Title
Essays on Capital Goods Trade Policy and Technology Diffusion

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Publication Date
2021

Peer reviewed|Thesis/dissertation

Essays on Capital Goods Trade Policy and Technology Diffusion

By

PATRICIA LANGSCH TECLES
DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Economics

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

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2021

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ABSTRACT

Essays on Capital Goods Trade Policy and Technology Diffusion

Investment in capital goods is a key determinant of productivity and economic growth. At the same time, machinery production is more geographically concentrated than other manufactured goods and strongly correlated to the R&D intensity across countries. Therefore, international trade in capital goods is expected to increase countries' access to different technologies and to have a growth effect beyond the traditional allocative efficiency trade gains. This dissertation focuses on the effects from capital goods trade policy on firms performance, welfare and technology diffusion.

The first chapter investigates the effect of a reduction in capital goods import tariff on firms' trade performance. To do so, I bring together rich data from Brazilian firms that imported capital goods in the last two decades. The empirical strategy compares the share of imports across firms that entered through a tariff exemption program and the firms' outcomes in the following years, using local projections estimates. The results point to a larger increase in exports, imports of inputs, number of destination countries and of export varieties for firms with larger shares of exempted capital goods imports. In order to address potential selection effect from program participation, I take a sub-sample of non-applicant firms, since the exemption, once approved, applies to all firms. I find very similar results. Regressions which instrument for the equipment imports further confirm the findings.

Chapter 2 studies the welfare effects of capital goods trade policy, using a quantitative general equilibrium framework with sector-specific trade elasticities and capital and intermediate inputs shares. I present an empirical implementation of the model and conduct

counterfactual analyses regarding the capital equipment liberalization program in Brazil, employing data on world input-output flows and on the Brazilian sector-level labor. I first assess the welfare effects of gradual reductions in import tariffs up to complete liberalization. The results suggest welfare gains of up to 2%. Then I compare the impact from unilateral tariff reductions, and find that equipment imports from China would benefit Brazil the most. Finally, further removing trade costs leads to an even stronger increase in welfare.

While the first two essays focus on tariff policy, the third part of the dissertation explores foreign capital policy in the context of the diffusion of technologies embodied in capital goods. Chapter 3 studies technology diffusion and multinational spillovers by taking advantage of the trade in capital goods dataset that contains narrowly defined products, different from the previous literature. This allows me to identify the first firm to adopt a technology and to track subsequent adoptions. I find evidence of important spillovers from multinationals: they are importers of new technology, later followed by other firms, relatively more often than domestic firms. I also show that equipment of higher value, imported by multinationals and by larger firms, take longer to be diffused. Finally, I report that first adopters experience a very large increase in their export growth following the investment in capital (23 percentage points), while follower firms can still get a nontrivial benefit from the import too (6 percentage points). The gains for followers of multinationals are higher (10.7 percentage points) than the average of followers. These findings have important implications for foreign capital policy.

ACKNOWLEDGEMENTS

I am forever grateful to my main advisor, Katheryn Russ, for her brilliant and kind guidance. I could not have asked for a better mentor. I am also deeply indebted to Deborah Swenson and Robert Feenstra for serving on my committee. Deborah Swenson never fell short of providing feedback and her thoughtful comments were crucial for this dissertation. It has been a privilege to learn from Robert Feenstra. I am grateful for his numerous suggestions that substantially improved parts of this dissertation.

I am thankful to the teams at the Secretariat of Foreign Trade Statistics and Intelligence (SITEC) and at the Secretariat of Industry (SI) of the Ministry of Economy of Brazil for providing the data and research environment that made possible this dissertation. The views and opinions in this dissertation do not necessarily represent those of the Ministry. I am especially grateful to Herlon Brandão and Carlos dos Santos for supporting my plans from the first time they heard about them. I would also like to thank Diego Castro, Miguel Cleaver, Paulo Felipe Alencar, Renato Barbosa and Saulo Guerra for their help with data questions and for such an awesome workplace.

Before coming to graduate school, I was fortunate to receive the assistance of Benjamin Tabak, José Guilherme de Lara Resende and Maria Eduarda Tannuri-Pianto. I deeply appreciate the support they have shown me throughout my career.

Finally, I owe my parents and sister so much that I will never be grateful enough. Thank you for the unlimited love and support. Vitor, thank you for encouraging me to do this. I will never forget how happy we were here in Davis.

Chapter 1

Capital Goods Trade Policy and Firms Performance

1.1 Introduction

The magnitude and the quality of equipment production and innovation vary greatly across countries. Because capital goods accumulation is one of the main determinants of productivity,[1] international trade in these products has a potential growth effect beyond the traditional allocative efficiency trade gains. This paper brings together rich Brazilian firm-level data in order to investigate the effect of a capital goods tariff liberalization on a variety of firm

[1]For instance, De Long and Summers (1991) use cross-country data and provide quantitative evidence that equipment investment has far more explanatory power for productivity growth than other components of investment. They also report a negative correlation between GDP per worker and the real price of equipment. Similarly, Greenwood et al. (1997) attribute 60% of U.S. growth to new technology embodied in capital equipment.

performance measures: exports, imports of equipment and of other inputs, employment and number of destination countries and of product varieties. I provide estimates over several time horizons, using local projections estimates (Jordà, 2005).

Despite the growing literature supporting the link between equipment trade policy and productivity, we have little evidence to date on the impact of equipment access at the firm level. Existing empirical studies have focused on cross-country comparisons of capital goods imports (Sala-i Martin et al., 2004; Estevadeordal and Taylor, 2013; Mutreja et al., 2018). The advantage of restricting the analysis to one country is that we do not need to worry about confounding effects from changes in institutions or in macro conditions. Past research advancing on the understanding of the effects of trade policy at the firm level has not focused on capital equipment, but on all kinds of inputs, instead. Moreover, these studies usually rely on the assumption of exogeneity of a national liberalization event. This study is one of the first to estimate the effects of tariff liberalization on firm-level performance, exploring the features of a tariff regime specifically designed for capital goods.

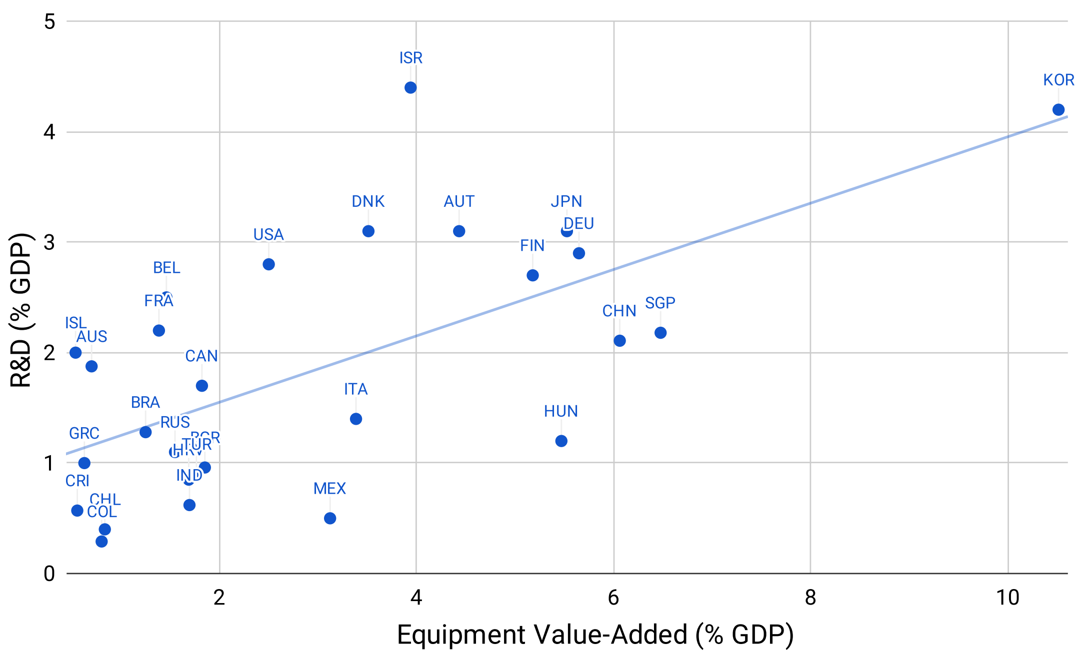
Around the world, the analysis is particularly relevant at this moment. For instance, U.S. tariffs have recently raised prices on imported aluminum and steel, increasing the cost to domestically manufacture equipment.[2] Lian et al. (2019) argue that hikes in tariffs and nontariff barriers could disrupt cross-border supply chains and, by making production less efficient, slow or even reverse the downward trend in capital goods prices. As net importers of capital goods, developing economies would also lose if the trade disputes escalate, leading

[2]Cavallo and Landry (2018) find that imposing an additional 20 percent tariff on capital-goods imports could lead to a 16 percent reduction in the average annual growth in U.S. output per hour predicted by their model.

to higher prices of machinery.

Why is equipment trade so important? First, as Eaton and Kortum (2001) argue, countries that are most R&D intensive are also the ones most specialized in making equipment. Using more recent data, from the 2015 Trade in Value-Added (TiVA) database, I show in Figure 1.1 that this correlation persists to this day.

Figure 1.1: R&D and equipment production correlation



Notes: R&D data are from UN INDSTAT and value-added data are from OECD TiVA, year 2015. Equipment is defined based on the ISIC classification, including Machinery and Electrical Equipment.

Second, machinery and electrical equipment production is more geographically concentrated than the average of manufacturing industries, as portrayed by the market share of the largest producer countries in Table 1.1. Thus, the benefits from new technology spread around the world through exports of capital goods. A country's productivity then depends on its access to capital goods from other countries. Lower trade costs reduce the price of capital goods, increasing production per capita.

Table 1.1: Capital goods market concentration

	Market share in Value Added (%)		
Top	Manufacturing	Machinery	Electrical equip.
3 Countries	47.4	54.8	53.2
5 Countries	55.9	69.4	66.7
10 Countries	53.2	79.3	76.4

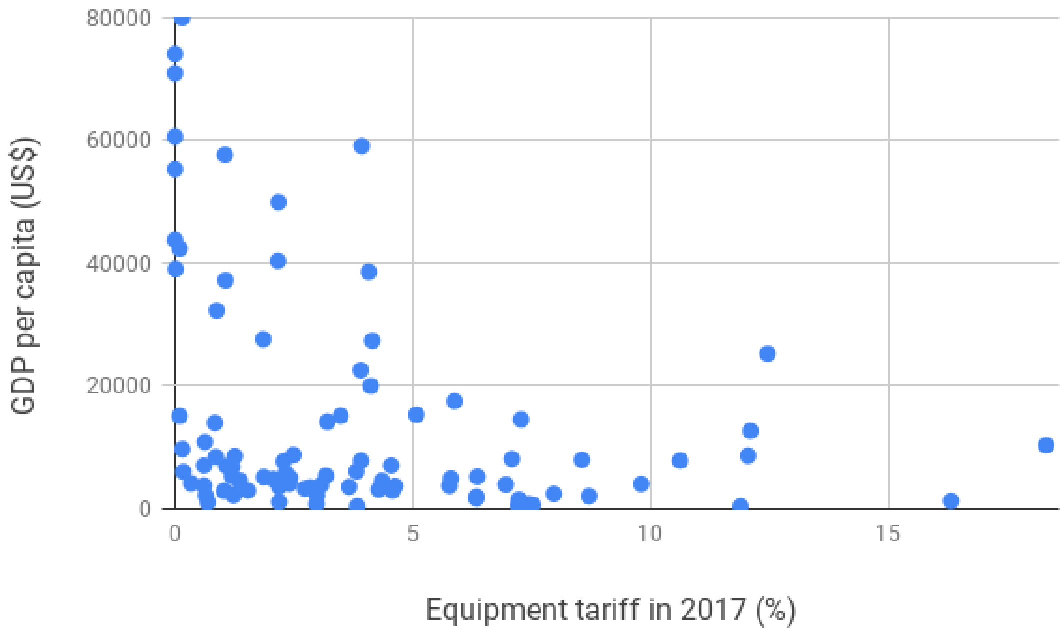
Notes: Value-added data are from OECD TiVA, year 2015. Equipment is defined based on the ISIC classification, including Machinery and Electrical Equipment.

According to estimates from Eaton and Kortum (2001), 25% of cross-country productivity differences are due to variation in the price of capital goods. Half of that can be attributed to trade barriers, which block the transmission of technological advance and impose a tax on capital accumulation. The other half can be attributed to differences in the price of consumption goods, which impacts the relative price of investment. From their model, one conjecture that we can make is that countries with a lower tariff on capital goods (which lowers price) should have higher productivity. Figure 1.2 plots different countries in terms of their per capita GDP[3] and average equipment tariff in 2017.[4] Even though there is not a unique pattern for all countries, we observe that those with the highest tariffs have low levels of GDP, and countries with the highest levels of GDP have very low tariffs.

[3]World Bank data.

[4]Available in World Integrated Trade Solution - WITS.

Figure 1.2: GDP and tariffs across countries

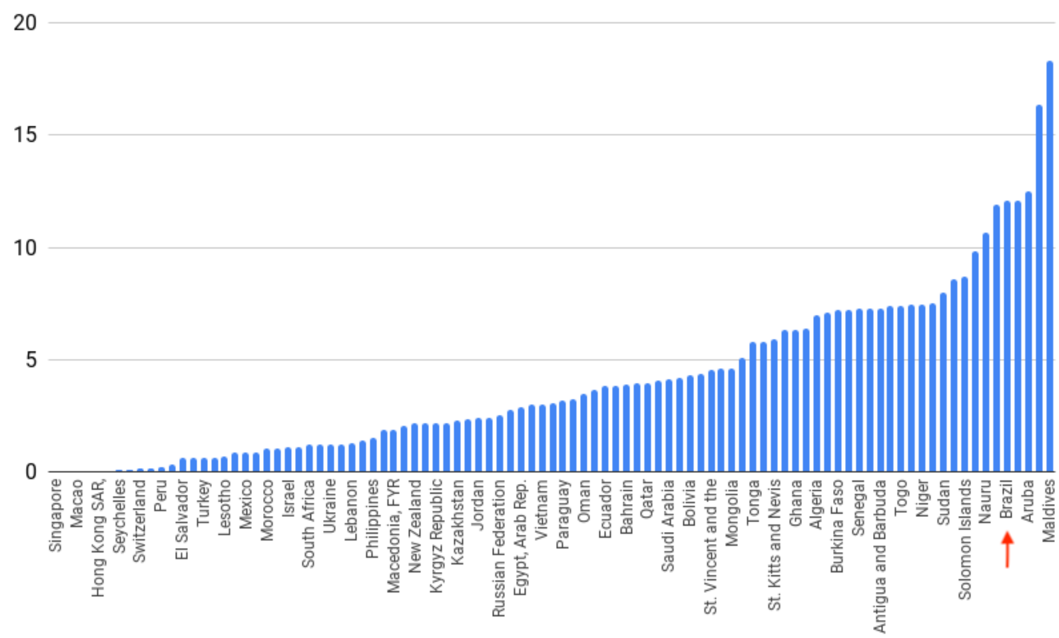


Notes: GDP per capita data are from the World Bank and tariff data are from WITS, year 2017.

The potential gains or losses from a shift in equipment trade policy is still an open question. In addition to the rich data environment, Brazil offers another advantage to study the effects of an increase in the access of imported equipment. As can be seen in Figure 1.3, Brazil is the large country with the highest level of average equipment tariffs, and thus, a good candidate for liberalization policies. This paper provides new evidence to the debate, by analyzing the impact of the "Ex-tarifário" (exemption of tariff) program, which consists of the temporary reduction (2 years) of the Import Tax of capital goods that are not produced in Brazil. The program has reduced the Import Tax from 14% to 2% or 0%, depending on the year. This reduction is even more relevant, considering that it is the basis for the calculation of other domestic taxes.[5]

[5]The import tax is incorporated in the value that serves as the basis for calculation of all national taxes

Figure 1.3: Equipment tariffs across countries



Notes: Tariff data are from WITS, year 2017.

I ask whether a lower tariff benefited the importing firms. According to the theoretical model, when they import capital goods for a lower price, they become more competitve. Thus, the conjecture is that they will import a higher volume of equipment, in terms of quantity or quality (more modern, technological), produce more and export more.

The main concern for identification is related to the ability of firms to learn about the program and the application process. For instance, Mobarak and Purbasari (2006) show that politically connected firms in Indonesia receive benefits by way of the right to import. If political economy factors are time invariant, the potential bias due to endogeneity is accounted for with the fixed effects model. But, time-varying firm political ability could

on goods.

simultaneously influence productivity and tariffs (Amiti and Konings, 2007). In order to deal with the selection bias in the case that firms that apply to the program are more or less productive than the ones that do not, I also estimate the results taking the subsample of firms that did not apply for the program but could still benefit from other firms' application. I exploit this rule of the regime for a robustness check to the main results.

Then, I provide several pieces of evidence to address other key challenges of potential selection effect regarding industrial policy, firm size, equipment quality and magnitude of investment. Controlling for the last factor requires additional attention, since the investment could be itself endogenous as well: firms might invest more when they already expect to export more in the future. I conduct an instrumental variable (IV) analysis in which investment is instrumented by the exchange rate change in the origin countries from which the industry of each firm commonly buys equipment, similar to Feng et al. (2016). The results point to a larger increase in investment and in exports for firms with larger shares of exempted capital goods imports. The findings are robust to controlling for the other determinants of firm performance.

In the last step of the empirical analysis, I document evidence on the mechanisms behind the exporting performance gains. I find that exempted firms increase their use of inputs, number of destination countries they export to and number of varieties of exporting goods. The exporting effect is stronger for capital intensive industries. I do not find a significant impact on employment from the increased automation experienced by the exempted firms. I also show that the empirical findings fit well the predictions from the Eaton and Kortum (2002) framework, when we incorporate capital goods as a production factor.

The remainder of the paper is organized as follows. Section 1.2 reviews previous literature.

Section 1.3 provides an overview of the data used in the analysis and the recent Brazilian capital goods trade policy. Section 1.4 details the estimation strategy. I organize the results in four subsections. In Section 1.5.1, I provide evidence linking the tariff exemption to higher volume of equipment imports. In Section 1.5.2, I report the baseline results for the effect of liberalization on firms' exports. Section 1.5.3 explores a series of robustness checks and Section 1.5.4 investigates the mechanisms by which tariff exemption affects firms' performance. Section 1.6 concludes.

