and withdrawal of NTMs.

Next, we study the margin with the greatest importance: regulations introduced between 2007 and 2017 and active in 2017. There the composition of NTMs is heavily skewed toward technical measures: SPS and TBTs make up 40 and 52%, respectively, of all new regulations introduced between 2007 and 2017. Table 2.7 shows the number of active regulations in 2017 by country and NTM-type and its share implemented after 2007, the first year of NTM data. The majority of NTMs reported in 2017 are implemented after 2007. For the whole sample, this is the case for 53% of SPS measures, 48% of TBTs and 59% of quantity control measures. Costa Rica and Panama stand out in particular as they have implemented more than 86% of their

TABLE 2.6: NTM turnover

	Entry before 2007		Entry after 2007	
	Abolished before 2017	Active in 2017	Abolished before 2017	Active in 2017
ARG	1.3	65.5	3.4	29.8
BOL	0.0	74.4	0.0	25.6
BRA	0.3	39.2	3.0	57.6
CHL	0.2	52.9	0.6	46.2
CRI	0.0	27.3	0.3	72.4
CUB	0.0	66.7	0.0	33.3
ECU	0.1	10.9	2.0	87.0
GTM	0.0	62.9	0.0	37.1
HND	0.0	49.3	0.0	50.7
MEX	1.7	40.5	2.7	55.1
NIC	0.0	39.9	0.0	60.1
PAN	0.0	15.1	1.0	83.9
PER	0.0	38.6	0.0	61.4
PRY	0.0	56.3	0.0	43.7
SLV	0.0	61.6	0.0	38.4
URY	0.0	43.2	0.3	56.5
VEN	0.0	59.7	1.1	39.2
Total	0.3	38.1	1.4	60.3

Source: Author's calculation based on UNCTAD's NTM data.
Note: This table reports the turnover of NTMs for each of the 17 LAC countries. The row "Total" reports the average of the total NTM turnover in all 17 LAC countries.

SPS measures and TBTs since 2007. Given the prominence of technical measures, the empirical section will focus on the effect of SPS, TBTs, quantity control and PSIs measures.

TABLE 2.7: Regulations implemented since 2007 and effective in 2017

	SPS measures		TBTs		Pre-shipment Inspections		Quantity control measures		Other	
	2017	Since 2007	2017	Since 2007	2017	Since 2007	2017	Since 2007	2017	Since 2007
ARG	143	41%	265	26%	9	22%	10	40%	18	28%
BOL	31	23%	37	19%	1	0%	5	60%	8	50%
BRA	199	54%	491	63%	3	67%	36	50%	7	29%
CHL	260	45%	194	49%	5	40%	4	50%	13	31%
CRI	163	86%	115	56%	0	0%	8	75%	6	33%
CUB	24	50%	40	25%	1	0%	6	33%	1	0%
ECU	150	73%	802	92%	6	67%	24	83%	6	67%
GTM	75	20%	71	56%	0	0%	8	50%	5	0%
HND	84	50%	52	50%	0	0%	0	0%	4	75%
MEX	134	45%	236	64%	3	33%	18	78%	3	0%
NIC	146	61%	258	57%	0	0%	22	91%	5	80%
PAN	539	95%	128	47%	11	100%	8	75%	8	0%
PER	231	72%	92	39%	3	33%	1	0%	10	30%
PRY	27	22%	74	49%	3	33%	15	73%	7	14%
SLV	18	78%	221	33%	0	0%	5	100%	6	50%
URY	114	60%	174	55%	6	33%	12	58%	8	62%
VEN	58	33%	91	40%	3	33%	10	80%	12	42%
Total	2,396	53%	3,341	48%	54	27%	192	59%	127	35%

Source: Author's calculation based on UNCTAD's NTM data.
Note: This table reports the number of active regulations in 2017 by country and NTM type.

In addition to the number of active regulations and the relative importance of each NTM-type, another way to measure the incidence of NTMs is through their product coverage. Table 2.8 reports the number and share of products affected by at least one active NTM in 2017. Cuba and Argentina exhibit the highest product coverage: 98% of products that could be produced and imported at the HS 6-digit level are affected by at least one technical measure (SPS, TBT or PSI) while non-technical measures, such as price and quantity restrictions, affect at least 96% of imported products. At the other extreme, Paraguay has the lowest product coverage with 9% of products affected by at least one technical measure measure and less than 6% by non-technical measures.

TABLE 2.8: Number (share) of products affected by at least one active NTM in 2017

	Technical	Non-technical
ARG	4,479 (81)	5,205 (95)
BOL	1,930 (35)	945 (17)
BRA	3,960 (72)	1,221 (22)
CHL	3,309 (60)	107 (2)
COL	2,963 (54)	3,254 (59)
CRI	1,777 (32)	322 (6)
CUB	5,363 (98)	5,362 (97)
ECU	2,937 (53)	2,198 (40)
GTM	1,233 (22)	54 (1)
HND	1,633 (30)	588 (11)
MEX	1,848 (34)	837 (15)
NIC	1,898 (35)	752 (14)
PAN	1,717 (31)	111 (2)
PER	2,045 (37)	84 (2)
PRY	1,527 (28)	393 (7)
SLV	1,937 (35)	88 (2)
URY	2,555 (46)	367 (7)
VEN	4,891 (89)	4,803 (87)

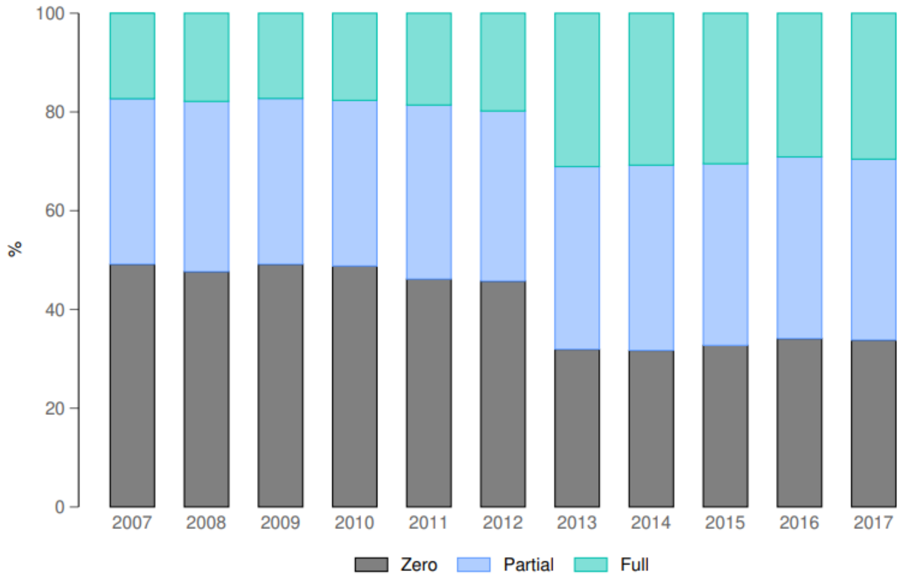
Source: Author's calculation based on UNCTAD's NTM data.
Note: The total number of products at the HS 6-digit is 5,400 (HS Combined).

2.3.4 Colombian firms and non-tariff measures in LAC

We now study the extent to which Colombian exporters face NTMs in their regional product-destination sales markets. The focus is on technical trade regulations since they are the most frequently used type of NTM, as discussed above. To make sense of the high-dimensional data, we define three groups of exporting firms. Fully exposed firms (green bar chart) are defined as those facing at least one NTM in each product-destination market. Partially exposed firms (blue bar chart) enjoy at least one product-destination market without trade regulation. The last group is made of firms whose exports do not face any trade regulations in product-destination markets.

Figure 2.1 illustrates a growing incidence of technical regulations in the product-destination markets of Colombian exporting firms. While in 2007 only 17% of Colombian exporters faced sales markets replete with trade regulations, the share

FIGURE 2.1: Incidence of technical regulations at the firm-level



Source: Author's calculation based on Colombian customs data and UNCTAD TRAINS NTM data. Note: Zero refers to the share of Colombian firms facing no technical NTMs in any of their product-destination markets. Partial refers to the share of Colombian firms facing at least one technical NTM in one of their product-destination markets. Full refers to the share of Colombian firms facing at least one in each of their product-destination markets.

grew to 30% in 2017. Conversely, the share of Colombian exporters facing zero trade regulations in their sales markets declined from 50% in 2007 to 34% in 2017.[7]

2.4 Methodology

2.4.1 Empirical framework

We use a firm-level structural gravity model to explain firm behavior at the intensive and extensive margin of exports as a function of *changes* in NTMs and tariffs. Specifically,

$$\begin{aligned} Y_{fjpt} =& exp\Big\{\beta_1 ln(1+\tau_{ijpt}) + \sum_{l \in L} \beta_{2,l} NTM^l_{ijpt} + \sum_{l \in L} \beta_{3,l} I\hat{M}R_{ljpt} \\ &+ \beta_4 ln(\text{Imports}_{fjpt}) + \omega_{fjp} + \omega_{fpt} + \omega_{jt}\Big\} + \varepsilon_{fjpt} \end{aligned} \tag{2.1}$$

$$i \in \text{ Colombia}, \forall f \in \{1,\ldots,17468\}, \forall j \in \{1,\ldots,17\},$$
$$\forall \; p \in \text{HS6} \{1,\ldots,4287\}, \forall t \in \{2007,\ldots,2017\},$$
$$l \in \{\text{TBT, SPS, Preshipment Control, Quantity Control, Price Control}\}$$

[7]The relative importance of these three groups of firms may be biased by the incidence of multi-product, multi-destination firms. However, as demonstrated by the previous analysis, the incidence of multi-product or multi-destination firms remains stable during the period of interest.

where the subscripts f, p, j and t denote, respectively, Colombian firm, HS 6-digit product, LAC destination country, and year. i refers to Colombia, the only exporting country.

We consider three dependent variables Y_{fpjt} to capture firm-level export decisions. This requires expanding the initial dataset so that each firm-product-destination has an observation in all sample years, with a 0 export value in a year when exports by the firm-product-destination are not occurring.[8] Setting up the dataset in this way for all three margins of exports and using stringent fixed effects allows us to exploit the panel dimension in the firms' decision to export or exit a product-destination market as NTMs change over time. Using this expanded dataset, we define our dependent variables Y_{fpjt} as follows:

1. Intensive margin: a continuous outcome variable Exp_{fpjt} capturing exports by Colombian firm f of product p to LAC destination country j in year t and equal to 0 otherwise;

2. Extensive margin I: a firm export participation dummy $\text{Participation}_{fpjt}$ equal to 1 in year t if Colombian firm f exports a positive value of products to destination j, and equal to 0 otherwise. Participation reflects both the creation and the continuation of a trade relationship;

3. Extensive margin II: a dummy for firm exit from a product-destination market Exit_{fpjt} equal to 1 if Colombian firm f does not export product p to destination j in year t but did so in year $t-1$ and equal to 0 if the firm exported product p to destination j in year $t-1$ and continues to do so in year t.[9]

Our variable of interest is NTM^{l}_{ijpt}, a count variable that indicates the number of NTMs of type l applied on imports from Colombia i of product p by country j at time

[8] The objectives in constructing the expanded dataset is to have observations that are computationally feasible and make economic sense, i.e., that indicate plausible firm choices with the fewest assumptions possible. To build intuition on our fill-in procedure, consider an observation from the initial dataset in which firm f starts to export product p to destination j in year t. If in the expanded dataset we add an observation with a 0 export value for firm f product p destination j, in year $t-1$, this implies that in year $t-1$ we are allowing firm f to choose whether to export product p to destination j and the firm chooses not to do so. This seems like a plausible and not overly restrictive assumption.

In contrast, expanding the initial dataset into a square matrix where every firm has an observation for every product-destination-year combination possible would retain many zeros – as most firms tend to export a single product to a single destination – and would impose computational challenges. Similarly, less data-intensive fill-in procedures lack economic sense. Consider a second example to that end: firm f exports products p1 and p2 at some point during the sample period in the initial data set. If in the expanded dataset we add observations with 0 export values for firm f for all other possible products in any year, this implies that in any year we are allowing firm f to choose whether to export any possible product. This is an implausible assumption because other products may be completely different from what the firm's capabilities in terms of its technology and other inputs allow her to produce.

[9] Firms that export to a product-destination market in every year and thus have a 0 in the dependent variable in every year will be effectively dropped from the estimating sample given the specific fixed effects (firm-product-destination) included in our specifications. Moreover, if a firm has positive exports to a product-destination market only in the last year of the sample (and no exports to that product-destination market in previous years of the sample) it is not included in the exit analysis.

t. The set L includes the most frequent NTM 1-digit chapters reported in the data: SPS measures, TBTs, PSIs, quantity control measures, and price control measures.

We include a variety of control variables in equation 2.1. First, we isolate the impact of tariffs from NTMs. $ln(1 + \tau_{ijpt})$ controls for the applied ad valorem tariff rate imposed by destination markets j on imports from Colombia i in HS 6-digit product p in year t. To include zero tariffs, we add 1 before taking the natural log.

Second, we control for product-level demand conditions in destination markets, such as time-varying business cycles or import-demand shocks. These are proxied by the natural log of Imports_{fpjt}, which represents imports by destination market j of product p in year t. Note that we subtract firm f's exports from these imports to avoid correlation by construction for large firms, hence the subscript f in Imports_{fpjt}.

Moreover, we exploit the granularity of the data to control for three types of interacted fixed effects. This strongly reduces concerns about alternative explanations. First, firm-destination-HS 6-digit product fixed effects ω_{fjp} account for unobserved heterogeneity at the panel level and allow us to identify our coefficients of interest based on within firm-destination-product changes in exports as NTMs enter into force over the sample period. Second, firm-product-year fixed effects ω_{fpt} capture product-specific productivity differences of Colombian firms and supply shocks. Third, destination-year fixed effects ω_{jt} account for time-variant demand and macroeconomic shocks in destination markets.[10] Taken together, these fixed effects control for multilateral resistance terms in a structural gravity equation (Baier and Bergstrand, 2007; Felbermayr et al., 2020). Our final control variables are the Inverse Mills Ratios of each NTM type l $I\hat{M}R_{ljpt}$, discussed in detail in the next section.

Our coefficients of interest $\beta_{2,l}$ measure the percentage change in export value, probability of participation, and exit, following the introduction of an NTM of type l for Colombian exporters to a destination-product market relative to product-destination markets without NTMs.

We estimate all three margins of exports in equation 2.1 with the Pseudo-Poisson Maximum Likelihood (PPML) estimator. It represents the standard in the trade literature for outcome variables with a high number of zeros and the presence of nonnegative data (Santos Silva and Tenreyro, 2006; Correia et al., 2020). Inference is based on Huber-White robust standard errors, clustered at the HS6 product-destination level to control for autocorrelation and heteroscedasticity.

2.4.2 Identification issues

Estimating equation 2.1 faces two econometric challenges. First, our sample may suffer from selection bias since not all Colombian firms export products to destination markets in every year of our sample. Indeed, the imposition of NTMs in destination markets may prevent Colombian firms from exporting products over time,

[10] Note that we cannot control for HS 6-digit product-destination-year fixed effects as they would absorb all variation in our variable of interest NTM^{l}_{pjt}.

meaning that these observations would not appear in our dataset. Thus, using a logarithmic dependent variable excludes cases with zero exports, generating selection bias in favor of bigger sales markets. To address selection bias at the intensive margin, we use an exponential formula in equation 2.1, include zeros to the export data along the time dimension and we estimate it with PPML.

Second, omitted variable bias may occur since NTMs may correlate with the unobserved component of a Colombian firm's exports ε_{fpjt}. This concern pertains especially to protectionist trade policy measures that might be imposed to control Colombia's exports. Specifically, if larger Colombian exports induce authorities in, say, Argentina, to impose more protectionist measures, then our NTM coefficients could be biased because the error term correlates with the NTM regressors. To account for omitted variable bias, we follow Kee and Nicita (2022) and estimate a probit control function for each type l of NTM:

$$NTM_{ljpt} = \Phi\left(\sum_{l' \in L} \gamma_{l'} \overline{NTM}_{l'jpt} + \varepsilon_{lpjt}\right) \tag{2.2}$$

where NTM_{ljpt} indicates a dummy outcome variable equal to 1 if destination j has an NTM of type l on product p in year t and 0 otherwise; Φ the cumulative distribution function of the standard distribution; $\gamma_{l'}$ evaluates to which extent a country is more likely to implement an NTM of type l if its three closest countries implement an NTM of type l'; and $\overline{NTM}_{l'jpt}$ the average NTM of type l' of the three closest countries of destination j.[11]

While the introduction of NTMs in Argentina could be correlated with that of Argentina's neighbors due to regional and cultural proximity, Colombia's exports to Argentina of a particular product should not influence the trade policies of Argentina's closes countries for the same product. Put differently, we argue that Argentina's political economy motives against Colombian imports will not directly shape trade policies among Argentina's neighbors for those Colombian products. As a result, these instruments meet the criteria for the exclusion restriction. Table B.1 shows positive estimates of the probit control function, suggesting that the neighbors' imposition of NTMs predicts the country's own implementation of NTMs.

Next, we obtain $\hat{\gamma}_{l'}$ to compute the Inverse Mills Ratio (IMR) for each type of NTM-type l:

$$I\hat{M}R_{ljpt} = \frac{\Phi\left(\sum_{l' \in L} \hat{\gamma}_{l'} \overline{NTM}_{l'jpt}\right)}{\phi\left(\sum_{l' \in L} \hat{\gamma}_{l'} \overline{NTM}_{l'jpt}\right)} \tag{2.3}$$

where ϕ represents the standard normal density function. IMR captures the hazard of non-selection: if the IMR for an NTM is higher, the importing country is less

[11]To define closeness, we rely on bilateral distance between countries, weighted by population of main cities, provided by Mayer and Zignago (2011).

likely to have implemented the NTM, considering the NTMs imposed by its neighbors. We include the IMR vector as a control variable in equation 2.1 to account for the correlation that the importing country enforces an NTM despite a high IMR, our endogeneity concern. This ensures that we compare treated and untreated units that have similar chances of being treated, based on the actions of neighboring countries. Our preference over an instrumental variable approach stems from the binary nature of the endogenous NTM variable and the utilization of a PPML estimator with high-dimensional fixed effects.

In addition, we conduct a host of robustness tests to rule out omitted variable bias. First, we lag both tariffs and NTM variables by one year, following Fugazza et al. (2018). Our expectation is that the use of an NTM in a previous year is exogenous to firms' exports in the current year. Second, following Fernandes et al. (2021), we exclude from the sample the largest exporting firms in Colombia which may influence the imposition of NTMs in destination markets. The largest exporting firms are identified for each destination market and year as those in the top 1% of the distribution of total firm exports. Third, and in the same vein, we exclude from the sample the HS 2-digit sectors with the highest degree of export concentration across firms. Concentrated sectors are defined as those for which the largest 1% of firms are responsible for more than 50% of sector exports in at least one sample year. Fourth, we run placebo tests to show that future NTMs do not have an effect on current firm-level export values, participation or entry. To that end, we evaluate the placebo treatment of leading NTM types and tariffs by one year.

In the Appendix B.2, we conduct additional robustness tests to show that NTM overlap and collinearity are not a concern for our identification strategy.

2.5 Results

2.5.1 Summary statistics

Table C.4 displays the summary statistics of our variables. Panel A displays the sample for the intensive margin of exports, i.e., for all observations in a firm, product, destination, and year combination. Conversely, Panel B reports the statistics for both extensive margins I and II: probability of export participation and exits.

In our sample, Colombian firms export, on average, around US $151,000 per product and destination market. However, this average masks a great dispersion of firm-level exports as seen by the massive standard deviation.[12]

Panel B shows that export participations happen in 57% of possible cases. That is, Colombian firms export, on average, into 57% of all product-destination-year combinations in our sample for the extensive margin I. This means export participation

[12] While the underlying export values are measured in nominal US dollars, note that our regressions have destination-year fixed effects among others, so our dependent variables can be interpreted in real, not nominal, terms.

TABLE 2.9: Summary statistics

Variable	N	Mean	Std. Dev.	Min	Max
Panel A - Intensive Margin of Exports					
Exports (in USD)$_{f,p,j,t}$	253,212	151,748	1,936,183	0.0	298,207,937
Log (Tariff$_{i,j,p,t}$)	253,212	1.224	1.27	0.0	4.4
SPS$_{i,j,p,t}$	253,212	1.910	3.02	0.0	69.0
TBT$_{i,j,p,t}$	253,212	3.577	3.60	0.0	31.0
Pre-Shipment$_{i,j,p,t}$	253,212	0.117	0.33	0.0	3.0
Quantity Control$_{i,j,p,t}$	253,212	0.493	0.79	0.0	5.0
Price Control$_{i,j,p,t}$	253,212	0.305	0.49	0.0	5.0
Log (Import Demand$_{f,p,j,t}$)	253,212	10.593	5.55	-2.7	20.8
Firm size 1: Exports per product (in USD)$_{f,t}$	39,365	679,199	6,211,960	0.0	327,057,215
Firm size 2: Exports per sector (in USD)$_{f,t}$	28,786	3,421,507	19,717,287	0.0	399,821,436
Firm size 3: Total exports (in USD)$_{f,t}$	24,247	6,850,923	25,315,153	0.1	399,821,877
GVC dummy: firm exports and imports$_{f,t}$	253,212	0.244	0.43	0.0	1.0
Panel B - Extensive Margin of Exports					
Prob (Export Participation$_{f,p,j,t}$)	253,212	0.570	0.50	0.0	1.0
Prob (Export Exit$_{f,p,j,t}$)	17,221	0.551	0.50	0.0	1.0
Log (Tariff$_{i,j,p,t}$)	17,221	1.167	1.26	0.0	4.0
SPS$_{i,j,p,t}$	17,221	1.998	2.95	0.0	29.0
TBT$_{i,j,p,t}$	17,221	3.951	3.65	0.0	28.0
Pre-Shipment$_{i,j,p,t}$	17,221	0.151	0.37	0.0	3.0
Quantity Control$_{i,j,p,t}$	17,221	0.528	0.79	0.0	5.0
Price Control$_{i,j,p,t}$	17,221	0.328	0.50	0.0	5.0
Log (Import Demand$_{f,p,j,t}$)	17,221	11.171	5.19	-0.4	19.8
Firm size 1: Exports per product (in USD)$_{f,t}$	5,239	659,912	2,991,801	0.1	42,844,647
Firm size 2: Exports per sector (in USD)$_{f,t}$	3,546	1,080,343	4,747,268	0.1	48,113,669
Firm size 3: Total exports (in USD)$_{f,t}$	2,762	1,496,305	5,610,819	0.1	48,113,669
GVC dummy: firm exports and imports$_{f,t}$	17,221	0.264	0.44	0.0	1.0

This table presents descriptive statistics for the three dependent variables between 2007 and 2017. The upper panel presents the sample used in the estimations of the intensive margin: export value. The lower panel presents results used in the estimations of the extensive margin I and II: probability of export participation and export exits. The table also includes statistics on the incidence of NTM types and tariffs, control variables and firm size measures.

is a likely event, on average. Similarly, the probability of firms leaving product-destination markets occurs in 55.1% of possible cases.

The incidence of NTMs varies by type. In our sample, TBTs are ubiquitous and occur, on average, 3.5 times in firm's export relationships (product-destination-year cells) at the intensive margin and 3.9 times at the extensive margin. SPS and quantity control measures are present, on average, 1.9 and 0.5 times of firms' export relationships. On average, Colombian firms face 1.2% of applied ad valorem tariffs in regional destination markets in our sample.

Our three proxies for firm size – explained in Section 2.5.5 – indicate that firms that already export (intensive margin) are bigger than those with intermittent exports (extensive margin II). Colombian firms participating in global value chains (GVC), defined as those that both import and export goods, make up 24% in our sample.[13]

[13] This GVC definition follows World Bank (2020).

2.5.2 Intensive margin of exports

Column (1) of table 2.10 evaluates the principal component of all five NTM types. Column (2) provides our baseline results with all NTM types and control variables. The remaining columns provide robustness tests. Specifically, column (3) lags all NTM types and tariff variables by one year. Column (4) excludes large Colombian exporting firms that may influence the imposition of NTMs in destination markets. To the same effect, column (5) excludes HS 2-digit sectors with the highest degree of export concentration across Colombian firms. Finally, in column (6) we run placebo tests to show that future NTMs do not have an effects on current firm-level export values. All columns use the battery of stringent fixed effects α_{fjp}, δ_{fpt} and η_{jt} that allow us to interpret coefficients akin to a difference-in-differences setup. For expositional clarity, the coefficients of the IMR are not reported. For comparison purposes, we report standardized coefficients in all tables by normalizing the regressors to have mean zero and unit standard deviation.

The impact of market access conditions on the intensive margin of exports is, on average, negative. Column (1) suggests that an increase of one standard deviation of the principal component of NTMs is associated, on average, with a decrease of 19% in firm exports.[14]

However, the impact of market access conditions varies greatly across NTM types. Column (2) shows that quantity controls undermine firm-level exports the most, followed by TBTs. Specifically, an increase of one standard deviation in quantity control in Colombia's destination markets associated with, on average, a 43% decrease of firm-level exports. In contrast, the introduction of new TBT measures in Colombia's destination markets translates into a 9% reduction of its firm-level exports. Tariffs, SPS, quantity and price control do not have, on average, an effect on Colombian firms' exports. As for control variables, their estimated coefficients yield the expected significance and sign; increases in import demand at destination increases Colombian firm-level exports.

Our robustness tests confirm the relative importance of quantity controls over TBTs at the intensive margin of exports. Columns (3) show that the results obtained with lagged NTMs and tariffs are consistent with our baseline estimates. Moreover, excluding the largest firms and concentrated sectors in columns (4) and (5) maintains the consistency of our findings, providing additional proof that reverse causality is not driving our results. Consistent with our baseline results, all three robustness tests highlight the importance of quantity controls, followed by TBTs, to discourage Colombian firm-level exports. Finally, column (6) provides evidence that future introductions of NTMs are not correlated with existing firm-level exports. Overall, we note the extremely high explanatory power of our model, as evidenced by the adjusted R^2 of 0.95.

[14] exp(-0.2179) -1

2.5.3 Extensive margin of exports I

Models with heterogeneous firms predict a negative effect of market access conditions on the extensive margin of exports, as measured by firms' export participation.

The empirical results shown in table 2.11 are in line with theoretical predictions. Column (1) suggests that an increase of one standard deviation of the principal component of NTMs is associated, on average, with a decrease of 13% of firms' probability of participating in exports. Considering the 57% unconditional probability of export participation, the estimated economic impact of NTMs is thus sizable.

Various NTM types influence firms' probability of export participation. While coefficients of tariffs, quantity controls, TBTs, and SPS are consistently negative and statistically coefficients across all specifications, quantity controls and tariffs undermine firms' export participation probabilities the most. However, the magnitude of coefficients is low compared to those at the intensive margin. Moreover, our robustness tests in columns (3)–(5) highlight the relative importance of tariffs and quantity controls in lowering firms' export participation. In demonstrating consistency with our baseline results, they marshal evidence that reserve causality is not driving our results. Finally, demand conditions at destination positively affect the extensive margin in all specifications. This implies that the likelihood of exporting is larger in bigger destination markets.

2.5.4 Extensive margin of exports II

NTMs may also force Colombian firms to stop exporting to a product-destination market. To explore this hypothesis, we evaluate the roles that tariffs and specific NTM types play for firms' probability of export exits, the second extensive margin of interest.

We find that, on average, NTMs increase firms' probability to stop exporting. Column (1) in table 2.12 suggests that a one standard deviation increase of the principal component of NTMs is associated, on average, with a increase of 22% in firms' exit probability. This implies a big economic impact, considering the 55% unconditional probability to stop exporting.

Our results show that new TBTs in product-destination markets lead to higher exit rates from those markets. Column (2) suggests that the introduction of TBT measures in Colombia's product-destination markets translates into a 22% increase in firms' likelihood of leaving export markets. Other NTM types and tariffs sustain no effect. Control variables have the expected sign and statistical significance.