1.2 Literature Review

The role of foreign machinery investment in increasing labor productivity and economic growth has been long emphasized in the literature. However, existing empirical studies have focused on cross-country comparisons of capital goods imports. For example, Mutreja et al. (2018), find that frictionless trade in capital goods reduces the income gap between rich and poor countries by 40 percent. Estevadeordal and Taylor (2013) emphasized the role of capital goods when assessing the impact of trade policy liberalization on economic growth. The authors find a significant effect of tariff reductions on growth acceleration. They find the correlation to be much stronger for tariffs on capital and intermediate goods than consumption tariffs. The estimated impact is about 1 percentage point per year higher growth for liberalizers. Sala-i Martin et al. (2004) show that a low price of investment goods at the beginning of the period is one of the strongest predictors of subsequent income growth. Lowering input tariffs is a direct way of reducing the price of investment goods.

Looking into the U.S. growth in the last decades, Cavallo and Landry (2010) notice that while capital goods imports were only 3.5 percent of equipment and software investment in 1967, by 2008 their share had risen to 36 percent. Based on a theoretical framework, they estimate that imports can explain 30 to 40 percent of the average contribution of the stock of capital goods to growth in output per hour in the period.

Most papers that look at the effect of importing on industry or firm performance focus on intermediate inputs. Feenstra et al. (1992) decompose growth into that due to a higher quantity of existing inputs, and that due to a greater range of inputs. They show that productivity, estimated at the industry level, is positively correlated with the introduction of new inputs in Korea. Some of these papers have focused on the impact of input access in developing countries. Fan et al. (2015) look at empirical evidence from Chinese firm-level production and customs data and find that lower tariffs on intermediate inputs lead firms to deliver higher quality goods to foreign markets. The result is stronger for highly differentiated products. Also using Chinese data, Feng et al. (2016) study whether the increased use of imported intermediate inputs contributed to firms' performance. They find that an increase in both expenditure and in the range of imported inputs lead to increased exports.

Amiti and Konings (2007) report that reducing input tariffs can raise productivity via learning, variety, and quality effects. Using Indonesian data, their study disentangles the productivity gains that arise from reducing tariffs on final goods from those that arise from reducing tariffs on intermediate inputs. They estimate the differential productivity effect from the reduction in input tariffs on firms that import these inputs to those firms that compete with them. Their results show that the largest productivity gains arise from reducing input tariffs: a 10 percentage point fall in input tariffs leads to a 12 percent productivity gain for importing firms, at least twice as high as any gains from reducing output tariffs. In contrast, Goldberg et al. (2010) main focus is not on TFP but rather on the domestic product margin. They estimate substantial gains from trade through access to new imported inputs in India, and find that lower input tariffs account on average for 31% of the new products introduced by domestic firms. This effect is driven to a large extent by increased firm access to new input varieties that were unavailable prior to the trade liberalization.

A related study by Schor (2004) shows that new access to intermediate and capital goods that embody better foreign technology also contributes to productivity gains after trade liberalization. The author uses a dataset of Brazilian manufacturing firms between 1986 and 1998, a period in which the country saw a large reduction in tariffs of all goods. The present paper differs from this study by looking at capital goods separately and studying exogenous tariff reductions through an exemption program, that has heterogeneous effects over firms, instead of relying on a national liberalization event.

More recent studies have also looked at capital goods import by firms, but different to this paper, they focus on investment effects only and not on outcome effects. Kandilov et al. (2019) estimate the effect of the Indian trade liberalization in the 1990s on investment in foreign capital goods. They show that a 10 percentage point decrease in the capital goods tariff led to a 9.44 percent increase in the average firm's investment rate in foreign capital goods. The authors find substantial heterogeneity across firms in how they responded to reductions in tariffs. Firms in the middle of the productivity and size distributions benefitted the most from lower tariffs on capital goods. Meleshchuk and Timmer (2019) study the tariff reform in Colombia in 2011 and report that a 1 percentage point reduction in capital goods input tariffs is associated with a 0.4 percentage point increase in investment.

Finally, this paper is connected to the literature that has studied the link between productivity and exports. One piece of empirical evidence is a strong positive association between productivity and exporting activity at the firm level. Bernard and Jensen (1999), Helpman et al. (2004) and Delgado et al. (2002) explain this pattern by self-selection of more efficient firms into the export market: only firms that are efficient enough to face the intense competition of the international market will start exporting.

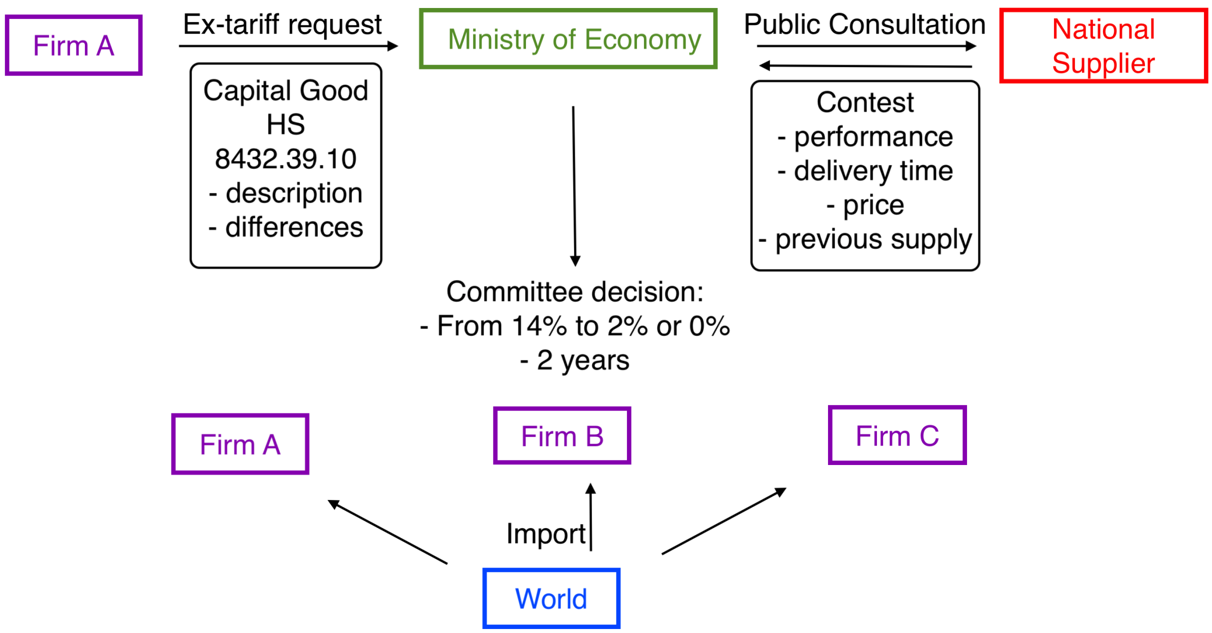
1.3 Data

The analysis combines data from different sources. The main dataset, provided by the Ministry of Economy of Brazil, tracks the universe of customs transactions, from 1997 to 2019. Trade data cover all exporting and importing firms. I focus on firms that imported capital goods and exported at least once during the sample period. I exclude the oil and gas industry from the sample, since it has its own special tariff regime for capital goods. The final dataset covers 26,969 firms, out of which 15,081 are manufacturing firms.

In order to select the products that correspond to capital goods, I follow the classification of Broad Economic Categories (BEC), Revision 4. The class of capital goods is defined by the sum of the categories 41 - Capital goods (except transport equipment) - and 521 - Transport equipment, industrial. I use the United Nations correspondence tables in order to convert the original Harmonized System product codes into BEC.

The second dataset comprehends the firm-level imports of equipment under the exemption regime between 2000 and 2018. The Ex-tarifário program in Brazil was established in 1990 with the goal of stimulating national production investment, by temporarily reducing the import tariff on capital goods that are not domestically produced. Each exemption refers to a specific equipment, described in detail, and not to a whole HS code or to some applicant firm. Figure 1.4 describes the steps of the application process.

Figure 1.4: Exemption application flow



Notes: Description of the application steps in the capital goods exemption regime.

The application must contain a description about the characteristics of the good, its specificities and technological differences over those produced nationally. Once the request is recorded, the Ministry of Economy opens a Public Consultation for a period of twenty days, so that national manufacturers may contest the request, by presenting proof of national supply of an equivalent machinery. It will only be considered that there is a national equivalent to the imported good when the national good presents: (i) equal or superior performance to that of the imported good; (ii) delivery time equal to or less than the same type of the imported goods; (iii) previous deliveries made in the last five years by the manufacturer; and (iv) price, calculated at the factory, without tax, not higher than the imported good, calculated in national currency, based on the CIF (Cost, Insurance and Freight) price. The comparative analysis takes into account the equipment's degree of automation, technology, performance warranty, consumption of raw material, use of labor, consumption of energy and unit cost of production. The Ex-tarifário Analysis Committee gathers the technical information about the product and makes a decision. The analysis takes on average 45 days. If the request is approved, any firm is allowed to import the equipment under tariff exemption.

The Foreign Trade Chamber resolutions with new exemptions are published every three months. In 2018, 1,916 firms made 3,211 request, out of which 2,783 were accepted (Ministry of Economy of Brazil, 2019).

Figure 1.5 presents the evolution of exempted capital goods import share over time in Brazil, in terms of value and number of benefited firms. Program participation was low at first, but, since 2003, the share of imports and firms under the program has floated around 10% and 17%.

The value share of exempted goods relative to the capital goods imports varies greatly among the firms that participate in the program. We can notice from Figure 1.6 that the majority of firms are concentrated in the two extremes of the share distribution. That is, most firms either import equipment through the Ex-program only or buy a small volume of tariff exempted equipment, relative to its imports.

Figure 1.7 presents the annual average import volume of capital goods across industries, divided into exempted and tariffed imports. The industry assignment follows the National Classification of Economic Activities (CNAE), a Brazilian categorization that defines the productive activity of a company, based on the International Standard Industrial Classification of All Economic Activities (ISIC). There is an heterogeneous proportion of exempted

Figure 1.5: Share of exempted capital goods

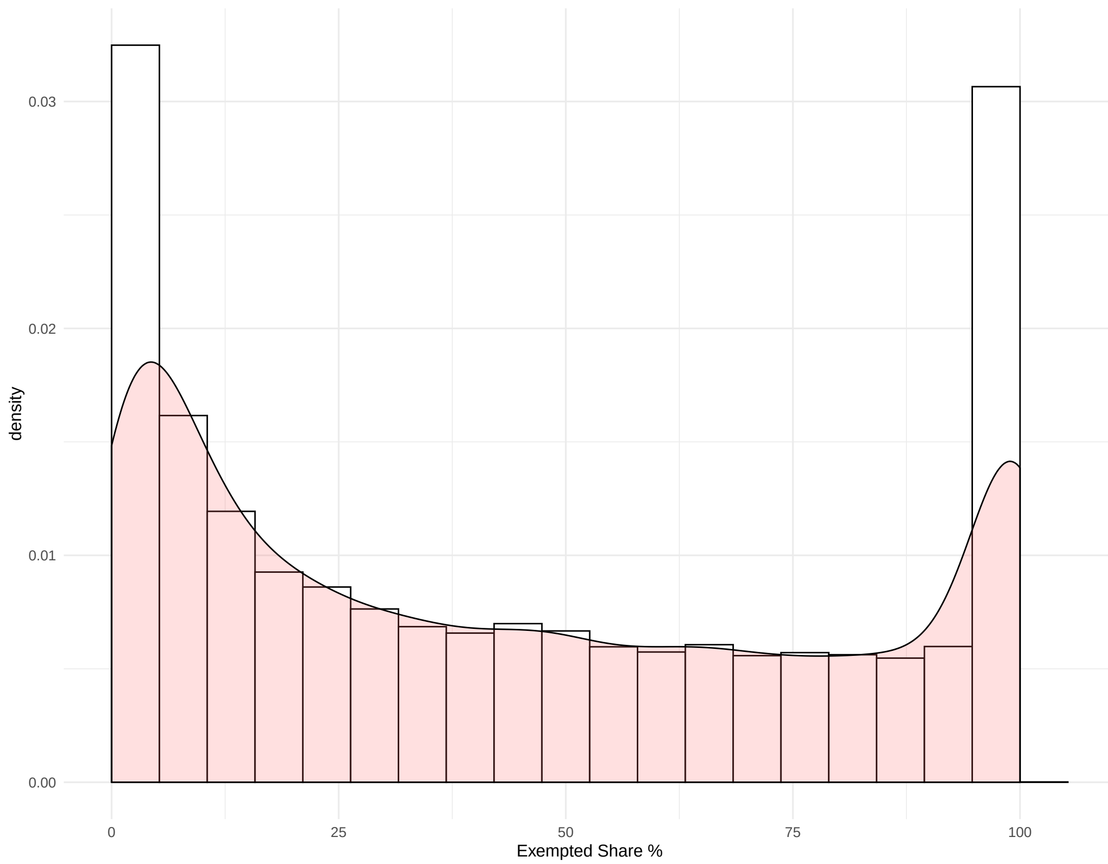
Notes: For the Value series, EX share is the ratio of exempted over total capital goods import value. For the Firm series, EX share is the ratio of the number of exempted firms over the total number of capital goods importing firms.

imports across sectors.

As a robustness check for the baseline results, I run estimates considering only firms that did not apply for the exemption, but took advantage of another firm's request. To do so, I consider a third dataset, that reports the firms that applied to the regime. Unfortunately, the information available covers the period between 2014 and 2018 only, significantly reducing my sample size. Therefore, it is used for the robustness estimates, but not throughout other results.

I then merge the resulting trade dataset with employer-employee data from the Brazilian

Figure 1.6: Firm-level exempted share distribution

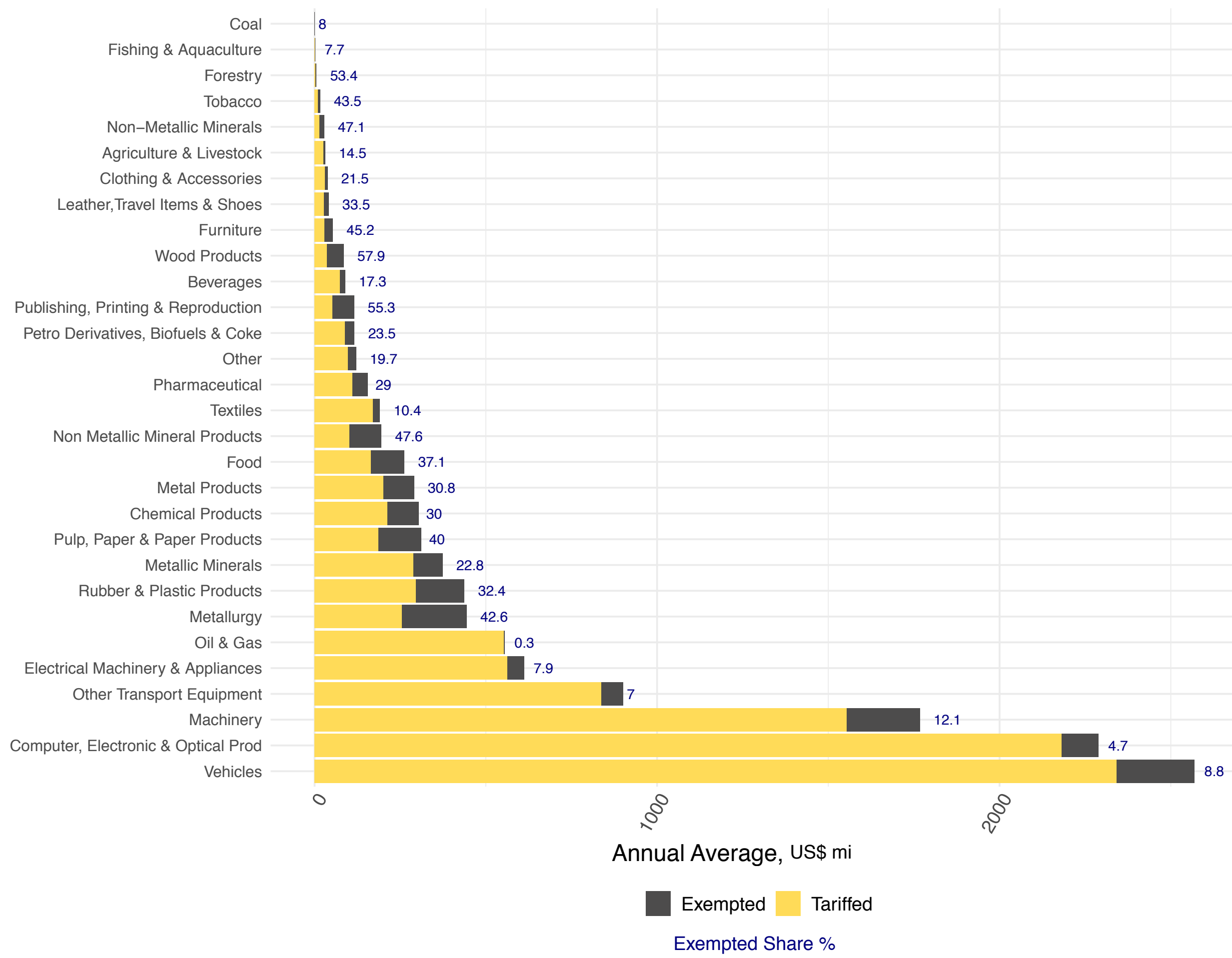


Notes: The figure plots the distribution of firm's exempted shares. The share is calculated as the ratio of exempted over total volume of capital goods imported by the firm.

Ministry of Labor and Employment, from 2000 to 2017. Labor data come from the survey Relação Anual de Informações (RAIS), which contains information of all tax-registered firms in the country. The datasets include a time-invariant firm identifier that allows for the merge.

The fifth dataset is made available by the Brazilian Development Bank (BNDES), the main financing agent for development in Brazil. Its operations include support for exports and technological innovation, and have encouraged Brazilian companies to compete with imported products on the domestic market, as well as stimulating exports. The data present

Figure 1.7: Capital goods import value by industry



Notes: The figure plots the annual average import value, in US$ mi, of exempted versus tariffed capital goods, by industry. The blue numbers at the right refer to the exempted shares.

the firm-level loan transactions with the BNDES, from 2002 to 2019. This information is used to investigate the potential correlation between financial support and the exemption regime, as a control for confounding effects from industrial policy.

Additionally, to account for the different capital shares across industries, I employ the Brazilian annual survey of manufacturing firms, PIA, by the Brazilian census bureau, IBGE, from 2007 to 2015. The capital share numerator is calculated by the sum of acquisitions and improvement in fixed assets from 2007 to 2015, minus write-offs, for each industry. This is the period for which data are available in the same industry classification revision used in trade data (CNAE 2.0). The labor denominator is measured as the average personnel expenditure in the same period. The capital-labor ratio is then calculated for 142 industries.