Intriguingly, however, we find that that new quantity controls in destination-product markets, on average, lower the exit rates of Colombian firms from those markets. The effect is consistently negative and statistically significant across all specifications in columns (2)–(5). A potential rationale for this finding is that we are picking up average firm-level responses across the entire firm-size distribution. Indeed, we will show in the next section 2.5.5 that small firms benefit from quantity controls to the detriment of bigger firms, which are more constrained by the imposition of quantity controls in product-destinationmarkets.

Our robustness tests in columns (3)–(5) confirm the importance of TBTs in increasing firms' exit rates, maintaining similar coefficients as in our baseline specification. Similarly, the robustness tests confirm that new quantity controls reduce exit rates for Colombian firms. This provides additional evidence against reverse causality, i.e., showing that the effect of quantity controls for firms' exit rates is not the result of pressure by influential domestic firms or sectors to design NTMs to their advantage. Finally, our placebo test in column (6) also shows that no future NTM-type correlates with firms' present exit rate.

We also find that increases in tariffs and SPS measures in product-destination markets make it less likely that Colombian firms will continue exporting to these markets. This effect is significant and robust across all specifications, revealing that firms are responsive to additional market access conditions at this margin.

2.5.5 Heterogeneous results for large firms

Larger firms may be able to more easily overcome the fixed costs needed to comply with a new market access conditions in the importing country. That is why we expect, on average, a smaller export-restricting effect of NTMs for larger firms. Indeed, the largest exporters could gain from new market access conditions as demand is redirected toward them when small exporters are priced out of the market through new market access conditions.

The literature, however, provides inconclusive evidence on the heterogeneous impact of NTM types and firm size. Fugazza et al. (2018) shows that new tariffs, TBT and PSI measures in destination markets benefit very large Peruvian exporters, while hurting smaller ones. On the other hand, Fernandes et al. (2021) finds that provisions that harmonize SPS and TBT regulations in PTAs are more beneficial for exports of smaller firms.

To explore this hypothesis, we consider the following specification:

$$\begin{aligned} Y_{fjpt} =exp\Big\{ & \beta_1 ln(1+\tau_{ijpt}) + \sum_{l \in L} \beta_{2,l} NTM^{l}_{ijpt} + \sum_{l \in L} \beta_{3,l} I\hat{M}R_{ljpt} \\ & + \beta_4 ln(Imports_{fjpt}) + \sum_{l \in L} \beta_{5,l} NTM^{l}_{ijpt} \times BigFirm_f \\ & + \beta_6 ln(1+\tau_{ijpt}) \times BigFirm_f + \omega_{fjp} + \omega_{fpt} + \omega_{jt} \Big\} + \varepsilon_{fjpt} \end{aligned} \tag{2.4}$$

Our coefficients of interest are $\beta_{5,l}$ and β_6 in equation 2.4. They measure how the size of a firm creates a varied impact of NTMs and tariffs on the three margins of firm-level exports.

We consider two mutually exclusive firm-size categories. As a baseline, we define firm size by the export market share a firm has in a 6-digit product market in its first defined year in the sample.[15] Our definition of firm size is guided by how specific NTMs are; we assume that most are applicable to very narrowly defined HS 6-digit products. The underlying reasoning is that the introduction or withdrawal of NTMs could differentially benefit small firms from the point of view of that product's market. We then binarize the continuous firm-size variable based on its median and evaluate the differential impact of NTMs on $BigFirm_f$ in equation 2.4.

We conduct two robustness checks on the definition of firm-size categories. First, we define firm size based on the export market share a firm has in an HS 2-digit sector in its first defined year in the sample. Second, we define firm size based on the export market share a firm has in its first defined year in the sample, considering all products and sectors. Thus, our additional firm-size definitions grow broader in scope.[16]

Our results confirm that market access conditions vary significantly based on firm size. Table 2.13 attests to that end for the intensive margin of Colombian firm-level exports. The exports of small firms decline significantly when TBT and in particular quantity control measures are introduced in their export markets. In contrast, the effect is muted for big firms. That is why the interaction effects between TBT and quantity controls and $BigFirm_f$ are statistically significant and positive. Moreover, this effect is consistent across our three definitions of firm size in columns (2)–(4). It confirms previous evidence of the export-promoting effect of TBTs for big Peruvian exporters in Fugazza et al. (2018).

Similarly, TBT and quantity control measures exert a regressive effect on the extensive margin of firm-level exports. Table 2.14 shows that small firms are significantly less likely to export when new TBT and quantity control measures are introduced in sales markets. Conversely, larger firms experience a diminished impact, regardless of the definitions of firm sizes used in columns (2) through (4).

Firm size also shapes how TBTs and quantity contol measures affect the likelihood of firms leaving markets. Table 2.15 reveals that small firms are more likely to leave sales market when TBT measures are introduced. That is why the baseline TBT coefficient – pertaining to small firms – is statistically significant and positive across all three definitions of firm size in columns (2)–(4). In contrast, the likelihood of leaving these markets is not elevated for big firms, even though the interaction effect is not statistically significant.

The only progressive NTM effect comes from new quantity controls. They decrease the likelihood of exits from product-destination markets for small firms, yet increase it for big firms. This finding is consistent across all three definitions of firm size, as shown in the coefficients of Quantity $\text{Control}_{i,j,p,t} \times$ Big Firm_f in columns

[15]We are limited to rely on export-based measures of firm characteristics because we do not have information on headcount, turnover or capital of Colombian exporting firms. We define firm size categories separately for each of the three margins of exports. This helps to account for the fact that firms have, on average, greater exports – and are thus bigger – at the intensive margin, as opposed to the extensive margins.

[16]As in equation 2.1, we use the same battery of three sets of high-dimensional fixed effects, include zeros along the time dimension and and rely on the PPML estimator for all three margins of exports.

(2)–(4). An explanation for this finding is a composition effect: quantity controls are more binding for big firms, increasing their likelihood to leave markets. Quantity controls, in turn, impose fewer constraints for smaller exporters, making them less likely to leave markets.

2.5.6 Heterogeneous results for global value chain firms

Firms participating in global value chains (GVCs) may face muted effects from NTMs. Because they have extensive contractual relationships, including with importers, these firms have greater access to information about regulatory changes, market conditions, and compliance requirements. As a result, GVC firms may find it easier to meet evolving regulatory requirements emanating from NTMs.

To explore this hypothesis, we re-estimate specification 2.4 by interacting GVC Firm_{ft} with tariffs and NTM types. We define GVC Firm_{ft} as an indicator variable equal to 1 if a firm both imports and exports goods in a given year and 0 otherwise. GVC firms make up around 24% of all observations, as seen in table C.4. Intriguingly, only 20% of big firms are also GVC firms, while 55% of GVC firms are also big firms.

Table 2.16 demonstrates a heterogeneous impact of market access conditions for GVC firms. Column (2) shows results for the intensive margin; column (4) for the extensive margin I and column (6) for the extensive margin II. To put these results into perspective, columns (1), (3) and (5) provide the respective baseline results presented above.

Looking at the intensive margin, GVC firms benefit from a dampened effect from new trade regulations in product destination markets. While non-GVC firms see a significant decline of their exports associated with new quantity control, SPS and TBT measures, the positive interaction coefficients for GVC firms in columns (2) suggest these effects are muted for them. Both effects are statistically significant and of economic relevance.

GVC firms are also more likely to export as market access conditions affect them less than non-GVC firms. Column (4) shows that tariffs, pre-shipment and quantity control measures undermine the likelihood of non-GVC firms of participating in exports. In contrast, these measures have a muted impact on GVC firms' likelihood to participate in exports as their positive and significant interaction effect attests to.

Intriguingly, GVC firms are more likely to leave markets when new quantity control measures are introduced. This is reflected in the positive and statistically significant interaction effect Quantity $\text{Control}_{i,j,p,t} \times \text{GVC Firm}_{ft}$ in column (6), indicating a higher exit probability for GVC firms. Conversely, non-GVC firms are less likely to exit markets when quantity controls are introduced. A potential explanation is that new quantity measures are more binding for GVC firms than non-GVC firms due to their elevated exports in the first place.

2.6 Conclusion

This paper studies how NTMs, the dominant instrument of today's trade policy, challenge firm-level export decisions to access foreign markets. Our panel analysis of Colombians firms exporting to Latin America reveals that both TBT and quantity control measures decrease their exports on average. We rationalize this trade-deterring effect through an increase in compliance costs of firms relative to consumer benefits. Other NTMs and tariffs play a minor role.

These average effects of trade regulations mask significant heterogeneities. TBT and quantity measures reallocate trade from small to big firms and those participating in global value chains. However, quantity control measures exert progressive effects under specific conditions, making it more likely that big firms will leave export markets, with the opposite effect occurring for small firms. We argue that the quantity controls are more binding for big firms, increasing their likelihood of leaving markets and conversely helping small firms to take over their space.

Our results are important for policy. First, they support the evidence that trade regulations are now more trade restrictive than tariffs Nicita and Melo (2018). This highlights the importance of mechanisms to harmonize trade regulations between countries to reduce their costs. The most significant are international trade agreements, facilitated by organizations such as the World Trade Organization (Fernandes et al., 2021). These agreements are crucial for helping firms to access international markets, which is essential for removing demand-side constraints on national development Goldberg and Reed (2023).

Second, our finding that even standard-like measures like TBTs undermine Colombian firm-level export decisions aligns with firms choosing not to embrace a new signal due to its associated costs and benefits. It questions the trade-promoting effects of TBTs and that consumers receive useful information about product quality and increase trade, relative to the adverse impact on trade caused by any increase in cost Zavala et al. (2023) and Beghin et al. (2015). Moreover, it underscores the need for assistance to help firms comply with these trade regulations. This is particularly justified where there is market failure, in particular where consumers take time to adjust their demand after receiving new quality signals (Bai, 2022).

Third, our finding that trade regulations tend to favor large firms at the expense of small ones implies a concentration of world markets. It suggests that big firms benefit from protectionism, not globalization. This contrasts with a liberalized trade order, which would lead to a more equal distribution of export market shares among firms. It would also likely reduce wage inequality within the exporting country as small firms tend to be less skilled compared to large firms(Cruz et al., 2017). However, with today's new economic interventionism fueling trade protectionism, this is all but happening. Technological change and the backlash against globalization are making export-oriented industrialization as seen in East Asia much more difficult to achieve.

TABLE 2.10: Intensive margin of exports

Dependent Variable: Exports$_{fpjt}$	PCA	Baseline	Robustness tests			
			Lags	w/o large firms	w/o concentrated sectors	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
NTM Principal Component$_{i,j,p,t}$	-0.2179					
	(0.044)***					
Log (Tariff$_{i,j,p,t}$)		-0.0351	-0.0696	-0.0438	-0.0982	-0.0333
		(0.036)	(0.054)	(0.047)	(0.051)*	(0.051)
SPS$_{i,j,p,t}$		0.0021	-0.0146	-0.0914	-0.0161	-0.0328
		(0.048)	(0.042)	(0.050)*	(0.048)	(0.048)
TBT$_{i,j,p,t}$		-0.0971	-0.0811	-0.0968	-0.1387	-0.0650
		(0.044)**	(0.028)***	(0.042)**	(0.039)***	(0.044)
Pre-Shipment$_{i,j,p,t}$		0.0388	-0.0154	0.0094	0.0323	0.0350
		(0.053)	(0.046)	(0.049)	(0.047)	(0.056)
Quantity Control$_{i,j,p,t}$		-0.5739	-0.4905	-0.2355	-0.3295	-0.2107
		(0.158)***	(0.155)***	(0.100)**	(0.115)***	(0.159)
Price Control$_{i,j,p,t}$		-0.0483	-0.0410	-0.1115	-0.0793	0.0420
		(0.040)	(0.036)	(0.028)***	(0.035)**	(0.046)
Other NTMs$_{i,j,p,t}$		0.1252	0.1040	0.2088	0.0491	0.0289
		(0.101)	(0.097)	(0.100)**	(0.097)	(0.075)
Log (Import Demand$_{f,p,j,t}$)	0.0448	0.0324	0.0251	0.0291	0.0285	0.0340
	(0.009)***	(0.006)***	(0.006)***	(0.005)***	(0.007)***	(0.007)***
Observations	253212	253212	227964	200738	250213	219733
Adjusted R^2	0.93	0.96	0.96	0.94	0.96	0.96
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.1 for the intensive margin of Colombian firm-level exports. Columns (2-6) show coefficients standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

TABLE 2.11: Extensive margin of exports I

Dependent Variable:Probability of Export Participation$_{fpjt}$	PCA	Baseline	Robustness tests			
			Lags	w/o large firms	w/o concentrated sectors	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
NTM Principal Component$_{i,j,p,t}$	-0.1448					
	(0.008)***					
Log (Tariff$_{i,j,p,t}$)		-0.0483	-0.0571	-0.0512	-0.0488	-0.0242
		(0.011)***	(0.011)***	(0.013)***	(0.011)***	(0.022)
SPS$_{i,j,p,t}$		-0.0280	-0.0283	-0.0363	-0.0307	-0.0219
		(0.013)**	(0.013)**	(0.016)**	(0.013)**	(0.024)
TBT$_{i,j,p,t}$		-0.0343	-0.0424	-0.0496	-0.0348	-0.0098
		(0.012)***	(0.012)***	(0.014)***	(0.012)***	(0.013)
Pre-Shipment$_{i,j,p,t}$		0.0099	-0.0142	0.0169	0.0089	-0.0030
		(0.009)	(0.009)	(0.012)	(0.009)	(0.013)
Quantity Control$_{i,j,p,t}$		-0.0537	-0.0454	-0.0391	-0.0501	-0.0193
		(0.021)***	(0.022)**	(0.022)*	(0.021)**	(0.022)
Price Control$_{i,j,p,t}$		-0.0043	0.0018	-0.0073	-0.0044	0.0008
		(0.014)	(0.014)	(0.016)	(0.014)	(0.014)
Other NTMs$_{i,j,p,t}$		-0.0091	0.0248	-0.0053	-0.0172	-0.0254
		(0.022)	(0.020)	(0.030)	(0.022)	(0.019)
Log (Import Demand$_{f,p,j,t}$)	0.0184	0.0110	0.0105	0.0138	0.0114	0.0107
	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.001)***	(0.002)***
Observations	253212	253212	227964	200738	250213	219733
Adjusted R^2	0.13	0.15	0.15	0.15	0.15	0.15
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.1 for the extensive margin I of Colombian firm-level exports. Columns (2-6) show coefficients standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*}p < 0.10$,** $p < 0.05$,*** $p < 0.01$

TABLE 2.12: Extensive margin of exports II

Dependent Variable: Probability of Export Exit$_{fpjt}$						
	PCA	Baseline	Robustness tests			
			Lags	w/o large firms	w/o concentrated sectors	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
NTM Principal Component$_{i,j,p,t}$	0.1995					
	(0.031)***					
Log (Tariff$_{i,j,p,t}$)		-0.0545	0.0382	-0.0614	-0.0493	-0.0390
		(0.057)	(0.055)	(0.059)	(0.058)	(0.070)
SPS$_{i,j,p,t}$		0.1098	0.0390	0.0860	0.1316	0.0898
		(0.087)	(0.084)	(0.094)	(0.088)	(0.093)
TBT$_{i,j,p,t}$		0.1939	0.2936	0.2148	0.2012	0.0538
		(0.072)***	(0.077)***	(0.083)***	(0.074)***	(0.080)
Pre-Shipment$_{i,j,p,t}$		0.0516	0.1018	-0.0357	0.0777	-0.1040
		(0.096)	(0.079)	(0.101)	(0.093)	(0.099)
Quantity Control$_{i,j,p,t}$		-0.2712	-0.1944	-0.3128	-0.3292	-0.1175
		(0.114)**	(0.101)*	(0.125)**	(0.114)***	(0.132)
Price Control$_{i,j,p,t}$		-0.0495	-0.1269	0.1028	-0.0229	-0.0480
		(0.087)	(0.118)	(0.108)	(0.090)	(0.092)
Other NTMs$_{i,j,p,t}$		-0.1053	-0.1477	-0.1053	-0.0639	-0.0706
		(0.074)	(0.060)**	(0.077)	(0.076)	(0.078)
Log (Import Demand$_{f,p,j,t}$)	-0.0282	-0.0211	-0.0210	-0.0310	-0.0218	-0.0322
	(0.006)***	(0.008)**	(0.008)**	(0.010)***	(0.008)***	(0.010)***
Observations	17221	17221	17221	13455	16961	13354
Adjusted R^2	0.13	0.18	0.18	0.18	0.18	0.18
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.1 for the extensive margin II of Colombian firm-level exports. Columns (2-6) show coefficients standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

TABLE 2.13: Intensive margin of exports - heterogeneous effects of firm size

Dependent variable: Exports$_{fpjt}$				
Big Firm: exports > median in		HS6 product-Year	HS2 sector-Year	Year
	(1)	(2)	(3)	(4)
Log (Tariff$_{i,j,p,t}$)	-0.0351	-0.0024	-0.0036	-0.2244
	(0.036)	(0.093)	(0.085)	(0.107)**
Log (Tariff$_{i,j,p,t}$) x Big Firm$_{f,t}$		-0.0332	-0.0314	0.1962
		(0.090)	(0.090)	(0.108)*
SPS$_{i,j,p,t}$	0.0021	-0.0840	-0.1102	0.0374
	(0.048)	(0.097)	(0.067)	(0.114)
SPS$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.1022	0.1256	-0.0300
		(0.115)	(0.079)	(0.126)
TBT$_{i,j,p,t}$	-0.0971	-0.2802	-0.2091	-0.0552
	(0.044)**	(0.078)***	(0.099)**	(0.160)
TBT$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.1452	0.1136	0.1566
		(0.071)**	(0.060)***	(0.073)**
Pre-Shipment$_{i,j,p,t}$	0.0388	-0.0929	-0.0327	0.1404
	(0.053)	(0.060)	(0.077)	(0.062)**
Pre-Ship.$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.1676	0.0797	-0.1017
		(0.064)***	(0.087)	(0.073)
Quantity Control$_{i,j,p,t}$	-0.5739	-0.5769	-0.7281	-0.7879
	(0.158)***	(0.134)***	(0.151)***	(0.150)***
Quantity Control$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.267	0.1658	0.2286
		(0.103)***	(0.082)**	(0.100)**
Price Control$_{i,j,p,t}$	-0.0483	-0.1686	-0.0706	-0.0782
	(0.040)	(0.059)***	(0.053)	(0.100)
Price Control$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.1442	0.0173	0.0242
		(0.072)**	(0.055)	(0.097)
Log (Import Demand$_{f,p,j,t}$)	0.0324	0.0319	0.0322	0.0323
	(0.006)***	(0.006)***	(0.006)***	(0.006)***
Observations	253212	253212	253212	253212
Adjusted R^2	0.96	0.96	0.96	0.96
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.4 for the intensive margin of Colombian firm-level exports. Columns (1-4) show coefficients standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

TABLE 2.14: Extensive margin of exports I - heterogeneous effects of firm size

Dependent variable: Probability of Export Participation$_{fpjt}$				
Big Firm: exports > median in		HS6 product-Year	HS2 sector-Year	Year
	(1)	(2)	(3)	(4)
Log (Tariff$_{i,j,p,t}$)	-0.0483	-0.0487	-0.0659	-0.0302
	(0.011)***	(0.015)***	(0.020)***	(0.020)
Log (Tariff$_{i,j,p,t}$) x Big Firm$_{f,t}$		0.0007	0.0228	-0.0223
		(0.017)	(0.022)	(0.022)
SPS$_{i,j,p,t}$	-0.0280	-0.0096	-0.0240	-0.0145
	(0.013)**	(0.022)	(0.023)	(0.025)
SPS$_{i,j,p,t}$ x Big Firm$_{f,t}$		-0.0313	-0.0077	-0.0198
		(0.025)	(0.026)	(0.028)
TBT$_{i,j,p,t}$	-0.0343	-0.0568	-0.0874	-0.0874
	(0.012)***	(0.017)***	(0.022)***	(0.023)***
TBT$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.0351	0.0700	0.0671
		(0.019)*	(0.025)***	(0.026)**
Pre-Shipment$_{i,j,p,t}$	0.0099	-0.0179	-0.0071	0.0155
	(0.009)	(0.013)	(0.016)	(0.019)
Pre-Ship.$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.0469	0.0226	-0.0062
		(0.012)***	(0.017)	(0.020)
Quantity Control$_{i,j,p,t}$	-0.0537	-0.1089	-0.1008	-0.0686
	(0.021)***	(0.022)***	(0.027)***	(0.028)**
Quantity Control$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.0925	0.0574	0.0553
		(0.017)***	(0.023)**	(0.025)**
Price Control$_{i,j,p,t}$	-0.0043	-0.0053	0.0004	-0.0427
	(0.014)	(0.019)	(0.024)	(0.025)*
Price Control$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.0016	-0.0074	0.0460
		(0.021)	(0.027)	(0.027)*
Log (Import Demand$_{f,p,j,t}$)	0.0110	0.0109	0.0110	0.0110
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Observations	253212	253212	253212	253212
Adjusted R^2	0.15	0.15	0.15	0.15
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.4 for the intensive margin of Colombian firm-level exports. Columns (1-4) show coefficients standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

TABLE 2.15: Extensive margin II of exports - heterogeneous effects of firm size

Dependent Variable: Probability of Export Exit$_{fpjt}$				
Big Firm: exports > median in		HS6 product-Year	HS2 sector-Year	Year
	(1)	(2)	(3)	(4)
Log (Tariff$_{i,j,p,t}$)	-0.0545	-0.0671	-0.0596	-0.0010
	(0.057)	(0.074)	(0.081)	(0.080)
Log (Tariff$_{i,j,p,t}$) x Big Firm$_{f,t}$		0.0723	0.0272	-0.0659
		(0.102)	(0.105)	(0.100)
SPS$_{i,j,p,t}$	0.1098	-0.0437	0.0408	-0.1746
	(0.087)	(0.124)	(0.128)	(0.142)
SPS$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.3218	0.1290	0.4476
		(0.168)*	(0.168)	(0.177)**
TBT$_{i,j,p,t}$	0.1939	0.2654	0.3064	0.2809
	(0.072)***	(0.106)**	(0.113)***	(0.116)**
TBT$_{i,j,p,t}$ x Big Firm$_{f,t}$		-0.0746	-0.1811	-0.1256
		(0.150)	(0.149)	(0.143)
Pre-Shipment$_{i,j,p,t}$	0.0516	0.0292	0.0221	0.0468
	(0.096)	(0.139)	(0.139)	(0.143)
Pre-Ship.$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.0108	0.0461	-0.0358
		(0.178)	(0.164)	(0.181)
Quantity Control$_{i,j,p,t}$	-0.2712	-0.2904	-0.3151	-0.2507
	(0.114)**	(0.133)**	(0.118)***	(0.120)**
Quantity Control$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.0857	0.0129	0.0921
		(0.095)	(0.090)	(0.088)
Price Control$_{i,j,p,t}$	-0.0495	-0.1460	-0.1276	-0.0254
	(0.087)	(0.110)	(0.106)	(0.160)
Price Control$_{i,j,p,t}$ x Big Firm$_{f,t}$		0.1414	0.1469	-0.0319
		(0.118)	(0.117)	(0.155)
Log (Import Demand$_{f,p,j,t}$)	-0.0211	-0.0208	-0.0217	-0.0215
	(0.008)**	(0.009)**	(0.009)**	(0.009)**
Observations	17221	16672	17077	17141
Adjusted R^2	0.18	0.18	0.18	0.18
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.4 for the intensive margin of Colombian firm-level exports. Columns (1-4) show coefficients standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*} p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$

TABLE 2.16: Heterogeneous effects of global value chain firms

Dependent variable:	**Exports** $_{f,j,p,t}$		**Prob (Export Participation$_{f,j,p,t}$)**		**Prob (Export Exits$_{f,j,p,t}$)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Log (Tariff$_{i,j,p,t}$)	-0.0351	0.1146	-0.0483	-0.0713	-0.0545	-0.0781
	(0.036)	(0.130)	(0.011)***	(0.018)***	(0.057)	(0.095)
Log (Tariff$_{i,j,p,t}$) x GVC Firm$_{f,t}$		-0.1509		0.0258		0.0516
		(0.118)		(0.014)*		(0.080)
SPS$_{i,j,p,t}$	0.0021	-0.1688	-0.0280	0.0126	0.1098	-0.1405
	(0.048)	(0.055)***	(0.013)**	(0.022)	(0.087)	(0.134)
SPS$_{i,j,p,t}$ x GVC Firm$_{f,t}$		0.1720		-0.0470		0.3144
		(0.062)***		(0.020)**		(0.129)**
TBT$_{i,j,p,t}$	-0.0971	-0.2451	-0.0343	-0.0293	0.1939	0.0967
	(0.044)**	(0.101)**	(0.012)***	(0.027)	(0.072)***	(0.182)
TBT$_{i,j,p,t}$ x GVC Firm$_{f,t}$		0.1463		-0.0046		0.0932
		(0.106)		(0.024)		(0.168)
Pre-Shipment$_{i,j,p,t}$	0.0388	-0.0033	0.0099	-0.0245	0.0516	0.1074
	(0.053)	(0.103)	(0.009)	(0.013)*	(0.096)	(0.119)
Pre-Ship.$_{i,j,p,t}$ x GVC Firm$_{f,t}$		0.0506		0.0391		-0.0740
		(0.079)		(0.010)***		(0.074)
Quantity Control$_{i,j,p,t}$	-0.5739	-0.7828	-0.0537	-0.0904	-0.2712	-0.5528
	(0.158)***	(0.185)***	(0.021)***	(0.026)***	(0.114)**	(0.132)***
Quantity Control$_{i,j,p,t}$ x GVC Firm$_{f,t}$		0.2191		0.0364		0.2449
		(0.119)*		(0.020)*		(0.081)***
Price Control$_{i,j,p,t}$	-0.0483	-0.1134	-0.0043	-0.0138	-0.0495	-0.0685
	(0.040)	(0.064)*	(0.014)	(0.021)	(0.087)	(0.126)
Price Control$_{i,j,p,t}$ x GVC Firm$_{f,t}$		0.0655		0.0102		0.0216
		(0.061)		(0.016)		(0.094)
Log (Import Demand$_{f,p,j,t}$)	0.0324	0.0321	0.0110	0.0110	-0.0211	-0.0212
	(0.006)***	(0.006)***	(0.001)***	(0.001)***	(0.008)**	(0.008)**
Observations	253212	253212	253212	253212	17221	17221
Adjusted R^2	0.96	0.96	0.15	0.15	0.18	0.18
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.4 for the intensive margin in columns (1) and (2); extensive margin I in column (3) and (4) and extensive margin II in column (5) and (6). GVC firm is an indicator variable equal to 1 if the firm both imports and exports goods in a given year and 0 otherwise. All columns show coefficients standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Chapter 3

High Tariffs, High Stakes: The Policy Drivers behind Firm-Level Adoption of Green Technologies[1]

3.1 Introduction

Addressing climate change requires the deployment of low-carbon or green technologies, such as solar photovoltaic (PV), wind power or batteries for electric vehicles (EV). Trade plays a crucial role in facilitating the diffusion of these technologies beyond their production centers. However, trade policy is increasingly being used – mostly in high-income countries – to restrict imports of green technologies to eliminate unfair competition and to protect national security. The recent tariffs imposed by the European Union (EU) and the United States (US) on imports of China's electric vehicles, lithium-ion batteries, and solar cells illustrate this trend. For most emerging markets, imports are the main channel to access green technologies, but we know very little about the patterns of trade protection in place and how they influence such imports.