Finally, to account for the technological level of the foreign equipment, I bring in the Product Complexity Index (PCI), by the Growth Lab at Harvard University (2019). PCI measures the knowledge intensity of a product by considering the knowledge intensity of its exporters. Data are available from 2000 to 2017, at the HS 4 digits level. The index ranges from -1.63 to 2.51 across capital goods in those years.

1.4 Estimation Strategy

In order to measure the impact of capital goods tariff liberalization on the firm-level performance, I start from the Eaton and Kortum (2001) framework. The production functions of the capital goods K and the consumption goods C in country $i \in 1, ..., N$ are given by:

$$Q_i^K = A_i F(K_i^K, L_i^K)$$

$$Q_i^C = F(K_i^C, L_i^C)$$

where A_i captures capital goods technology and F is constant returns to scale in labor L and capital K. According to Solow (1960) model, the technological change in some countries N is given by $\dot{A}_N/A_N = g$. In the Ricardian trade model part, there is a continuum of capital goods $j \in [0,1]$. Country i provides capital with quality $z_i(j)$. Price per quality unit of capital depends on production cost, c_i, and on iceberg costs of delivering one unit of the good in destination n from i, d_{ni}:

$$p_{ni}(j) = \frac{c_i d_{ni}}{z_i(j)}.$$

The capital price index is given by

$$P_n^K = \gamma[\sum_{i=1}^{N} T_i c_i^{-\theta} d_{ni}^{-\theta}]^{-1/\theta},$$

where γ is a constant, T_i is the technological knowledge of the country, that determines absolute advantage in the Ricardian model, and θ reflects the variability in the distribution from which quality $z(h)$ is drawn.

The product per capita results from the steady-state solution of the model:

$$y_n = [\frac{s_n}{(\delta + \frac{g}{1-\alpha})\frac{P_n^K}{P_n^C}}]^{\alpha/(1-\alpha)},$$

where g is technological change rate, δ is the capital depreciation rate, α is the capital share in the Cobb-Douglas production function and s is the savings rate. We can see that lower trade costs reduce the price of capital goods, increasing production per capita.

We can extend this model with the framework developed in Eaton and Kortum (2002) and assume a continuum of consumption goods $h \in [0,1]$. If a firm can buy cheaper capital goods, the unit cost $c_i^C(h)$ goes down. The price of the consumption good thus drops:

$$p_{ni}^C(h) = \frac{c_i^C(h) d_{ni}^C}{z_i^C(h)}.$$

If the firm was already exporting, it will still have the minimum price and export more in terms of quantity and volume, under elastic demand. From a CES demand:

$$x^C(h) = (\frac{p_h^C}{P^C})^{-\sigma}\frac{I}{P^C}$$

If the firm was not exporting, the cost drop increases its probability π of being the lowest price firm supplying each country n:

$$\pi_{ni}(h) = \frac{T_i(c_i^C(h)d_{ni})^{-\theta}}{\sum_{i=1}^{N} T_i(c_i^C(h)d_{ni})^{-\theta}}.$$

According to the theoretical model, a lower tariff on capital goods leads to lower production costs and encourages firms to import a higher volume of capital (quantity or more modern/ technological equipment), making them more competitive. Thus, they will increase production, exports and imports of inputs.

To empirically verify this, I start by computing for each firm h the fraction, denoted by EX share, of capital goods (CG) imports that enter under the exemption program, in year t:

$$\text{EX share}_{ht} = \frac{\text{CG Imports under EX}_{ht}}{\text{CG Imports}_{ht}} * 100,$$

which is proportional to the average tariff.[6]

The first result of interest is the effect of capital goods tariff reductions, measured by the share of exempted imports, on their import volume. I estimate:

$$\ln\ (\text{CG Imports})_{ht} = \beta_0 + \beta_1 \text{EX share}_{ht} + h + t + \varepsilon_{ht}$$

[6] Average Tariff $= 0\% \times \text{EX share} + 14\% \times (1 - \text{EX share})$. I use this measure instead of the average tariff because I do not have access to the exact tariff applied under exemption in every year. It varies from 0% to 2%.

for every firm h, in year t. Firm and year fixed effects are included to control for potential unobserved firm and year-level heterogeneity. In order to control for the correlation between the exemption share and the number of varieties of capital goods that firms import,[7] I also estimate:

$$\ln\frac{\text{CG Imports}_{ht}}{\text{Varieties}_{ht}} = \beta_0 + \beta_1 \text{EX share}_{ht} + h + t + \varepsilon_{ht}$$

with the caveat that this specification eliminates the extensive margin effect of importing new varieties under lower tariffs.

The lower tariff is expected to encourage larger volumes of capital goods imports by the firm. The question then is whether the increased imports of foreign equipment will enhance firm productivity and whether this translates into higher export volume in the data. I estimate the following equation using local projections:

$$\%\Delta\text{Exports}_{ht} = \delta_l + \beta_l \text{EX share}_{ht-l} + h + t + \varepsilon_{ht}, \text{ for l=1,...,L,}$$

where h and t are firm and year fixed effects, respectively. This equation will give estimates β_l of the impact of a percentage point increase in the exemption share in year $t-l$ on exports growth between $t-1$ and t. In order to take into account the fact that firms might make sequential capital investments, benefiting from different levels of exemption each year, I also estimate the following equation that incorporates subsequent exemption shares:

$$\%\Delta\text{Exports}_{ht} = \beta_0 + \sum_{l=1}^{L} \beta_l \text{EX share}_{ht-l} + h + t + \varepsilon_{ht},$$

for every firm h, in year t. This strategy, however, reduces the sample size. I test for a different number of lags L, between 1 and 8.

[7] A firm with 100% exemption share is more likely to be importing only one type of variety than a firm that has 95% exemption share, for example.

Due to the many zeros in exports data, I measure percentage growth using the two years average of the export values in the denominator:

$$\%\Delta\text{Exports}_{ht} = \frac{\Delta\text{Exports}_{ht}}{0.5(\text{Exports}_{ht} + \text{Exports}_{ht-1})} * 100.$$

This average base growth rate measure is symmetric about zero, lies in the closed interval [-2,2] and is identical to the log difference up to a second-order Taylor series expansion (Davis and Haltiwanger, 1999; Casler, 2015). Another strategy will be to split the sample between firms that were already exporting at the beginning of the sample and those that were not and calculate absolute growth for the non exporters. This allows us to study a broader sample of firms, which are dropped out otherwise.

The next step is to take into account the number of varieties of capital goods imported by the firm. However, the investment decision of firms is likely endogenous. Therefore, I use the weighted average of the source countries' real exchange rates, rer_n, as an instrument for the varieties of capital goods imports:

$$\frac{\sum_{n=1}^{N} \%\Delta\text{rer}_{nt} * \text{CG imports}_{nb}^{-h}}{\sum_{n=1}^{N} \text{CG imports}_{nb}^{-h}},$$

where b is a base period of 3 years prior to the treatment and $-h$ corresponds to the industry of firm h, excluding firm h. Previous studies have used similar strategies (Feng et al., 2016; Bastos et al., 2018).

In all the above models, the main outcome of interest is the export volume, but I also investigate the effects over imports of inputs, number of destination countries and exports varieties. The results are estimated using both the full sample, from 2000 to 2019, and the subsample of non-applicant firms, from 2014 to 2018.

1.5 Empirical Results

1.5.1 Capital Goods Imports

I begin with the analysis of the impact that capital goods tariff reductions, measured by the share of exempted imports, have on their import volume. The hypothesis is that lower tariffs (higher exempted shares) lead to larger imports of capital goods. The first column of Table 1.2 shows the result from the regression including year fixed effects. A 1 percentage point increase in the fraction of untaxed imports augments equipment imports in 2.7 percent. The specification presented in the second column takes into account the potential correlation between the exemption share and the number of varieties of capital goods imported by the firm. I divide the dependent variable, value of imports of capital goods, by the number of imported varieties. The downside of this approach is missing the extensive margin channel in the effects from the exemption. The estimated effect for the exemption share is 2.5 percent, thus, not very different than the estimate without the varieties ratio.

Next, we might be concerned that a firm only takes the time and effort to apply for tariff exemption when importing large volumes. Column three shows that the result for the subsample of imports above US$ 1 million is reduced to 0.5 percent, but it is still economically and statistically significant. The last three columns add firm fixed effects, in case certain firms import a higher volume of capital goods and specialize in applying for exemptions. The estimated effects are similar to those from the three specifications: 2.2, 1.9 and 0.5 percent, respectively. Table A1 in the Appendix presents the results when considering a binary treatment variable, equal to 1 for firms that imported at least one equipment with tariff exemption in year t, and equal to zero otherwise. In this case, I also find a significant and positive effect from the exemption.

Table 1.2: Effect of exemption shares on equipment import value

	Dependent variable: ln of Capital Goods Imports					
	(1)	(2)	(3)	(4)	(5)	(6)
Ex share	0.027***	0.025***	0.005***	0.022***	0.019***	0.005***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Year FE	✓	✓	✓	✓	✓	✓
Firm FE				✓	✓	✓
Varieties Ratio		✓	✓		✓	✓
CG >US$1 mi			✓			✓
Observations	203,740	203,740	31,608	203,740	203,740	31,608
R^2	0.069	0.093	0.035	0.061	0.063	0.017

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Varieties Ratio specification: the dependent variable, capital goods imports value, is divided by the number of imported varieties. CG >US$1 mi: subsample of capital goods imports over US$ 1 million.

Next, I consider the results for the subsample of non-applicants, that is, firms that did not apply for a tariff exemption during 2014-2018, the period for which applicant identifiers are available. In this way, I account for the potential bias coming from political connections or application specialization of firms. In order to compare samples covering the same period, Table 1.3 presents the results obtained with all firms and non-applicant firms only for the available data period of 2014 to 2018. Results are similar between the two samples, which is reassuring. The first four columns present the results considering first imports of any size, and then the subsample of import values above US$ 1 million. The last two columns present the estimates considering firm fixed effects. For both models and for both samples of firms, a 1 percentage point increase in the exemption share is correlated with an increase in imports of 0.4 to 0.6 percent, just like presented before in Table 1.2, when considering the 20 year period.

One last concern is that the capital goods that are imported through the exemption program might be of higher quality or technology than those equipment that are not benefited by the program. This hypothesis arises from the fact that the benefit is granted to capital goods that are not produced in Brazil. Thus, the observed increase in the total value of machinery imports, for higher shares of program participation, could be caused by a price difference between goods that have a national production and goods that do not. However, the data show that the opposite is true. I divide the US$ imports sum of capital goods covered under the benefit by their imports weight (in kilograms) sum, and compare it with the measure relative to all capital goods. The former corresponds to US$ 221.90 per kilogram and the latter to US$ 366.88 per kilogram. That is, the untaxed machinery actually has a below-average price. Furthermore, in order to compare prices across similar products, I take the ratio between exempted and all equipment prices for each code in the Harmonized System. Figure 1.8 plots the distribution of this ratio, divided by the blue line at 1, where prices are the same. We notice a larger density of products with a smaller than 1 ratio. That is, with exempted goods less costly than the average.

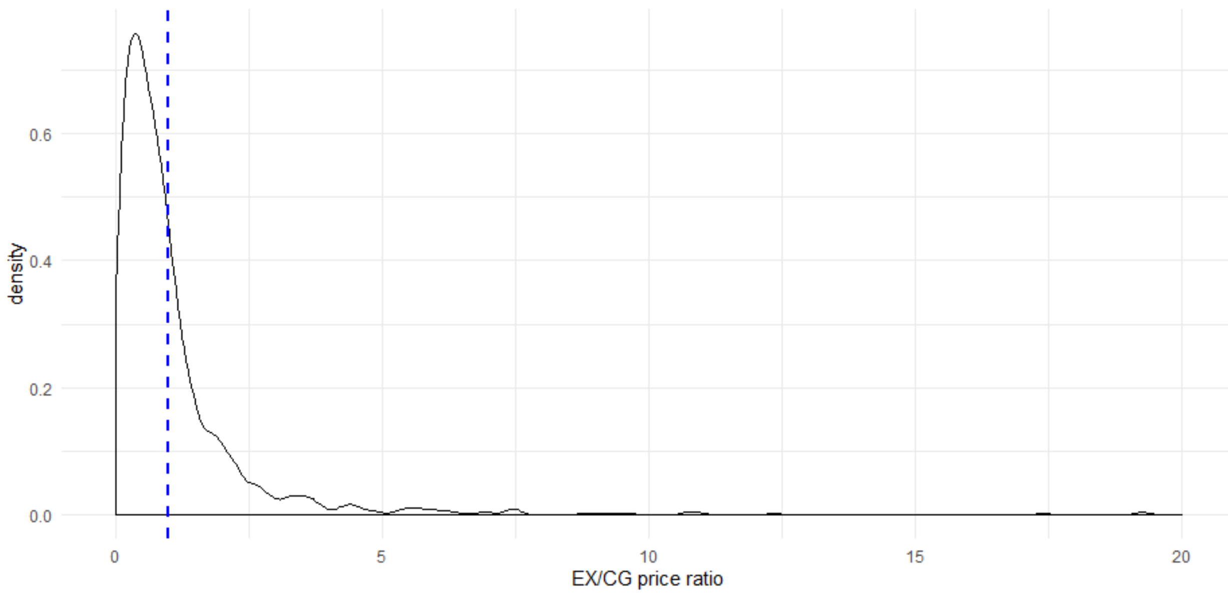
Table 1.3: Effect of exemption shares on import value

- Non-Applicants subsample comparison (2014-2018)

	Dependent variable: ln of Capital Goods Imports					
	All	Non-app	All	Non-app	All	Non-app
	(1)	(2)	(3)	(4)	(5)	(6)
EX share	0.026***	0.023***	0.005***	0.006***	0.006***	0.004***
	(0.0003)	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0009)
Year FE	✓	✓	✓	✓	✓	✓
Firm FE					✓	✓
Varieties Ratio	✓	✓	✓	✓	✓	✓
CG > $1mi			✓	✓	✓	✓
Observations	59,133	48,963	9,470	5,322	9,470	5,322
R^2	0.100	0.056	0.023	0.017	0.034	0.006

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Non-app stands for the subsample of firms that did not apply for a tariff exemption during 2014-2018. Varieties Ratio specification: the dependent variable, capital goods imports value, is divided by the number of imported varieties. CG >US$1 mi: subsample of capital goods imports over US$ 1 million.

Figure 1.8: HS products price comparison



Notes: The figure plots the distribution of the ratio between exempted and all equipment prices for each code in the Harmonized System. The blue line marks the value 1, where prices are the same.

1.5.2 Exports Growth - Baseline Results

The question then is whether the increased imports of foreign equipment will enhance firm productivity and whether this translates into higher export volume in the data.

Table 1.4 shows the results considering all observations for which the calculation of the average base growth is possible, that is, whenever firms either exported in the base year or in the current year of the growth measurement. Observations in which a firm did not export in the two consecutive years have a value of zero in the growth rate denominator $(Exp_{t-1} + Exp_t)$, and are dropped out.

The first four columns show Local Projections (LP) results and, in order to account for unobserved firms characteristics that might be correlated with their ability of importing through the exemption program and their exporting performance, columns 5 to 8 consider firm fixed effects in the model (FELP). The first two lags of the exemption share are significant for both models and are estimated to be around 0.07 and 0.05, respectively. That is, a 1 percentage point increase in the exemption share is correlated with a 7 basis point increase in exports one year later and to a 5 basis point increase two years later. A shift from no exemption (0%) to full exemption from tariff (100%) is associated with a 5 to 7 percentage point increase in exports per year. LP estimates imply that the increase in the exemption participation also affects exports three years later, but by a smaller amount: 4.5 basis point. Starting from the fourth lag, the estimates are no longer significant.

Table 1.4: Local Projections estimates of the effect of exemption shares on exports growth

- All firms that exported in base or current year

	Dependent variable: Average Base Exports Growth (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.073***				0.076***			
	(0.014)				(0.017)			
EX share$_{t-2}$		0.052***				0.050***		
		(0.014)				(0.018)		
EX share$_{t-3}$			0.045***				0.029	
			(0.015)				(0.019)	
EX share$_{t-4}$				0.011				-0.022
				(0.016)				(0.019)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE					✓	✓	✓	✓
Observations	135,010	125,674	115,160	105,173	135,010	125,674	115,160	105,173
R^2	0.007	0.007	0.007	0.007	0.0004	0.0001	0.0001	0.0001

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The number of observations varies across each lag regression because with higher lags we lose the observations in the panel from initial years, but also because most firms do not import capital goods every year. Thus, we are not comparing the exact same pool of firms across regressions. In order to do so, Table A2 in the Appendix fixes the observations across each lag specification, by considering only firms that imported equipment in five consecutive years. This ensures that the different estimates across lags do not result from different samples of firms. The downside is losing many observations and focusing only on a specific group of recurring importers, that could be themselves special in some way. This yields significant and similar in size estimates for the first lag only.

Next, I separately analyze firms that were and those that were not exporting in the base year of growth measurement. Because the decision to start exporting can be complex and related to different factors not accounted for in here, the two groups of firms could, in principle, present very different policy responses. Table 1.5 presents the local projections estimates for the subsample of firms that were not exporting in the base year. Since for all observations within this subsample the average growth is exactly the same[8], I use the logarithm of the US$ exports at year t as the dependent variable, instead. For this subsample, I find the four lags to be significant, ranging from 0.0044 to 0.0053. Therefore, increasing the exemption share by a 1 percentage point, we expect to see about 0.44 to 0.53 percent higher exports one to four years later. This suggests that it takes more years for new exporters to fully realize the benefits from the exemption. Since firms are only considered to be new exporters once, it is not possible to include firm fixed effects here.

So far, firms that were not exporting in the base year $t-1$ and still do not export in the

[8] New exporters average growth $= 2 * \text{Exports}_t / (\text{Exports}_t + \text{Exports}_{t-1}) = 2$

Table 1.5: Local Projections estimates of the effect of exemption shares on exports growth - Subsample of firms that were not exporting in the base year

	Dependent variable: log of US$ Exports at t			
	Non Exporters at $t-1$			
	(1)	(2)	(3)	(4)
EX share$_{t-1}$	0.0046***			
	(0.0008)			
EX share$_{t-2}$		0.0053***		
		(0.0009)		
EX share$_{t-3}$			0.0051***	
			(0.0009)	
EX share$_{t-4}$				0.0044***
				(0.0010)
Year FE	✓	✓	✓	✓
Observations	19,827	17,140	15,140	13,240
R^2	0.0134	0.0137	0.0128	0.0112

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

current year t, such that growth could not be assessed in percentage terms, were excluded from the sample. In order to also analyze these observations, Table A3 in the Appendix considers all base year non-exporters and reports the LP regression estimates for growth in the absolute form (US$). I find a significant effect for the first and second lags of the exempted imports ratio. For the full sample of non-exporters, a 1 percentage point increase in the exemption share leads to a rise of US$5,425 in the exports of the following year and US$5,951 two years later. If we consider new exporting firms only, the effect is much larger: US$17,174 and US$20,113, respectively.