In this paper, we use novel firm-level import transaction data for 35 emerging markets over the period 2017-2021 to examine the trade policy drivers of firms' green technology imports at the intensive and extensive margins. We focus on the dominant instruments of today's trade policy: tariffs and non-tariff measures (NTMs), with variation over time, across countries of origin and products. Specifically, we

[1]Rosenow, Samuel, Alvaro Espitia and Ana Fernandes (2024). *World Bank Policy Research Working Paper* 10977. Washington, D.C.: World Bank Group. 10.1596/1813-9450-10977, licensed under Creative Commons Attribution 3.0 IGO (CC BY 3.0 IGO). We thank Ralf Martin, Fabian Scheifele, Penelope Mealy, Peter Eggers, Joseph Francois, Miriam Manchin, Eddy Bekkers, Trang Tran, Marcio Cruz, Cesaire Meh, Deborah Winkler, Jeff Chelsky and Hiau-Looi Kee for their comments. Paula Suarez provided excellent assistance with the customs data. This paper has been partly supported by the Umbrella Facility for Trade trust fund (financed by the governments of the Netherlands, Norway, Sweden, Switzerland, and the United Kingdom). This paper's findings, interpretations, and conclusions are entirely the authors. They do not necessarily represent the views of the World Bank, its affiliated organizations, or those of the Executive Directors of the World Bank, their Managements, or the governments they represent. All errors are ours.

consider the two most common types of NTM: Sanitary and Phytosanitary measures (SPS) and Technical Barriers to Trade (TBT) that regulate the appearance of imported products (e.g., nutritional labeling requirements), but also their production process (e.g., pesticide residue restrictions).[2] Using a careful mapping of products associated with green value chains of EV, solar, and wind turbines recently proposed by Rosenow and Mealy (2024) in a dynamic structural gravity framework, this allows us to assess the relative importance of different trade policy instruments and their heterogeneous effects among importing firms.[3]

Our main findings are as follows. First, firms' import response to tariffs is particularly adverse for green value chain products relative to average imports. On average, a one standard deviation decrease in tariffs is associated with a 3.3% increase in firms' imports of green value chain products. Second, trade regulations like SPS and TBT have a smaller and ambiguous impact on firms' imports of green value chain products. While imports decrease with the stringency of TBT ad-valorem equivalents (AVEs), they increase with SPS AVE stringency. Third, importing firms in the solar value chain and importing firms in the downstream segments of green value chains are the most responsive to trade policies. Fourth, the adverse impact of tariffs on the imports of green value chain products is particularly strong for undiversified firms. Finally, this effect is pervasive for both the level and the probability of firms importing green value chain products.

This paper advances our understanding of the role of trade policy in green value chain trade, contributing to three strands of literature. First, our paper relates to the trade and climate literature, which highlights the interplay between trade policy and climate change mitigation efforts. Trade challenges climate goals through carbon leakage, as Grossman and Krueger (1991) pollution-haven hypothesis suggests that trade liberalization causes polluting industries to relocate to countries with weaker environmental regulations. While many countries, including the EU, adopted carbon taxes and other measures to reduce greenhouse gas emissions, non-taxing countries gained a trade advantage through lower production costs. The EU's Carbon Border Adjustment Mechanism (CBAM), a tariff on imports based on their carbon content, and other trade policies seek to induce these countries to decarbonize their economies according to Climate Club members (Nordhaus, 2015). Such carbon taxes are being introduced to counteract the evidence of stronger trade protection for green goods relative to emissions-intensive goods obtained for the US and other advanced economies (Shapiro, 2020).

Second, our paper relates to the decades-old literature on trade and endogenous growth, which argues that imports of capital goods and intermediate inputs are a

[2] See UNCTAD (2012) and Espitia et al. (2020). An example of an SPS on green value chain products is a maximum residue limit established for heavy metals. An example of a TBT on green value chain products is a requirement that machines need to carry a label indicating their size, weight, and level of electricity consumption.

[3] In what follows, we use interchangeably the terminology 'green technologies', 'green products', 'green value chain products', and 'products associated with green value chains'.

key channel for the diffusion of advanced technologies to firms in emerging markets (Coe et al., 1997; Eaton and Kortum, 2002; Keller, 2004). Specifically, our paper contributes to an emerging literature on the adoption and diffusion of green technologies. Bastos et al. (2024) examine the diffusion of low-carbon technologies between regions, countries, and industries.[4] Their evidence shows a rapid increase in the deployment of low-carbon technologies in 2022, particularly in advanced economies, which is linked to the global energy crisis resulting from the Russian invasion of Ukraine.

Third, our article refers to the literature on the impact of NTMs on trade.[5] The studies generally find negative effects of NTMs, but often rely on a cross section of products subject to different NTMs at a fixed point in time. An emerging set of studies exploit the time variation in NTMs to estimate their impact on trade at the product level. While tariffs are expected to hurt imports, the effects of NTMs on trade depend on compliance costs relative to information benefits and are, in theory, ambiguous. At the firm level, to our knowledge, existing studies focus only on the decisions of exporting firms as a function of the NTMs they face in their destination markets (Fontagné et al., 2015; Fontagné and Orefice, 2018; Fernandes et al., 2019; Rosenow, 2024).

Our study complements these three strands of literature in several ways. First, we consider the adoption of green technologies through firms' import decisions at the intensive and extensive margins, a crucial channel for the diffusion of embedded knowledge in emerging markets. Using transaction-level import data from 35 emerging markets, we capture the heterogeneity and specific behavior of firms. Unlike country- or product-level trade data, this provides detailed insight into how firms respond to trade policies and adopt new technologies. Second, we examine the relative importance of different trade policies in mitigating climate change. We highlight the trade-off between decarbonization and economic security faced by high-income countries as they adopt protectionist policies to reduce dependence on China, the leading producer of green technologies. Our findings show a strong adverse response to tariffs, suggesting that emerging market firms should avoid similar policies, as they rely on imports for the short-term diffusion of green technologies. Third, we focus on a broad and diverse group of emerging markets, where current understanding of green technology adoption and existing trade policies remains limited. Fourth, we gather novel evidence on the role of firm heterogeneity in responses to trade policy for importing firms and specifically for their green value chain imports.

The remainder of the paper is structured as follows. Section 3.2 provides a brief

[4] They define low-carbon technologies according to the European Patent Office's classification of patents related to climate change mitigation technologies and capture diffusion through their inclusion in the text of job postings or in quarterly earnings calls of large firms. Some of the key groups of their low-carbon technologies are renewable energy, new energy vehicles, improved thermal performance, and electricity generation and storage.

[5] See Ederington and Ruta (2016) for surveys of the literature.

conceptual discussion. Section 3.3 describes our data sources. Section 3.4 documents stylized facts about firms importing green technologies and the trade policy measures they face. Section 3.5 explains our empirical strategy. The results and robustness tests are presented in section 3.6. Finally, section 3.7 concludes and discusses the implications of our results.

3.2 Conceptual discussion

Since the seminal paper by Melitz (2003) and subsequent work by Chaney (2008) and Bernard et al. (2012), trade models with firm heterogeneity generate responses at the intensive and extensive margins to changes in trade costs. In models focused on exports, fixed and variable trade costs are predicted to negatively affect firms' export decisions at the extensive margin. However, the impact on the intensive margin is less clear. Fixed trade costs should not have an effect, as existing exporters have already incurred these costs. Additionally, under certain model assumptions, variable trade costs may also have no impact on firm exports.[6]

Firm import decisions have also been considered in the context of models with self-selection based on firm productivity (Gopinath and Neiman, 2014; Laszlo Halpern and Szeidl, 2015; Antràs et al., 2017). A key assumption in such models is that firms must pay a fixed cost to import which, in principle, generates a response of imports at the extensive margin.[7]

The literature on production fragmentation and vertical specialization with foreign sourcing suggests that high fixed costs influence import dynamics (Yi, 2003). This implies that small reductions in variable trade costs will lead primarily to increased imports (of intermediates) at the intensive margin by existing firms, with little change on the extensive margin. Empirical evidence confirms a modest response of firms' import participation decisions to modest tariff reductions (Feinberg and Keane, 2009). Similarly, the same is found when the extensive margin is measured at the product level (Debaere and Mostashari, 2010).

Trade policy instruments can act as variable and/or fixed trade costs. Tariffs are variable trade costs that vary over time and are charged as a percentage of the import value. In contrast, regulatory NTMs, such as SPS and TBT regulations, and associated compliance costs imply fixed trade costs and possibly also fixed production costs.[8] On the other hand, when SPS standards become more prevalent in an industry, small, low-quality firms are forced to leave (Macedoni and Weinberger, 2022).

[6] Under the assumption of a Pareto distribution for firm productivity, variable trade costs do not affect the intensive margin of exports.

[7] Antràs et al. (2017) motivate such assumption by their evidence across countries that importers are larger than non-importers and that such relative size advantage increases in the number of countries from which importers source.

[8] The evidence supports the modeling of regulatory NTMs as fixed cost. On the one hand, export destinations with a higher number of regulations see fewer exporters (extensive margin), but an unchanged average value per exporter (intensive margin), as shown in Macedoni and Weinberger (2024).

Although understood as fixed trade costs, regulatory NTMs in theory have an ambiguous effect on imports at both margins. On the one hand, labeling requirements or safety certifications are telling examples of regulatory NTMs, assuring safety and product quality for consumers and encouraging imports. However, these regulations also increase importers' compliance and thus production costs since additional investment in technology and processes may be required. This implies that regulatory NTMs can both reduce the supply of and increase the demand for tradable goods. As a result, their impact on imports depends on compliance costs relative to information benefits.[9]

Overall, the literature does not offer clear predictions on the impact of variable and fixed trade costs on imports at intensive and extensive margins. Therefore, this remains an empirical question that we address in our analysis.[10]

3.3 Data

The empirical investigation is based on four different databases, all covering the period 2017–2021. The first database contains novel information on import transactions. The second database is a classification of HS 6 digit products included in trade data into three green value chains, taken from Rosenow and Mealy (2024). The third and fourth databases measure trade policy: bilaterally applied ad valorem tariffs and ad valorem equivalents (AVE) of different types of NTMs.

3.3.1 Firm-level imports in emerging markets

We use firm-level import data for 35 emerging markets that is part of the expansion of the Exporter Dynamics Database, described in Fernandes et al. (2016). The countries listed in the Appendix table C.1 are diverse and spread across all regions.[11]

For each country, the data cover the universe of all importing firms in all sectors at the importing firm-HS 6-digit product-origin country-year level and includes

[9] Bratt (2017) draws on the models by Marette and Beghin (2010) and Beghin et al. (2012) to formalize how NTMs can have dual effects on imports: if an NTM raises fixed or variable costs, it may lower demand and reduce imports; however, if the NTM acts as a screening tool to reduce information asymmetries, it can lower transaction costs and increase imports by improving product quality. Zavala et al. (2023) provide evidence supporting this last effect, showing increased imports associated with NTMs.

[10] In particular it is difficult to generalize predictions from models with firm heterogeneity for exports to imports due to an important difference in how import decisions are modeled under firm heterogeneity and fixed sourcing costs, with interdependence across markets whereas export decisions are separate across markets.

[11] The import data is obtained from customs agencies but for India, Mexico, Sri Lanka and Viet Nam, the import data is obtained from the S&P Global Market Intelligence's *Panjiva* data platform. See Ghose et al. (2023) for a description of how firm identifiers are constructed for Sri Lanka. A similar approach is followed for the other three countries.

seven variables: importing country, importing firm unique identifier, country of origin, HS 6-digit product, import value, import quantity, and year.[12] Information on import values is expressed in US dollars, while information on import quantity is expressed in kilograms.[13] Raw data for each country were subjected to a series of cleaning procedures, as described in Fernandes et al. (2016). In particular, we exclude from each country's data all observations for HS 6-digit products belonging to the oil sector (HS chapter 27).[14] The reason for this is the poor coverage of oil imports in customs data. In addition, this helps to avoid potential distortions from commodity price cycles. As our analysis focuses on the data for the period 2017–2021, we use the HS 2017 nomenclature as it appears in the raw data. The bulk of our analysis focuses on the subset of importing firms and their products in green value chains, as described in the next section. However, for some calculations, our analysis uses the universe of importing firms and products.

We consider two outcome variables to capture both the intensive and extensive margins of firm-level imports. For the intensive margin, the outcome variable $Y_{i,f,j,p,t}$ is the logarithm of firm f's import value from origin country j for 6-digit HS product p in year t, where the importing firm is located in country i. For the extensive margin, the outcome variable $Y_{i,f,j,p,t}$ is a binary variable equal to 1 if firm f imports a positive value of product p from origin country j in year t, and 0 otherwise. This requires expanding the initial database so that for each importing country, each firm-product-origin country has an observation in all sample years, with an import value of zero in a year when imports by the firm-product-origin country do not occur.[15]

For our heterogeneity analysis, we identify firms' import diversification, by first determining the number of HS 6-digit products that each firm imports in its first year in the sample t_0. We then define an indicator variable I[Single Product $_{f,t_0,vc}$], which is equal to one for firms that import only a single product, and zero for firms

[12]Concerns about imports being simply re-exports are mitigated by two factors. First, our country sample does not include transshipment locations, such as Singapore; Hong Kong SAR, China; or the Netherlands, where firms import to then export the same products without transformation. Second, our cleaning of firm-level import data excludes from import value flows that are re-imports, temporary imports, and warehouse import regimes.

[13]Chile, India, Mexico and Viet Nam do not include quantity (in kilograms) information and are thus excluded from the analysis of firm import quantities.

[14]Total imports for each country and year based on our customs data are very similar to the corresponding total non-oil imports reported by UN COMTRADE.

[15]The objectives in constructing the expanded database is to have observations that are economically meaningful, i.e., that indicate plausible firm choices with as few assumptions as possible, and keep the size of the database computationally manageable. To build intuition about our filling procedure, consider an observation from the initial database in which firm f begins to import product p from the origin country j in year t. If in the expanded database we add an observation with a zero import value for firm f product p origin country j in year t–1, this implies that in year t–1 we allow firm f to choose whether to import product p from origin country j and the firm chooses not to do so. This is a plausible and not overly restrictive assumption. Firms that import from a product-origin market in every year and thus have a zero in the dependent variable in every year, are effectively dropped from the estimation sample for the extensive margin given the specific fixed effects (firm-product-origin) included in our specifications.

that import multiple products.[16]

3.3.2 Mapping of green value chain products

To identify products in the value chains of decarbonization technologies, we follow the approach of Rosenow and Mealy (2024). That study provides a mapping of the 6-digit HS products corresponding to the segments of raw and processed materials, subcomponents, and end products in the value chains of solar panels, wind turbines, and electric vehicles.[17] The mapping was constructed based on (i) a thorough review of the literature on the identification of products associated with the value chains of solar panels, wind turbines and electric vehicles, (ii) a careful examination of the description of these products to classify them into the various segments of the value chains (raw and processed materials, subcomponents, and finished products), and (iii) a validation of the mapping by industry specialists in each of the value chains who compared the technical specifications of the products in the value chains to the HS 6-digit descriptions.[18] Appendix table C.2 provides a definition of the value chain segments, as well as HS 6-digit product examples for raw and processed materials, subcomponents, and end products. Appendix table C.3 compares the number of HS 6-digit products mapped to each value chain and segment.[19]

3.3.3 Tariff data

For our key trade policy measure, tariffs, we rely on two data sources to maximize time series coverage for the 35 countries: ITC's Macmap (for 27 countries) and WTO-IDB (for 8 countries).[20] From each data source we take applied tariff rates by importing country-HS 6-digit product-origin country for each year between 2017 and 2021. Applied tariff rates reflect the lowest available tariff. If a preferential tariff exists, it is used as the effectively applied tariff. Otherwise, the Most-Favored-Nation (MFN) tariff is used.

3.3.4 Non-tariff measures

For NTMs, we rely on time-varying bilateral AVE at the HS 6-digit product level from Ghodsi et al. (2024), constructed following the methodology proposed by Kee et al. (2008) and Kee et al. (2009). Ghodsi et al. (2024) obtain AVEs for two types

[16]The use of a time-invariant indicator variable defined in the first year of a firm's observation helps to mitigate endogeneity bias by addressing reverse causality in the relationship between firm-level imports and the explanatory variables. See Rosenow (2024) or Fernandes et al. (2021).

[17]A caveat to this mapping is that HS 6-digit products may have dual use, being used for decarbonization technologies as well as for other purposes. Such granularity cannot be measured using HS 6-digit data.

[18]For electric vehicles, Rosenow and Mealy (2024) propose a narrow and a broad mapping. We choose the narrow mapping, which ensures that we do not consider HS 6-digit products that are also used for internal combustion engine vehicles.

[19]The full list of HS 6-digit products mapped to each value chain is provided in Annex A3 of Rosenow and Mealy (2024).

[20]The websites for these two sources of tariff data are: https://www.macmap.org/ and http://tariffdata.wto.org/Default.aspx?culture=en-US.

of regulatory NTMs: SPS and TBT. SPS and TBT measures are the most commonly used NTM types.

To construct NTM AVEs for TBT and SPS measures, Ghodsi et al. (2024) first obtain the impact of the stock of NTMs on bilateral import volumes of HS 6-digit products for the period 1996-2021 estimating a gravity regression using Poisson pseudo maximum likelihood (PPML) to account for zeros in import volumes.[21] To address the potential endogeneity of NTMs on import volumes, an instrumental variable approach is used following Kee et al. (2009). The exogenous instruments for NTMs are bilateral HS 6-digit product-year export volumes, lagged growth in bilateral HS 6-digit product year import volumes, and a price-weighted average of NTMs imposed by other countries on the same HS 6-digit product. In a second step, Ghodsi et al. (2024) divide the estimated impacts of the two types of NTM by bilateral import demand elasticities that vary between the importing and exporting countries' HS 6-digit product using estimates from Adarov and Ghodsi (2023).[22]

The resulting AVEs for SPS and for TBT are ad valorem and vary at the importing country-exporting country-HS 6-digit product-year level. For example, an AVE for SPS of 5% indicates that the set of SPS measures imposed by the importing country on that product from that origin country in a year is equivalent to a tariff rate of 5% being imposed on imports of that product. NTM AVEs are set to zero by Ghodsi et al. (2024) when estimates are insignificant and can be negative, in which case they indicate that the measures encourage imports. This occurs for 26.2% of the observations in our sample, and we test the robustness of our results to excluding such observations.

We express NTMs in AVE terms to capture their stringency and make them comparable to tariffs, which are also expressed in ad valorem terms. However, as a robustness test, we also consider simple indicator variables for the presence of SPS or TBT at the importing country-exporting country-HS 6-digit product-year level.

3.4 Stylized facts

The share of green products in total imports increased in most countries between 2017 and 2021, particularly in wealthier ones like Costa Rica, Mexico, and Viet Nam, as seen in Appendix figure C.1. This patterns holds for all green value chains, but EVs' share of total imports remains small, under 5% in all countries except Mexico

[21]Their regression controls for bilateral HS 6-digit product-year tariffs, GDP and GDP per capita of the importing and exporting country, and bilateral controls: geographic distance between the country pair, colonial links, common language, contiguity, and having been a single country in the past, and a variable indicating that both countries are members of the World Trade Organization (WTO). Information on the number of SPS and TBT measures is obtained from the WTO Integrated Trade Intelligence Portal (I-TIP).

[22]Import demand elasticities indicate how much, in percentage terms, import volumes change when import prices change by 1%. Adarov and Ghodsi (2023) estimate import demand elasticities using data for the period 1996-2018.

and Viet Nam. Next, we look at the microeconomics behind these imports, presenting a set of stylized facts about importing firms in the three green value chains and the trade policies they face.

First, while average imports of green products per firm vary widely, most firms show an increased but sporadic likelihood of importing green products. Figure C.2 shows the evolution over time in our firm-level outcome variables across countries to make this point. Panel (a) shows that countries with higher average import values per firm in green value chains in 2018 maintained higher average import values per firm until 2021.

However, there is substantial heterogeneity in average imports per firm between countries, value chains, and segments. Firms in Zambia (raw materials for solar), Viet Nam, or Georgia (both raw materials for electric vehicles) import on average millions of US dollars' worth of green products while firms in Malawi (raw materials for solar) and Georgia (raw materials for solar) import on average green products worth less than 10,000 US dollars.

Panel (b) reveals that firms' probability of importing green products increased for most countries across value chains and segments. This suggests a dynamic and expanding market for green value chain products for our emerging markets sample. However, many firms are importing green products only sporadically, as shown by import probabilities in the 20%-40% range.[23]

Second, tariffs on green value chain products have consistently been lower than those on other products, with the gap widening over time. Figure C.3 illustrates this by showing the distribution of tariffs on imports of green versus non-green products in our sample.[24] Three findings merit attention. First, tariffs on green value chain products were, on average, lower than those on other products in all years. Second, the gap between tariffs for green and non-green products widened over time: the median tariff on green value chain products dropped from around 6% until 2019 to 4% in 2020. Third, there is substantial heterogeneity in tariffs across countries. Georgia and Mauritius allow duty-free imports of green value chain products whereas Ethiopia and Togo impose average tariffs of more than 15%.[25]

Third, tariffs rates and AVE of NTMs exhibit heterogeneity across green value chains and their segments. Panel (a) of figure C.4 shows that import tariffs on raw materials are low in the value chains of electric vehicles and wind, with a median

[23] Product and origin diversification of importing firms in green value chains increased between 2017 and 2021, as seen in Appendix figure C.6. The number of HS 6-digit products per importing firm increased for several countries in the wind and solar value chain, but remains relatively small for electric vehicles between 2017 and 2021. The number of origin countries per importing firm increased from 2017 to 2021 for several countries, but it hovered from 1 to 3 for all countries over time.

[24] Non-green products are defined here as all that are not part of a green value chain according to Rosenow and Mealy (2024).

[25] India diverges from the global trend of reducing import tariffs on green value chains, as seen in Appendix figure C.7. For all green value chains, India imposes some of the highest tariff rates among countries and tariffs for solar and wind products exhibit a significant upward trend. This reflects India's protectionist policies recently documented in World Bank (2024) and efforts to encourage domestic production in green product industries by discouraging imports.

across countries of 0%. In contrast, import tariffs are much higher in the solar value chain, with a median across countries greater than 5% and an average tariff of 27% in Gabon. On average, SPS and TBT have positive AVEs, as seen in panels (b) and (c). The AVEs are particularly high for end-products in the solar and wind value chains and for EV subcomponents, with medians across countries exceeding 20%. However, negative AVEs are also found, especially for SPS on processed materials and for TBT within the solar value chain.

Fourth, EV products face tariff escalation, while wind products experience tariff de-escalation. Panel (a) shows that tariffs on EV products are higher for processed materials and subcomponents, with particularly steep tariffs on end products. In Cambodia, Ecuador, Sri Lanka and some Sub-Saharan African countries (Gabon, Kenya, Senegal, Tanzania, and Uganda), the average tariffs imposed on imports of products in the end segment of the EV value chain exceed 20%. In contrast, products in the solar value chain face tariff de-escalation, with significantly lower tariffs on processed materials and subcomponents, and especially low tariffs on end products. Solar panels can be imported duty-free in 26 countries in our sample. Finally, in the wind value chain, tariffs decrease from the processed materials segment to the subcomponent segment and further to the end product segment.

Fifth, unconditional correlations suggest that, on average, tariffs are associated with a reduction in both the value of firms and the likelihood of imports within green value chains for our sample of emerging markets. Panel (a) of figure C.5 illustrates the inverse relationship between firms' average imports and tariff rates. Panel (b) shows a negative correlation between firms' average probability of importing and tariff rates. We delve deeper into these relationships in the subsequent section with our econometric analysis.

3.5 Methodology

We use a firm-product dynamic structural gravity model to examine the impact of trade policy on firms' green technology import behavior at the intensive and extensive margins. Our specification for both margins is as follows:

$$
\begin{aligned}
Y_{i,f,j,p,t} = \beta_1 ln(1+\tau_{i,j,p,t-1}) + \beta_2 ln(1+\text{AVE SPS}_{i,j,p,t-1}) \\
+\beta_3 ln(1+\text{AVE TBT}_{i,j,p,t-1}) + \gamma \text{X}_{i,j,p,t} \\
+\omega_{f,j,p} + \omega_{f,t} + \varepsilon_{i,f,j,p,t}
\end{aligned}
\tag{3.1}
$$

where f is a firm in country i that imports from origin country j HS 6-digit product p in year t. The outcome variable $Y_{i,f,j,p,t}$ is: (i) for the intensive margin either the logarithm of firm import value, import quantity[26] or import unit prices, and (ii) for the extensive margin the indicator variable for import participation, as defined in

[26] Import quantity is measured by import weight and import unit prices are defined as import value divided by import weight.

section 3.3.1. Our regressors of interest are tariffs and AVEs for SPS and for TBT, all entering as the logarithm of 1 plus their percentage rate.

The vector $X_{i,j,p,t}$ of control variables includes three bilateral time-varying variables: (i) an indicator variable for the existence of a Preferential Trade Agreement ($PTA_{i,j,t}$) between importing country and sourcing country in year t; (ii) the logarithm of the average bilateral tariff on products that are not part of green value chains ($\overline{\text{Non-Green Tariff}_{i,j,t}}$) and (iii) a measure of market size in origin countries defined as the total exports from a given origin country in an HS 6-digit product in a green value chain to the world excluding the importing country ($\text{Market Size}_{i,j,p,t}$). This control accounts for supply shocks at the product level, in particular the growth of China as a supplier of green goods.

We exploit the granularity of the data to control for two types of stringent fixed effects. This greatly reduces concerns about alternative explanations for our effects. First, fixed effects at the firm-origin country-HS 6-digit product level $\omega_{f,j,p}$ account for unobserved heterogeneity in the panel dimension of the data, and thus allow us to identify our coefficients of interest based on *within* firm-origin country-product changes in imports as tariffs or AVEs for NTMs change at the origin country-product level over time. Second, firm-year fixed effects $\omega_{f,t}$ capture firm productivity or other granular firm demand or supply shocks that can influence firm import decisions. Note that since each firm is located in a unique importing country, the firm-year fixed effects are a richer substitute for the importing country-year fixed effects that would be expected in a structural gravity regression. Moreover, such effects account for a large global shock experienced during our sample period: the Covid-19 pandemic. Together, our two fixed effects control for multilateral resistance terms in a structural gravity equation (Baier and Bergstrand, 2007; Felbermayr et al., 2020).

To explore heterogeneous effects of trade policies across firm types, we estimate:

$$\begin{aligned} Y_{i,f,j,p,t} = {} & \beta_1 \ln(1+\tau_{i,j,p,t-1}) + \beta_2 \ln(1+\tau_{i,j,p,t-1}) \cdot \text{I[Single Product}_{f,t_0,vc}] \\ & + \beta_3 \ln(1+\text{AVE SPS}_{i,j,p,t-1}) + \beta_4 \ln(1+\text{AVE SPS}_{i,j,p,t-1}) \cdot \text{I[Single Product}_{f,t_0,vc}] \\ & + \beta_5 \ln(1+\text{AVE TBT}_{i,j,p,t-1}) + \beta_6 \ln(1+TBT_{i,j,p,t-1}) \cdot \text{I[Single Product}_{f,t_0,vc}] \\ & + \gamma X_{i,j,p,t} + \omega_{f,j,p} + \omega_{f,t} + \varepsilon_{i,f,j,p,t} \end{aligned} \tag{3.2}$$

where variables are defined as above, and $\text{I[Single Product}_{f,t_0,vc}]$ represents a time-invariant indicator for firms importing a single product in a given value chain, as defined in section 3.3.1. Small firms tend to be less diversified, hence in the absence of an ideal measure of firm size this single-product indicator also acts as a proxy for firm size.[27]

We estimate both intensive and extensive margins of firm import decisions in Equations 3.1 and 3.2 with high-dimensional ordinary least squares (OLS). Our model for import participation follows recent contributions, such as that of Boschma

[27] The correlation between indicator variables for single-product firms and small firms, defined as those with import values below their median in a value chain and segment in their first year in the sample t_0, is 0.4273.

and Capone (2015), and sticks to the linear probability model for the binary outcome. There are many reasons to do so. First, non-linear models suffer from the so-called incidental parameter problem with many fixed effects, as described by Greene (2004). In these models, the maximum likelihood estimator tends to be inconsistent when T, the length of the panel, is fixed, as in our case with four time intervals. Second, non-linear fixed effects models are not the most commensurate estimation technique, given Angrist and Pischke (2009) argument that average effects from the linear probability resemble marginal effects of non-linear models. Third, and crucial for our case, non-linear fixed effects models impose a challenging computational complexity. Estimating two large groups of interacted fixed effects in our expanded firm database across 35 emerging markets proved untenable.

For comparison purposes, we report standardized coefficients in all tables by normalizing the independent variables to have a mean of zero and a unit standard deviation in their respective samples. The inference is based on Huber-White robust standard errors, clustered at the level of the importing country-origin country-HS 6-digit product to account for the source of variation in the three policy variables of interest.

One concern when estimating these equations is the potential endogeneity of trade policy with respect to import performance. However, from the perspective of an individual firm in Equation 3.1, it is unlikely that trade policies are specifically tailored to its import performance. If anything, one could argue that a higher level of import penetration might encourage increased trade restrictions. Still, to assuage potential endogeneity concerns, we include a one-year lag of all trade policy measures. Additionally, the inclusion of a rich set of fixed effects in our specifications helps mitigate concerns about omitted variable bias. Moreover, in robustness tests we follow an estimation approach that controls for an Inverse Mills Ratio (IMR) to address non-random firm selection into importing. The results from this approach confirms our baseline findings and show that selection bias is accounted for.

3.6 Results

3.6.1 Summary statistics

Before delving into econometric estimates, we present summary statistics on the variables entering the regressions in table 3.1. Panel A displays statistics for the sample used for analysis on the intensive margin of imports, at the importing country-firm-origin country-HS 6-digit product-year level. On average, firms in our 35 emerging markets import $171,146 worth per year per product in a green value chain from an origin country.[28] Firms face, on average, tariffs of 1.2% and SPS and TBT regulations with ad valorem equivalents of 0.9% and 1.3%, respectively. In the

[28] For clarity we report average imports in levels rather than logarithms, which will be used in the empirical specifications. We also report tariffs and SPS and TBT AVE as rates rather than logarithms, which will be used in the empirical specifications.

sample, 4% of observations correspond to firms importing a single product.[29] Our sample includes 66% of observations for firm imports from origin countries with a bilateral trade agreement.

Panel B reports the statistics for the sample used for analysis on the extensive margin of imports, also at the importing country-firm-origin country-HS 6-digit product-year level. The probability of importing is a frequent phenomenon: on average, firms import green products in 37% of the possible cases.

TABLE 3.1: Summary statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
Panel A - Intensive Margin of Imports					
Ln(Import Value)$_{i,f,j,p,t}$	1,911,864	8.228	2.67	-9.2	22.1
Ln(1+Tariff)$_{i,j,p,t-1}$	1,911,864	0.021	0.05	0.0	0.3
Ln(1+AVE SPS)$_{i,j,p,t-1}$	1,911,864	0.009	0.16	-9.5	4.6
Ln(1+AVE TBT)$_{i,j,p,t-1}$	1,911,864	0.013	0.09	-6.8	4.1
PTA$_{i,j,t}$	1,911,864	0.661	0.47	0.0	1.0
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	1,911,864	0.036	0.04	0.0	0.2
Ln(Market Size)$_{i,j,p,t}$	1,911,864	13.433	2.06	-6.9	18.6
I[Single Product$_{f,t_0,vc}$]	1,911,864	0.039	0.19	0.0	1.0
SPS count$_{i,j,p,t-1}$	1,911,864	0.293	0.88	0.0	6.0
TBT count$_{i,j,p,t-1}$	1,911,864	5.327	7.21	0.0	40.0
I[SPS$_{i,j,p,t-1}$]	1,911,864	0.117	0.32	0.0	1.0
I[TBT$_{i,j,p,t-1}$]	1,911,864	0.654	0.48	0.0	1.0
Panel B - Extensive Margin of Imports					
Probability of Importing$_{i,f,j,p,t}$	15,396,435	0.371	0.48	0.0	1.0
Ln(1+Tariff)$_{i,j,p,t-1}$	15,396,435	0.033	0.06	0.0	0.7
Ln(1+AVE SPS)$_{i,j,p,t-1}$	15,396,435	0.012	0.18	-9.5	4.6
Ln(1+AVE TBT)$_{i,j,p,t-1}$	15,396,435	0.013	0.10	-9.6	4.5
PTA$_{i,j,t}$	15,396,435	0.570	0.50	0.0	1.0
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	15,396,435	1.366	0.98	0.0	3.0
Ln(Market Size)$_{i,j,p,t}$	15,396,435	13.088	2.31	-6.9	18.6
I[Single Product$_{f,t_0,vc}$]	15,396,435	0.160	0.37	0.0	1.0
SPS count$_{i,j,p,t-1}$	15,396,435	0.199	0.73	0.0	6.0
TBT count$_{i,j,p,t-1}$	15,396,435	4.256	6.54	0.0	40.0
I[SPS$_{i,j,p,t-1}$]	15,396,435	0.082	0.27	0.0	1.0
I[TBT$_{i,j,p,t-1}$]	15,396,435	0.596	0.49	0.0	1.0

This table presents descriptive statistics for our key dependent variables: firms' import value and import probability. It also includes statistics for all our explanatory and control variables. Panel A presents the sample used for the estimation of the intensive margin of firm-level imports. Panel B presents for the sample used in the estimations of the extensive margin of firm-level imports.

3.6.2 Intensive margin of imports

We first evaluate the impact of trade policy on firms' imports of green value chain products at the intensive margin. Table 3.2 presents the results from estimating Equation 3.1, considering the complete sample for all three green value chains in column (1) and results for sub-samples of each green value chain in columns (2)-(4),

[29] By definition, single-product firms have fewer observations in the database. However, the majority of importers are single-product firms, making up 71.3% of all firms in our sample.

and for subsamples of each of value chain segment in columns (5)-(8).[30] Tables 3.3, 3.4, and 3.5 present further results for the intensive margin, showing heterogeneity for India and non-green products as well as a decomposition into import quantity and unit prices.

Seven key findings emerge. First, firms' imports of green value chain products are most responsive to tariffs, relative to NTMs. The negative effect of tariffs is both statistically and economically significant. Column (1) of table 3.2 suggests that, on average, a one standard deviation decrease in tariffs (about 5%) is associated on average with a 3.3% increase in firms' imports of green value chain products. Given the 2 percentage point reduction in import tariffs on green technologies between 2017 and 2021 shown for countries in our sample in figure C.3, our estimates suggest an average increase of 1.2% in firms' imports.[31]

Second, trade regulations have less impact on firms' imports of green value chain products, and the impact is actually ambiguous depending on the type of regulation. TBT reduce firms' imports of green technologies. The estimates in column (1) suggest that a one standard deviation increase in their AVE stringency (about 1.3%) is associated on average with a 0.32% decrease in firms' imports per product-origin country. In contrast, SPS do not have any statistical impact on firm-level imports, with the notable exception of products within the solar value chain.

Third, firms imports in the solar value chain are the most sensitive to trade policies. A one standard deviation decrease in tariffs or in the AVE for TBT for products in the solar value chain is associated with an increase in imports of 4.3% and 0.7%, respectively (column 3). In contrast, a one standard deviation increase in SPS AVE stringency is associated with an average 0.6% increase in firms' imports per product-origin country. This aligns with positive import responses to some trade regulations found by (Zavala et al., 2023), suggesting a role for regulatory NTMs in ensuring consumers of product quality and thus increasing demand.

Fourth, firms' imports are more responsive to tariffs in the downstream segments of green value chains. A one standard deviation increase in tariffs on end-products is associated with decreases in firms' imports of 33% (column 8). In contrast, the elasticities for AVEs of SPS and TBT by value chain segment are inconclusive due to the heterogeneity of the value chain and the importing country.

Fifth, contrary to expectations, Indian firms' imports respond favorably to tariffs. Table 3.3 presents the results from estimating Equation 3.1 including an indicator for the importing country India interacted with each of the three trade policy instruments. Column (1) shows that Indian firms increased their imports of green technologies in response to rising tariffs. This interaction effect is statistically significant and different from the average effect across the other 34 emerging markets, which is negative. Moreover, this effect is particularly pronounced for products in

[30] A similar column structure is followed in all subsequent tables.

[31] This value is calculated by multiplying the coefficient of -0.0327 by the standardized change: a reduction of 2 percentage points, expressed in standard deviations, is $-2\%/5\%$.

India's solar value chain and especially for end-product segments in all green value chains, as shown in columns (3) and (8), respectively. This supports anecdotal evidence that Indian companies continued importing solar panels despite rising tariffs. Our findings align with new trade theory, which suggests that imports may persist under high tariffs due to consumers' preference for diverse product varieties. This challenges the standard model of tariff-induced losses, which assumes that domestic and imported goods are perfect substitutes.

Sixth, tariffs hurt firms' green imports more than the average import. Table 3.4 presents the results of estimating Equation 3.1 for a much larger database that adds to the sample all non-green products and includes an indicator for green products interacted with each of the three trade policy instruments. A one standard deviation increase in tariffs reduces firm-level imports of the average product by 0.9%, while for green products there is an additional significant reduction of 0.8%. This effect is even more pronounced when India is excluded in column (2). To investigate the factors behind this stronger adverse tariff effect, we perform three exercises. In the first exercise, we narrow the sample to include a more relevant comparison group: HS 4-digit subsectors including at least one green value chain product. Columns (3)-(4) of table 3.4 show that, within those subsectors, tariffs have no distinct effect on imports of green compared to non-green products. Hence, the differential effect in columns (1)-(2) is driven primarily by products in other HS 4-digit subsectors. In the second exercise, we show that processed materials and subcomponents of green value chains drive the stronger adverse tariff effects observed for the full sample (Appendix table C.5). Both segments consist of intermediate products, which exhibit greater sensitivity to tariffs as they tend to cross borders multiple times within global supply chains. In fact, in the third exercise, we confirm that HS 4-digit subsectors including products associated with green value chain have larger shares of homogeneous products and of intermediates, two product characteristics associated with higher trade elasticities (Fontagné et al., 2022; Grübler et al., 2022; Kee and Nicita, 2022).[32]

Seventh, import quantities drive firms' responses to trade policy. To investigate the mechanisms through which firms' import responses to trade policy changes operate, we decompose the effects into the contribution of import quantity and import price. We estimate Equation 3.1 with these two variables as the outcome variables and present the results in table 3.5: Panel B focuses on import quantities, while panel C examines unit import prices, measured before tariffs are applied. The results indicate that decreases in tariff rates are associated with significantly higher import quantities, especially in the solar value chain.[33]

[32] See Appendix tables C.6 and C.7. We define homogeneous products following Rauch (1999) and intermediate goods based on the United Nations Classification by Broad Economic Categories (BEC).

[33] Since the sample with quantity information is smaller than that in table 3.2, Panel A of table 3.5 provides estimates of the impact of trade policy on firm import values for this smaller sample. The sample used for the quantity and import price regressions excludes Chile, India, Mexico, and Viet Nam.

The absence of tariff pass-through to unit prices (not inclusive of tariffs) in the regression that pools across all green value chains (column 1) aligns with recent findings on the China-US tariff war. Studies by Amiti et al. (2019), Cavallo et al. (2019), and Fajgelbaum et al. (2019) found no significant effect of tariff increases on US prices (excluding tariff changes). This evidence is consistent with the predictions of a partial equilibrium model of the impact of tariffs when export supply is inelastic. This is likely to be the case in the context of our emerging markets, which are arguably too small to affect the prices set by foreign suppliers of green value chain products.

The three control variables included in Equation 3.1 have the expected signs and statistical significance. In particular, the presence of a PTA between the importing country and the country of origin supports a significant increase in firm-level imports of subcomponents of green value chains.[34] In addition, an increase in the market size of a firm's sourcing countries is associated with higher import values. Finally, increases in average tariffs on non-green products dampen firm-level imports in green value chains.

Overall, Latin American importing firms explain these results. Appendix C.5 supports this point by estimating Equation 3.1 separately for each region.[35]

3.6.3 Extensive margin of imports

Table 3.6 presents the results from estimating Equation 3.1 to examine the impact of trade policies on the probability that firms will import green products. Table 3.7 provides additional results for the extensive margin that separates India.

Five findings stand out. First, similar to the intensive margin, column (1) of table 3.6 shows that firms respond most strongly to import tariffs, followed by TBT. On average, a one percent decrease in tariffs is associated with a 0.7 percentage point increase in firms' import probability. Compared to the unconditional import probability of 37%, this represents a relatively muted effect in terms of economic significance. The overall effect is driven by dynamics in the solar and wind value chains (columns 3 and 4) and in the processed and subcomponents segments (columns 6 and 7).

Second, TBT regulations have a more systematic negative impact on imports at the probability of importing for the complete sample as well as the different value chains and segments. However, the economic magnitude of the impact is small; a one standard change in their AVE stringency is associated with a 0.1 percentage point decrease in firms' import probability.

Third, firms in the solar value chain are more responsive to trade policies. This is consistent with the findings for the intensive margin of imports.

[34] This is aligned with Foster (2012) who shows that imports respond positively to the presence of a PTA between countries.

[35] Country-specific regression results are available from the authors upon request.

Fourth, firms are more responsive to tariffs in the upstream segments of green value chains. In contrast to the findings in section 3.6.2, tariffs do not significantly affect the probability of firms importing end products. More liberal trade policies elicit increased import volumes from incumbent firms, but do not significantly affect new import participation.

Fifth, Indian firms do not show a differential response in their import probability to tariff increases. Table 3.7 shows that the interaction effect for India is statistically insignificant compared to the average for the other 34 emerging markets across all value chains and segments. Given the differential response of Indian firms on the intensive margin, this suggests that trade policy in India affects only the imports of incumbent firms, not the overall dynamics of market entry.

Latin American importing firms drive the results at the extensive margin, similar to the intensive margin. This is supported by Appendix C.6, which estimates Equation 3.1 separately for each region.

3.6.4 Robustness tests

We perform several tests to confirm the robustness of our findings on the trade policy drivers of firm imports within green value chains. We first analyze the intensive margin of imports, followed by the extensive margin.

First, while theoretically correct, negative AVEs for NTMs may not be desirable (Kee et al., 2009). Therefore, we re-estimate Equation 3.1 excluding observations whose AVEs for NTMs are negative. The impacts of tariffs and AVEs of NTMs on firms' imports of green value chain products are maintained (see Appendix table C.8).

Second, we consider alternative standard errors for our baseline specification. Our results are robust to the use of robust standard errors clustered by firm, which allow controlling for within-firm serial correlation (see Appendix table C.9) as well as to the use of bootstrapped standard errors, which may be important in the presence of estimated regressors, such as our AVEs of SPS and TBT (see Appendix table C.10).

Third, while the simple presence of an NTM on imports of a product does not indicate the stringency of such measure as AVEs of NTMs do, it is important to examine whether our findings hold when measures for such presence are used. We consider as NTM measures the number of SPS and TBT measures or an indicator variable for the presence of at least one SPS or TBT, defined at the level of the importing country-origin country-HS 6-digit product-year. In both cases, our baseline results are qualitatively preserved (see Appendix tables C.11 and C.12).

Fifth, we estimate Equation 3.1 by setting the AVE of SPS and TBT to zero when their count variable is zero. This accounts for a potential overestimation of trade costs associated with these NTMs when they are not present. Our baseline results are preserved (see Appendix table C.13).

Sixth, to account for the non-random selection of firms into importing, we follow a control function approach by including the Inverse Mills Ratio (IMR) in the estimation of Equation 3.1. A control function approach is preferred over an instrumental variable method due to the fact that the primary concern is the potential for selection bias resulting from the firm's individual decision to import, rather than the issue of reverse causality in Equation 3.1 and the associated endogeneity of the regressors. Moreover, since we model the second stage linearly for both margins, controlling for the IMR is appropriate.

Specifically, we follow the control function approach set forth by Kee and Nicita (2022) and estimate an IMR for each of the three continuous trade policy instruments (TPI): tariffs, AVE of SPS and TBT given by:

$$TPI^{l}_{i,j,p,t} = \Phi\left(\sum_{l\in L}\gamma_l \overline{TPI}^{l}_{i',j,p,t} + +\gamma X_{i,j,p,t} + \omega_{f,j,p} + \omega_{f,t} + \varepsilon_{l,i,j,p,t}\right) \tag{3.3}$$

where $TPI^{l}_{i,j,p,t}$ indicates the trade policy instrument of type l imposed by importing country i on origin country j and product p in year t; Φ represents the cumulative distribution function of the standard distribution; γ_l evaluates to which extent an importing country i is more likely to implement a TPI of type l given its three closest countries i' implement TPI of type l; and $\overline{TPI}^{l}_{i',j,p,t}$ represents the simple average of the TPI of type l of the three countries i' that are closest to importing country i.[36] The control variables and fixed effects are identical to those used in Equation 3.1.[37] Appendix table C.14 shows the estimates of the control function for each of the three TPIs that confirm that the adoption of TPIs in the closest countries is predictive of a country's own TPI.

We use the estimated $\hat{\gamma}_l$ to compute the IMR for each type of TPI l:

$$I\hat{M}R^{l}_{i,j,p,t} = \frac{\Phi\left(\sum_{l\in L}\hat{\gamma}_l \overline{TPI}^{l}_{i'j,p,t}\right)}{\phi\left(\sum_{l\in L}\hat{\gamma}_l \overline{TPI}^{l}_{i'j,p,t}\right)} \tag{3.4}$$

where ϕ represents the standard normal density function.

Next, we include the three IMR for tariffs, SPS and TBT as additional control variables in Equation 3.1 to account for the correlation that the importing country enforces a TPI despite a high IMR, our concern about endogeneity. This ensures that we compare treated and untreated units that have similar chances of being treated, based on the actions of closest three countries.[38] Table C.15 confirms our baseline result, providing evidence that selection bias is mitigated.

[36] To define closeness, we rely on bilateral distance between countries, weighted by population of main cities, provided by Mayer and Zignago (2011).

[37] While the TPI variables are defined at the country level, Equation 3.3 is estimated using firm-level data. This allows us to include the same control variables and fixed effects as in Equation 3.1.

[38] The IMR captures the hazard of non-selection: if the IMR is higher, the importing country is less likely to have implemented the TPI, considering the TPI imposed by its closest countries.

The results for the extensive import margin are subjected to the same robustness tests as for the intensive margin. The results are maintained whether we exclude observations with negative AVEs (Appendix table C.16), cluster the standard errors by firm (Appendix table C.17), or bootstrap standard errors (Appendix table C.18). The results are also retained when NTMs are measured with a count variable (Appendix table C.19), an indicator variable capturing the presence of at least one NTM (Appendix table C.20) or when setting the AVE of SPS and TBT to zero when their count variable is zero (Appendix table C.21). Finally, the results remain consistent, though the coefficients reduced in magnitude, after controlling for the Inverse Mills Ratio (Appendix table C.22).

3.6.5 Heterogeneous results for undiversified firms

More diversified and generally larger firms, which tend to be more productive and often more profitable, are likely to be better able to absorb the tariff and NTM costs required to import green technologies. The literature shows a clear disadvantage for small exporting firms in overcoming the fixed costs required to comply with NTMs in their destination markets (importing countries).[39] To our knowledge, there is no evidence on the role of firm size —proxied by the lack of product diversification— in how importing firms respond to trade policy. We provide such evidence for green value chain imports.

Table 3.9 shows the heterogeneity of trade policy responses for firms of single products by estimating Equation 3.2 with an interaction term for the single-product firm indicator. Column (1) shows that firms importing a single green product reduce their imports nearly twice as much as diversified importers in response to higher tariffs. This effect is of statistical and economic significance. Moreover, it is primarily driven by the negative import response to tariffs by single-product firms in the wind value chain and in subcomponents segments, as shown in columns 4 and 7, respectively. Another regressive effect for single-product firms imports comes from TBT. While increased stringency of TBT is associated with higher imports for diversified importers, firms importing a single product in the raw materials segment see reduced imports in response to AVE of TBT increases, as shown in column 5.

Table 3.8 presents the heterogeneity in trade policy responses for single-product firms at the extensive margin. This is done by estimating Equation 3.2 with an interaction term for the single-product firm indicator.

Column (1) shows that tariffs reduce the import probability of firms importing a single green product by an additional 0.4 percentage points compared to diversified importers. This interaction effect of single-product firms is statistically significant. This regressive effect of tariffs is driven by the negative import response of single-product firms in the solar value chain and in subcomponent segments, as shown in columns 3 and 7, respectively.

TBT and SPS do not have a regressive effect on importers of single products.

[39] See Fugazza et al. (2018), Fernandes et al. (2019), and Rosenow (2024).

3.7 Conclusion

This paper studies how trade policy challenges firm-level import decisions to source products in green value chains, critical to mitigating climate change. Our panel analysis of firms in 35 emerging markets indicates that tariffs reduce imports of green products more than the average product. This is particularly evident in the solar value chain and the downstream segments of all green value chains. Trade regulations, such as SPS and TBT, play a lesser role in shaping firms' imports of green value chain products. However, the overall impact of tariffs and trade regulations varies significantly between firms. TBTs redirect imports from less diversified to more diversified firms.

Our findings have important policy implications. First, with China being the dominant producer of green technologies, there is a growing trade-off between decarbonization and economic security in high-income countries as they seek to reduce their dependence on China. This tension is particularly evident in the EU and the US, where recent industrial policies protect domestic firms but make EVs more expensive for consumers and delay the decarbonization of transport (Kee and Xie, 2024). Our results suggest that firms in emerging markets are highly sensitive to tariffs imposed on imports of green technologies, particularly of end products. Thus, emerging markets should refrain from following the policy choices of the EU and the US, as they are dependent on imports for the diffusion of these green technologies and cannot expect to develop sufficient domestic production in the short term.

Second, preferential trade agreements increase firms' imports of green technologies by reducing tariffs and other trade barriers between member countries. This helps accelerate the adoption of green technologies in emerging markets and can help them to meet their decarbonization goals more effectively.

Third, the additional sensitivity of undiversified firms to both import tariffs and NTMs highlights the need for targeted policies that support these vulnerable segments. This will ensure that they have access to green technologies without being disproportionately burdened by trade barriers.

TABLE 3.2: Intensive margin of firm-level import - baseline results

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$								
Sample	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0327	-0.0604	-0.0425	-0.0235	-0.3285	-0.0746	-0.0173	-0.3295
	(0.012)***	(0.128)	(0.019)**	(0.019)	(0.263)	(0.040)*	(0.013)	(0.135)**
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0022	-0.0182	0.0066	-0.0007	-0.0461	0.0036	0.0009	0.0072
	(0.002)	(0.016)	(0.002)***	(0.002)	(0.030)	(0.004)	(0.002)	(0.011)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0032	0.0101	-0.0067	-0.0009	0.0569	-0.0025	-0.0025	-0.0135
	(0.002)**	(0.009)	(0.002)***	(0.002)	(0.029)**	(0.004)	(0.002)	(0.011)
PTA$_{i,j,t}$	0.0234	-0.0029	0.0273	0.0170	0.1594	0.0282	0.0220	-0.0120
	(0.009)***	(0.067)	(0.012)**	(0.013)	(0.124)	(0.022)	(0.009)**	(0.050)
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-0.0630	-0.6125	-0.0453	-0.0544	0.0757	-0.0319	-0.0694	0.2809
	(0.035)*	(0.258)**	(0.046)	(0.054)	(0.339)	(0.086)	(0.037)*	(0.246)
Ln(Market Size)$_{i,j,p,t}$	0.2364	0.1178	0.2822	0.2089	0.1264	0.1717	0.2907	0.0480
	(0.021)***	(0.103)	(0.036)***	(0.027)***	(0.158)	(0.045)***	(0.026)***	(0.098)
Observations	1,911,864	22,961	908,830	868,615	5,017	307,773	1,444,775	37,894
Adjusted R2	0.80	0.82	0.80	0.79	0.85	0.80	0.79	0.79
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the appendix table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3.3: Intensive margin of firm-level import - heterogeneous effects of India

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$								
Sample	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0343	-0.0565	-0.0463	-0.0240	-0.3394	-0.0759	-0.0185	-0.3192
	(0.013)***	(0.119)	(0.021)**	(0.019)	(0.268)	(0.041)*	(0.013)	(0.131)**
Ln(1+Tariff)$_{i,j,p,t-1}$ · I[India$_i$]	0.0355	-0.0181	0.0521	-0.0268	0.5446	-0.1455	0.0286	-0.3761
	(0.016)**	(0.150)	(0.026)**	(0.021)	(0.640)	(0.095)	(0.017)*	(0.193)*
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0022	-0.0182	0.0067	-0.0007	-0.0692	0.0035	0.0010	0.0072
	(0.002)	(0.016)	(0.002)***	(0.002)	(0.044)	(0.004)	(0.002)	(0.011)
Ln(1+AVE SPS)$_{i,j,p,t-1}$ · I[India$_i$]	-0.0019	-0.0019	-0.0019	-0.0033	-0.0164	-0.0019	-0.0011	-0.0001
	(0.002)	(0.025)	(0.002)	(0.003)	(0.047)	(0.006)	(0.002)	(0.015)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0032	0.0103	-0.0068	-0.0009	0.0559	-0.0025	-0.0025	-0.0136
	(0.002)**	(0.010)	(0.002)***	(0.002)	(0.028)**	(0.004)	(0.002)	(0.012)
Ln(1+AVE TBT)$_{i,j,p,t-1}$ · I[India$_i$]	-0.0010	-0.0190	-0.0023	0.0013	-0.0534	0.0017	0.0003	-0.0024
	(0.002)	(0.013)	(0.002)	(0.003)	(0.030)*	(0.005)	(0.002)	(0.021)
Observations	2,160,566	28,013	1,032,768	972,236	7,350	342,611	1,635,823	42,792
Adjusted R2	0.79	0.83	0.79	0.78	0.87	0.79	0.79	0.79
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 35 countries in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables and their interactions with India$_i$ are included in the regression: PTA$_{i,j,t}$, Ln$(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3.4: Intensive margin of firm-level import - heterogeneous effects of green products

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Full Sample		HS 4-digit headings with products in green value chains	
	With India	Without India	With India	Without India
	(1)	(2)	(3)	(4)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0092	-0.0071	-0.0486	-0.0498
	(0.003)***	(0.003)**	(0.014)***	(0.014)***
Ln(1+Tariff)$_{i,j,p,t-1}$ × I[Green Products$_p$]	-0.0088	-0.0160	0.0171	0.0023
	(0.005)*	(0.004)***	(0.014)	(0.013)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0005	-0.0008	0.0006	-0.0007
	(0.001)	(0.001)	(0.002)	(0.002)
Ln(1+AVE SPS)$_{i,j,p,t-1}$ × I[Green Products$_p$]	0.0005	0.0009	0.0007	0.0023
	(0.001)	(0.001)	(0.002)	(0.002)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0001	-0.0006	0.0040	0.0053
	(0.001)	(0.001)	(0.003)	(0.003)**
Ln(1+AVE TBT)$_{i,j,p,t-1}$ × I[Green Products$_p$]	-0.0013	-0.0010	-0.0065	-0.0071
	(0.001)**	(0.001)	(0.002)***	(0.003)***
Observations	14,148,626	12,718,663	3,271,974	2,892,980
Adjusted R^2	0.84	0.84	0.81	0.81
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. Columns (1) and (2) include firm-level import data for the full sample and exclude India, respectively. Columns (3) and (4) reduce the sample to HS 4-digit headings with at least one product associated with green value chains. Coefficients are standardized with zero mean and unit standard deviation. Additional controls include PTA$_{i,j,t}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3.5: Intensive margin of firm-level import - margin of imports