Now I investigate whether the subsample of continuing exporters only shows similar responses to those found considering both old exporters and new exporters (Table 1.4). This is true for the FELP results presented in Table 1.6. Interestingly, the LP estimates indicate three times as large effects to those found considering exporters and non exporters. The most relevant difference is found in the fourth lag, which coeffcient is now significant and twelve times larger: 13.4 basis point increase in exports for each 1 percentage point increase in the exemption share. This implies that new exporting firms, with the highest growth rates, had lower exemption shares when investing in imported equipment than old exporters.

Table 1.6: Local Projections estimates of the effect of exemption shares on exports growth

- Subsample of firms that were exporters in the base year

	Dependent variable: Average Base Exports Growth (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.207***				0.041***			
	(0.012)				(0.014)			
EX share$_{t-2}$		0.192***				0.048***		
		(0.013)				(0.015)		
EX share$_{t-3}$			0.164***				0.017	
			(0.013)				(0.016)	
EX share$_{t-4}$				0.134***				-0.013
				(0.014)				(0.016)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE					✓	✓	✓	✓
Observations	115,183	108,533	100,028	91,940	115,183	108,533	100,028	91,940
R^2	0.011	0.010	0.010	0.009	0.0001	0.0001	0.0001	0.0001

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Additional lag structures are used to test for the robustness of the results above. The use of single lags in each specification has the advantage of increasing the sample, since it does not require consecutive years of equipment import in order to include a firm in the panel. Furthermore, firms that are continuingly importing capital goods could be somehow different than the average firm. On the other hand, multiple lags can take into account the investment in the other years.

Table 1.7 reports the estimates when using multiple lags and the subsample of new exporting firms. This yields significant results for the first and second lags of the exemption share. A 1 percentage point increase in the exemption share leads to a rise between 0.28 and 0.46 percent in the exports of the following two years. Thus, in comparison to the single lags specifications in Table 1.5, the first two lags show similar results and the third and fourth lags indicate weaker effects.

For the old exporters, Table 1.8 indicates that the first lag coefficient is consistently significant across all specifications and very similar in size to the single lag regressions. The estimates range from 13.4 to 16.3 basis point in the LP regressions and from 4.5 to 5.2 basis point in the FELP regressions. The second and third lags are also significant for the LP regressions, likewise in Table 1.6, but not the fourth lag anymore.

Table 1.7: Local Projections estimates of the effect of exemption shares on exports growth with multiple lags - Subsample of firms that were not exporting in the base year

	Dependent variable: log of US$ Exports at t			
	Non Exporters at $t-1$			
	(1)	(2)	(3)	(4)
EX share_{t-1}	0.0046***	0.0028**	0.0012	0.0001
	(0.0008)	(0.0012)	(0.0014)	(0.0016)
EX share_{t-2}		0.0046***	0.0046***	0.0043**
		(0.0013)	(0.0015)	(0.0017)
EX share_{t-3}			0.0017	0.0027
			(0.0014)	(0.0018)
EX share_{t-4}				0.0009
				(0.0017)
Year FE	✓	✓	✓	✓
Observations	19,827	13,804	10,762	8,655
R^2	0.0134	0.0138	0.0139	0.0115

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.8: Local Projections estimates of the effect of exemption shares on exports growth, with multiple lags - Subsample of firms that were exporters in the base year

	Dependent variable: Average Base Exports Growth (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.207***	0.163***	0.137***	0.134***	0.041***	0.052***	0.045**	0.046**
	(0.012)	(0.016)	(0.017)	(0.019)	(0.014)	(0.017)	(0.018)	(0.019)
EX share$_{t-2}$		0.134***	0.093***	0.082***		0.042**	0.030	0.038*
		(0.016)	(0.018)	(0.020)		(0.018)	(0.019)	(0.020)
EX share$_{t-3}$			0.079***	0.079***			0.009	0.023
			(0.018)	(0.020)			(0.019)	(0.020)
EX share$_{t-4}$				0.019				-0.026
				(0.020)				(0.021)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE					✓	✓	✓	✓
Observations	115,183	88,641	73,314	62,460	115,183	88,641	73,314	62,460
R^2	0.011	0.012	0.012	0.011	0.0001	0.0002	0.0001	0.0002

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.5.3 Robustness Checks

I investigate the sensitivity of the baseline results to a broad range of alternative specifications, including controls for varieties of capital goods and firm size, and alternative samples of program non-applicants and large import values.

Controlling for varieties - Instrumental Variables Estimates

The underlying hypothesis in the export growth regressions is that a tariff cut will encourage firms to raise their investment in imported capital goods. Thus, a higher participation in the exemption program will lead to a higher value of equipment imports. Baseline estimates may be biased if the exemption share is also correlated with the number of varieties of capital goods that firms are importing in the other direction. For instance, a firm that imports a low number of varieties is more likely to have 100% exempted imports than a firm importing many different equipments. Similarly for a 0% participation share. Thus, the direction of bias is not clear.

To address endogeneity of the exemption shares, I account for the number of capital goods varieties imported by the firms, measured at the HS 8 digits level. The limitation of this strategy is losing the extensive margin effect of the tariff cut. That is, we will only be able to assess the growth in import value, given a fixed number of imported types of machinery. Despite this limitation, if we can still find a significant effect from the liberalization on exports, it will reassure the previous findings. The next challenge is that the number of varieties could be itself endogenous as well. Thus, it is instrumented by the exchange rate change in the origin countries which the industry of each firm commonly buys equipment from.

LP and IV results are shown in Table 1.9. We notice that the LP results are mostly insensitive to the inclusion of the number of varieties of capital goods, differing from Table 3 by 0.001 only. This indicates that the absolute number of varieties is not correlated with the exports growth, such that it does not represent a concern to our estimates. I still run the IV regressions in any case. The IV estimates are significant for the first lag, with a larger coefficient of 0.102. Yet, the standard errors are also larger, so that we cannot reject the hypothesis that the OLS and the 2SLS estimates are equal (Wu-Hausman test statistic of 0.32). The weak instruments hypothesis is rejected, with a F-statistic of 29.

Focus on Manufacturing

Part of the previous literature has focused on manufacturing industries when studying the effects of capital goods imports. In order to provide comparable results, and also to account for the fact that commodity sectors might presenta large volatility due to factors not controlled for in this study, I re-estimate the previous results for the subsample of manufacturing firms. Table 1.10 shows similar results to those in Table 1.9: the first lag coefficient is estimated to be 0.126 and the weak instruments hypothesis is rejected, with a F-statistic of 33.

Firm Size

Now, I address the possibility that the results are driven by the ability of larger firms to apply for the exemption program. This is specially relevant for the non-exporters sample of firms, since growth is measured in absolute terms in this case and is expected to be larger for

Table 1.9: IV estimates of the effect of exemption shares on exports growth

- All firms that exported in base or current year

	Dependent variable: Average Base Exports Growth (%)							
	LP				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.07***				0.10**			
	(0.01)				(0.05)			
Varieties$_{t-1}$	0.0006				-0.63			
	(0.02)				(1.22)			
EX share$_{t-2}$		0.05***				-0.07		
		(0.01)				(0.05)		
Varieties$_{t-2}$		-0.02				2.95**		
		(0.02)				(1.26)		
EX share$_{t-3}$			0.05***				0.04	
			(0.02)				(0.04)	
Varieties$_{t-3}$			-0.03**				0.163	
			(0.02)				(1.16)	
EX share$_{t-4}$				0.01				-0.06
				(0.02)				(0.04)
Varieties$_{t-4}$				-0.02				2.01
				(0.02)				(1.24)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	116,494	107,734	98,540	89,720	116,494	107,734	98,540	89,720
R^2	0.007	0.007	0.007	0.007	0.0001	0.0001	0.0062	0.0001
First Stage F					29***	30***	30***	28***
Wu-Hausman					0.32	6.94***	0.03	3.22*

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.10: IV estimates of the effect of exemption shares on exports growth

- All manufacturing firms that exported in base or current year

	Dependent variable: Average Base Exports Growth (%)							
	LP				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.06***				0.13***			
	(0.01)				(0.05)			
Varieties$_{t-1}$	-0.01				-1.56			
	(0.01)				(1.05)			
EX share$_{t-2}$		0.05***				-0.04		
		(0.01)				(0.04)		
Varieties$_{t-2}$		-0.04**				2.33**		
		(0.02)				(1.09)		
EX share$_{t-3}$			0.04***				0.012	
			(0.02)				(0.04)	
Varieties$_{t-3}$			-0.06***				0.84	
			(0.02)				(0.94)	
EX share$_{t-4}$				0.01				-0.03
				(0.02)				(0.03)
Varieties$_{t-4}$				-0.03				1.01
				(0.02)				(0.92)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	78,145	72,774	67,116	61,652	78,145	72,774	67,116	61,652
R^2	0.010	0.010	0.010	0.010	0.001	0.001	0.062	0.001
First Stage F					33***	31***	33***	38***
Wu-Hausman					3.82*	6.08**	0.91	1.49

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

bigger firms. The size of firms is proxied by their number of employees, which unfortunately is not available to every firm in the data. Thus, the number of observatios is smaller in this subsection.

As expected, the average base exports growth, for the full sample of firms that exported in the base or in the current year, cannot be explained by differences in the number of employees. The firm size coefficients are not economically significant across regressions in Table 1.11. Coefficients on the exemption shares are attenuated when compared to the baseline model in Table 1.4. The value of exports of new exporters, on the other hand, is affected by firm size, as one could anticipate, as presented in Table 1.12. Reassuringly, the results for the exemption coefficients are robust to the inclusion of the firm size variable, although smaller when compared to those in Table 1.5.

Non-applicants Subsample

The next robustness check estimates the effects of the tariff exemption for firms that did not apply to the program, but that might have free-rided by importing the same equipment requested by others. If this is a story of institutional relationship with government, we should expect different effects for the non-applicant firms. Because data on the applicants are only available from 2014 to 2018, I reestimate the results for the full sample of firms in this reduced time range, for comparison purpose. The first four columns of Table 1.13 present the estimates considering all firms, and the last four columns, considering non-applicants only.

I find that the estimated coefficient for the first lag of the exemption share is still significant and it is actually larger, after controlling for the program application. Thus, we confirm

Table 1.11: Local Projections estimates of the effect of exemption shares on exports growth with firm size - All firms that exported in base or current year

Dependent variable: Average Base Exports Growth (%)				
	Exporters at $t-1$ or t			
	(1)	(2)	(3)	(4)
EX share$_{t-1}$	0.052***			
	(0.014)			
EX share$_{t-2}$		0.031**		
		(0.015)		
EX share$_{t-3}$			0.026*	
			(0.015)	
EX share$_{t-4}$				-0.003
				(0.016)
Employees	-0.0005***	-0.0002	$<$0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Year FE	✓	✓	✓	✓
Observations	108,517	101,385	93,745	85,606
R^2	0.009	0.008	0.009	0.009

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.12: Local Projections estimates of the effect of exemption shares on exports growth with firm size - Subsample of firms that were not exporting in the base year

Dependent variable: log of US$ Exports at t				
	Non Exporters at $t-1$			
	(1)	(2)	(3)	(4)
EX share$_{t-1}$	0.0023**			
	(0.0009)			
EX share$_{t-2}$		0.0029***		
		(0.0010)		
EX share$_{t-3}$			0.0041***	
			(0.0010)	
EX share$_{t-4}$				0.0033***
				(0.0011)
log Employees	0.247***	0.244***	0.232***	0.222***
	(0.015)	(0.016)	(0.016)	(0.018)
Year FE	✓	✓	✓	✓
Observations	13,830	12,241	11,042	9,648
R^2	0.032	0.032	0.031	0.029

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

that the results found in the baseline model cannot be attributed to political connections. Similarly to other specifications though, the second lag is not found to be significant for non-applicants.

The analysis of the effect on exports using yearly data allows to explore the evolution and persistence of the trade policy returns. However, due to the reduced time coverage of the data in this section, I also estimate the results considering a unique time period before treatment and one time period after treatment. I sum the value of imports and exports during the following years: 2012 to 2013 for the pre-treatment data, 2014 to 2016 for the treatment and 2017 to 2018 for the after treatment period. Thus, I allow for a 3-years gap between pre and after treatment. This solution has the advantage of increasing the number of firms included in the regressions, since those that did not import equipment during some of the years are not dropped out of the sample due to missing values. The results considering all firms for which growth rate can be assessed are presented in Table A4 of the Appendix. The comparison between the full sample and non-applicant firms is also reassuring in this case.

The finding of strong effects for non-applicants raises a concern that some firms might choose to not take advantage of the exemption in order to avoid imitation from their competitors, since this seems to bring just as good outcomes for the free-riders. If this is the case, then the reported estimates are biased downward due to the negative competition effect over firms importing new technologies that are of public knowledge. That is, the estimates are lower than what we would expect under normal technology diffusion, outside the regime, when the knowledge takes longer to spread.

Table 1.13: Local Projections estimates of the effect of exemption shares on exports growth - Non-Applicants comparison (2014-2018), all firms that exported in base or current year

	Dependent variable: Average Base Exports Growth (%)							
	All Firms				Non-Applicants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.09***				0.11***			
	(0.02)				(0.04)			
Varieties$_{t-1}$	-0.04				-0.01			
	(0.03)				(0.05)			
EX share$_{t-2}$		0.09***				0.05		
		(0.03)				(0.04)		
Varieties$_{t-2}$		-0.02				-0.02		
		(0.03)				(0.06)		
EX share$_{t-3}$			0.05*				0.04	
			(0.03)				(0.05)	
Varieties$_{t-3}$			-0.05				-0.08	
			(0.03)				(0.07)	
EX share$_{t-4}$				0.02				0.01
				(0.04)				(0.05)
Varieties$_{t-4}$				-0.06				0.01
				(0.04)				(0.09)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	40,181	32,119	23,696	15,899	31,658	25,276	18,568	12,441
R^2	0.001	0.002	0.001	0.001	0.002	0.002	0.001	0.001

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Industrial Policy

In the previous subsection, I argued that the results are not driven by other uncontrolled for factors, boosting the export growth of the firm, that are correlated to the exemption share. Now, I consider the possibility that specific industries, rather than specific firms, are benefiting from other policies at the same time that they are granted the tariff exemption. In this case, we would overestimate the effect of the exemption regime. I analyze whether we can find a correlation between the industry average exemption share and the sector-level financial support offered by the Brazilian Development Bank. This is the main financing agent for development in Brazil, stimulating the expansion of industry and infrastructure in the country. Its operations include support for exports and technological innovation. The Bank offers several financial mechanisms to companies of all sizes, in all economic sectors. In order to take into account the size of the sectors, I construct two different measures: I divide the value of the loans by the sector-level value added and expenses.

I experiment with different specifications and I do not find a significant correlation between the exemption share and the industry loans in any of them. If anything, there is a negative correlation between them. In Table 1.14, the first three columns consider the share of loans over value added and the last three columns consider the share of loans over expenses. I test for the inclusion of year and industry fixed effects. This suggests that the results in the previous sections are not driven by a targeted industrial policy.

Table 1.14: Estimates of the correlation between industry loans and the exemption share

Dependent variable: Exemption Share (%)						
	(1)	(2)	(3)	(4)	(5)	(6)
Loans/VA (%)	-0.072	-0.053	0.007			
	(0.056)	(0.057)	(0.061)			
Loans/Expenses (%)				-20.933	-0.097	-0.001
				(17.091)	(0.111)	(0.124)
Year FE		✓	✓		✓	✓
Industry FE			✓			✓
Observations	959	959	959	959	959	959
R^2	0.002	0.005	0.250	0.002	0.005	0.253

Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Large Investments

We are also concerned that the results could be explained by the value of the machinery being imported by the participating firms. As discussed before, in the import value regressions section, firms that are importing a large volume of capital goods probably have a higher incentive to apply for the exemption, due to the time and effort burden. If this is the case, the exemption share is correlated with the size of investment, and, consequently, to the export growth in the following years, for unintended reasons. Thus, I need to make sure that this effect is not part of my estimates on the effects of liberalization.

I estimate additional regressions for the subsample of imports over US$ 1 million. The results in Table 1.15 indicate that the effect from the first and the third lags of exemption on exports growth is not driven by this potential differential in the incentives to participate in

Table 1.15: Local Projections estimates of the effect of exemption shares on exports growth - All firms that exported in base or current year, and imported capital goods over US$ 1 mi

Dependent variable: Average Base Exports Growth (%)				
	(1)	(2)	(3)	(4)
EX share$_{t-1}$	0.083***			
	(0.025)			
EX share$_{t-2}$		0.031		
		(0.026)		
EX share$_{t-3}$			0.049*	
			(0.027)	
EX share$_{t-4}$				0.002
				(0.028)
Year FE	✓	✓	✓	✓
Observations	25,126	25,557	21,816	20,185
R^2	0.006	0.006	0.005	0.004

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the program. The coefficients are significant and their magnitude is even larger than those estimated with the full sample (Table 1.4). The second lag, however, is not found to be significant anymore, similar to the other robustness results.

1.5.4 Policy Transmission Mechanisms

To investigate the mechanism by which the tariff liberalization on capital goods increases firms' exports, I perform additional estimates exploring alternative outcome variables and interaction terms between the tariff exemption and capital characteristics.

Capital Intensity

I first investigate how results differ by firms capital intensity. To do so, I consider an interaction term between the exemption share and the industry capital-labor share. Table 1.16 reports the estimates for all firms that exported in either base or current year (in percentage growth) and for non-exporters only (in absolute growth). For the first sample of firms, the interaction term between the exemption share and the capital intensity does not have a significant coefficient. On the other hand, for the non exporters sample, there is a significant and positive estimate for the first lag.

Figure 1.9 plots the predicted values of exports growth in log US$ for ten percentile levels of capital intensity across industries, considering the effect of the first lag. As expected, industries with the highest level of capital share have the steepest positive curves, indicating a stronger effect of the tariff exemption on their firms. For industries below the 30 percentile, that is, labor-intensive ones, the effect of exemption is not significantly positive anymore.

Table 1.16: Local Projections estimates of the effect of exemption shares on exports growth, with capital intensity

Dependent variable:	Average Base Exports Growth		log US$ Exports at t	
	Exporters at $t-1$ or t		Non Exporters at $t-1$	
	(1)	(2)	(3)	(4)
EX share$_{t-1}$	0.059***		0.0001	
	(0.021)		(0.002)	
K/L$_{t-1}$	-0.041		0.138***	
	(0.182)		(0.024)	
EX share*K/L$_{t-1}$	0.0002		0.001**	
	(0.006)		(0.0006)	
EX share$_{t-2}$		0.042*		0.003
		(0.022)		(0.002)
K/L$_{t-2}$		-0.178		0.157***
		(0.191)		(0.027)
EX share*K/L$_{t-2}$		0.003		-0.0001
		(0.006)		(0.001)
Year FE	✓	✓	✓	✓
Observations	93,866	87,902	9,451	8,168
R^2	0.010	0.010	0.029	0.025

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

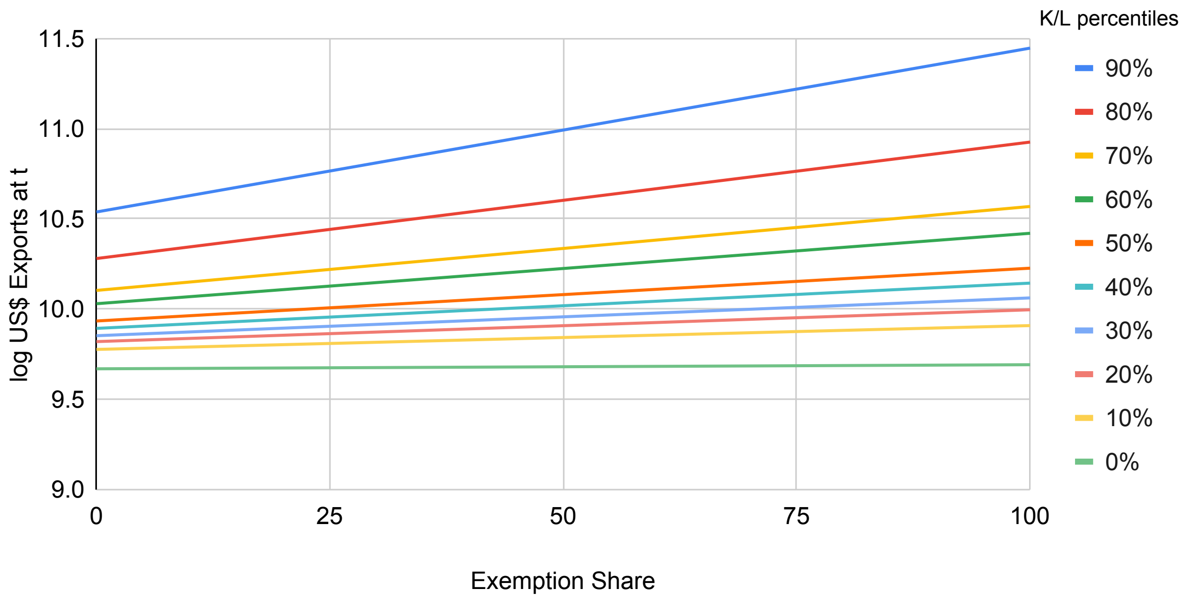


Figure 1.9: Predicted exemption effects by capital intensity. Subsample of new exporting firms.

Inputs Imports

Next, I investigate whether firms participating in the program will increase their imports in the following years. Remember that the main hypothesis is that these firms become more competitive through the lower investment cost and will increase their production and, consequently, their input need. We already observed increased sales for the international market and now we are interested in analyzing the volume of inputs imported by the firms. For this purpose, I take the total import value and subtract the capital goods amount.

The first four columns in Table 1.17 consider all firms that imported in the base or in the current year of the average base import growth measurement. In order to focus on a pool of firms closer to the one that we have analyzed in the exports growth rate regressions, the last four columns consider the subsample of firms that also exported in at least one of the two years. The results show positive and significant coefficients for both samples and all four lags of the exemption share. Their magnitude range from 2.2 to 9.4 basis point, similar to the observed growth in exports.

Exports Destinations and Product Varieties

Exports growth may be driven by an increase in the number of markets served by the firm, in the number of varieties of goods sold, or in the intensive margin, that is, in the amount exported of each good-destination pair.

Table 1.18 shows that part of the growth found in Table 1.4 is explained by the destination extensive margin. Both the LP and the FELP models estimate an increase of 2.1 basis point in the number of destination countries for each percentage point increase in the exemption share. Thus, a full tariff exemption corresponds to 2.1 percentage point more countries buying from the firm.

As for the extensive margin in terms of the varieties of goods being exported, Table 1.19 shows a significant and positive coefficient for lags two and four, ranging from 1.9 to 2.5 basis point. Therefore, we can conclude that part of the exports growth is not explained by the increase in the number of destinations or by the introduction of new products in the market, and must be caused by a higher value of exports for products already sold to continuing buyers.

Table 1.17: Local Projections estimates of the effect of exemption shares on inputs imports growth

- All firms that imported in base or current year

	Dependent variable: Average Base Imports Growth							
	Importers at $t-1$ or t				Imp and Exporters at $t-1$ or t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.09***				0.09***			
	(0.01)				(0.01)			
Varieties$_{t-1}$	0.03***				0.03***			
	(0.01)				(0.01)			
EX share$_{t-2}$		0.06***				0.04***		
		(0.01)				(0.01)		
Varieties$_{t-2}$		-0.02**				-0.02*		
		(0.01)				(0.01)		
EX share$_{t-3}$			0.04***				0.03**	
			(0.01)				(0.01)	
Varieties$_{t-3}$			-0.01				-0.01	
			(0.01)				(0.01)	
EX share$_{t-4}$				0.04***				0.02*
				(0.01)				(0.01)
Varieties$_{t-4}$				-0.03***				-0.02*
				(0.01)				(0.01)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	190,385	171,663	154,830	139,611	128,295	117,066	106,451	96,630
R^2	0.192	0.205	0.211	0.237	0.233	0.246	0.254	0.280

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.18: Local Projections estimates of the effect of exemption shares on export destinations growth - All firms that exported in base or current year

	Dependent variable: Average Base Export Destinations Growth (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.021***				0.021***			
	(0.006)				(0.007)			
EX share$_{t-2}$		0.013**				0.002		
		(0.006)				(0.008)		
EX share$_{t-3}$			0.006				0.004	
			(0.006)				(0.008)	
EX share$_{t-4}$				0.001				-0.004
				(0.006)				(0.008)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE					✓	✓	✓	✓
Observations	96,617	90,478	83,820	77,407	96,617	90,478	83,820	77,407
R^2	0.013	0.014	0.014	0.013	0.0001	0.0001	0.0001	0.0001

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.19: Local Projections estimates of the effect of exemption shares on the export varieties growth - All firms that exported in base or current year

	Dependent variable: Average Base Export Varieties Growth (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share_{t-1}	0.008				0.003			
	(0.007)				(0.010)			
EX share_{t-2}		0.025***				0.019**		
		(0.008)				(0.010)		
EX share_{t-3}			0.005				0.001	
			(0.008)				(0.011)	
EX share_{t-4}				0.020**				0.017
				(0.008)				(0.011)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE					✓	✓	✓	✓
Observations	96,617	90,478	83,820	77,407	96,617	90,478	83,820	77,407
R^2	0.009	0.009	0.009	0.009	0.0001	0.0001	0.0001	0.0001

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Employment

The empirical analysis so far focuses on the growth rate of key firm trade performance measures. Still, a possible concern that could arise is that the observed expansion of firms' export activity comes at the cost of factory automation and unemployment. To address this concern I match the trade dataset with the Brazilian employer-employee survey dataset and explore the effects of the tariff exemption, which is correlated with increased automation, on employment growth. Although I do not find evidence of a greater number of hires, following the increased equipment investment, I also do not find evidence of substitution of the initial labor force. In other words, firms that are automating their factories are expanding and not hiring more, but at least not at the cost of dismissing their employees. Table 1.20 shows that the estimates of the coefficients of the exemption share are not significant across different lags and fixed effects specifications.

Table 1.20: Local Projections estimates of the effect of exemption shares on the employment growth - All firms that exported in base or current year

	Dependent variable: Employment Growth (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	0.016				0.088			
	(0.079)				(0.107)			
EX share$_{t-2}$		0.050				-0.036		
		(0.058)				(0.071)		
EX share$_{t-3}$			-0.007				0.060	
			(0.045)				(0.059)	
EX share$_{t-4}$				-0.048				-0.073
				(0.008)				(0.065)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE					✓	✓	✓	✓
Observations	161,701	149,641	136,423	122,640	161,701	149,641	136,423	122,640
R^2	0.0003	0.0003	0.0006	0.0005	0.0001	0.0001	0.0001	0.0001

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Equipment Technology

The last variable of interest is the technology level of the machinery being imported by firms. The Product Complexity Index (PCI), by The Growth Lab at Harvard University (2019), is used as a proxy. PCI measures the knowledge intensity of a product by considering the knowledge intensity of its exporters. The index ranges from -1.63 to 2.51 across capital goods in those years.

Table 1.21 reports significant coefficients for the interactions terms between the exemption shares and the equipment technology for the sample of continuing exporters. Interestingly, the exemption effect is smaller for firms importing equipment of higher technology.

We can have a better understanding of the estimated effects by looking at Figure 1.10, that shows the predicted growth for 10 different levels of capital technology. Firms importing higher technology capital have a larger predicted growth rate, but the growth curves are steeper for firms importing machinery of lower technology. In other words, the exemption from capital goods tariff has a larger effect over the later.

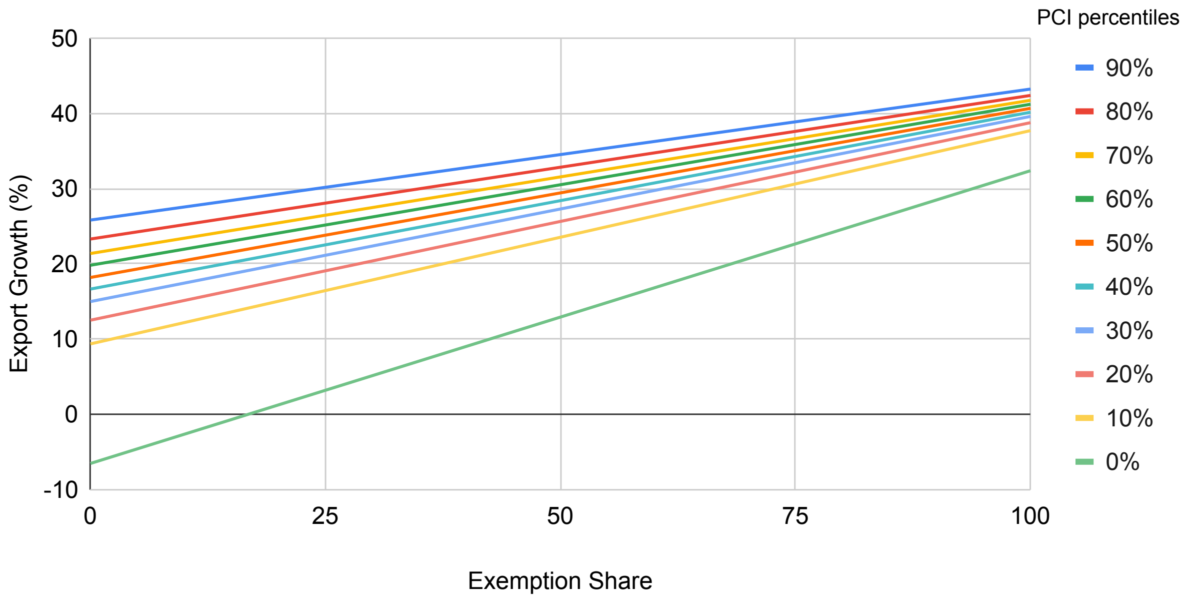
Table 1.21: Local Projections estimates of the effect of exemption shares on exports growth, with PCI

- Exporters and non exporters at base year

	Dependent variable: Average Base Exports Growth (%)			
	Exporterts at $t-1$ or t		Exporters at $t-1$	
	(1)	(2)	(3)	(4)
EX share$_{t-1}$	0.075**		0.280***	
	(0.038)		(0.034)	
PCI$_{t-1}$	3.218***		10.080	
	(0.888)		(0.807)	
EX share*PCI$_{t-1}$	-0.004		-0.067***	
	(0.031)		(0.028)	
EX share$_{t-2}$		0.069**		0.281***
		(0.038)		(0.034)
PCI$_{t-2}$		3.291***		9.833***
		(0.888)		(0.804)
EX share*PCI$_{t-2}$		-0.017		-0.083***
		(0.030)		(0.027)
Year FE	Yes	Yes	Yes	Yes
Observations	126,230	125,133	107,708	108,039
R^2	0.008	0.007	0.014	0.012

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1.10: Predicted exemption effects by capital technology



Notes: The figure plots the predicted exports growth for 10 different levels of capital technology. Subsample of continuing exporters.

1.6 Concluding Remarks

Capital goods imports have been found to be an important determinant of productivity growth across countries. Until now, we lacked evidence of their effects at the firm level. In this study, I exploit the features of a tariff exemption regime in Brazil regarding equipment trade. The findings show that the coefficient on the share of exempted capital goods imports is significant and robust across different specifications, including a variety of firm outcomes as the dependent variable.

A potential threat to the empirical approach is that firms applying for the exemption regime might be more productive or have a stronger institutional relations sector. To address this issue, I reestimate the results with the subsample of non-applicant firms, that experienced an exogenous tariff-reduction. In order for account for the potential endogeneity of the number of varieties of capital goods imported, I use instruments based on the exchange rate at the industry level. I address a series of possible confounding effects, regarding firm size and equipment value and quality.

I also propose a simple model based on Eaton and Kortum (2001) and Eaton and Kortum (2002), where equipment tariff affects firms performance. The findings are consistent with the hypothesis of increased investment in capital goods and, consequently, improved performance of firms with higher levels of exemption.

Appendix 1.A Other Results

Table A1: Effect of tariff exemption on equipment import value

	Dependent variable: ln of Capital Goods Imports					
	OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
Exemption	2.904***	1.997***	0.143***	1.637***	1.226***	0.177***
	(0.013)	(0.009)	(0.013)	(0.018)	(0.015)	(0.012)
Year FE	✓	✓	✓	✓	✓	✓
Varieties Ratio		✓	✓		✓	✓
CG >US$1 mi			✓			✓
Observations	203,740	203,740	31,608	203,740	203,740	31,608
R^2	0.159	0.130	0.031	0.079	0.061	0.008

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Exemption is a binary variable, equal to 1 when the firm has tariff exemption for at least one capital good in the year. Varieties Ratio: the dependent variable, capital goods imports value, is divided by the number of imported varieties. CG >US$1 mi: subsample of capital goods imports over US$ 1 million.

Table A2: Local Projections estimates of the effect of exemption shares on exports growth - Firms that imported capital goods in 5 consecutive years

Dependent variable: Average Base Exports Growth					
	Exporters at $t-1$ or t				
	(1)	(2)	(3)	(4)	(5)
EX share$_{t-1}$	0.053***				
	(0.019)				
EX share$_{t-2}$		0.030			
		(0.020)			
EX share$_{t-3}$			0.030		
			(0.020)		
EX share$_{t-4}$				-0.017	
				(0.020)	
EX share$_{t-5}$					-0.002
					(0.021)
Year FE	✓	✓	✓	✓	✓
Observations	60,876	60,876	60,876	60,876	60,876
R^2	0.007	0.007	0.007	0.007	0.007

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Local Projections estimates of the effect of exemption shares on exports growth

- Subsample of firms that were not exporting in the base year

	Dependent variable: US$ Exports Growth							
	Non Exporters at $t-1$				New Exporters at t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EX share$_{t-1}$	5,425*				17,174*			
	(3,120)				(10,516)			
EX share$_{t-2}$		5,951*				20,113		
		(3,577)				(13,374)		
EX share$_{t-3}$			-1,691				-7,609	
			(3,841)				(15,332)	
EX share$_{t-4}$				3,854				15,671
				(2,425)				(10,553)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	109,327	102,179	96,521	91,763	30,943	26,364	22,952	20,072
R^2	0.0002	0.0002	0.0001	0.0001	0.0006	0.0007	0.0004	0.0005

Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Notes: The first four columns show the results for all non-exporting firms in the base year $t-1$ and the last four columns show the results for the subsample of firms that started exporting in the following year t.

Table A4: Effect of exemption shares on exports growth - Non-Applicants comparison (2014-2018) and all firms that exported in base or current period of 3 years

Dependent variable: Average Base Exports Growth (%)		
	Full Sample	Non-Applicants
	(1)	(2)
EX share$_{t-1}$	0.183***	0.138**
	(0.050)	(0.070)
Varieties$_{t-1}$	-0.050**	-0.069
	(0.022)	(0.043)
Year FE	✓	✓
Observations	12,368	10,331
R^2	0.001	0.001

Robust standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 2

A General Equilibrium Analysis of the Gains from Trade Liberalization in Capital Equipment

2.1 Introduction

A long tradition in economics argues that investment in capital goods is a key determinant of productivity and economic growth (De Long and Summers, 1991; Greenwood et al., 1997). At the same time, recent literature points to the fact that machinery production is more geographically concentrated than gross domestic product and other manufactured goods (Mutreja et al., 2018).[1] Therefore, trade liberalization in capital goods is expected to

[1] They show that ten countries account for almost 80 percent of world capital goods production while sixteen countries account for 80 percent of the world GDP and seventeen countries account for 80 percent of the global output of intermediate goods.

increase countries' access to different technologies and have a significant impact on welfare. This is especially relevant for developing countries, which are traditionally net importers of equipment (Eaton and Kortum, 2001). In this paper, I ask what are the welfare gains from a capital goods tariff reduction, using a general equilibrium framework to model the Brazilian trade policy.

I focus on the Brazilian case due to its long history of high capital goods import tariff, when compared to the rest of the world. For instance, according to the tariff database from World Integrated Trade Solution (WITS), in 2017, Chile, the European Union and the United States imposed average tariffs of 0.84%, 0.88% and 1.05%, respectively. The tariff on equipment coming into Brazil is set at 14%.[2] One exception is the "Ex-Tarifario" regime, which consists of the temporary reduction of the tariff rate on the import of capital goods, as defined in the Common External Tariff of Mercosur, when there is no national production equivalent. Currently, when the Ministry of Economy of Brazil grants the benefit, a firm can import the equipment under complete elimination of the tariff.

However, given the recent policies against international trade in some countries, the question of which imports have the largest impact on firms' productivity becomes of widespread relevance. Capital equipment is argued to embody more advanced technology and thus, to be associated with a larger effect.

To answer these questions, I use a parameterized model with multiple sectors, tradable capital and intermediate inputs, and identify the set of sufficient statistics in the data which, in addition to the trade elasticities and capital shares of the production function, are needed to compute changes in welfare. To parametrize the trade elasticities I rely on existing

[2]Source: Ministry of Economy of Brazil.

values from the literature that has estimated equations that are consistent with this model. Specifically, I draw estimates from Caliendo and Parro (2015).