Sample	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$								
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0335	-0.1912	-0.0651	-0.0060	-0.3881	-0.0213	-0.0250	-0.3203
	(0.016)**	(0.159)	(0.029)**	(0.023)	(0.473)	(0.057)	(0.017)	(0.175)*
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0016	-0.0073	0.0037	-0.0006	-0.0302	0.0016	0.0008	0.0199
	(0.002)	(0.020)	(0.003)	(0.003)	(0.032)	(0.005)	(0.003)	(0.013)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0042	0.0009	-0.0091	-0.0011	0.0656	-0.0081	-0.0030	-0.0047
	(0.002)*	(0.019)	(0.003)***	(0.003)	(0.047)	(0.007)	(0.003)	(0.016)
Adjusted R2	0.77	0.82	0.77	0.75	0.89	0.77	0.76	0.76
Panel B: Dependent variable: Ln(Import Weight)$_{i,f,j,p,t}$								
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0378	-0.2001	-0.0672	-0.0239	-0.5777	-0.0214	-0.0323	-0.2678
	(0.018)**	(0.179)	(0.031)**	(0.025)	(0.408)	(0.053)	(0.019)*	(0.197)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0001	-0.0127	0.0031	-0.0014	-0.0390	0.0008	0.0013	-0.0042
	(0.002)	(0.024)	(0.004)	(0.003)	(0.035)	(0.005)	(0.003)	(0.019)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0032	0.0085	-0.0072	-0.0007	0.1000	-0.0089	-0.0026	-0.0074
	(0.002)	(0.020)	(0.004)*	(0.004)	(0.052)*	(0.007)	(0.003)	(0.016)
Adjusted R2	0.81	0.89	0.81	0.79	0.94	0.83	0.79	0.82
Panel C: Dependent variable: Ln(Import Unit Value)$_{i,f,j,p,t}$								
Ln(1+Tariff)$_{i,j,p,t-1}$	0.0043	0.0089	0.0022	0.0180	0.1896	0.0001	0.0073	-0.0525
	(0.011)	(0.098)	(0.020)	(0.015)	(0.345)	(0.035)	(0.012)	(0.092)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0017	0.0054	0.0007	0.0008	0.0089	0.0009	-0.0004	0.0241
	(0.002)	(0.016)	(0.003)	(0.002)	(0.014)	(0.004)	(0.002)	(0.013)*
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0009	-0.0076	-0.0019	-0.0004	-0.0344	0.0008	-0.0005	0.0027
	(0.001)	(0.010)	(0.002)	(0.002)	(0.036)	(0.004)	(0.001)	(0.009)
Adjusted R2	0.80	0.89	0.80	0.77	0.87	0.79	0.78	0.79
Observations	876,638	12,170	410,528	390,627	1,761	136,394	658,255	16,611
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 31 countries in appendix table C.1 as those with quantities information. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, Ln$(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3.6: Extensive margin of firm-level import - baseline results

Dependent variable: Probability of Importing$_{i,f,j,p,t}$								
Sample	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0069	-0.0010	-0.0056	-0.0092	-0.0032	-0.0175	-0.0054	0.0041
	(0.003)**	(0.014)	(0.003)*	(0.005)*	(0.033)	(0.010)*	(0.003)**	(0.011)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0000	0.0048	0.0007	-0.0009	0.0017	0.0003	-0.0008	0.0029
	(0.000)	(0.001)***	(0.000)*	(0.000)*	(0.004)	(0.001)	(0.000)***	(0.002)*
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0008	-0.0018	-0.0008	-0.0006	-0.0099	-0.0012	-0.0009	0.0020
	(0.000)***	(0.001)	(0.000)**	(0.000)	(0.006)*	(0.001)**	(0.000)***	(0.001)
PTA$_{i,j,t}$	0.0120	0.0026	0.0119	0.0123	0.0089	0.0094	0.0118	0.0082
	(0.002)***	(0.009)	(0.002)***	(0.002)***	(0.018)	(0.004)**	(0.002)***	(0.007)
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-0.0205	0.0142	-0.0238	-0.0182	0.0468	-0.0042	-0.0251	-0.0101
	(0.008)***	(0.027)	(0.010)**	(0.011)	(0.054)	(0.020)	(0.009)***	(0.023)
Ln(Market Size)$_{i,j,p,t}$	0.0376	-0.0046	0.0524	0.0327	0.0110	0.0385	0.0434	-0.0000
	(0.003)***	(0.011)	(0.005)***	(0.004)***	(0.018)	(0.007)***	(0.004)***	(0.010)
Observations	15,396,435	289,004	7,366,189	7,055,080	41,735	2,748,228	11,448,457	415,215
Adjusted R2	0.24	0.12	0.24	0.22	0.13	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the appendix table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3.7: Extensive margin of firm-level import - India interaction

Dependent variable: Probability of Importing$_{i,f,j,p,t}$								
Sample	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0068	-0.0010	-0.0057	-0.0090	-0.0030	-0.0170	-0.0054	0.0039
	(0.003)**	(0.013)	(0.003)*	(0.005)*	(0.030)	(0.010)*	(0.003)**	(0.010)
Ln(1+Tariff)$_{i,j,p,t-1}$ · I[India$_i$]	0.0010	-0.0050	-0.0017	-0.0032	-0.0726	-0.0393	-0.0001	-0.0171
	(0.003)	(0.029)	(0.004)	(0.005)	(0.060)	(0.013)***	(0.003)	(0.022)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0000	0.0048	0.0007	-0.0009	0.0024	0.0003	-0.0008	0.0029
	(0.000)	(0.001)***	(0.000)*	(0.000)*	(0.006)	(0.001)	(0.000)***	(0.002)*
Ln(1+AVE SPS)$_{i,j,p,t-1}$ · I[India$_i$]	-0.0002	0.0016	-0.0006	-0.0001	-0.0280	-0.0020	0.0005	-0.0009
	(0.000)	(0.002)	(0.000)	(0.000)	(0.007)***	(0.001)**	(0.000)*	(0.002)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0008	-0.0018	-0.0009	-0.0006	-0.0099	-0.0012	-0.0009	0.0020
	(0.000)***	(0.001)	(0.000)**	(0.000)	(0.006)*	(0.001)**	(0.000)***	(0.001)
Ln(1+AVE TBT)$_{i,j,p,t-1}$ · I[India$_i$]	0.0000	0.0009	-0.0003	0.0003	0.0028	0.0007	-0.0002	0.0009
	(0.000)	(0.001)	(0.000)	(0.000)	(0.004)	(0.001)	(0.000)	(0.002)
Observations	17,797,628	343,365	8,602,617	8,059,403	60,564	3,121,734	13,291,238	470,165
Adjusted R2	0.24	0.12	0.23	0.22	0.14	0.20	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 35 countries in the appendix table C.1. Columns (1–8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables and their interactions with India$_i$ are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3.8: Extensive margin of firm-level import - heterogeneous effects of single-product firm

Dependent variable: Probability of Importing$_{i,f,j,p,t}$								
Sample	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0056	0.0118	-0.0043	-0.0089	-0.0066	-0.0177	-0.0039	0.0020
	(0.003)*	(0.017)	(0.004)	(0.005)*	(0.035)	(0.010)*	(0.003)	(0.013)
Ln(1+Tariff)$_{i,j,p,t-1}$ · I[Single Product$_{f,t_0,vc}$]	-0.0040	-0.0268	-0.0050	-0.0010	-0.0021	0.0008	-0.0051	0.0036
	(0.002)**	(0.019)	(0.003)**	(0.003)	(0.029)	(0.004)	(0.002)***	(0.014)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0001	0.0051	0.0006	-0.0008	-0.0024	0.0004	-0.0010	0.0029
	(0.000)	(0.002)***	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)***	(0.002)
Ln(1+AVE SPS)$_{i,j,p,t-1}$ · I[Single Product$_{f,t_0,vc}$]	0.0002	-0.0004	0.0004	-0.0004	0.0105	-0.0003	0.0005	0.0003
	(0.000)	(0.002)	(0.000)	(0.000)	(0.006)*	(0.001)	(0.000)**	(0.001)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0008	-0.0023	-0.0009	-0.0006	-0.0103	-0.0011	-0.0008	0.0017
	(0.000)***	(0.001)*	(0.000)**	(0.000)*	(0.006)*	(0.001)**	(0.000)**	(0.002)
Ln(1+AVE TBT)$_{i,j,p,t-1}$ · I[Single Product$_{f,t_0,vc}$]	-0.0000	0.0017	0.0001	0.0002	0.0014	-0.0001	-0.0003	0.0012
	(0.000)	(0.002)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.001)
Observations	15,396,435	289,004	7,366,189	7,055,080	41,735	2,748,228	11,448,457	415,215
Adjusted R2	0.24	0.12	0.24	0.22	0.13	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.2 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the appendix table C.1, excluding India. Single product firms import a unique product per vc. Columns (1–8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables and their interactions with firm types are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3.9: Intensive margin of firm-level import - heterogeneous effects of single-product firm

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$								
Sample	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0289	-0.0892	-0.0400	-0.0205	-0.3294	-0.0726	-0.0146	-0.3483
	(0.012)**	(0.168)	(0.019)**	(0.019)	(0.265)	(0.042)*	(0.013)	(0.155)**
Ln(1+Tariff)$_{i,j,p,t-1} \cdot$ I[Single Product$_{f,t_0,vc}$]	-0.0243	0.0655	-0.0258	-0.0360	0.5107	-0.0119	-0.0194	0.1819
	(0.011)**	(0.185)	(0.020)	(0.015)**	(0.449)	(0.025)	(0.010)**	(0.212)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0024	-0.0178	0.0067	-0.0009	-0.0437	0.0034	0.0010	0.0072
	(0.002)	(0.017)	(0.002)***	(0.002)	(0.030)	(0.004)	(0.002)	(0.011)
Ln(1+AVE SPS)$_{i,j,p,t-1} \cdot$ I[Single Product$_{f,t_0,vc}$]	-0.0015	0.0020	-0.0016	0.0031	-0.0443	0.0012	-0.0006	0.0002
	(0.001)	(0.017)	(0.002)	(0.002)	(0.051)	(0.003)	(0.002)	(0.009)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0033	0.0078	-0.0067	-0.0009	0.0573	-0.0029	-0.0025	-0.0132
	(0.002)**	(0.010)	(0.002)***	(0.002)	(0.029)**	(0.004)	(0.002)	(0.012)
Ln(1+AVE TBT)$_{i,j,p,t-1} \cdot$ I[Single Product$_{f,t_0,vc}$]	0.0021	0.0157	0.0001	0.0010	-0.0309	0.0073	-0.0007	-0.0039
	(0.001)	(0.011)	(0.002)	(0.002)	(0.016)**	(0.003)**	(0.002)	(0.015)
Observations	1,911,864	22,961	908,830	868,615	5,017	307,773	1,444,775	37,894
Adjusted R2	0.80	0.82	0.80	0.79	0.85	0.80	0.79	0.79
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.2 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the appendix table C.1, excluding India. Single product firms import a unique product per vc. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables and their interactions with firm types are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix to Chapter 1

A.1 Alternative agnostic relatedness

The Ellison and Glaeser (1997) EG index measures the intensity with which two given sectors are co-located in the same area, and in our case, co-exported by the same country. To compute the EG relatedness index between sectors i and j for a particular year, we use the formulation of the EG co-agglomeration index suggested by Ellison and Glaeser (1997):

$$\varphi_{i,j}^{EG} = \frac{\sum_{c=1}^{C}(s_{c,i} - x_c)(s_{c,j} - x_c)}{1 - \sum_{c=1}^{C} x_c^2} \tag{A1}$$

where $s_{c,i}$ and $s_{c,j}$ are, respectively, a country $c's$ share of sector i and j in world sector exports and x_c represents the share of country c's exports in global exports. The EG co-agglomeration index posits that two sectors are more related to each other the more similar their proportion in the export basket is relative to that of their respective country in global exports.

Both relatedness measures are averaged over the previous three years (i.e., the value of $\varphi_{i,j}^{HK}$ in year 2010 is the average between the values for years 2008, 2009 and 2010), and normalized such that it will distribute between 0 and 1 by using the corresponding percentiles of the values in the distribution (i.e., when $\varphi_{i,j}^{HK} = 0.9$ it implies that the relatedness value between sectors i and j is in the 90th percentile). The HK and EG indices are two different measures of the same underlying phenomenon. Namely, they reflect how much two sectors tend to be co-located. It is important to note that the EG index uses continuous export data values, as opposed to the HK index which relies on a threshold of RCA above 1 to compute the probabilities.[1]

A.2 Take-off and growth of exports as explained by agnostic measures

We verify that the emergence of new export sectors is influenced by existing exports, as indicated by co-location patterns, in our sample. This is a known fact that has already been established at the country level by Hausmann and Klinger (2006),

[1] See Tables A.5 and A.6 in Appendix A.5 for the fifteen most related sector pairs based on the two relatedness measures HK and EG, respectively.

TABLE A.1: Export take-offs and growth with agnostic HK density

Panel A - Dependent Variable: Export Take- off if initial $RCA_{c,p,t} < 0.1$		
	(1)	(2)
Φ_{cpt}	0.3377	0.3332
	(0.080)***	(0.080)***
Initial RCA	0.1099	0.1123
	(0.034)***	(0.034)***
N	73988	73988
R^2	0.53	0.53
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p
Panel B - Dependent Variable: Export Growth if initial $Exports_{c,p,t} > 0$		
	(1)	(2)
Φ_{cpt}	0.5040	0.3389
	(0.098)***	(0.105)***
Initial Exports	-0.1389	-0.1382
	(0.001)***	(0.001)***
Pre-period CAGR	0.0061	0.0057
	(0.001)***	(0.001)***
Pre-period zero exp	-0.0235	-0.0202
	(0.010)**	(0.010)**
N	101698	101698
R^2	0.82	0.82
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p

This table estimates specification (1.5) using agnostic or co-location density measures. The upper panel estimates the specification for export sectors take-offs and the lower panel does so for the export growth. Columns 1 and 2 use the HK density measures, while columns 3 and 4 use the EG ones. All specifications include country-by-decade and product-by-decade fixed effects. Columns 2 and 4 also include and product-by-country fixed effects. All coefficients are standardized with zero mean and unit standard deviation. Standard errors are clustered at the country level and presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Hidalgo et al. (2007), and Hausmann et al. (2014). Our analysis serves as a sanity check to confirm these findings within our own sample. After this first step, section 3 of the paper unpacks this agnostic effect into the various channels, which are the center of our paper. Details of the methods and measures used are provided below.

We follow a regression model that is equivalent to that in Section 1.3, but using the so-called "agnostic" relatedness. Table A.1 displays the results using also a 10 year period to define the change $Y_{c,p,t\rightarrow T}$. The upper panel shows results for the estimation of the extensive margin while the bottom does so for the intensive margin. Note that the coefficients of the regression tables in the main paper were standardized. Instead, the coefficients of the agnostic measures in Table A.1 are not standardized. Therefore, these are not directly comparable in their magnitude.

The main finding from Table A.1 is that the emergence of new sectors and the future growth of already existing sectors tend to be positively correlated with the pre-existence of related exports ten years earlier, in the same country. These results are not new to the literature (e.g., Hausmann and Klinger, 2006; Hidalgo et al., 2007; Hausmann et al., 2014). In particular, the results in column 1, which use HK proximities, imply that a sector is 3.4 percentage points, on average, more likely to take off if the baseline density is larger by one standard deviation.[2] This represents a five-fold increase in the unconditional probability of taking off (which was 0.6 percent). Using EG proximities (column 2), the corresponding numbers represent an increase of, also, 3.3 percentage points. The estimation using both different measures are strikingly similar.

The lower panel reveals that an increase of one standard deviation of a product's density also positively associates with faster export annual growth for both measures. Note that the results in both panels are robust to using the very conservative specification that includes country-year, product-year and country-industry fixed effects.

A.3 Alternative two-step unpacking of co-location

Table A.2 repeats the exercise of Table 1.8, but now using the EG agnostic measure instead. Even though all residual densities prove statistically significant for export take-offs, the proportion that the channels explain the EG agnostic relatedness measure is robust and similar to that of the HK agnostic relatedness measure (see Section 1.5.4).

One way to see these results is through figures A.1 and A.2. Both offer a visualization of the results in Tables 1.8 and A.2, respectively. For example, in figure A.1 the take-off panel, the point estimates of the agnostic relatedness measured purged from customer linkages are smallest. This implies that it is the customer channel which correlates mostly with export take off. Moreover, the comparison of both figures shows that the point estimates of the channels exhibit the same importance relative to the agnostic relatedness measures, both for export take off and growth.[3]

A.4 Estimating channels-specific measures controlling for agnostic ones

Tables A.3 and A.4 replicate Table 1.3, controlling for the agnostic density measures by HK and EG, respectively. The results confirm the relative importance of customer linkages for the emergence of exports and patent linkages for export growth, respectively.

[2] The percentage point increase of 2.7 results from multiplying the densities' standard deviation of 0.08 with the estimated coefficient of 0.3323.

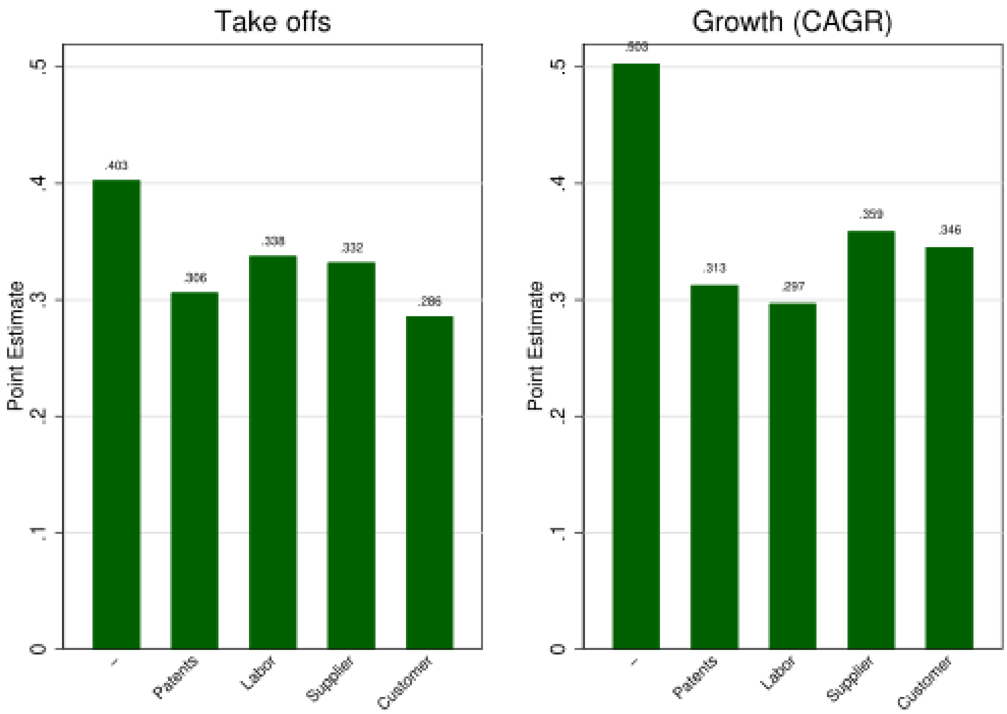
[3] It is important to note that, statistically, there is often no difference between all estimators, each one using different measures of relatedness. Yet, we focus our interpretation on the point estimates.

TABLE A.2: Export take-offs and growth, unpacking agnostic EG density

Panel A - Dependent Variable: Export Take-off if initial $RCA_{c,p,t} < 0.1$					
	(1)	(2)	(3)	(4)	(5)
	-	Patents	Labor	Supplier	Customer
$\widetilde{\Phi cpt}$	0.3875	0.2879	0.3262	0.3179	0.2741
	(0.097)***	(0.082)***	(0.092)***	(0.079)***	(0.088)***
N	63232	63232	63232	63232	63232
R^2	0.53	0.53	0.53	0.53	0.53
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p
Panel B - Dependent Variable: Export Growth if initial $Exports_{c,p,t} > 0$					
	(1)	(2)	(3)	(4)	(5)
	-	Patents	Labor	Supplier	Customer
$\widetilde{\Phi cpt}$	0.3447	0.1126	0.0916	0.1865	0.1609
	(0.108)***	(0.101)	(0.099)	(0.096)*	(0.101)
N	90798	90798	90798	90798	90798
R^2	0.82	0.82	0.82	0.82	0.82
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p

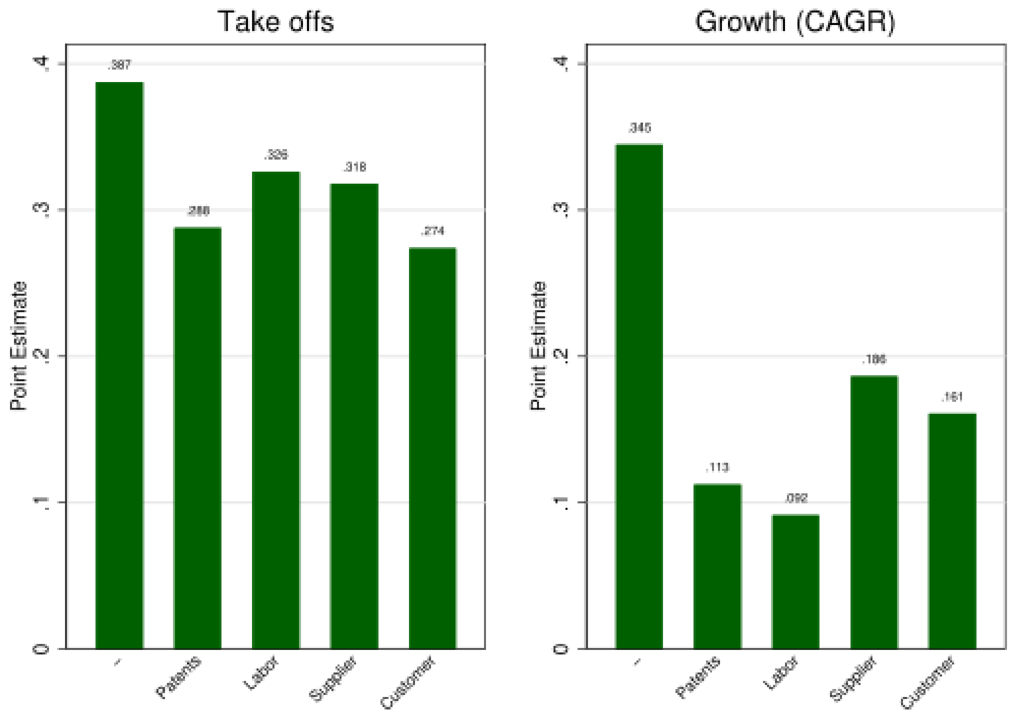
This table estimates specification (1.6) with the agnostic (EG) relatedness measure orthogonal to every channel specific based density. The upper panel estimates the specification for take-off events and the lower panel does so for export growth. Column 1 is the benchmark: it reports results using the coefficient for the agnostic density HK, without extracting the effect of any channel. Columns 2 to 5 evaluate the impact of the agnostic density cleaned from each channel specific based densities. All specifications include country-by-year, product-by-year and country-by-product fixed effects. Control variables are not shown for expositional purposes. Standard errors are clustered at the country level and presented in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

FIGURE A.1: Export take-offs and growth, unpacking agnostic HK density



This figure compares the point estimate of the agnostic HK relatedness measure, called None, from Specification (1.6) to those that are orthogonal to channel-defined density.

FIGURE A.2: Export take-offs and growth, unpacking agnostic EG density



This figure compares the point estimate of the agnostic EG relatedness measure, called None, from specification (1.6) to those that are orthogonal to channel-defined density.

TABLE A.3: Export take-offs and growth, controlling for agnostic HK density

Panel A - Dependent Variable: Export Take-off if initial $RCA_{c,p,t} < 0.1$					
	(1)	(2)	(3)	(4)	(5)
$\Phi^{Patents}_{c,p,t}$	0.0406				0.0564
	(0.017)**				(0.026)**
$\Phi^{Labor}_{c,p,t}$		0.0119			-0.0252
		(0.013)			(0.018)
$\Phi^{Supplier\ Linkages}_{c,p,t}$			-0.0001		-0.0175
			(0.008)		(0.009)*
$\Phi^{Customer\ Linkages}_{c,p,t}$				0.0430	0.0375
				(0.014)***	(0.013)***
$\Phi_{c,p,t}(HK)$	0.0256	0.0274	0.0287	0.0259	0.0262
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.007)***
Initial RCA	0.1146	0.1172	0.1182	0.1158	0.1148
	(0.036)***	(0.036)***	(0.036)***	(0.036)***	(0.036)***
N	63232	63232	63232	63232	63232
R^2	0.53	0.53	0.53	0.53	0.53
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p
Panel B - Dependent Variable: Export Growth if initial $Exports_{c,p,t} > 0$					
	(1)	(2)	(3)	(4)	(5)
$\Phi^{Patents}_{c,p,t}$	0.1744				0.1479
	(0.034)***				(0.042)***
$\Phi^{Labor}_{c,p,t}$		0.1236			0.0479
		(0.028)***			(0.036)
$\Phi^{Supplier\ Linkages}_{c,p,t}$			0.0534		-0.0193
			(0.022)**		(0.020)
$\Phi^{Customer\ Linkages}_{c,p,t}$				0.1240	0.0499
				(0.030)***	(0.029)*
$\Phi_{c,p,t}(HK)$	0.0493	0.0495	0.0589	0.0550	
	(0.012)***	(0.012)***	(0.012)***	(0.012)***	
Initial Exports	-0.1398	-0.1396	-0.1395	-0.1396	-0.1390
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Pre-period CAGR	0.0068	0.0068	0.0067	0.0068	0.0065
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Pre-period zero exp	-0.0308	-0.0304	-0.0300	-0.0303	-0.0273
	(0.010)***	(0.010)***	(0.010)***	(0.010)***	(0.010)***
N	90798	90798	90798	90798	90798
R^2	0.82	0.82	0.82	0.82	0.82
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p

This table estimates specification (1.5) with the channel-specific density measures, controlling for the agnostic (HK) density. The upper panel estimates the specification for export sectors take-offs and the lower panel does so for the export growth. Columns 1 to 4 evaluate the impact of each channel-specific density measure separately, while column 5 include all channel-based measures jointly. All specifications include country-by-decade, product-by-decade and product-by-country fixed effects. All coefficients are standardized with zero mean and unit standard deviation. Standard errors are clustered at the country level and presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

TABLE A.4: Export take-offs and growth, controlling for agnostic EG density

Panel A - Dependent Variable: Export Take-off if initial $RCA_{c,p,t} < 0.1$					
	(1)	(2)	(3)	(4)	(5)
$\Phi^{Patents}_{c,p,t}$	0.0423				0.0598
	(0.017)**				(0.026)**
$\Phi^{Labor}_{c,p,t}$		0.0120			-0.0272
		(0.013)			(0.018)
$\Phi^{Supplier\ Linkages}_{c,p,t}$			0.0006		-0.0171
			(0.008)		(0.009)*
$\Phi^{Customer\ Linkages}_{c,p,t}$				0.0431	0.0367
				(0.013)***	(0.013)***
$\Phi_{c,p,t}(EG)$	0.0246	0.0263	0.0276	0.0246	0.0254
	(0.006)***	(0.007)***	(0.007)***	(0.007)***	(0.007)***
Initial RCA	0.1168	0.1196	0.1207	0.1182	0.1170
	(0.036)***	(0.036)***	(0.036)***	(0.036)***	(0.036)***
N	63232	63232	63232	63232	63232
R^2	0.53	0.53	0.53	0.53	0.53
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p
Panel B - Dependent Variable: Export Growth if initial $Exports_{c,p,t} > 0$					
	(1)	(2)	(3)	(4)	(5)
$\Phi^{Patents}_{c,p,t}$	0.1909				0.1479
	(0.034)***				(0.042)***
$\Phi^{Labor}_{c,p,t}$		0.1399			0.0479
		(0.028)***			(0.036)
$\Phi^{Supplier\ Linkages}_{c,p,t}$			0.0622		-0.0193
			(0.022)***		(0.020)
$\Phi^{Customer\ Linkages}_{c,p,t}$				0.1357	0.0499
				(0.031)***	(0.029)*
$\Phi_{c,p,t}(EG)$	0.0218	0.0216	0.0334	0.0286	
	(0.012)*	(0.012)*	(0.012)***	(0.012)**	
Initial Exports	-0.1392	-0.1391	-0.1389	-0.1390	-0.1390
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Pre-period CAGR	0.0065	0.0065	0.0064	0.0064	0.0065
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Pre-period zero exp	-0.0280	-0.0277	-0.0271	-0.0274	-0.0273
	(0.010)***	(0.010)***	(0.010)***	(0.010)***	(0.010)***
N	90798	90798	90798	90798	90798
R^2	0.82	0.82	0.82	0.82	0.82
Fixed Effects	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p	c-t, p-t,c-p

This table estimates specification (1.5) with the channel-specific density measures, controlling for the agnostic (EG) density. The upper panel estimates the specification for export take-offs and the lower panel does so for the export growth. Columns 1 to 4 evaluate the impact of each channel-specific density measure separately, while column 5 include all channel-based measures jointly. All specifications include country-by-decade, product-by-decade and product-by-country fixed effects. All coefficients are standardized with zero mean and unit standard deviation. Standard errors are clustered at the country level and presented in parenthesis.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

A.5 Relatedness between sectors

Tables A.5, A.6, A.7, A.8, A.9 and A.10 show the 15 most related sector pairs for all different relatedness measures used in this paper. Sectors are defined at the 4-digit level in the Standard International Trade Classification (SITC).