I then combine the framework with world input-output data, and conduct counterfactuals to quantitatively explore the impact of different tariff levels. Through the first counterfactual, I quantify how much real consumption would change with gradual reductions in import tariffs in Brazil, up to complete liberalization. In the second counterfactual, I compare the impact of tariff reductions for one country at a time in the sample, holding the tariff towards the remaining countries fixed. The last analysis considers the effects from further removing other variable trade costs, such as transportation costs.

This paper builds on a growing literature empirically documenting the impact on productivity growth from cross-country technology diffusion through international trade in capital goods. Caselli and Wilson (2004) break down overall capital in nine equipment categories in order to understand cross-country differences in income levels. They show that there is enormous cross-country variation in the composition of capital: different types of equipment constitute widely varying fractions of the overall capital stock across countries. Their model describes the intrinsic efficiency and factor-complementarity of various types of capital, and relate these parameters to the R&D intensity of the industries where that capital is produced. The quality of capital employed in production can explain a significant part of income differences. For most countries, imports of capital of a certain type constitute almost the whole investment in that type of equipment.

The pattern of worldwide technical change is thus determined in large part by international trade and technology diffusion. Keller (2004) points out that for most countries, foreign sources of technology account for 90 percent or more of domestic productivity growth.

Looking at OECD countries, Xu and Wang (1999) assess the impact of international R&D spillovers, distinguishing capital goods from non-capital goods. Trade in capital goods was found to be a significant channel of R&D spillovers. Capital goods have higher content of technology than non-capital goods and hence are the major carriers of R&D spillovers embodied in trade flows.

Comin and Hobijn (2004) examine the diffusion of more than 20 technologies across 23 economies. They document that most of the technologies considered originate in advanced economies and are adopted there first. Subsequently, they trickle down to less developed countries. The most important determinants of the speed at which a country adopts technologies are the country's human capital endowment, type of government, degree of openness to trade, and adoption of predecessor technologies.

Caselli (2018) conducts empirical work focusing on how imports of equipment are related with productivity growth, using production and cost data from a panel of Mexican manufacturing plants. He identifies self-selection and learning effects separately for intermediate and capital goods. The evidence shows that not only more productive plants tend to become importers of machinery, but plants that start importing equipment also experience an increase in productivity, while the same does not occur when plants start importing intermediate goods. His results suggest that capital goods imports are more likely to embody technological improvements than intermediate inputs.

Previous studies model the process by which embodied knowledge spreads across countries, with trade at the center. Rodriguez-Clare (1996) constructs a model with two countries, North and South. Innovation occurs only in North, where entrepreneurs spend resources to upgrade the quality of equipment goods. South can potentially benefit from this innovation by importing the higher quality equipment, but it needs to spend resources in order to adapt those goods to the local conditions. The argument is that importing new inputs is not easy, not only because people must learn about the new production process associated with them, but also because of the costs of adapting those production processes to the local environment and setting up the infrastructure needed for the actual importing, maintenance and support for the new equipment. In that way, the gains from imported machinery are not obvious. A country might have different soil conditions, environmental regulations, working traditions and labor skills than the countries where those inputs are introduced. Muendler (2004), for example, does not find significant productivity impact in the short run from the adoption of foreign equipment, following a trade liberalization policy. Yet, a large body of literature has estimated positive effects from lower barriers. Rodriguez-Clare (1996) finds a fall of 8.5 percent in the relative income of the importer country after the imposition of a 10 percent tariff on equipment goods.

Shikher (2012b) develops a Ricardian model to explore how technology interacts with geography and inter-industry linkages to affect specialization, employment, and welfare. The author simulates a 5% increase in the average productivity of the U.S. machinery industry. The findings show that, as a result of this increase in technology, the cost of production and the price of goods fall in all industries and countries. Other industries benefit from the access to cheaper domestic machinery goods and, therefore, face lower production costs. Other countries also benefit from access to cheaper intermediate machinery goods, but the degree to which they benefit depends on their proximity to the US. The world manufacturing employment falls because production moves from less productive countries to the US, which is one of the most productive countries in the sample. Nevertheless, in a simulation of a technological improvement in the Mexican machinery industry, the world manufacturing employment grows.

This study is also related to the literature of applied general equilibrium trade models, that have become a widely used tool for analyzing the welfare impact of trade liberalization. However, there are few that incorporate trade in capital goods. Eaton and Kortum (2001) develop a theoretical framework that combines Solow's (1960) model of technological change embodied in new capital equipment with a model of Ricardian trade similar to Eaton and Kortum (2002). The model connects cross-country productivity levels to observed variation in capital accumulation, that arises from differences in savings rates and in relative prices of capital goods among countries. Their work contributes to incorporate geographic barriers between countries that generate these relative price differences. A country's productivity then depends on its access to capital goods from around the world. While only a few countries concentrate much of the R&D activities, the resulting benefits may spread around through exports of capital goods that embody new technology. Their model allows one to infer differences in equipment prices across countries from data on bilateral trade in these goods. Applying the model to data on production and bilateral trade in capital equipment, they estimate the barriers to trade, which imply substantial differences in equipment prices across countries. The authors attribute about 25 percent of cross-country productivity differences to variation in the relative price of equipment, about half of which they ascribe to barriers to trade in equipment, and half to differences in consumption prices. I compare my results to their model predictions in Section 4.2.

Mutreja et al. (2018) develop a multisector, multicountry, Ricardian model of trade, embedded into a neoclassical growth model, with capital accumulation. In their framework, countries have different technologies for producing a continuum of tradable capital goods and a continuum of tradable intermediate goods. Capital formation is endogenous and depends on trade frictions. International trade in capital goods affects economic development through two channels: capital formation and total factor productivity. First, reductions in barriers to capital goods trade enable poor countries to access capital goods produced in rich countries. This reduces their relative price of investment and increases their investment rate and capital-output ratio. Second, by importing more capital goods, poor countries allocate their resources more efficiently which increases their productivity. Their model is consistent with the world distribution of capital goods production, cross-country differences in income, investment rate, and price of final goods, and cross-country equalization of the price of capital goods. The quantitative results from the model show that the removal of capital goods trade frictions implies a 40 percent reduction in the income gap between rich and poor countries.

Another part of the general equilibrium trade literature has also accounted for capital goods imports, but with the goal of evaluating the effects of trade on the skill premium, given capital-skill complementarities. Burstein et al. (2013) do so by embedding a production function that allows for capital-skill complementarity into the multi-country Ricardian trade model of Eaton and Kortum (2002). They propose a framework with capital equipment accumulation, where changes in trade costs affect a country's steady-state stock of capital equipment through changes in its domestic sectoral expenditure share. An increase in the stock of capital equipment, in turn, raises the demand for skilled labor relative to unskilled labor. The authors incorporate dynamics, modelling the aggregate law of motion of equipment. The stock of capital equipment is endogenous, and depends on changes in bilateral trade costs and in each country-sector-specific productivity. They show, however, that there is a small set of sufficient statistics that fully determine the equilibrium change in the stock of capital equipment.

Parro (2013) also constructs a general-equilibrium model with trade in capital goods and capital-skill complementarity. A reduction in trade costs decreases the price of capital goods, fostering increasing trade in these goods, and raising the productivity of skilled relative to unskilled workers. They work with an extension of the model developed in Caliendo and Parro (2015), introducing trade in capital goods. The model is static and capital goods are simply treated like intermediate goods. This treatment assumes full depreciation of capital goods during the period of analysis.

There is now a large number of empirical papers focusing on the measurement of the gains from trade. A central aspect of the model they are based on is the gravity equation; see Anderson (1979) and Anderson and Van Wincoop (2003). Structural gravity models provide micro-theoretical foundations underlying gravity equations; see Eaton and Kortum (2002). The literature develops multicountry gravity models and demonstrate how they can be used for counterfactual analysis.

Influential work by Arkolakis et al. (2012), commonly referred to as ACR, studies the welfare predictions from different trade models. They start from the Armington model, based on the assumption that goods are differentiated by country of origin. Then they focus on quantitative trade models that feature one factor of production, perfect or monopolistic competition, balanced trade and Constant Elasticity of Subtitution demand systems. The authors show that for this broad range of trade models encompassing homogeneous and heterogeneous firm models, one can measure welfare gains associated with a change in iceberg trade costs with just two parameters: (i) changes in the share of expenditure on domestic goods; and (ii) the elasticity of bilateral imports with respect to variable trade costs, the trade elasticity. Changes in bilateral trade flows and the share of domestic expenditure can be computed using only information about the trade elasticity and macroeconomic data. They refer to this approach popularized by Dekle et al. (2008) as "exact hat algebra". Generalized versions of their welfare formula can also be derived for environments with multiple sectors and tradable intermediate goods.

In the work of Costinot and Rodríguez-Clare (2014), the idea is to construct middle-sized models that are rich enough to speak to first-order features of the data, like the role of country size and geography, yet parsimonious enough so that one can identify its key parameters and understand how their magnitude affects counterfactual analysis. One does not need to estimate all structural parameters of the model to estimate the welfare effect of a tariff change.

The authors illustrate how gravity models can be used to quantify the gains from international trade defined as the percentage change in real income that would be associated with moving one country from the current, observed trade equilibrium to a counterfactual equilibrium with no trade, i.e. an equilibrium with infinite iceberg trade costs. Since the share of domestic expenditure on domestic goods under autarky is equal to one, the welfare consequences associated with this counterfactual exercise are easy to compute. Although this is an extreme counterfactual scenario, it is a useful benchmark that can shed light on the quantitative importance of the various channels through which globalization affects the welfare of countries. With a different approach, Adao et al. (2017) show how to conduct counterfactual predictions in neo-classical trade models without imposing gravity.

Other studies provide a universal gravity framework combining aggregate demand and supply equations that incorporates not only many workhorse trade models of perfect, monopolistic and Bertrand competition, but also economic geography models. Allen et al. (2020) characterize the theoretical and empirical properties common to a large class of gravity models spanning the fields of international trade and economic geography. The study shows that key theoretical properties and positive counterfactual predictions of all gravity models depend ultimately on the value of two parameters, the elasticities of supply and demand, which can be estimated using an instrumental variables approach that relies on the general equilibrium structure of the model.

The existence of multiple sectors and tradable intermediate goods tend to increase significantly the magnitude of the gains from trade. Furthermore, these models usually proceed under the assumption of a single factor input, labor. I focus instead on incorporating tradable capital equipment.

We can see that quantitative results from a large class of structural gravity models of international trade depend critically on the elasticity of trade with respect to trade frictions. Conditional on observed trade shares, it determines both the response of bilateral trade flows and real consumption. However, estimates of the trade elasticity can vary significantly with model specifications and estimation methodologies, even after taking into account differences in the data coverage. For instance, a survey by Anderson and Van Wincoop (2004) finds that elasticity estimates range from 5 to 10, in absolute terms. Thus, a key challenge in the empirical literature is to define the best approach.

In their seminal work, Eaton and Kortum (2002) estimate structurally the trade elasticity, following their Ricardian trade model and using product-level price data. Their estimates range from 3.60 to 12.86 with a preferred value of 8.28 when using the maximum price difference across goods between countries as a proxy for bilateral trade frictions. The price gap between two countries is bounded by the trade friction between the two countries via no-arbitrage arguments.

Simonovska and Waugh (2014) refine their preferred estimation strategy to take into account the fact that price gaps are only lower-bounds on trade costs. They correct for the fact that the previous method understates the true trade friction and results in overestimates of the trade elasticity. The authors propose a simulated method of moments and find a preferred estimate of 4.14. This difference doubles the measured welfare gains from trade.

Feenstra et al. (2018) distinguish between the upper-level macroelasticity, governing the substitution between home and foreign goods, and a lower-level microelasticity, governing the substitution between varieties of foreign goods. The authors use U.S. production data matched to imports and simulated data, building on the Melitz (2003) trade model of heterogeneous firms, with a nested CES preference structure. They find empirical evidence that the microelasticity is larger than the macroelasticity. Industry-level estimates for the former are in the 3.22-4.05 range, and twice as large as the macroelasticity estimates.

Recent studies assume heterogeneous export supply and import demand elasticities for every country pair and good traded worldwide. Soderbery (2018) demonstrates how price and quantity variation over time for the same good across export and import markets can be exploited to identify importer by exporter by product elasticities. With heterogeneity in elasticities, the optimal tariff set by an importer is no longer the inverse of a single elasticity. It should weight the relative contribution of each variety to terms of trade gains and efficiency losses resulting from the tariff. Imbs and Mejean (2017) provide estimates of the aggregate elasticity of trade, given by a weighted average of sector-level elasticities, for 28 countries. Their findings are heterogeneous across countries, with values ranging between 3.4 and 9.9.

Ossa (2015) argues that the workhorse models of trade predict much larger gains once the cross-industry variation in trade elasticities is taken into account. The idea is that while imports in the average industry do not matter too much, imports in some industries are critical to the functioning of the economy, such that restricting international trade is very costly overall. He shows that the industry-level formula predicts that a move from autarky to 2007 levels of trade increases real income by 49 percent on average which is around three times the number the aggregate formula predicts.

One approach for understanding the reaction of aggregate exports to trade costs uses knowledge of the firm-level response. Bas et al. (2017) combine two firm-level customs datasets with French and Chinese individual sales on the same destination market. They are able to estimate all the components of the bilateral aggregate elasticity: i) the demand-side parameter that governs the intensive margin and ii) the supply side parameters that drive the extensive margin. These components are then used to calculate theoretical predictions of bilateral aggregate elasticities over the whole set of destinations, and how those elasticities decompose into different margins.

Yilmazkuday (2019) uses U.S. imports data to estimate the trade elasticity distinguishing between short-run versus long-run measures. He finds a short-run value of about 1 (after one quarter), a medium-run value of about 5 (after one year), and a long-run value of about 7 (after five years).

In this study, I employ the estimates from Caliendo and Parro (2015). Their sectoral estimations are performed without assuming bilaterally symmetric trade costs as is standard in the literature. Moreover, the method is consistent with any trade model that delivers a gravity-type trade equation. Therefore, the estimated trade cost elasticity from using this method does not depend on the underlying microstructure assumed in the model.

The rest of the paper is organized as follows. Section 2.2 develops the model and describes the equilibrium. Section 2.3 describes the data. The quantitative results are presented in Section 2.4. Section 2.5 concludes.

2.2 Model

I develop a quantitative general equilibrium model with multiple sectors and tradable intermediate and capital goods, with input-output linkages. I then follow the steps of Costinot and Rodríguez-Clare (2014) to derive the welfare gains from trade. The model builds on the Ricardian trade model of Eaton and Kortum (2002),[3] introducing the capital goods sector, denoted by k. Consider a world economy featuring $i = 1, ..., n$ countries and sectors $s = 1, ..., S, k$. All sectors are assumed to be perfectly competitive.

Preferences: There is a representative agent in each country with a two-tier utility function in which the upper-level is Cobb-Douglas and the lower-level is Constant Elasticity of Substitution (CES). The representative agent in country j aims to maximize

$$C_j = \prod_{s=1}^{k} C_{j,s}^{\beta_{j,s}},$$

where $\beta_{j,s} \geq 0$ denotes the share of final consumption going to varieties from sector s, with $\sum_{s=1}^{k} \beta_{j,s} = 1$, and $C_{j,s}$ is the total consumption of a composite of varieties, indexed by

[3] See Shikher (2012b), Shikher (2012a) and Caliendo and Parro (2015) for the multiple sectors case.

$\omega \in \Omega_{j,s}$, from sector s in country j. The lower-level CES utility function is given by

$$C_{j,s} = \left(\int_{\omega \in \Omega_{j,s}} q_{j,s}(\omega)^{(\sigma_s - 1)/\sigma_s} d\omega \right)^{\sigma_s/(\sigma_s - 1)},$$

where $q_{j,s}(\omega)$ is the quantity of variety ω from sector s demanded in country j for final consumption and $\sigma_s > 1$ is the elasticity of substitution between different varieties, which is allowed to vary across sectors.

In equilibrium, each variety is sourced from the lowest cost supplier country only. The consumption of sector s composite good from country i in country j is given by

$$C_{ij,s} = \left(\int_{\omega \in \Omega_{ij,s}} q_{j,s}(\omega)^{(\sigma_s - 1)/\sigma_s} d\omega \right)^{\sigma_s/(\sigma_s - 1)},$$

where $\Omega_{ij,s} \subset \Omega_{j,s}$ denotes the set of sector s varieties that country j buys from country i.

Production of Intermediate and Capital Goods: There are composite intermediate goods from sectors $s = 1, ..., S$ and a composite capital good from sector $s = k$, produced in the same way as composite goods for final consumption in country j:

$$M_{j,s} = \left(\int_{\omega \in \Omega_{j,s}} m_{j,s}(\omega)^{(\sigma_s - 1)/\sigma_s} d\omega \right)^{\sigma_s/(\sigma_s - 1)},$$

where $m_{j,s}(\omega)$ is the amount of variety ω used in the production of the composite intermediate and capital goods of each sector.

Given the CES utility function, the sector-specific price indices of goods for final consumption and production is given by

$$P_{j,s} = \left(\int_{\omega \in \Omega_{j,s}} p_{j,s}(\omega)^{1-\sigma_s} d\omega \right)^{1/(1-\sigma_s)},$$

where $p_{j,s}(\omega)$ is the price in country j of variety ω, discussed in further detail below.

Production Costs: Firms use labor, intermediate and capital goods in their production process. Following Parro (2013), capital goods are treated similarly to intermediate goods.

This treatment assumes full depreciation of capital goods during the period of analysis. Following Costinot and Rodríguez-Clare (2014), I assume that labor costs in country i are proportional to total labor income Y_i. The sector-specific unit cost of production is given by

$$c_{i,s} = Y_i^{1-\alpha_{i,s}-\alpha_{i,ks}} P_{i,k}^{\alpha_{i,ks}} \prod_{r=1}^{S} P_{i,r}^{\alpha_{i,rs}}, \tag{2.1}$$

where $\alpha_{i,ks}$ and $\alpha_{i,rs}$ are exogenous technology parameters and $\alpha_{i,s} = \sum_{r=1}^{S} \alpha_{i,rs}$, such that $\alpha_{i,ks} + \alpha_{i,s} \in [0, 1]$. Thus, the unit cost of production varies across sectors, reflecting the different employment of intermediate and capital goods.

Trade Costs: International trade between countries is subject to iceberg trade costs. In order to sell one unit of a variety from sector s in country j, firms from country i must ship $\tau_{ij,s} \geq 1$ units, with $\tau_{ii,s} = 1$ for all sectors. Varieties imported by country j from country i have to pay the ad-valorem tariff $t_{ij,s}$ over unit prices. Total variable trade costs are then given by $\phi_{ij,s} = \tau_{ij,s}(1 + t_{ij,s})$. This study will focus on the effects of capital goods trade policy, $t_{ij,k}$, assuming $t_{ij,r} = 0$ for all other sectors $r = 1, ..., S$.