TABLE A.5: Relatedness of top 15 sectors, agnostic HK density

$SITC_i$	**Sector Name**	$SITC_j$	**Sector Name**
8423	Men's trousers	8439	Other women outerwear
8459	Other knitted outerwear	8462	Knitted undergarments of cotton
8433	Dresses	8435	Blouses
8433	Dresses	8452	Knitted women's suits & dresses
8434	Skirts	8439	Other women outerwear
8439	Other women outerwear	8459	Other knitted outerwear
8439	Other women outerwear	8462	Knitted undergarments of cotton
7764	Electronic microcircuits	7768	Parts N.E.S. of electronic circuits
8439	Other women outerwear	8441	Men's undershirt
8435	Blouses	8452	Knitted women's suits & dresses
7361	Metal cutting machine-tools	7368	Dividing heads for machine-tools
1212	Wholly or partly stripped tobacco	1213	Tobacco refuse
8423	Men's trousers	8459	Other knitted outerwear
8451	Knitted jerseys, pullovers & cardigans	8459	Other knitted outerwear
2874	Lead ore	2875	Zinc

This table shows the 15 most related sector pairs, based on HK's measure of agnostic relatedness, which is the minimum probability of co-exporting two given sectors.

TABLE A.6: Relatedness of top 15 sectors, agnostic EG density

$SITC_i$	**Sector Name**	$SITC_j$	**Sector Name**
2655	Manila hemp	2659	Vegetable textile fibres N.E.S.
2613	Raw Silk	8994	Umbrellas & canes
2655	Manila hemp	4243	Coconut oil
4245	Castor oil	6545	Jute woven fabrics
8933	Plastic ornaments	8994	Umbrellas & canes
2613	Raw Silk	8933	Plastic ornaments
2613	Raw Silk	6597	Plaited products
6597	Plaited products	8994	Umbrellas & canes
2714	Crude natural potassium salts	2784	Asbestos
2613	Raw Silk	8942	Toys
6597	Plaited products	8933	Plastic ornaments
8942	Toys	8994	Umbrellas & canes
4245	Castor oil	6593	Kelem, schumacks & karamanie
6583	Travelling rugs & blankets	8994	Umbrellas & canes
2613	Raw Silk	8999	Manufactures N.E.S.

This table shows the 15 most related sector pairs, based on EG's measure of agnostic relatedness, which is the co-location of export industries in the same country of origin.

TABLE A.7: Relatedness of top 15 sectors, labor linkages

$SITC_i$	Sector Name	$SITC_j$	Sector Name
1221	Cigars	1222	Cigarretes
1222	Cigarretes	1223	Tobbacco, extract, essences & manufactures
1221	Cigars	1223	Tobbacco, extract, essences & manufactures
6413	Rolls/sheets of kraft paper	6419	Converted paper N.E.S.
6413	Rolls/sheets of kraft paper	6417	Rolls/sheets of creped paper
6417	Rolls/sheets of creped paper	6419	Converted paper N.E.S.
2517	Chemical wood pulp, soda or sulphate	2518	Chemical wood pulp, sulphite
2519	Other cellulosic pulps	6412	Printing & writing paper in rolls or seets
2512	Mechanical wood pulp	2518	Chemical wood pulp, sulphite
6415	Paper & paperboad in rolls or sheets	6422	Correspondence stationary
2516	Chemical wood pulp, dissolving grades	6411	Newsprint
6412	Printing & writing paper in rolls or seets	6415	Paper & paperboad in rolls or sheets
2512	Mechanical wood pulp	6415	Paper & paperboad in rolls or sheets
6412	Printing & writing paper in rolls or seets	6417	Rolls/sheets of creped paper
2512	Mechanical wood pulp	2516	Chemical wood pulp, dissolving grades

This table shows the 15 most related sector pairs, based on labor flows between industry pairs.

TABLE A.8: Relatedness of top 15 sectors, patent linkages

$SITC_i$	Sector Name	$SITC_j$	Sector Name
7931	Warships	7932	Ships & boats
5414	Vegetable alkaloids & derivatives	5415	Bulk hormones
5413	Antibiotics	5414	Vegetable alkaloids & derivatives
5413	Antibiotics	5415	Bulk hormones
5415	Bulk hormones	5416	Glycosides & vaccines
5411	Provitamins & vitamins	5414	Vegetable alkaloids & derivatives
5411	Provitamins & vitamins	5413	Antibiotics
5411	Provitamins & vitamins	5415	Bulk hormones
5411	Provitamins & vitamins	5416	Glycosides & vaccines
5413	Antibiotics	5416	Glycosides & vaccines
5414	Vegetable alkaloids & derivatives	5416	Glycosides & vaccines
5415	Bulk hormones	5417	Medicaments
5411	Provitamins & vitamins	5417	Medicaments
5413	Antibiotics	5417	Medicaments
5414	Vegetable alkaloids & derivatives	5417	Medicaments

This table shows the 15 most related sector pairs, based on patent citations between industry pairs.

TABLE A.9: Relatedness of top 15 sectors, customer linkages

$SITC_i$	Sector Name	$SITC_j$	Sector Name
118	Other animal meats	142	Sausages
113	Swine meat	2117	Raw sheep skin with wool
115	Equine meat	116	Bovine & equine entrails
113	Swine meat	252	Fresh dried or preserved bird eggs not in shell
113	Swine meat	116	Bovine & equine entrails
118	Other animal meats	2117	Raw sheep skin with wool
113	Swine meat	114	Poultry meat
115	Equine meat	121	Other animal entrails
129	Dried, salted or smoked meat & entrails	2116	Raw sheep skin without wool
115	Equine meat	129	Dried, salted or smoked meat & entrails
116	Bovine & equine entrails	2911	Bones, horns, corals & ivory
111	Bovine meat	129	Dried, salted or smoked meat & entrails
112	Sheep & goat meat	2117	Raw sheep skin with wool
115	Equine meat	2114	Raw goat skins
142	Sausages	2114	Raw goat skins

This table shows the 15 most related sector pairs, based on customer linkages between industry pairs.

TABLE A.10: Relatedness of top 15 sectors, supplier linkages

$SITC_i$	**Sector Name**	$SITC_j$	**Sector Name**
7851	Motorcycles	7852	Bicycles
7810	Cars	7832	Tractors for semi-trailers
7810	Cars	7831	Public transportation vehicles
7831	Public transportation vehicles	7832	Tractors for semi-trailers
7912	Rail tenders	7913	Mechanically propelled railway
7911	Electric trains	7912	Rail tenders
7914	Not mechanically propelled railway for passengers	7915	Not mechanically propelled railway for freight
7912	Rail tenders	7914	Not mechanically propelled railway for passengers
7911	Electric trains	7915	Not mechanically propelled railway for freight
7911	Electric trains	7914	Not mechanically propelled railway for passengers
7911	Electric trains	7913	Mechanically propelled railway
7913	Mechanically propelled railway	7914	Not mechanically propelled railway for passengers
7912	Rail tenders	7915	Not mechanically propelled railway for freight
7913	Mechanically propelled railway	7915	Not mechanically propelled railway for freight
7931	Warships	7932	Ships & boats

This table shows the 15 most related sector pairs, based on supplier linkages between industry pairs.

Appendix to Chapter 2

B.1 Control function estimates

Table B.1 shows positive estimates of the probit control function, suggesting that the neighbors' imposition of NTMs predicts the country's own implementation of NTMs.

TABLE B.1: Control function estimates

Dependent variable:	**SPS**	**TBT**	**Pre-Shipment**	**Quantity Control**	**Price Controls**	**Other**
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor $SPS_{j,p,t}$	0.2903	-0.0916	0.0394	-0.0825	-0.0651	-0.1370
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***
Neighbor $TBT_{j,p,t}$	0.0918	0.1835	0.0051	-0.0805	-0.0301	0.0085
	(0.002)***	(0.002)***	(0.002)**	(0.002)***	(0.002)***	(0.002)***
Neigbor $\text{Pre-Shipment}_{j,p,t}$	-0.3264	1.3487	0.0281	0.6419	0.3193	1.0509
	(0.020)***	(0.021)***	(0.019)	(0.015)***	(0.017)***	(0.022)***
Neighbor Quantity $\text{Controls}_{j,p,t}$	-0.3772	-0.2079	-0.1883	-0.6891	-0.2958	-0.6978
	(0.014)***	(0.014)***	(0.017)***	(0.014)***	(0.015)***	(0.023)***
Neighbor Price $\text{Controls}_{j,p,t}$	-0.1582	0.0111	0.1451	-0.1864	0.5267	0.5255
	(0.009)***	(0.008)	(0.010)***	(0.009)***	(0.008)***	(0.011)***
Neighbor $\text{Other}_{j,p,t}$	-1.0265	-0.1832	0.6604	-1.8394	0.1387	-1.8006
	(0.017)***	(0.016)***	(0.017)***	(0.022)***	(0.015)***	(0.040)***
Observations	468889	468889	468889	468889	468889	468889

This table presents probit estimates of Equation 2.3. Each column uses a different NTM type as dependent variable.
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

B.2 Robustness tests

B.2.1 NTM overlap

Simultaneous changes in several NTM types can make it difficult to isolate their respective effects. This occurs when two or more NTM types enter the same product-destination market over time. We refer to this phenomenon as NTM overlap and define it as the multiple entry or exit of different NTM types in a product-destination cell. The classic example is a situation where both an import quota and a TBT are applied. A company may be able to comply with the TBT requirements, but may not be able to export to the destination because of the quota imposed at the destination. The effect of the TBT is modified by the presence of the quota. Indeed, the effect of a specific NTM may absorb the effect of any other.

However, Table B.2 shows that the overlap in NTM changes is limited. In fact, policies with multiple NTM changes affect, on average, 22.3% of export relationships at the HS 6-digit product-destination level.[1] Given the limited overlap of NTMs, we are thus confident that our empirical framework clearly identifies the impact of NTM types on Colombian export patterns.

Overlap may also occur when two or more measures of the same type (e.g., two SPS measures) come into effect for the same product. This, however, is less of a concern, since the scope of our empirical assessment is to identify the average effect of the presence of broad categories of NTMs, rather than the impact of some specific regulation.

TABLE B.2: Distribution of NTM changes (in %)

Number of changes:	**1**	**2**	**3**	**4**	**5+**
2008	0.90	0.10	0.00	0.00	0.00
2009	0.91	0.09	0.00	0.00	0.00
2010	0.95	0.05	0.00	0.00	0.00
2011	0.68	0.06	0.02	0.10	0.15
2012	0.99	0.01	0.00	0.00	0.00
2013	0.30	0.12	0.46	0.12	0.00
2014	0.99	0.01	0.00	0.00	0.00
2015	0.61	0.39	0.00	0.00	0.00
2016	1.00	0.00	0.00	0.00	0.00
2017	0.97	0.03	0.00	0.00	0.00
Pooled	0.78	0.07	0.10	0.04	0.02

This table shows how NTMs, organized by chapter, have changed over time at the product-destination level. The pooled sample reports the distribution of NTM changes across all years.

B.2.2 Collinearity between NTMs

The simultaneous introduction of different types of NTMs could complicate our identification strategy due to collinearity issues. In particular, it may complicate the interpretation of significance as we evaluate the coefficients of NTM types together. This raises the empirical question of the extent to which NTMs are correlated *after* controlling for our fixed effects. We put forward three arguments that collinearity between NTMs is not a concern. First, Table B.3 shows correlations between NTM types, conditional on firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. The correlations between NTM types are positive, but not strikingly large.[2] Therefore, multi-collinearity seems a less relevant concern for our empirical strategy.

Second, we address concerns that NTM types exhibit collinearity by running specification 2.1 with only two cross sections, using data from the first and last year

[1] 1-77.7%.

[2] Moreover, the correlation between tariffs and NTM types is about 0, allaying concerns over our estimation strategy.

TABLE B.3: Correlations of NTMs after fixed effects

	Tariff	SPS	TBT	Pre-shipment	Quantity control	Price control
Tariff	1.000					
SPS	-0.008	1.000				
TBT	-0.010	0.344	1.000			
Pre-Shipment	-0.013	0.358	0.123	1.000		
Quantity Control	-0.000	0.420	0.209	0.404	1.000	
Price Control	-0.002	0.005	0.074	-0.007	0.000	1.000

This table displays bivariate correlation coefficients for tariffs and NTM types after conditioning on firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects.

of data. To that end, Table B.4 shows results based on data from 2007 and 2017 only. The results are consistent with our baseline specification in column (2) of Table 2.10 (intensive margin) and 2.11 (extensive margin I).[3]

Third, we conduct a principal component analysis (PCA) of all NTM types. This helps us define a continuous NTM index and evaluate its role to explain Colombian firm-level exports across the three margins considered. All NTM indexes prove statistically significant and with the expected sign.

[3] We can't estimate the extensive margin II (probability of export exits) in Table B.4 because exits are not defined with data from 2007 and 2017 only.

TABLE B.4: Results with two cross-sections only

Dependent variable:	**Exports$_{f,j,p,t}$**	**Prob (Export Participation$_{f,j,p,t}$)**
	(1)	(2)
Log (Tariff$_{i,j,p,t}$)	-0.1715	-0.0818
	(0.123)	(0.037)**
SPS$_{i,j,p,t}$	-0.1221	-0.0053
	(0.092)	(0.031)
TBT$_{i,j,p,t}$	-0.1052	-0.0873
	(0.049)**	(0.031)***
Pre-Shipment$_{i,j,p,t}$	0.0409	-0.0614
	(0.074)	(0.025)**
Quantity Control$_{i,j,p,t}$	-1.1977	-0.1079
	(0.226)***	(0.057)*
Price Control$_{i,j,p,t}$	-0.1056	0.0099
	(0.084)	(0.035)
Other NTMs$_{i,j,p,t}$	0.1318	-0.0048
	(0.141)	(0.059)
Log (Import Demand$_{f,p,j,t}$)	0.0331	0.0157
	(0.018)*	(0.006)***
Observations	14622	14622
Adjusted R^2	0.98	0.12
Fixed Effects	f-p-j, f-p-t, j-t	f-p-j, f-p-t, j-t

This table estimates equation 2.1 with two cross section of data in 2007 and 2017 only. Column (1) shows results for the intensive margin and column (2) for the extensive margin I of Colombian firm-level exports. All coefficients are standardized with zero mean and unit standard deviation. All columns use firm-HS6 product-destination, firm-HS6 product-year and destination-year fixed effects. All columns also control for the Inverse Mills Ratios for each NTM type following estimation of probit model of NTM selection based on NTM intensity in neighboring countries. Clustered standard errors at the HS6 product-year level are presented in parenthesis.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Appendix to Chapter 3

C.1 Data

TABLE C.1: Country coverage

Importing Country	World Bank Region	Year	% Share of Observations	Import Quantity	Tariff Source
Albania	Europe and Central Asia	2017-2021	1.0	Yes	MacMap
Benin	Sub-Saharan Africa	2017-2021	0.2	Yes	MacMap
Burundi	Sub-Saharan Africa	2017-2021	0.1	Yes	MacMap
Cambodia	East Asia and Pacific	2017-2021	0.5	Yes	MacMap
Cabo Verde	Sub-Saharan Africa	2017-2021	0.5	Yes	WTO-IDB
Chile	Latin America and Caribbean	2017-2021	4.1	No	MacMap
Colombia	Latin America and Caribbean	2017-2021	4.4	Yes	MacMap
Comoros	Sub-Saharan Africa	2017-2021	0.1	Yes	MacMap
Costa Rica	Latin America and Caribbean	2017-2021	3.9	Yes	MacMap
Côte d’Ivoire	Sub-Saharan Africa	2017-2021	1.4	Yes	MacMap
Dominican Republic	Latin America and Caribbean	2017-2021	3.1	Yes	WTO-IDB
Ecuador	Latin America and Caribbean	2017-2021	3.4	Yes	MacMap
El Salvador	Latin America and Caribbean	2017-2021	1.9	Yes	MacMap
Ethiopia	Sub-Saharan Africa	2017-2021	1.2	Yes	MacMap
Gabon	Sub-Saharan Africa	2017-2021	0.7	Yes	WTO-IDB
Georgia	Europe and Central Asia	2017-2021	1.9	Yes	WTO-IDB
India	South Asia	2017-2021	13.0	No	MacMap
Kenya	Sub-Saharan Africa	2017-2021	1.6	Yes	MacMap
Lao PDR	East Asia and Pacific	2017-2021	0.1	Yes	MacMap
Malawi	Sub-Saharan Africa	2017-2021	0.5	Yes	MacMap
Mauritius	Sub-Saharan Africa	2017-2021	1.4	Yes	MacMap
Mexico	Latin America and Caribbean	2017-2021	21.4	Yes	WTO-IDB
Pakistan	South Asia	2019-2021	1.5	Yes	WTO-IDB
Paraguay	Latin America and Caribbean	2017-2021	1.2	Yes	MacMap
Peru	Latin America and Caribbean	2017-2021	4.9	Yes	MacMap
Senegal	Sub-Saharan Africa	2017-2020	0.6	Yes	MacMap
South Africa	Sub-Saharan Africa	2017-2021	9.2	Yes	WTO-IDB
Sri Lanka	South Asia	2017-2021	2.3	Yes	MacMap
Tanzania	Sub-Saharan Africa	2017-2021	1.6	Yes	MacMap
Timor-Leste	East Asia and Pacific	2017-2021	0.2	Yes	WTO-IDB
Togo	Sub-Saharan Africa	2018-2021	0.2	Yes	MacMap
Uganda	Sub-Saharan Africa	2017-2020	0.7	Yes	MacMap
Uruguay	Latin America and Caribbean	2017-2021	2.0	Yes	MacMap
Viet Nam	East Asia and Pacific	2018-2021	8.6	Yes	MacMap
Zambia	Sub-Saharan Africa	2017-2021	1.0	Yes	MacMap

TABLE C.2: Description of value chain segments and examples

Value Chain Segment	Definition
Raw Materials	Basic, unprocessed materials that are mined, extracted or harvested from the earth. Value added comes from extracting, harvesting, and preparing raw materials for international marketing in substantial volumes. **Wind**: Lumber, balsa (HS 440722) **Solar**: Silicon >99.999% pure (HS 280461) **EV**: Nickel ore and concentrates (HS 260400)
Processed Materials	Materials that have been transformed or refined from basic raw materials as an intermediate step in the manufacturing process. Value added comes from processing raw materials into precursors that can be easily transported, stored and used for downstream subcomponent fabrication. **Wind**: Bar/rod iron or non-alloy steel, indented or twisted (HS 721420) **Solar**: Float glass sheets, absorbent or reflecting layer (HS 700510) **EV**: Nickel sulphates (HS 283324)
Subcomponents	Unique constituent parts or elements that contribute to a finished product. Value is added by transforming materials into subcomponents, which are then assembled into final products. **Wind**: Electric conductors, 80-1,000 volts, no connectors (HS 854459) **Solar**: Glass mirrors, framed (HS 700992) **EV**: Parts of electric accumulators, including separators (HS 850790)
End Products	The finished product of the manufacturing process, assembled from subcomponents and ready for sale to customers as a completed item. Value added comes from assembling components into a marketable product that customers value. **Wind**: Towers and lattice masts, iron or steel (HS 730820) **Solar**: Photosensitive/photovoltaic/LED semiconductor devices (HS 854140) **EV**: Lead-acid electric accumulators (vehicle) (HS 850710)

TABLE C.3: Number of HS 2017 6-digit products, by value chain and segment

VC \ Segment	Raw Materials	Processed Materials	Sub-Components	End Products	Total
Electric Vehicles	9	23	6	8	46
Solar	12	22	57	1	92
Wind	4	60	43	3	110
Total	25	105	106	12	248

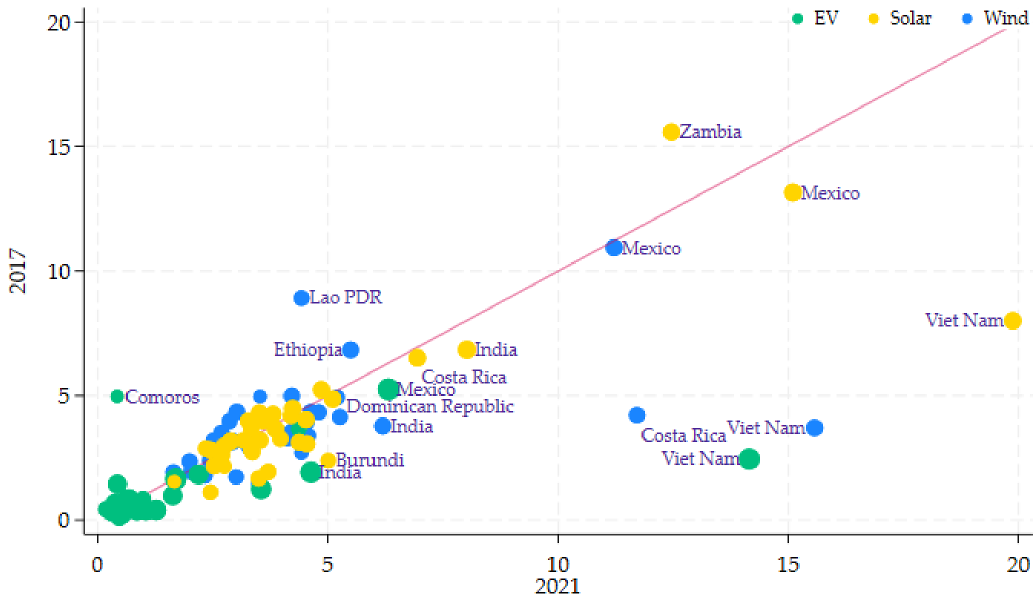
TABLE C.4: Summary statistics including India

Variable	**N**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Panel A - Intensive Margin of Imports					
Ln(Import Value)$_{i,f,j,p,t}$	2,160,566	8.328	2.69	-9.2	22.1
Ln(1+Tariff)$_{i,j,p,t-1}$	2,160,566	0.027	0.05	0.0	0.3
Ln(1+AVE SPS)$_{i,j,p,t-1}$	2,160,566	0.010	0.16	-9.5	4.6
Ln(1+AVE TBT)$_{i,j,p,t-1}$	2,160,566	0.013	0.09	-6.8	4.1
PTA$_{i,j,t}$	2,160,566	0.607	0.49	0.0	1.0
$Ln(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	2,160,566	0.046	0.05	0.0	0.2
Ln(Market Size)$_{i,j,p,t}$	2,160,566	13.430	2.05	-6.9	18.6
I[Single Product$_{f,vc}$]	2,160,566	0.041	0.20	0.0	1.0
SPS count$_{i,j,p,t-1}$	2,160,566	0.309	0.93	0.0	8.0
TBT count$_{i,j,p,t-1}$	2,160,566	5.260	6.85	0.0	40.0
I[SPS$_{i,j,p,t-1}$]	2,160,566	0.122	0.33	0.0	1.0
I[TBT$_{i,j,p,t-1}$]	2,160,566	0.694	0.46	0.0	1.0
Panel B - Extensive Margin of Imports					
Probability of Importing$_{i,f,j,p,t}$	17,797,628	0.368	0.48	0.0	1.0
Ln(1+Tariff)$_{i,j,p,t-1}$	17,797,628	0.039	0.06	0.0	0.8
Ln(1+AVE SPS)$_{i,j,p,t-1}$	17,797,628	0.013	0.18	-9.5	4.6
Ln(1+AVE TBT)$_{i,j,p,t-1}$	17,797,628	0.013	0.10	-9.6	4.5
PTA$_{i,j,t}$	17,797,628	0.514	0.50	0.0	1.0
$Ln(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	17,797,628	1.530	1.01	0.0	3.0
Ln(Market Size)$_{i,j,p,t}$	17,797,628	13.096	2.29	-6.9	18.6
I[Single Product$_{f,vc}$]	17,797,628	0.165	0.37	0.0	1.0
SPS count$_{i,j,p,t-1}$	17,797,628	0.236	0.87	0.0	8.0
TBT count$_{i,j,p,t-1}$	17,797,628	4.310	6.17	0.0	40.0
I[SPS $_{i,j,p,t-1}$]	17,797,628	0.092	0.29	0.0	1.0
I[TBT$_{i,j,p,t-1}$]	17,797,628	0.650	0.48	0.0	1.0

This table presents descriptive statistics for all variables in Panel A for the sample used in the estimations of the intensive margin, import value, regressions, and in Panel B for the sample used in the estimations of the extensive margin, the probability of importing.

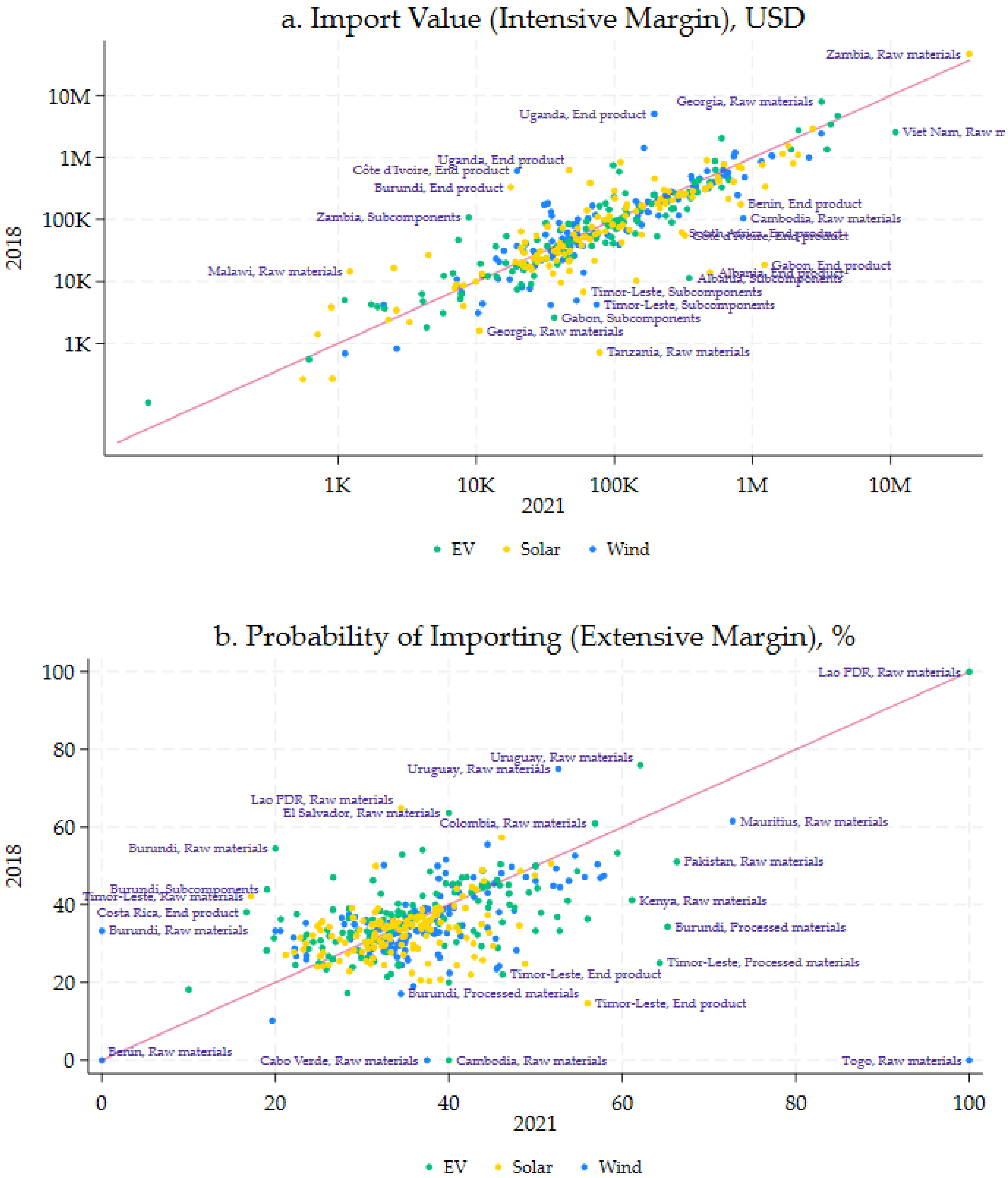
C.2 Stylized facts

FIGURE C.1: Green value chain imports as a share of total imports, 2017 and 2021 (%)



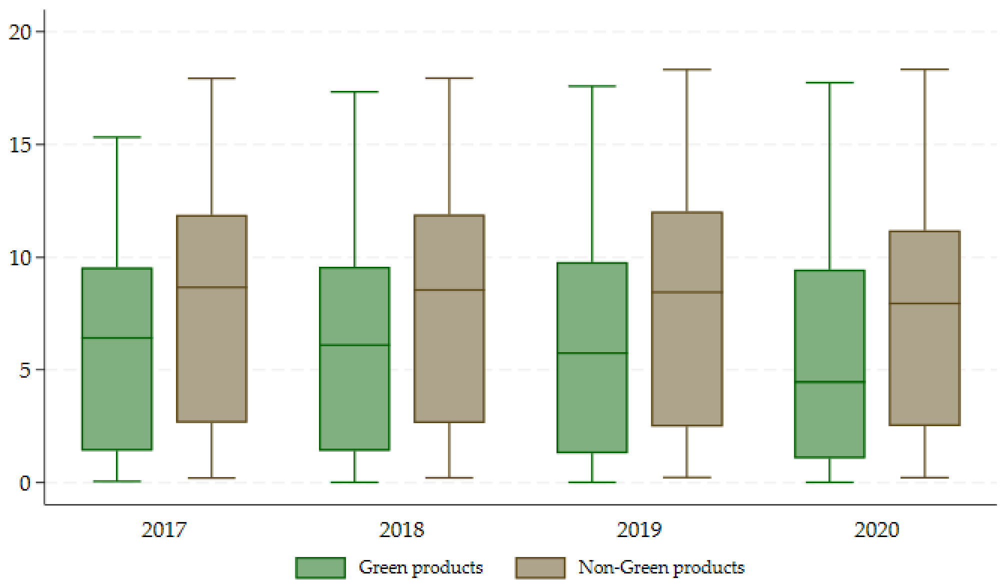
Note: Each node represents the average import value share for a given country and value chain in the first and last year of the sample. The first year with information is 2018 for Timor-Leste, Togo, and Viet Nam and 2019 for Lao PDR and Pakistan. The last year of information is 2020 for Senegal and Uganda. Node size represents the number of green value chain products imported in the most recent year. For countries and value chain segments whose differences between periods are most prominent, the dot with the country's name and the segment name is labelled.