Prices: After taking into account trade costs, one unit of a variety ω from country i is available in country j at unit prices $p_{ij,s}(z_i) = \phi_{ij,s} c_{i,s} / z_i(\omega)$, where $z_i(\omega)$ denotes the efficiency of country i in producing variety ω. I assume it to be the realization of a random variable z, drawn from the Fréchet distribution $F_{i,s}(z) = e^{-T_{i,s} z^{-\theta_s}}$. The location parameter $T_{i,s}$ varies by country and sector and the shape parameter θ_s varies by sector. A higher $T_{i,s}$ means larger average sector productivity, a notion of absolute advantage. A smaller value of θ_s implies a higher dispersion of productivity across varieties within the sector, a notion of comparative advantage.

Under perfect competition, buyers pay the lowest price of a variety ω in country j across all sources i, $p_{j,s}(\omega) = \min\{p_{ij,s}(\omega), i = 1, ..., N\}$. Under these assumptions, Appendix A shows that the price in country j of the composite sector s good is given by

$$P_{j,s} = A_s[\sum_i (\phi_{ij,s}c_{i,s})^{-\theta_s} T_{i,s}]^{-\frac{1}{\theta_s}},$$

where $A_s = \Gamma(1 + \frac{1-\sigma_s}{\theta_s})$ and Γ is a Gamma function.

The price in country j of the composite sector s good from country i, as demonstrated in Appendix B, is given by

$$P_{ij,s} = \frac{(\phi_{ij,s}c_{i,s})^{1+\eta_s}}{(P_{j,s})^{\eta_s}} \xi_{i,s}, \tag{2.2}$$

where $\xi_{i,s} = A_s^{1+\eta_s} T_{i,s}^{1/(1-\sigma_s)}$ and $\eta_s = (\frac{\theta_s}{\sigma_s - 1})(1 + \frac{1-\sigma_s}{\theta_s})$. Changes in prices, $P_{ij,s}$, may reflect both: (i) changes at the intensive margin, i.e., changes in the price of goods imported in country j, and (ii) changes at the extensive margin, i.e., changes in the set of goods imported in country j, $\Omega_{ij,s}$, due to the selection of a different subset of firms from i in j. If firms from country i are less competitive relative to other firms serving market j (when $\phi_{ij,s}c_{i,s}/P_{j,s}$ is high), then less firms from country i will serve this market. This will lead to a decrease in the number of varieties from i available in j and an increase in $P_{ij,s}$. The magnitude of selection effects is formally determined by η_s.

Trade Flows and Expenditure Shares: Let $X_{ij,s}$ denote the value of country j's imports of sector s goods from country i (inclusive of tariffs), $E_{j,s} = \sum_{i=1}^{n} X_{ij,s}$ denote expenditure on sector s goods in country j, and $R_{i,s} = \sum_{j=1}^{n} X_{ij,s}$ denote the sector-level revenue in country i. I assume that trade is balanced, such that total expenditure equals total revenues, $E_i = R_i$.[4] Bilateral trade flows include trade in consumption, intermediate

[4]I follow Costinot and Rodríguez-Clare (2014)'s static models, that aim to capture the long-run consequences of trade liberalization. Given the static nature, they predict that trade should be balanced

and capital goods and satisfy

$$X_{ij,s} = \left(\frac{P_{ij,s}}{P_{j,s}}\right)^{1-\sigma_s} E_{j,s}. \tag{2.3}$$

Let $\lambda_{ij,s}$ denote the share of expenditure on varieties from sector s sold in country j, that are produced in country i: $\lambda_{ij,s} = X_{ij.s}/E_{j,s}$. In Appendix A, I show that

$$\lambda_{ij,s} = \frac{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}{\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}},$$

where $\theta_s = (\sigma_s - 1)(1 + \eta_s)$ is the trade elasticity. It denotes the elasticity of imports relative to domestic demand, $X_{ij,s}/X_{jj,s}$, with respect to bilateral trade costs, $\phi_{ij,s}$, holding income levels fixed.

Total Expenditure and Real Consumption: Total expenditure on varieties from sector s in country j can be expressed as

$$E_{j,s} = \beta_{j,s}(Y_j + T_j) + \sum_{r=1}^{k} \alpha_{j,sr}R_{j,r}, \tag{2.4}$$

where $T_j = \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} X_{ij,k}$ are tariff revenues, assuming that only capital goods are charged import tariffs.

Revenues for the capital goods sector equal the sum of expenditure on these goods across countries, discounted by their import tariffs:

$$R_{i,k} = \sum_{j=1}^{n} \frac{\lambda_{ij,k}}{1 + t_{ij,k}} E_{j,k}.$$

Revenues for all other sectors $r = 1, ..., S$ are not affected by tariffs, such that they are given by

$$R_{i,r} = \sum_{j=1}^{n} \lambda_{ij,r} E_{j,r}.$$

country-by-country.

Table 2.1: Model Summary

Cost of the input bundles	$\hat{c}_{i,s} = \hat{Y}_i^{1-\alpha_{i,s}-\alpha_{i,ks}} \hat{P}_{i,k}^{\alpha_{i,ks}} \prod_{r=1}^{S} \hat{P}_{i,r}^{\alpha_{i,rs}}$
Price index for capital goods	$\hat{P}_{i,k} = \left(\sum_{j=1}^{n} \lambda_{ji,k} (\hat{\phi}_{ji,k} \hat{c}_{j,k})^{-\theta_k} \right)^{-\frac{1}{\theta_k}}$
Price index for intermediate goods	$\hat{P}_{i,r} = \left(\sum_{j=1}^{n} \lambda_{ji,r} (\hat{\tau}_{ji,r} \hat{c}_{j,r})^{-\theta_r} \right)^{-\frac{1}{\theta_r}}$
Expenditure shares	$\hat{\lambda}_{ij,s} = \frac{(\hat{\phi}_{ij,s} \hat{c}_{i,s})^{-\theta_s}}{\sum_l \lambda_{lj,s} (\hat{\phi}_{lj,s} \hat{c}_{l,s})^{-\theta_s}}$
Total expenditure	$\hat{E}_{j,s} E_{j,s} = \beta_{j,s} (\widehat{Y_j + T_j})(Y_j + T_j) + \sum_{r=1}^{k} \alpha_{j,sr} \hat{R}_{j,r} R_{j,r}$
Revenues	$\hat{R}_{i,s} R_{i,s} = \sum_{j=1}^{n} \frac{\hat{\lambda}_{ij,s} \lambda_{ij,s}}{1+t'_{ij,s}} \hat{E}_{j,s} E_{j,s}$
Total income	$\hat{Y}_i Y_i = \sum_{s=1}^{k} (1 - \alpha_{i,s} - \alpha_{i,ks}) \hat{R}_{i,s} R_{i,s}$

Total income accounts for intermediate and capital consumption in the production process:

$$Y_i = \sum_{s=1}^{k} (1 - \alpha_{i,s} - \alpha_{i,ks}) R_{i,s}.$$

Following Costinot and Rodríguez-Clare (2014), I use world GDP as the numeraire such that $\sum_{i=1}^{n} Y_i = 1$.

Real consumption is given by

$$C_j = \frac{(Y_j + T_j)}{P_j}.$$

Equilibrium in Relative Changes: I solve for an equilibrium after changing from policy t to policy t', using the exact hat algebra, where $\hat{\nu} = \nu'/\nu$ denotes the proportional change in any variable ν between the initial and counterfactual equilibria. Appendix E shows the derivation of the equilibrium conditions in relative changes, summarized in Table 2.1.

In performing counterfactuals I proceed as follows. The equations in the table constitute a system of $n \times (S+1) + n + n \times S + n \times n \times (S+1) + n \times (S+1) + n \times (S+1) + n$ equations that can be solved for $n \times (S+1) + n + n \times S + n \times n \times (S+1) + n \times (S+1) + n \times (S+1) + n$

unknowns, $\hat{c}_{i,s}, \hat{P}_{i,k}, \hat{P}_{i,r}, \hat{\lambda}_{ij,s}, \hat{E}_{i,s}, \hat{R}_{i,s}, \hat{Y}_i$. Once the unknowns are obtained, the magnitude of the welfare gains from the change in trade policy is computed as changes in real consumption, through the following equation, derived in Appendix E:

$$\hat{C}_j = \frac{\widehat{(Y_j + T_j)}}{\hat{Y}_j} \times \prod_{s=1} \prod_{r=1} [\hat{\lambda}_{jj,r}^{-1}]^{\beta_{j,s} a_{j,sr}/\theta_r}. \tag{2.5}$$

This expression is similar to the general result in Arkolakis et al. (2012), that relates the trade gains to the expenditure shares λ and to the trade elasticity θ. Here, the additional term on the left accounts for the change in import tariffs. The parameter $a_{j,sr}$ is the (s, r) entry of the Leontief inverse of the input-output matrix, including capital goods k (see Appendix D for details). These technology parameters reflect the elasticity of the price index in sector s with respect to changes in the price index in sector r.

Table 2.2 presents the summary of the endogenous variables and the parameters, and how they are obtained. The details about the data sources are described in Section 3. Due to our focus on counterfactual changes in capital goods trade policy and to the fact that most countries have imposed close to zero tariffs on equipment in the last two decades, I assume that there are no other tariffs, besides the tariff on imported capital goods in Brazil, $t_{ij,r} = 0$ for all $i, j, r = 1, ..., S$ and $t_{ij,k} = 0$ for all $j \neq$ Brazil. The initial equilibrium tariff on imported equipment in Brazil is set to 14%, $t_{iBRA,k} = 0.14$, and I explore the effects on welfare from reducing it by different levels: from 10% up to 100% (full liberalization).

2.3 Data

Trade and input-output data used in the quantitative analysis are from the World Input-Output Database (WIOD), for the year 2008 (Timmer et al., 2015). The database covers 40

Table 2.2: Summary of Parameters and Variables

$\hat{c}_{i,s}, \hat{P}_{i,s}, \hat{\lambda}_{ij,s}, \hat{E}_{i,s}, \hat{Y}_{i,s}, \hat{R}_{i,s}, \hat{C}_i$	Unkowns
θ_r, θ_k	Literature estimates
$\alpha_{i,ks}$	Brazilian data
$\alpha_{i,rs}, \lambda_{ji,k}, \lambda_{ji,r}, \beta_{j,s}, E_{i,s}, Y_{i,s}, R_{i,s}, a_{j,sr}$	World input-output data
$\hat{\phi}_{ji,k}$	Counterfactual changes exercises
$\hat{\tau}_{ji,r}$	Set equal to 1 (no change)

countries and an aggregate of the rest of the World. There are 27 European Union countries and 13 other countries, including Brazil. Fortunately, it comprehends the leading countries in the production of capital equipment: China, Germany, Japan, Italy, United States and Korea. I follow the Costinot and Rodríguez-Clare's (2014) region aggregation, characterized by the 33 largest countries and the sum of the rest of the World with the 7 smallest countries in the original dataset, as described in Table 2.3.

There are 35 sectors in the World Input-Output Database. To avoid the problems associated with zero output or zero consumption, data are aggregated to 31 sectors, all with non-zero outputs and consumption in all countries, described in Table 2.4. Trade elasticities for agriculture and manufacturing sectors are from Caliendo and Parro (2015). Trade elasticity for service sectors follows Costinot and Rodríguez-Clare (2014) and is set equal to 5. The authors argue that the value of this elasticity has very small effects on the quantitative results, since there is little trade in services.

In order to compile capital shares by sector, it is not enough to observe the WIOD data, since they do not present capital investment disaggregated by sector. I proceed in the

Table 2.3: Aggregation of regions

Country's name	**WIOD code**	**Aggregation**
Australia	AUS	Australia
Austria	AUT	Austria
Belgium	BEL	Belgium
Brazil	BRA	Brazil
Canada	CAN	Canada
China	CHN	China
Czech Republic	CZE	Czech Republic
Germany	DEU	Germany
Denmark	DNK	Denmark
Spain	ESP	Spain
Finland	FIN	Finland
France	FRA	France
United Kingdom	GBR	United Kingdom
Greece	GRC	Greece
Hungary	HUN	Hungary
India	IDN	India
Indonesia	IND	Indonesia
Ireland	IRL	Ireland
Italy	ITA	Italy
Japan	JPN	Japan
Korea	KOR	Korea
Mexico	MEX	Mexico
Netherlands	NLD	Netherlands
Poland	POL	Poland
Portugal	PRT	Portugal
Romania	ROM	Romania
Russia	RUS	Russia
Slovakia	SVK	Slovakia
Slovenia	SVN	Slovenia
Sweden	SWE	Sweden
Turkey	TUR	Turkey
Taiwan	TWN	Taiwan
United States	USA	United States
Bulgaria	BGR	Rest of the World
Cyprus	CYP	
Estonia	EST	
Latvia	LVA	
Lithuania	LTU	
Luximburg	LUX	
Malta	MLT	
Rest of the World	ROW	

following way. I construct capital-labor ratios using data from the Brazilian annual survey of manufacturing firms, Pesquisa Industrial Anual, conducted annually by the Brazilian census bureau, IBGE. The labor expenses are measured as the average personnel expenditure at the industry level of the manufacturing sector in 2008. To construct the labor share, I divide labor expenses by the total value-added of the sector in the WIOD table. Subtracting the labor share from one, I obtain the total capital share. I assume that half of capital is composed of tradable capital goods and half is composed of non-tradable fixed capital. The results are presented in Table 2.4. I do not consider capital in the petroleum sector, due to the different regulation on equipment imports for that sector in Brazil. For the services sectors, I set the capital share to one third.

In the WIOD database, we directly observe purchases, $X_{ij,rs}$, of intermediate goods from sector r and country i in sector s and country j. Final consumption, $C_{ij,s}$, is calculated as the sum of observations in private consumption (households and non-profit), government consumption, gross fixed capital formation and changes in inventories. The negative entries in the column of inventories are not included in the sum, in order to avoid negative final demand values. Therefore, they are treated as output that was produced and consumed in the current period.[5] Bilateral sector-level trade flows are then given by $X_{ij,s} = \sum_r X_{ij,sr} + C_{ij,s}$. Sector expenditure is $E_{j,s} = \sum_i X_{ij,s}$, the sector share of expenditure on domestic goods is $\lambda_{jj,s} = X_{jj,s} / \sum_i X_{ij,s}$ and sector revenue is $R_{j,s} = \sum_l X_{jl,s}$. At the aggregate level, expenditure is $E_j = \sum_{i,s} X_{ij,s}$, the share of expenditure on domestic goods is $\lambda_{jj} = \sum_s X_{jj,s} / \sum_{i,s} X_{ij,s}$ and total revenue is $R_j = \sum_s \sum_l X_{jl,s}$.

[5]This requires adjusting the total output vector X and the matrix of inputs flows AX to establish the balance $X = AX + F$, in which the vector of final demand F does not include the negative entries.

We can compute final demand by country and sector $C_{j,s} = \sum_i C_{ij,s}$ and final demand shares $\beta_{j,s} = C_{j,s}/\sum_r C_{j,r}$. Finally, we can construct the shares of intermediate purchases from sector r used in sector s and coutry j, $\alpha_{j,rs} = \sum_i X_{ij,rs}/R_{j,s}$ and value added by sector $Y_{j,s} = R_{j,s} - \sum_r X_{j,rs}$.

Before conducting the exercises, I follow Costinot and Rodríguez-Clare (2014) steps to modify the WIOD data such that overall trade is balanced country-by-country. First, I solve the system of equations summarized in Table 2.1, imposing zero trade imbalances, but no change in trade policy yet, and compute the counterfactual changes in $\hat{c}_{i,s}, \hat{P}_{i,k}, \hat{P}_{i,r}, \hat{\lambda}_{ij,s}, \hat{E}_{i,s}$, $\hat{R}_{i,s}, \hat{Y}_i$. This allows me to set new initial values for the unknowns, consistent with a no-deficit world economy. Then, I use the resulting dataset without trade imbalances to conduct the counterfactual tariff analysis. Starting from this new equilibrium, I solve the system of equations and compute the changes in the unknows, associated with a given change in import tariffs from $t_{ij,k}$ to $t'_{ij,k}$ and in other variable trade costs, from $\tau_{ij,k}$ to $\tau'_{ij,k}$. I then compute the welfare change using Equation (2.5).

2.4 Empirical results

This section presents the estimates for the welfare effects from changes in the tariff structure and in iceberg trade costs of capital goods in Brazil, assuming a number of different scenarios under our model, and compares the findings to an alternative approach.

Table 2.4: Aggregation of Sectors, Trade Elasticities and Capital Shares

WIOD sector	Agg.	Trade elasticity	Capital share
1 Agriculture, Hunting, Forestry and Fishing	1	8.11	0.330
2 Mining and Quarrying	2	15.72	0.461
3 Food, Beverages and Tobacco	3	2.55	0.223
4 Textiles and Textile Products 5 Leather, Leather and Footwear	4	5.56	0.225
6 Wood and Products of Wood and Cork	5	10.83	0.315
7 Pulp, Paper, Paper , Printing and Publishing	6	9.07	0.356
8 Coke, refined Petroleum and Nuclear Fuel	7	51.08	-
9 Chemicals and Chemical Products	8	4.75	0.281
10 rubber and Plastics	9	1.66	0.199
11 Other Non-Metallic Mineral	10	2.76	0.248
12 Basic Metals and Fabricated Metal	11	7.99	0.322
13 Machinery, Nec	12	1.52	0.280
14 Electrical and Optical Equipment	13	10.6	0.384
15 Transport Equipment	14	0.37	0.138
16 Manufacturing, Nec; recycling	15	5.00	0.331
17 Electricity, Gas and Water Supply	16	5.00	0.330
18 Construction	17	5.00	0.330
19 Sale, Maintenance and repair of Motor Vehicles and Motorcycles; retail Sale of Fuel 20 Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	18	5.00	0.330
21 retail Trade, Except of Motor Vehicles and Motorcycles; repair of Household Goods	19	5.00	0.330
22 Hotels and restaurants	20	5.00	0.330
23 Inland Transport	21	5.00	0.330
24 Water Transport	22	5.00	0.330
25 Air Transport	23	5.00	0.330
26 Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	24	5.00	0.330
27 Post and Telecommunications	25	5.00	0.330
28 Financial Intermediation	26	5.00	0.330
29 real Estate Activities	27	5.00	0.330
30 renting of M&Eq and Other Business Activities	28	5.00	0.330
32 Education	29	5.00	0.330
33 Health and Social Work	30	5.00	0.330
31 Public Admin and Defence; Compulsory Social Security 34 Other Community, Social and Personal Services 35 Private Households with Employed Persons	31	5.00	0.330

2.4.1 Counterfactual Analysis

What are the effects of the tariff policy regarding imports of capital equipment on the Brazilian economy? Firms who buy foreign machinery lose from higher tariffs while others might benefit from the tariff protection and revenue. Increased shares of expenditures into domestic products induced by tariffs may lead to changes in resources allocation across sectors. The tariff policy may have distributional consequences across sectors, with different patterns of input employment. I quantify the net economic effects of tariff changes performing three different counterfactual exercises, based on the general equilibrium model developed above. Welfare effects are defined as changes in real consumption, presented in Equation (2.5).