FIGURE C.2: Evolution of firm-level outcome variables, averages by country, value chain and year



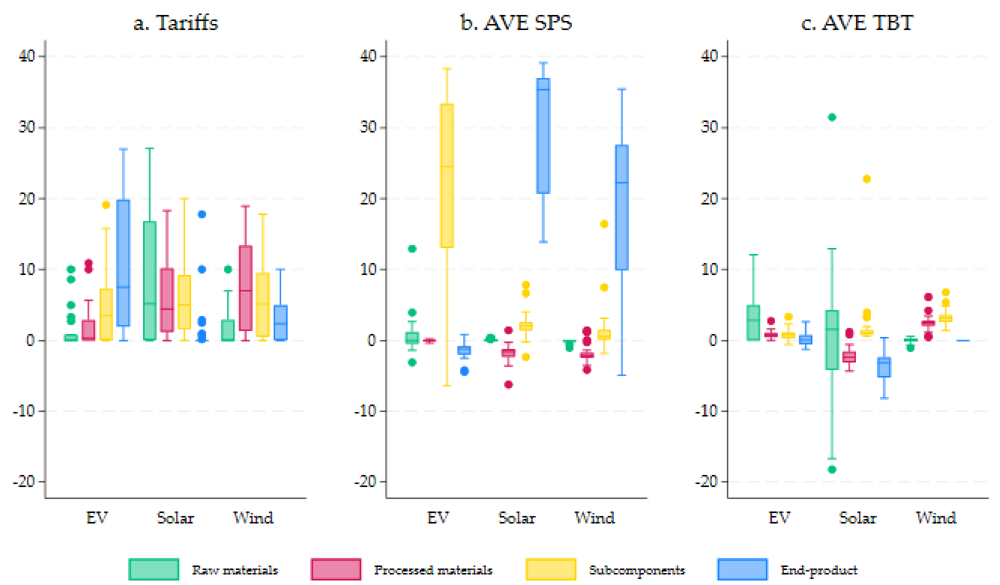
Note: Each node represents the average of a country-value chain-segment in the first and last year of the sample. The initial year with information for Timor-Leste, Togo and Viet Nam is 2018, while for Lao PDR and Pakistan, it is 2019. The last year with information for Senegal and Uganda is 2020. For countries and value chain segments whose differences between periods are most prominent, the dot with the country's name and the segment name is labeled.

FIGURE C.3: Evolution of tariffs, by product group and year (%)



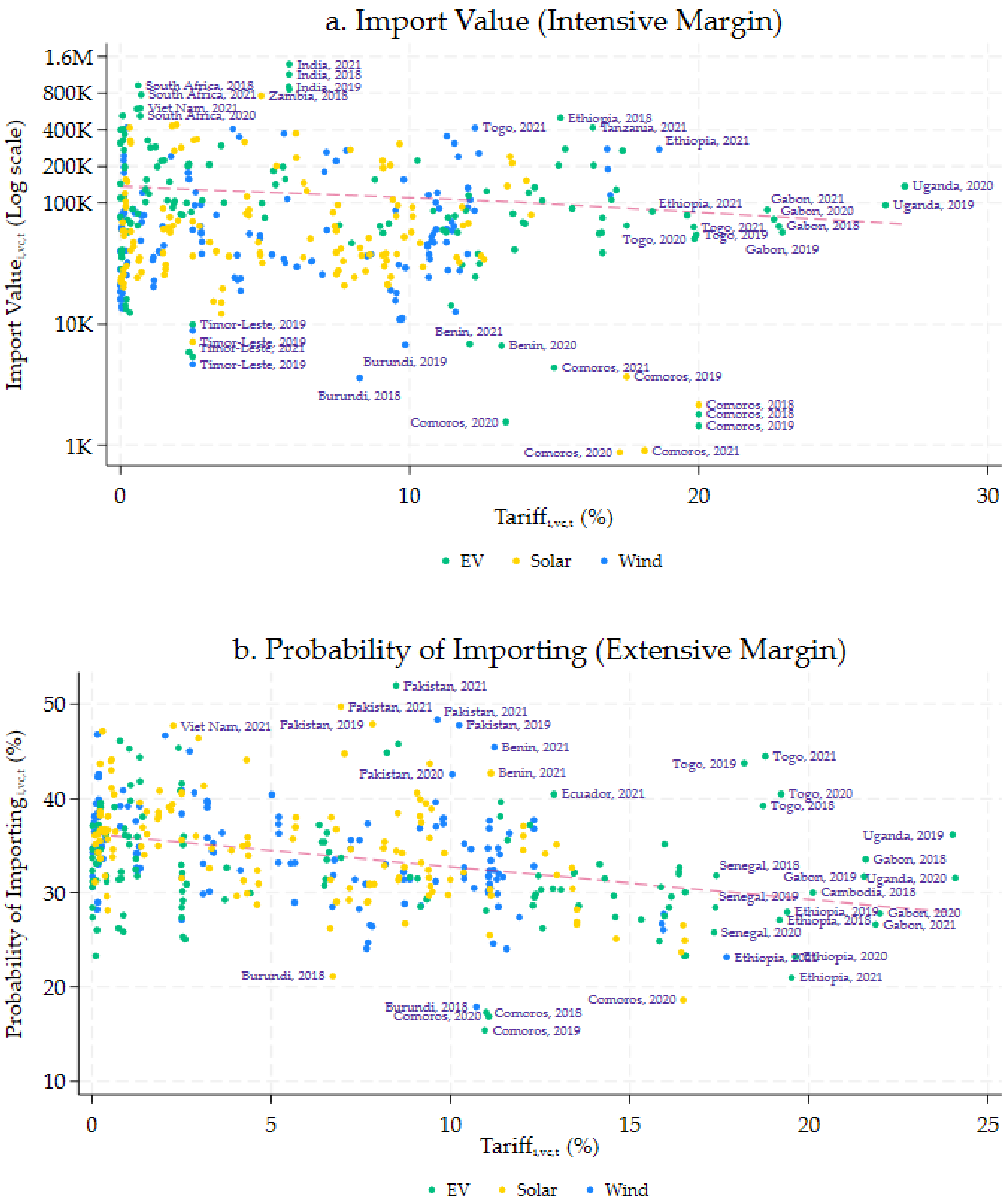
Note: Each box plot illustrates the distribution of tariffs in our country sample of 35 emerging markets for a specified year, displaying the range, median, and interquartile spread of tariff rates. The median is the horizontal bar in the box that represents the interquartile spread.

FIGURE C.4: Tariffs and advalorem equivalents (AVEs) of Sanitary and Phytosanitary (SPS) and Technical Barriers to Trade (TBT), by value chain and segment (%)



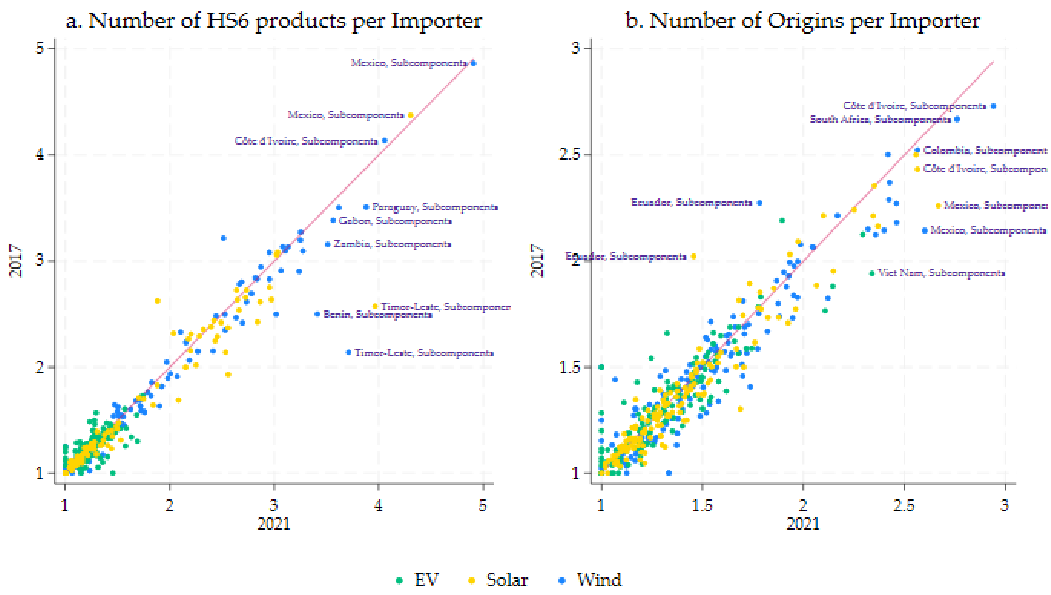
Note: Each box plot illustrates the distribution of tariffs and NTMs in our country sample of 35 emerging markets, displaying the range, median, and interquartile spread. The median is the horizontal bar in the box that represents the interquartile spread.
Nodes represent the average value at the country-value chain-segment level.
For presentation purposes, outliers defined as tariff or AVE rates above 40 percent are excluded.

FIGURE C.5: Outcome variables vs. tariffs



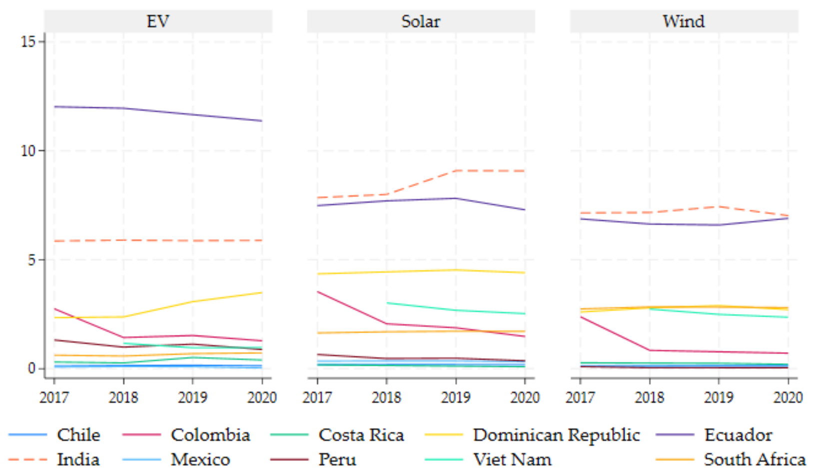
Note: Each node represents the average value of outcome variables and tariffs for each country, value chain and year.

FIGURE C.6: Firm-level import diversification, 2017 vs. 2021



Note: Each node represents the average of a country-value chain segment in the first and last year of the sample. The first year with information is 2018 for Timor-Leste, Togo, and Viet Nam and 2019 for Lao PDR and Pakistan. The last year of information is 2020 for Senegal and Uganda. For countries and value chain segments whose differences between periods are most prominent, the dot with the country's name and the segment name is labeled.

FIGURE C.7: Evolution of tariffs over time by green value chain, top-10 countries



Note: Each box plot illustrates the distribution of tariffs in our country sample of 35 emerging markets for a specified year, displaying the range, median, and interquartile spread of tariff rates. The median is the horizontal bar in the box that represents the interquartile spread.

C.3 Intensive margin of imports: robustness tests

TABLE C.5: Intensive margin of firm-level imports - heterogeneous effects of green product segments

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	With India	Without India
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0092	-0.0071
	(0.003)***	(0.003)**
Ln(1+Tariff)$_{i,j,p,t-1}$ · I[Raw Materials$_p$]	0.0009	-0.0002
	(0.004)	(0.003)
Ln(1+Tariff)$_{i,j,p,t-1}$ · I[Proccessed Materials$_p$]	-0.0111	-0.0068
	(0.006)*	(0.005)
Ln(1+Tariff)$_{i,j,p,t-1}$ · I[Subcomponents$_p$]	-0.0049	-0.0137
	(0.005)	(0.004)***
Ln(1+Tariff)$_{i,j,p,t-1}$ · I[End-product$_p$]	-0.0046	-0.0037
	(0.005)	(0.005)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0005	-0.0008
	(0.001)	(0.001)
Ln(1+AVE SPS)$_{i,j,p,t-1}$ · I[Raw Materials$_p$]	-0.0002	0.0001
	(0.001)	(0.000)
Ln(1+AVE SPS)$_{i,j,p,t-1}$ · I[Processed Materials$_p$]	-0.0001	0.0000
	(0.001)	(0.001)
Ln(1+AVE SPS)$_{i,j,p,t-1}$ · I[Subcomponents$_p$]	0.0006	0.0008
	(0.001)	(0.001)
Ln(1+AVE SPS)$_{i,j,p,t-1}$ · I[End-product$_p$]	-0.0002	0.0001
	(0.001)	(0.001)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0001	-0.0006
	(0.001)	(0.001)
Ln(1+AVE TBT)$_{i,j,p,t-1}$ · I[Raw Materials$_p$]	-0.0011	-0.0004
	(0.000)**	(0.000)
Ln(1+AVE TBT)$_{i,j,p,t-1}$ · I[Proccessed Materials$_p$]	0.0002	0.0001
	(0.000)	(0.000)
Ln(1+AVE TBT)$_{i,j,p,t-1}$ · I[Subcomponents$_p$]	-0.0010	-0.0009
	(0.001)*	(0.001)
Ln(1+AVE TBT)$_{i,j,p,t-1}$ · I[End-product$_p$]	-0.0012	-0.0010
	(0.001)**	(0.001)*
Observations	14,148,626	12,718,663
Adjusted R2	0.84	0.84
Fixed Effects	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. Column (1) covers firm-level import data from 35 countries in the in the appendix table C.1. Column (2) excludes India from the sample of importing countries. Coefficients are standardized with zero mean and unit standard deviation. Additional controls include PTA$_{i,j,t}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.6: Two-sample t-test: homogeneity in HS 4-digit subsectors

Group	Obs	Mean	Std. Err.	Std. Dev.	95% Conf. Interval
Subsectors w/o Green Value Chain Products	830	0.3772	0.0166	0.4794	[0.3446, 0.4099]
Subsectors with Green Value Chain Products	98	0.4426	0.0506	0.4955	[0.3433, 0.5419]
Combined	928	0.3841	0.0158	0.4813	[0.3531, 0.4151]
Difference		-0.0654	0.0514		[-0.1662, 0.0355]

t-statistic	Degrees of Freedom	p-value
-1.2720	926	0.2037

Note: These tables present the results of a two-sample t-test with equal variances, comparing the share of homogeneous products at the HS 4-digit subsector level. We use the classification of differentiated products from (Rauch, 1999), covering 928 HS4 headings.

TABLE C.7: Two-sample t-test: intermediate products in HS 4-digit subsectors

Group	Observations	Mean	Std. Dev.	95% Conf. Interval
Subsectors w/o Green Value Chain Products	1,100	0.6317	0.4582	[0.6046, 0.6588]
Subsectors with Green Value Chain Products	123	0.8061	0.3608	[0.7417, 0.8705]
Combined	1,223	0.6492	0.4523	[0.6238, 0.6746]
Difference		-0.1744		[-0.2582, -0.0906]

t-statistic	Degrees of Freedom	p-value
-4.0819	1221	0.0000

Note: These tables present the results of a two-sample t-test with equal variances, comparing the share of intermediate products at the HS 4-digit subsector level. The BEC classification is used to identify Intermediates (categories 21, 22, 111, and 121), including Parts and Accessories (categories 42 and 53).

TABLE C.8: Excluding negative AVE NTMs

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0463	0.1479	-0.0540	-0.0407	-0.1777	-0.0651	-0.0344	-0.7211
	(0.016)***	(0.326)	(0.026)**	(0.023)*	(0.369)	(0.052)	(0.016)**	(0.238)***
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0046	-0.0218	0.0063	-0.0001	-0.0584	0.0016	0.0051	0.0338
	(0.002)**	(0.025)	(0.004)*	(0.003)	(0.037)	(0.004)	(0.002)**	(0.060)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0018	0.0229	-0.0042	-0.0010	0.0341	-0.0002	-0.0008	-0.0456
	(0.002)	(0.023)	(0.003)	(0.002)	(0.045)	(0.005)	(0.003)	(0.028)
Observations	1,097,697	10,436	496,280	516,206	2,920	160,890	858,798	9,237
Adjusted R2	0.80	0.82	0.80	0.78	0.84	0.79	0.79	0.77
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.9: Standard errors clustered at firm level

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0327	-0.0604	-0.0425	-0.0235	-0.3285	-0.0746	-0.0173	-0.3295
	(0.011)***	(0.124)	(0.018)**	(0.017)	(0.280)	(0.032)**	(0.013)	(0.133)**
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0022	-0.0182	0.0066	-0.0007	-0.0461	0.0036	0.0009	0.0072
	(0.001)	(0.018)	(0.002)***	(0.002)	(0.032)	(0.004)	(0.002)	(0.012)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0032	0.0101	-0.0067	-0.0009	0.0569	-0.0025	-0.0025	-0.0135
	(0.001)**	(0.009)	(0.002)***	(0.002)	(0.041)	(0.003)	(0.002)	(0.011)
Observations	1,911,864	22,961	908,830	868,615	5,017	307,773	1,444,775	37,894
Adjusted R2	0.80	0.82	0.80	0.79	0.85	0.80	0.79	0.79
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the firm level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.10: Bootstrapped standard errors

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0326	-0.0544	-0.0422	-0.0232	-0.2864	-0.0749	-0.0171	-0.3379
	(0.013)**	(0.182)	(0.022)*	(0.021)	(0.516)	(0.047)	(0.015)	(0.221)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0032	-0.0080	0.0084	-0.0002	-0.0332	0.0046	0.0025	-0.0004
	(0.002)*	(0.027)	(0.003)***	(0.002)	(0.057)	(0.004)	(0.002)	(0.018)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0026	0.0105	-0.0052	-0.0007	0.0603	-0.0013	-0.0020	-0.0230
	(0.002)	(0.018)	(0.003)*	(0.002)	(0.050)	(0.004)	(0.002)	(0.017)
Observations	1,917,756	23,165	911,962	870,975	5,124	308,613	1,448,432	38,989
Adjusted R2	0.80	0.82	0.80	0.78	0.85	0.80	0.79	0.80
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1 + \overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Bootstraped standard errors (100) at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.11: Count variables for SPS and TBT measures

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0325	-0.0551	-0.0421	-0.0229	-0.2782	-0.0753	-0.0171	-0.3368
	(0.012)***	(0.128)	(0.019)**	(0.019)	(0.248)	(0.040)*	(0.012)	(0.133)**
SPS count$_{i,j,p,t-1}$	0.0233	0.0000	0.0309	-0.1517	0.0000	-0.5006	0.0240	0.0118
	(0.015)	(.)	(0.022)	(0.094)	(.)	(0.351)	(0.017)	(0.001)***
TBT count$_{i,j,p,t-1}$	0.0128	0.0070	0.0459	0.0132	-0.0695	-0.0083	-0.0010	-0.2577
	(0.020)	(0.081)	(0.031)	(0.023)	(0.089)	(0.018)	(0.023)	(0.106)**
Observations	1,917,756	23,165	911,962	870,975	5,124	308,613	1,448,432	38,989
Adjusted R2	0.80	0.82	0.80	0.78	0.85	0.80	0.79	0.80
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.12: Indicator variables for SPS and TBT measures

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0325	-0.0549	-0.0420	-0.0232	-0.2826	-0.0760	-0.0168	-0.3316
	(0.012)***	(0.128)	(0.019)**	(0.019)	(0.248)	(0.040)*	(0.012)	(0.132)**
I[SPS $_{i,j,p,t-1}$]	0.1448	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0117
	(0.129)	(.)	(.)	(.)	(.)	(.)	(.)	(0.001)***
I[TBT$_{i,j,p,t-1}$]	-0.0208	0.0469	-0.0241	-0.0092	-0.1661	-0.0303	-0.0234	0.2660
	(0.009)**	(0.076)	(0.010)**	(0.023)	(0.174)	(0.029)	(0.010)**	(0.157)*
Observations	1,917,756	23,165	911,962	870,975	5,124	308,613	1,448,432	38,989
Adjusted R2	0.80	0.82	0.80	0.78	0.85	0.80	0.79	0.80
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.13: SPS and TBT AVEs set to zero if their count variables equals zero

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0324	-0.0542	-0.0425	-0.0228	-0.2951	-0.0757	-0.0168	-0.3414
	(0.012)***	(0.128)	(0.019)**	(0.019)	(0.263)	(0.040)*	(0.012)	(0.132)***
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0010	-0.0111	-0.0001	0.0004	-0.0406	-0.0030	0.0000	0.0094
	(0.002)	(0.009)	(0.003)	(0.002)	(0.018)**	(0.005)	(0.003)	(0.002)***
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0035	0.0291	-0.0069	-0.0002	0.0232	-0.0030	-0.0026	-0.0153
	(0.001)**	(0.011)**	(0.002)***	(0.002)	(0.032)	(0.004)	(0.002)	(0.011)
Observations	1,916,961	23,145	911,391	870,753	5,090	308,488	1,447,829	38,960
Adjusted R2	0.80	0.82	0.80	0.78	0.85	0.80	0.79	0.80
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.14: Control function estimates

Dependent variable	Intensive margin of imports			Extensive margin of imports		
	Ln(1+Tariff)$_{i,j,p,t}$	Ln(1+AVE SPS)$_{i,j,p,t}$	Ln(1+AVE TBT)$_{i,j,p,t}$	Ln(1+Tariff)$_{i,j,p,t}$	Ln(1+AVE SPS)$_{i,j,p,t}$	Ln(1+AVE TBT)$_{i,j,p,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(1+ Tariff)$_{i',j,p,t}$	0.0300	-0.0157	-0.0102	0.0262	0.0598	-0.0732
	(0.016)*	(0.078)	(0.058)	(0.014)*	(0.066)	(0.046)
Ln(1+ AVE SPS)$_{i',j,p,t}$	-0.0003	0.5471	0.0015	-0.0004	0.5129	0.0047
	(0.000)*	(0.063)***	(0.007)	(0.000)***	(0.049)***	(0.005)
Ln(1+ AVE TBT)$_{i',j,p,t}$	-0.0003	0.0085	0.3540	0.0007	0.0263	0.3888
	(0.000)*	(0.016)	(0.080)***	(0.000)**	(0.019)	(0.056)***
Observations	1,828,402	1,828,402	1,828,402	14,383,553	14,383,553	14,383,553
Adjusted R2	0.9883	0.4858	0.3252	0.9866	0.4652	0.3757
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.3 for each trade policy instrument t issued by importing country i on origin country j and product p in year t. The sample covers firm-level import data from 34 countries in the appendix table C.1, excluding India. Each column presents the estimation of trade policy measures based on the average intensity in three closest countries i'.Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.15: Controlling for inverse mills ratio

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0329	-0.0026	-0.0395	-0.0264	-0.3699	-0.0818	-0.0140	-0.2540
	(0.013)***	(0.097)	(0.021)*	(0.019)	(0.308)	(0.036)**	(0.014)	(0.107)**
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0026	-0.0205	0.0069	0.0002	-0.9292	0.0054	0.0001	0.0034
	(0.002)	(0.012)*	(0.003)**	(0.003)	(0.566)	(0.006)	(0.003)	(0.003)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0030	0.0100	-0.0066	-0.0005	0.0139	-0.0037	-0.0025	-0.0198
	(0.002)*	(0.020)	(0.002)***	(0.002)	(0.010)	(0.004)	(0.002)	(0.017)
Observations	1,828,402	20,813	869,719	831,742	4,425	292,600	1,383,926	36,291
Adjusted R2	0.80	0.81	0.80	0.78	0.84	0.79	0.79	0.79
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the appendix table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. All columns include controls for three Inverse Mills Ratios, each corresponding to a trade policy instrument. These ratios are based on OLS estimates, using the average intensity of the three nearest countries, as specified in Equation 3.3. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

C.4 Extensive margin of imports: robustness tests

TABLE C.16: Excluding negative AVE NTMs

Dependent variable: Probability of Importing$_{i,f,j,p,t}$								
	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0086	0.0017	-0.0082	-0.0075	-0.1193	-0.0206	-0.0049	-0.0143
	(0.003)**	(0.028)	(0.004)*	(0.005)	(0.066)*	(0.010)**	(0.003)	(0.033)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0005	-0.0072	0.0010	-0.0001	0.0031	0.0029	-0.0001	-0.0007
	(0.000)	(0.003)***	(0.001)	(0.001)	(0.005)	(0.001)*	(0.000)	(0.005)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0009	-0.0014	-0.0005	-0.0012	0.0016	-0.0012	-0.0010	0.0036
	(0.000)***	(0.003)	(0.001)	(0.000)***	(0.007)	(0.001)	(0.000)***	(0.002)
Observations	9,340,713	128,049	4,189,079	4,523,911	25,587	1,524,571	7,204,900	109,148
Adjusted R2	0.23	0.02	0.21	0.20	-0.02	0.16	0.23	0.01
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.17: Standard errors clustered at firm level

Dependent variable: Probability of Importing$_{i,f,j,p,t}$								
	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0069	-0.0010	-0.0056	-0.0092	-0.0032	-0.0175	-0.0054	0.0041
	(0.001)***	(0.013)	(0.002)***	(0.002)***	(0.034)	(0.003)***	(0.001)***	(0.009)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0000	0.0048	0.0007	-0.0009	0.0017	0.0003	-0.0008	0.0029
	(0.000)	(0.001)***	(0.000)***	(0.000)***	(0.004)	(0.000)	(0.000)***	(0.001)***
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0008	-0.0018	-0.0008	-0.0006	-0.0099	-0.0012	-0.0009	0.0020
	(0.000)***	(0.001)	(0.000)***	(0.000)**	(0.004)***	(0.000)***	(0.000)***	(0.001)*
Observations	15,396,435	289,004	7,366,189	7,055,080	41,735	2,748,228	11,448,457	415,215
Adjusted R2	0.24	0.12	0.24	0.22	0.13	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the firm level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.18: Bootstrapped standard errors

Dependent variable: Probability of Importing$_{i,f,j,p,t}$								
	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0066	-0.0017	-0.0056	-0.0087	0.0021	-0.0173	-0.0051	0.0028
	(0.001)***	(0.017)	(0.002)***	(0.002)***	(0.056)	(0.004)***	(0.002)***	(0.014)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0001	0.0042	0.0004	-0.0008	0.0025	0.0008	-0.0009	0.0018
	(0.000)	(0.002)**	(0.000)	(0.000)**	(0.005)	(0.001)	(0.000)***	(0.001)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0007	-0.0005	-0.0006	-0.0006	-0.0034	-0.0008	-0.0009	0.0026
	(0.000)***	(0.002)	(0.000)**	(0.000)**	(0.005)	(0.000)*	(0.000)***	(0.001)*
Observations	15,458,958	293,057	7,400,535	7,077,715	42,602	2,754,879	11,491,035	425,567
Adjusted R2	0.24	0.12	0.24	0.22	0.14	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Bootstraped standard errors (100) at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.19: Count variables for SPS and TBT measures

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0066	-0.0017	-0.0047	-0.0087	0.0074	-0.0170	-0.0049	0.0037
	(0.003)**	(0.014)	(0.003)	(0.005)*	(0.033)	(0.010)*	(0.003)*	(0.011)
SPS count$_{i,j,p,t-1}$	0.0080	0.0008	0.0176	-0.0051	-0.0169	-0.0030	0.0121	0.0002
	(0.002)***	(0.007)	(0.003)***	(0.001)***	(0.015)	(0.004)	(0.002)***	(0.002)
TBT count$_{i,j,p,t-1}$	-0.0070	-0.0277	0.0016	-0.0097	-0.0329	-0.0020	-0.0132	-0.0191
	(0.003)**	(0.009)***	(0.004)	(0.003)***	(0.015)**	(0.002)	(0.004)***	(0.008)**
Observations	15,458,958	293,057	7,400,535	7,077,715	42,602	2,754,879	11,491,035	425,567
Adjusted R2	0.24	0.12	0.24	0.22	0.14	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.20: Indicator variables for SPS and TBT measures

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0067	-0.0022	-0.0053	-0.0087	0.0034	-0.0172	-0.0053	0.0036
	(0.003)**	(0.014)	(0.003)	(0.005)*	(0.033)	(0.010)*	(0.003)*	(0.011)
I[SPS $_{i,j,p,t-1}$]	-0.0032	0.0048	0.0093	-0.0039	-0.0248	-0.0049	-0.0025	-0.0019
	(0.003)	(0.006)	(0.004)**	(0.001)***	(0.014)*	(0.004)	(0.004)	(0.002)
I[TBT$_{i,j,p,t-1}$]	-0.0065	-0.0206	-0.0049	-0.0115	0.0028	-0.0083	-0.0059	-0.0254
	(0.001)***	(0.005)***	(0.001)***	(0.001)***	(0.015)	(0.002)***	(0.001)***	(0.005)***
Observations	15,458,958	293,057	7,400,535	7,077,715	42,602	2,754,879	11,491,035	425,567
Adjusted R2	0.24	0.12	0.24	0.22	0.14	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.21: AVEs equal to zero if count equal zero

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0066	-0.0023	-0.0057	-0.0086	0.0009	-0.0174	-0.0050	0.0029
	(0.003)**	(0.014)	(0.003)*	(0.005)*	(0.032)	(0.010)*	(0.003)*	(0.010)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0010	0.0004	0.0012	-0.0006	0.0059	-0.0007	0.0014	0.0010
	(0.001)**	(0.001)	(0.001)*	(0.000)	(0.004)*	(0.001)	(0.001)**	(0.001)*
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0001	-0.0006	-0.0007	0.0005	-0.0025	0.0005	-0.0002	0.0001
	(0.000)	(0.002)	(0.000)*	(0.000)	(0.004)	(0.000)	(0.000)	(0.002)
Observations	15,458,958	293,057	7,400,535	7,077,715	42,602	2,754,879	11,491,035	425,567
Adjusted R2	0.24	0.12	0.24	0.22	0.14	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the Appendix Table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.22: Controlling for inverse mills ratio

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled	Value chain			Value chain segment			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0062	-0.0021	-0.0053	-0.0090	0.0045	-0.0147	-0.0052	0.0018
	(0.003)*	(0.010)	(0.004)	(0.005)*	(0.034)	(0.009)	(0.003)*	(0.009)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0001	0.0028	0.0004	-0.0005	0.0314	0.0012	-0.0005	0.0009
	(0.000)	(0.001)***	(0.000)	(0.001)	(0.073)	(0.002)	(0.000)	(0.001)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0005	-0.0021	-0.0004	-0.0006	-0.0030	-0.0014	-0.0006	0.0030
	(0.000)*	(0.004)	(0.000)	(0.000)	(0.002)*	(0.001)**	(0.000)	(0.002)*
Observations	14,383,553	262,817	6,893,291	6,586,374	35,969	2,555,706	10,705,352	388,952
Adjusted R2	0.24	0.12	0.24	0.23	0.14	0.21	0.24	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 34 countries in the appendix table C.1, excluding India. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. All columns include controls for three Inverse Mills Ratios, each corresponding to a trade policy instrument. These ratios are based on OLS estimates, using the average intensity of the three nearest countries, as specified in Equation 3.3. Three additional control variables are included in the regression: PTA$_{i,j,t}$, $\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$ and Ln(Market Size)$_{i,j,p,t}$. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

C.5 Intensive margin of imports: results by region

TABLE C.23: Intensive margin of firm-level imports - results by region

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	East Asia and Pacific	Europe and Central Asia	Latin America and Caribbean	South Asia	Sub-Saharan Africa
	(1)	(2)	(3)	(4)	(5)
Ln(1+Tariff)$_{i,j,p,t-1}$	0.0024	-0.0443	-0.0314	0.0224	-0.0836
	(0.025)	(0.165)	(0.012)***	(0.022)	(0.045)*
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0057	0.0026	0.0027	-0.0010	-0.0021
	(0.007)	(0.007)	(0.002)	(0.004)	(0.004)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	0.0048	-0.0117	-0.0019	-0.0063	-0.0085
	(0.005)	(0.011)	(0.002)	(0.005)	(0.003)***
PTA$_{i,j,t}$	0.0182	-0.0612	0.0223	0.5578	0.0224
	(0.011)*	(0.106)	(0.015)	(0.112)***	(0.018)
$Ln(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-0.0395	-2.2506	-0.1106	0.0068	0.0576
	(0.044)	(2.317)	(0.041)***	(0.059)	(0.178)
Ln(Market Size)$_{i,j,p,t}$	0.2481	0.2635	0.2413	0.0807	0.2357
	(0.086)***	(0.093)***	(0.028)***	(0.044)*	(0.038)***
Observations	167,912	47,252	1,279,760	303,277	362,365
Adjusted R2	0.79	0.74	0.80	0.77	0.77
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 35 countries in the appendix table C.1. Columns (1)–(5) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.24: Intensive margin of firm-level imports - East Asia and Pacific

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	0.0024	-0.0200	-0.0252	0.0259	-0.3048	-0.0460	0.0272	-0.1867
	(0.025)	(0.221)	(0.042)	(0.045)	(0.470)	(0.071)	(0.031)	(0.152)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0057	-0.0751	0.0182	-0.0108	-0.0914	0.0163	-0.0025	0.1095
	(0.007)	(0.065)	(0.010)*	(0.008)	(0.148)	(0.011)	(0.006)	(0.049)**
Ln(1+AVE TBT)$_{i,j,p,t-1}$	0.0048	0.0460	-0.0037	0.0079	0.0031	0.0150	0.0018	0.0628
	(0.005)	(0.034)	(0.009)	(0.007)	(0.051)	(0.012)	(0.006)	(0.034)*
PTA$_{i,j,t}$	0.0182	0.0843	0.0281	0.0023	0.2334	0.0344	0.0113	-0.0434
	(0.011)*	(0.091)	(0.016)*	(0.017)	(0.134)*	(0.023)	(0.013)	(0.113)
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-0.0395	-0.6838	-0.0161	-0.0367	-0.0762	0.0190	-0.0648	0.5062
	(0.044)	(0.262)***	(0.056)	(0.076)	(0.441)	(0.097)	(0.048)	(0.221)**
Ln(Market Size)$_{i,j,p,t}$	0.2481	0.2395	0.2525	0.2536	-0.1973	0.2717	0.2237	0.7092
	(0.086)***	(0.383)	(0.126)**	(0.114)**	(0.394)	(0.137)**	(0.110)**	(0.309)**
Observations	167,912	2,004	84,297	69,106	781	36,950	114,552	2,611
Adjusted R2	0.79	0.80	0.78	0.77	0.82	0.77	0.78	0.78
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 4 countries in East Asia and the Pacific listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.25: Intensive margin of firm-level imports - Europe and Central Asia

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0443	0.0000	-0.0292	0.0875	.	-0.1194	0.0460	0.0000
	(0.165)	(.)	(0.129)	(0.280)	.	(0.332)	(0.056)	(.)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0026	-0.0785	-0.0072	0.0031	.	0.0036	0.0048	0.1179
	(0.007)	(0.290)	(0.012)	(0.010)	.	(0.028)	(0.009)	(0.084)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0117	-0.0554	-0.0048	-0.0182	.	-0.0519	-0.0070	-0.0239
	(0.011)	(0.085)	(0.010)	(0.019)	.	(0.038)	(0.009)	(0.099)
PTA$_{i,j,t}$	-0.0612	-0.5749	-0.1717	0.2021		0.0726	-0.0931	-0.3716
	(0.106)	(0.256)**	(0.105)	(0.265)	.	(0.364)	(0.104)	(0.046)***
Ln$(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-2.2506	14.3055	-1.6247	0.0558	.	-4.9553	-1.0806	2.4611
	(2.317)	(8.301)*	(3.262)	(4.337)	.	(4.043)	(2.958)	(16.294)
Ln(Market Size)$_{i,j,p,t}$	0.2635	0.3055	0.4117	0.1783	.	0.1125	0.4004	-0.0211
	(0.093)***	(0.989)	(0.130)***	(0.158)	.	(0.263)	(0.108)***	(0.794)
Observations	47,252	393	23,203	18,306	.	9,251	31,711	520
Adjusted R2	0.74	0.84	0.74	0.70	.	0.69	0.74	0.82
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 2 countries in Europe and Central Asia listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. There are not enough observations for Column (5). Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.26: Intensive margin of firm-level imports - Latin America and the Caribbean

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0314	-0.0651	-0.0428	-0.0172	-0.2913	-0.0541	-0.0227	-0.0897
	(0.012)***	(0.142)	(0.020)**	(0.016)	(0.270)	(0.039)	(0.012)*	(0.130)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0027	-0.0160	0.0061	0.0022	-0.0625	0.0046	0.0012	0.0029
	(0.002)	(0.020)	(0.002)***	(0.002)	(0.038)	(0.004)	(0.002)	(0.013)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0019	0.0130	-0.0042	-0.0008	0.0605	-0.0010	-0.0014	-0.0180
	(0.002)	(0.012)	(0.003)	(0.002)	(0.038)	(0.004)	(0.002)	(0.019)
PTA$_{i,j,t}$	0.0223	-0.0576	0.0195	0.0312	0.0241	0.0273	0.0256	-0.0161
	(0.015)	(0.090)	(0.020)	(0.023)	(0.243)	(0.049)	(0.015)*	(0.054)
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-0.1106	-0.2428	-0.0825	-0.1188	0.0020	-0.1328	-0.0861	-0.3771
	(0.041)***	(0.364)	(0.059)	(0.060)**	(0.364)	(0.098)	(0.046)*	(0.408)
Ln(Market Size)$_{i,j,p,t}$	0.2413	0.1028	0.2997	0.1990	0.1435	0.2101	0.2834	-0.0138
	(0.028)***	(0.117)	(0.049)***	(0.033)***	(0.171)	(0.057)***	(0.034)***	(0.130)
Observations	1,279,760	13,360	611,589	588,337	3,406	201,983	979,878	23,652
Adjusted R2	0.80	0.82	0.80	0.79	0.83	0.81	0.80	0.80
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 10 countries in Latin America and the Caribbean listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.27: Intensive margin of firm-level imports - South Asia

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	0.0224	-0.0744	0.0177	-0.0629	0.3016	-0.2132	0.0224	-1.2612
	(0.022)	(0.222)	(0.031)	(0.032)**	(0.478)	(0.157)	(0.023)	(0.450)***
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0010	-0.0233	0.0050	-0.0090	-0.1237	0.0001	0.0002	0.0209
	(0.004)	(0.050)	(0.006)	(0.007)	(0.046)***	(0.016)	(0.006)	(0.039)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0063	-0.0306	-0.0160	0.0043	-0.0441	0.0007	-0.0018	0.0076
	(0.005)	(0.025)	(0.006)***	(0.007)	(0.043)	(0.014)	(0.005)	(0.058)
PTA$_{i,j,t}$	0.5578	0.0000	0.6063	0.0000	0.0000	0.0000	0.5182	0.0000
	(0.112)***	(.)	(0.122)***	(.)	(.)	(.)	(0.129)***	(.)
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	0.0068	0.6181	0.0052	0.0021	-0.0848	0.0735	0.0203	1.1237
	(0.059)	(0.286)**	(0.079)	(0.092)	(0.298)	(0.185)	(0.065)	(0.442)**
Ln(Market Size)$_{i,j,p,t}$	0.0807	0.0352	0.0700	0.0714	0.1765	0.0601	0.0769	0.0353
	(0.044)*	(0.110)	(0.069)	(0.077)	(0.123)	(0.099)	(0.061)	(0.264)
Observations	303,277	5,582	150,035	126,702	2,569	42,323	232,688	5,387
Adjusted R2	0.77	0.84	0.75	0.77	0.85	0.77	0.76	0.73
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 3 countries in South Asia listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.28: Intensive margin of firm-level imports - Sub-Saharan Africa

Dependent variable: Ln(Import Value)$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0836	-0.1525	-0.0380	-0.1506	0.0000	-0.1605	-0.0598	-1.0248
	(0.045)*	(0.184)	(0.074)	(0.082)*	(.)	(0.132)	(0.061)	(0.298)***
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0021	-0.0158	0.0013	-0.0054	-0.0089	-0.0023	-0.0008	-0.0058
	(0.004)	(0.031)	(0.007)	(0.005)	(0.044)	(0.009)	(0.005)	(0.025)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0085	-0.0090	-0.0130	-0.0024	0.1297	-0.0107	-0.0061	-0.0213
	(0.003)***	(0.020)	(0.003)***	(0.005)	(0.060)**	(0.009)	(0.004)	(0.015)
PTA$_{i,j,t}$	0.0224	-0.0875	0.0228	0.0151	-0.0864	-0.0350	0.0309	-0.0210
	(0.018)	(0.129)	(0.026)	(0.027)	(0.324)	(0.051)	(0.020)	(0.105)
$\mathrm{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	0.0576	-1.3348	-0.2186	0.2973	1.0820	0.2285	-0.0003	-1.5095
	(0.178)	(1.670)	(0.245)	(0.297)	(1.036)	(0.497)	(0.213)	(1.594)
Ln(Market Size)$_{i,j,p,t}$	0.2357	0.1304	0.2392	0.2355	0.1736	0.0017	0.3316	0.0214
	(0.038)***	(0.223)	(0.059)***	(0.055)***	(0.484)	(0.093)	(0.047)***	(0.157)
Observations	362,365	6,674	163,644	169,785	582	52,104	276,994	10,622
Adjusted R2	0.77	0.81	0.77	0.76	0.91	0.77	0.76	0.76
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 16 countries in Sub-Saharan Africa listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

C.6 Extensive margin of imports: results by region

TABLE C.29: Extensive margin of firm-level imports - results by region

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	East Asia and Pacific	Europe and Central Asia	Latin America and Caribbean	South Asia	Sub-Saharan Africa
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0084	0.0013	-0.0090	-0.0043	0.0034
	(0.007)	(0.002)	(0.002)***	(0.004)	(0.004)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0028	0.0012	0.0003	-0.0002	0.0002
	(0.001)*	(0.001)	(0.000)	(0.001)	(0.000)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0038	-0.0017	-0.0002	-0.0010	-0.0005
	(0.002)**	(0.001)	(0.000)	(0.001)*	(0.000)
PTA$_{i,j,t}$	0.0098	-0.0117	0.0140	-0.0204	0.0040
	(0.002)***	(0.005)**	(0.003)***	(0.026)	(0.002)*
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	0.0087	-0.8708	-0.0878	0.0254	0.0154
	(0.010)	(0.563)	(0.011)***	(0.009)***	(0.009)*
Ln(Market Size)$_{i,j,p,t}$	0.0429	0.0277	0.0506	0.0199	0.0214
	(0.013)***	(0.009)***	(0.005)***	(0.006)***	(0.004)***
Observations	1,728,781	519,541	8,350,983	3,221,239	3,977,084
Adjusted R2	0.20	0.25	0.26	0.22	0.21
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 35 countries in the appendix table C.1. Columns (1)–(5) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.30: Extensive margin of firm-level imports - East Asia and Pacific

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled		Value Chain			Value chain segments		
	EV	Solar	Wind	Raw	Processed	Subcomponents	End-product	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0084	0.0087	-0.0098	-0.0111	0.0310	-0.0201	-0.0059	0.0201
	(0.007)	(0.013)	(0.007)	(0.010)	(0.048)	(0.019)	(0.006)	(0.010)**
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0028	0.0028	0.0001	-0.0047	-0.0166	-0.0060	-0.0047	0.0199
	(0.001)*	(0.006)	(0.002)	(0.002)**	(0.011)	(0.003)**	(0.001)***	(0.014)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0038	0.0094	-0.0028	-0.0047	-0.0331	-0.0071	-0.0045	0.0239
	(0.002)**	(0.005)*	(0.002)	(0.003)	(0.009)***	(0.003)***	(0.003)	(0.011)**
PTA$_{i,j,t}$	0.0098	0.0018	0.0095	0.0105	-0.0005	0.0051	0.0104	-0.0116
	(0.002)***	(0.012)	(0.003)***	(0.004)***	(0.021)	(0.005)	(0.003)***	(0.012)
$\mathrm{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	0.0087	0.0478	0.0097	0.0089	0.0045	0.0307	0.0031	0.0161
	(0.010)	(0.024)**	(0.010)	(0.015)	(0.056)	(0.023)	(0.010)	(0.019)
Ln(Market Size)$_{i,j,p,t}$	0.0429	-0.0519	0.0555	0.0574	0.0721	0.0635	0.0302	0.0359
	(0.013)***	(0.031)*	(0.019)***	(0.019)***	(0.055)	(0.022)***	(0.017)*	(0.041)
Observations	1,728,781	23,473	844,542	791,913	6,817	399,406	1,209,697	33,358
Adjusted R2	0.20	0.09	0.19	0.18	0.13	0.17	0.20	0.13
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 4 countries in East Asia and the Pacific listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.31: Extensive margin of firm-level imports - Europe and Central Asia

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	0.0013	0.0000	0.0019	-0.0012	0.0000	0.0056	-0.0022	0.3723
	(0.002)	(.)	(0.002)	(0.012)	(.)	(0.003)*	(0.004)	(0.063)***
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0012	0.0234	0.0004	-0.0006	0.1323	0.0047	0.0008	0.0163
	(0.001)	(0.010)**	(0.001)	(0.001)	(0.095)	(0.002)**	(0.001)	(0.007)**
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0017	-0.0142	-0.0005	-0.0037	-0.0542	-0.0066	-0.0011	0.0001
	(0.001)	(0.009)	(0.001)	(0.002)*	(0.035)	(0.004)	(0.001)	(0.007)
PTA$_{i,j,t}$	-0.0117	-0.0180	-0.0083	-0.0225	-0.3762	-0.0102	-0.0107	-0.0705
	(0.005)**	(0.038)	(0.006)	(0.007)***	(0.180)**	(0.006)	(0.006)*	(0.019)***
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-0.8708	3.8307	-1.0920	-0.8741	2.0573	-0.2032	-1.2318	0.8339
	(0.563)	(4.045)	(0.775)	(0.822)	(10.870)	(1.184)	(0.625)**	(3.402)
Ln(Market Size)$_{i,j,p,t}$	0.0277	0.0915	0.0297	0.0191	-0.0618	0.0188	0.0314	-0.0604
	(0.009)***	(0.064)	(0.013)**	(0.014)	(0.095)	(0.022)	(0.011)***	(0.059)
Observations	519,541	6,914	264,880	213,167	516	120,486	350,233	9,642
Adjusted R2	0.25	0.01	0.22	0.23	-0.15	0.21	0.23	0.00
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 2 countries in Europe and Central Asia listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. There are not enough observations for Column (5). Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.32: Extensive margin of firm-level imports - Latin America and the Caribbean

Dependent variable: Probability of Importing$_{i,f,j,p,t}$								
	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0090	-0.0125	-0.0093	-0.0085	-0.0380	-0.0179	-0.0074	-0.0071
	(0.002)***	(0.022)	(0.004)**	(0.003)***	(0.043)	(0.006)***	(0.003)***	(0.013)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0003	0.0078	0.0006	-0.0003	0.0033	0.0026	-0.0003	-0.0001
	(0.000)	(0.002)***	(0.001)	(0.001)	(0.005)	(0.001)**	(0.000)	(0.002)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0002	-0.0028	0.0002	-0.0005	-0.0027	-0.0007	-0.0002	0.0002
	(0.000)	(0.002)	(0.000)	(0.000)	(0.004)	(0.001)	(0.000)	(0.003)
PTA$_{i,j,t}$	0.0140	0.0072	0.0138	0.0133	0.0361	0.0150	0.0124	0.0194
	(0.003)***	(0.014)	(0.004)***	(0.003)***	(0.022)*	(0.007)**	(0.003)***	(0.009)**
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	-0.0878	-0.0886	-0.0981	-0.0775	0.0679	-0.0949	-0.0876	-0.0865
	(0.011)***	(0.049)*	(0.018)***	(0.013)***	(0.092)	(0.026)***	(0.012)***	(0.041)**
Ln(Market Size)$_{i,j,p,t}$	0.0506	-0.0055	0.0671	0.0459	0.0020	0.0487	0.0612	-0.0005
	(0.005)***	(0.014)	(0.008)***	(0.006)***	(0.028)	(0.010)***	(0.006)***	(0.013)
Observations	8,350,983	138,496	3,984,893	3,906,223	24,261	1,438,646	6,322,786	210,341
Adjusted R2	0.26	0.13	0.26	0.24	0.16	0.22	0.26	0.16
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 10 countries in Latin America and the Caribbean listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.33: Extensive margin of firm-level imports - South Asia

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	-0.0043	-0.0133	-0.0069	-0.0115	-0.1092	-0.0598	-0.0044	0.0585
	(0.004)	(0.043)	(0.005)	(0.007)	(0.061)*	(0.017)***	(0.003)	(0.049)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	-0.0002	0.0069	-0.0000	-0.0006	-0.0431	-0.0040	0.0006	-0.0006
	(0.001)	(0.003)**	(0.001)	(0.001)	(0.008)***	(0.002)**	(0.001)	(0.005)
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0010	-0.0014	-0.0023	0.0003	-0.0058	0.0009	-0.0015	0.0014
	(0.001)*	(0.002)	(0.001)**	(0.001)	(0.004)	(0.001)	(0.001)**	(0.004)
PTA$_{i,j,t}$	-0.0204	0.0000	-0.0220	-0.0040	0.0000	-0.0059	-0.0263	0.0000
	(0.026)	(.)	(0.042)	(0.027)	(.)	(0.024)	(0.033)	(.)
$Ln(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	0.0254	0.0648	0.0284	0.0233	-0.0104	0.0428	0.0260	-0.0500
	(0.009)***	(0.043)	(0.010)***	(0.013)*	(0.070)	(0.021)**	(0.008)***	(0.040)
Ln(Market Size)$_{i,j,p,t}$	0.0199	-0.0349	0.0392	0.0081	-0.0179	0.0241	0.0252	-0.0018
	(0.006)***	(0.013)***	(0.010)***	(0.009)	(0.030)	(0.010)**	(0.007)***	(0.037)
Observations	3,221,239	67,764	1,629,859	1,379,642	21,233	502,375	2,471,751	73,330
Adjusted R2	0.22	0.15	0.21	0.20	0.16	0.17	0.22	0.13
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 3 countries in South Asia listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.34: Extensive margin of firm-level imports - Sub-Saharan Africa

Dependent variable: Probability of Importing$_{i,f,j,p,t}$	Pooled	Value Chain			Value chain segments			
		EV	Solar	Wind	Raw	Processed	Subcomponents	End-product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+Tariff)$_{i,j,p,t-1}$	0.0034	-0.0066	0.0071	0.0005	0.5467	0.0031	0.0008	-0.0183
	(0.004)	(0.025)	(0.005)	(0.006)	(0.338)	(0.011)	(0.004)	(0.016)
Ln(1+AVE SPS)$_{i,j,p,t-1}$	0.0002	-0.0014	0.0011	-0.0003	0.0036	-0.0012	-0.0007	0.0043
	(0.000)	(0.002)	(0.001)**	(0.001)	(0.010)	(0.001)	(0.000)*	(0.002)**
Ln(1+AVE TBT)$_{i,j,p,t-1}$	-0.0005	-0.0027	-0.0016	0.0011	0.0010	0.0013	-0.0009	0.0009
	(0.000)	(0.002)	(0.001)***	(0.001)**	(0.008)	(0.001)	(0.000)**	(0.002)
PTA$_{i,j,t}$	0.0040	-0.0071	0.0024	0.0058	0.0510	0.0044	0.0036	0.0050
	(0.002)*	(0.013)	(0.003)	(0.003)**	(0.087)	(0.005)	(0.002)	(0.011)
$\text{Ln}(1+\overline{\text{Non-Green Tariff}})_{i,j,t-1}$	0.0154	0.0321	0.0106	0.0153	0.3079	-0.0017	0.0143	0.0413
	(0.009)*	(0.053)	(0.014)	(0.014)	(0.133)**	(0.021)	(0.011)	(0.055)
Ln(Market Size)$_{i,j,p,t}$	0.0214	0.0012	0.0338	0.0130	0.0032	0.0147	0.0254	-0.0040
	(0.004)***	(0.019)	(0.006)***	(0.005)***	(0.034)	(0.008)*	(0.005)***	(0.018)
Observations	3,977,084	106,718	1,878,443	1,768,458	7,737	660,821	2,936,771	143,494
Adjusted R2	0.21	0.11	0.19	0.19	0.01	0.17	0.20	0.15
Fixed Effects	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j	f-t, f-p-j

Note: This table estimates Equation 3.1 for firm f in importing country i of product p from origin country j in year t. The sample covers firm-level import data from 16 countries in Sub-Saharan Africa listed in the appendix table C.1. Columns (1)-(8) show coefficients standardized with zero mean and unit standard deviation in their respective sample. Clustered standard errors at the origin-destination-HS6 product level are presented in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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Declaration of Originality

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I hereby declare that this thesis represents my original work and that I have used no other sources except as noted by citations.

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I am aware that in case of non-compliance, the Senate is entitled to withdraw the doctorate degree awarded to me on the basis of the present thesis, in accordance with the "Statut der Universität Bern (Universitätsstatut; UniSt)", Art. 69, of 7 June 2011.

Mexico City, December 8, 2024

Samuel Rosenow