In the first counterfactual exercise, I introduce into the model the change in the trade policy imposed by the capital goods tariff exemption program in Brazil, that exempts a portion of the imports from the 14% tariff that is normally levied on foreign capital equipment. In all the analyses conducted here, I fix the tariff structure for the rest of the world and for the other sectors. In other words, the counterfactual measures the effect of tariff reductions conditional on no other tariff changing. Because the exercise relies on aggregate data, I am not able to simulate the tariff cuts at the transaction or firm-level, as they took place in Brazil. Instead, I consider the tariff reduction as a percentage cut on the average tariff levied over all equipment imports. In that way, an exercise with a tariff reduction of 10% could either mean that all firms pay 10% less tariffs in all equipment import transactions, or that 10% of the transactions, in terms of value, have full exemption.

The black line in Figure 2.1 illustrates the welfare gains considering tariff cuts of 10% up to 100% on capital equipment. I highlight in the graph the average tariff reduction that took place in 2008, of 13.9%.[6] This result shows that the exemption program increased welfare by 0.73%. This amounts to US$12.4 billions, or US$248 per household.[7] Further extension of the program would lead to even higher gains, with a full liberalization generating gains of 1.97%, or US$33.4 billions. The grey line shows the slope of the welfare curve at the 13.9% point, in order to better illustrate how the welfare curve becomes steeper the larger the tariff reduction is. That is, although the program benefited the Brazilian economy, deeper liberalization policies would have even stronger returns.

In the second counterfactual I measure the effects of a hypothetical liberalization policy towards each one of the partner countries. In each estimation, tariffs for all other countries are held fixed at the 14% level between the initial equilibrium and the counterfactual equilibrium. The rows in Table 2.5 present the welfare gains in Brazil from separate exercises, eliminating the tariff levied on imports from the single listed country, one at a time. As we can see, the magnitude of the gains in real consumption is larger for a trade liberalization in equipment imports from China, United States and Germany.

In the last comparative static exercise, I consider a counterfactual equilibrium in which Brazil eliminates the tariffs imposed towards every country and also reduces other variable trade costs, denoted by τ_{ij} in the model, such as transportation costs, bureaucratic delays and problems with negotiating a deal from afar. These barriers have been the subject of

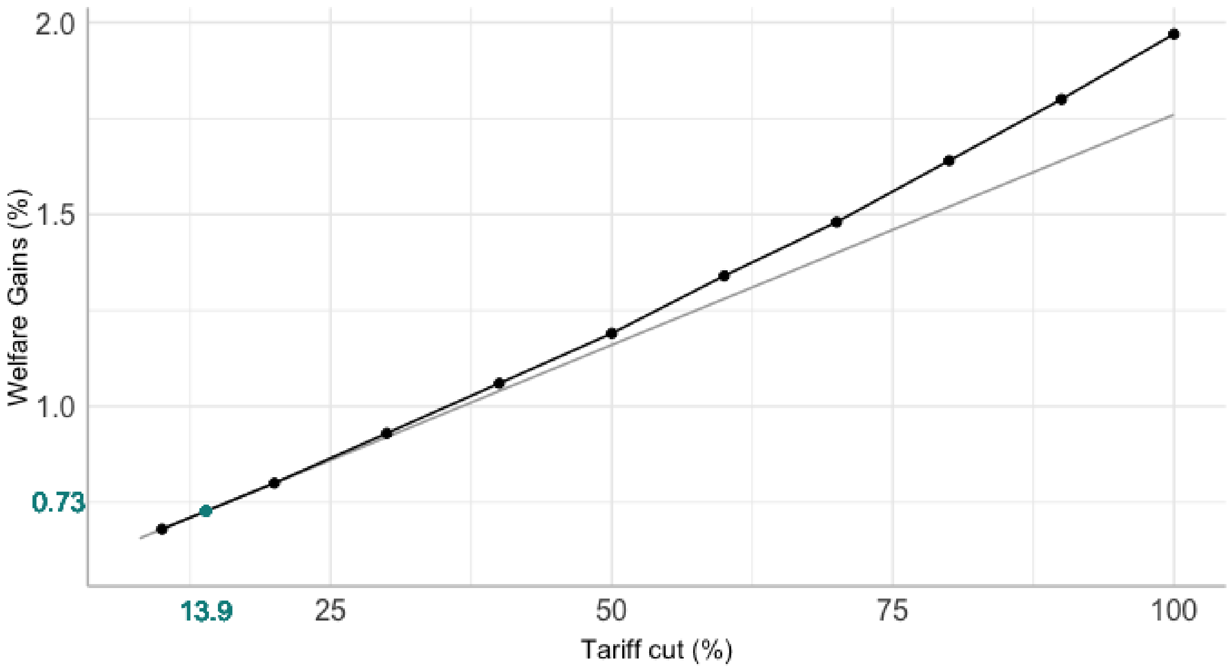
[6]This average tariff cut was calculated using Brazilian customs data from the Ministry of Economy. It implies an average machinery tariff of 14%*(1-13.9%)=12.05% for Brazil in 2008, which is also the number reported by the World Integrated Trade Solution (WITS) Database.

[7]Considering the GDP in current dollars from the World Bank national accounts data, in 2008. According to the 2010 Brazilian census, there were 49.976 million households in Brazil.

Table 2.5: Welfare Gains from Unilateral Liberalization in Capital Goods

Partner Country	**Welfare Gains %**
Australia	0.57
Austria	0.58
Belgium	0.57
Canada	0.58
China	0.90
Czech republic	0.57
Germany	0.70
Denmark	0.57
Spain	0.59
Finland	0.59
France	0.62
United Kingdom	0.59
Greece	0.57
Hungary	0.57
India	0.57
Indonesia	0.58
Ireland	0.57
Italy	0.64
Japan	0.62
Korea	0.61
Mexico	0.59
Netherlands	0.58
Poland	0.57
Portugal	0.57
Romania	0.57
Russia	0.57
Slovakia	0.57
Slovenia	0.57
Sweden	0.59
Turkey	0.57
Taiwan	0.59
United States	0.80

Figure 2.1: Percentage welfare change from a percentage tariff reduction in capital goods imports

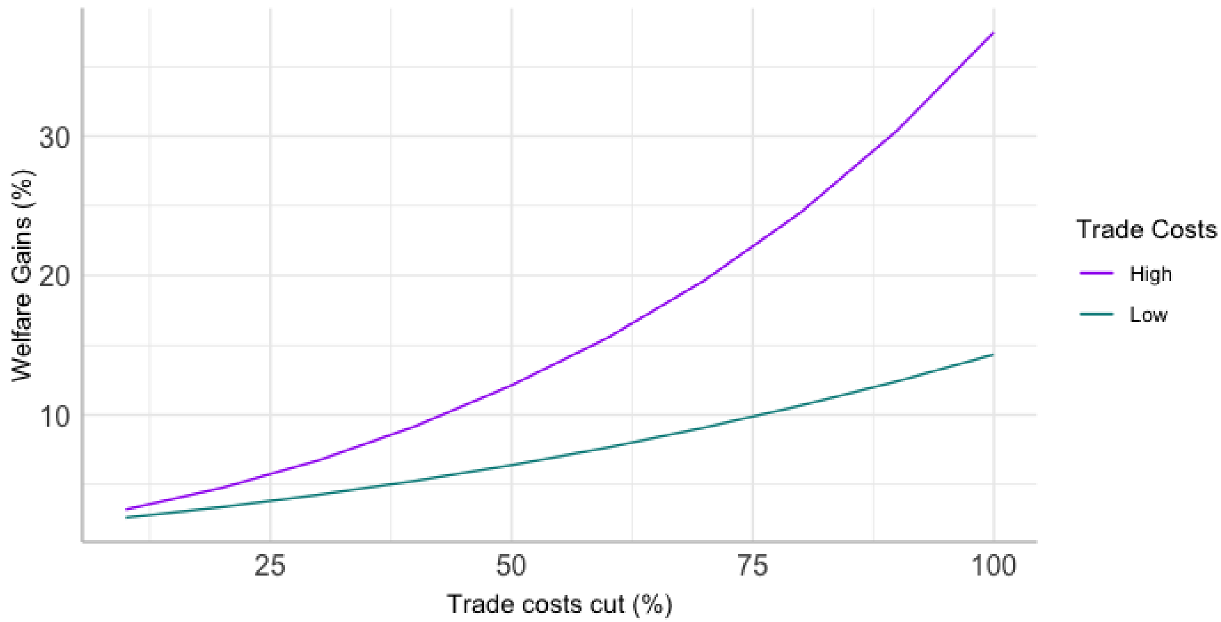


Notes: The horizontal axis shows the gradual percentage reduction of tariffs on imports of capital goods, from 10% up to 100% (complete elimination of tariffs). The green dot marks the average tariff cut under the Brazilian exemption program. The grey line shows the slope of the welfare curve at that average.

recent efforts to improve the simplification and harmonization of trade processes, through trade facilitation agreements.

I borrow the estimates of the percentage cost increase due to geographic barriers from Eaton and Kortum (2002). They estimate that a typical country in a close distance faces a 45 percent barrier relative to home sales, rising to 121 percent in the farthest distance category. I denote the former estimate by low trade costs and the latter by high trade costs. Figure 2.2 shows the percentage change in welfare estimated for decreases in the iceberg trade costs of 10% up to 100% (zero-gravity world). The complete elimination, or even the reduction of large shares of trade costs, are certainly not realistic and they are presented here with the sole purpose of serving as benchmarks. It turns out that, considering the lower threshold of trade costs, gains go from 2.62% to 14.33%, following reductions in costs of 10% to 100%, respectively. For the highest level estimate of trade costs, gains range between 3.20% and 37.46%.

Figure 2.2: Percentage welfare change from a percentage iceberg trade costs reduction in capital goods imports



Notes: The horizontal axis shows the gradual percentage reduction of iceberg trade costs, from 10% up to 100% (complete elimination of costs), in addition to a full tariff cut on imports of capital goods. The purple line illustrates the case in which iceberg trade costs are 121%. The green line shows the curve for trade costs of 45%. Trade costs estimates are borrowed from Eaton and Kortum (2002).

2.4.2 Alternative Approach

So far I have employed a static quantitative trade model. Eaton and Kortum (2001) develop a model to observe how the economy evolves over time in order to endogenize capital stocks.

In this subsection I implement their solution for the steady state productivity, derived from the model, and make a comparison with the results I obtained above.

The evolution of the capital stock is governed by investment and depreciation. The depreciation rate is denotated by δ and investment derives from the Solow assumption that each country i spends a fraction s_i of its income on capital goods. The driving force for long-term growth is technical progress in the production of capital, which proceeds at a constant rate g. Innovation can lower the price of the capital bundle P_{ik}. Assume a Cobb-Douglas production function, with capital share α, and denote the aggregate price of consumption goods by P_{iC}. The real product per capita results from the steady-state solution of the model:

$$y_i = [\frac{s_i}{(\delta + \frac{g}{1-\alpha})\frac{P_{ik}}{P_{iC}}}]^{\alpha/(1-\alpha)}.$$

The authors use the price index of consumption goods in the importing country as numeraire, $P_{iC} = 1$. Treating the technical progress and depreciation rates and the savings share as constant over time, we get

$$\hat{y} = (\frac{1}{\hat{P}_{ik}})^{\frac{\alpha}{1-\alpha}}.$$

Using the WIOD Database, I compute the share of imported capital equipment λ_k as the ratio of the sum of machinery and equipment trade flows into Brazil, in the column Gross Fixed Capital Formation, from all countries, except Brazil, $\sum_{j\neq BRA} X_{jBRA,k}$, over the total sum, including domestic flows, $\sum_j X_{jBRA,k}$:

$$\lambda_k = \frac{\sum_{j\neq BRA} X_{jBRA,k}}{\sum_j X_{jBRA,k}}$$

The value found for this import share is 32.8%. Considering a complete elimination of the import tariff on capital goods, from 14% to 0%, and a capital share α of one third, we find a welfare increase of 2.27%.[8] As we can see, the welfare change for Brazil is only slightly larger to the one we find in the previous subsection, which is reassuring.

2.5 Conclusion

This study develops a general equilibrium model to quantify the welfare effects, measured in terms of percentage changes in real consumption, from a tariff policy change in capital goods. Our findings add new evidence to the literature advocating that accounting for tradable capital goods in trade models is economically meaningful. Exploring the Brazilian case, the results show that the tariff exemption program increased welfare by 0.73%, equivalent to US$12.4 billions. Further extension of the program would lead to even higher gains, with a full liberalization generating gains of 1.97%, or US$33.4 billions.

The net effect results from heterogeneous impacts across partner countries driven by patterns of specialization in producing and exporting equipment. The unilateral policy change counterfactual exercises imply that increased access to capital goods from all countries lead to gains, with China being the partner country that presents the largest potential gains to Brazil.

The economy would have experienced an even more substantial gain if it made further efforts to reduce other variable trade costs, such as transportation and bureaucracy costs, when importing capital equipment. This suggests an important role for trade facilitation agreements focusing on capital goods.

These estimates using an ACR-type formula of comparative static analysis are comparable

[8] $1/\hat{P}_{ik} = 1.14 * 32.8\% + 1 * 67.2\% = 1.046$ and $\hat{y} = 1.0227$.

to what one obtains using Eaton and Kortum's (2001) dynamic setting and calibration technique.This alternative approach, based on Solow's (1960) model of technological change embodied in new capital equipment generates a much simpler back of the envelope way of calculating welfare gains from a reduction in capital goods tariffs. In that way, we have a new capital goods trade model and same old gains.

Appendix 2.A Prices and Expenditure Shares Solution

Following Eaton and Kortum (2002) and Caliendo and Parro (2015), the efficiency of country i in producing a variety ω is the realization of a random variable z, drawn from the Fréchet distribution $F_{i,s}(z) = e^{-T_i z^{-\theta_s}}$. Remember that the cost of purchasing a variety ω from country i, denoted by $p_{ij,s}(z_i)$, is the realization of the random variable $p_{ij,s}(z_i) = \phi_{ij,s} c_{i,s}/z_i$. It follows that $p_{ij,s}(z_i)$ has a Fréchet distribution:

$$G_{ij,s}(p) = \Pr[p_{ij,s}(z_i) \leq p] \Leftrightarrow$$

$$G_{ij,s}(p) = \Pr[\frac{\phi_{ij,s} c_{i,s}}{z_i} \leq p] \Leftrightarrow$$

$$G_{ij,s}(p) = \Pr[\frac{\phi_{ij,s} c_{i,s}}{p} \leq z_i] \Leftrightarrow$$

$$G_{ij,s}(p) = 1 - e^{-T_i(\phi_{ij,s} c_{i,s})^{-\theta_s} p^{\theta_s}}.$$

The lowest price of a variety ω in country j, $p_{j,s}(\omega) = \min\{p_{ij,s}(\omega), i = 1, ..., N\}$, has also a Fréchet distribution:

$$G_{j,s}(p) = \Pr[p_{j,s} \leq p] \Leftrightarrow$$

$$G_{j,s}(p) = 1 - \prod_{i=1}^{N} \Pr[p_{ij,s} \geq p] \Leftrightarrow$$

$$G_{j,s}(p) = 1 - e^{-\Phi_{j,s} p^{\theta_s}},$$

where $\Phi_{j,s} = \sum_{i=1}^{N} T_i(\phi_{ij,s} c_{i,s})^{-\theta_s}$. The price index of sector s varieties in country j is then:

$$P_{j,s} = \left(\int_{\Omega_{j,s}} p_{j,s}(\omega)^{1-\sigma_s} d\omega \right)^{1/(1-\sigma_s)} \Leftrightarrow$$

$$P_{j,s}^{1-\sigma_s} = \int_0^\infty p^{1-\sigma_s} dG_{j,s}(p) \Leftrightarrow$$

$$P_{j,s}^{1-\sigma_s} = \int_0^\infty \theta_s \Phi_{j,s} p^{\theta_s - \sigma_s} e^{-\Phi_{j,s} p^{\theta_s}} dp.$$

Consider the change of variables $u = p^{\theta_s}\Phi_{j,s}$. Then:

$$P_{j,s}^{1-\sigma_s} = \Phi_{j,s}^{-(1-\sigma_s)/\theta_s}\left(\int u^{(1-\sigma_s)/\theta_s}e^{-u}du\right)$$

$$P_{j,s} = A_s\Phi_{j,s}^{-\frac{1}{\theta_s}}$$

where $A_s = \Gamma(1+\frac{1-\sigma_s}{\theta_s})^{1/(1-\sigma_s)}$ and Γ is a Gamma function. Thus:

$$P_{j,s} = A_s[\sum_i(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}]^{-\frac{1}{\theta_s}}. \tag{2.6}$$

Now consider the probability that country i is the the lowest cost supplier of variety ω to destination j, which equals the fraction of varieties that country i sells to j. This probability is also the fraction of j's expenditure spent on varieties from i:

$$\lambda_{ij,s} = \Pr(p_{ij,s} \leq \min_l\{p_{lj,s}(\omega)\}) \Leftrightarrow$$

$$\lambda_{ij,s} = \int_0^\infty \Pr(p \leq \min_l\{p_{lj,s}(\omega)\})dG_{ij,s}(p) \Leftrightarrow$$

$$\lambda_{ij,s} = \int_0^\infty \prod_l(1-G_{lj,s}(p))dG_{ij,s}(p) \Leftrightarrow$$

$$\lambda_{ij,s} = \int_0^\infty T_{i,s}(\phi_{ij,s}c_{i,s})^{-\theta_s}\theta_s p^{\theta_s-1}e^{-\Phi_{j,s}p^{\theta_s}}dp \Leftrightarrow$$

$$\lambda_{ij,s} = \frac{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}{\Phi_{j,s}}.$$

Thus:

$$\lambda_{ij,s} = \frac{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}{\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}}. \tag{2.7}$$

Appendix 2.B Price Index by Origin

I present the expression for the price of the composite good of varieties from sector s and country i purchased in country j, $P_{ij,s}$, as seen in Costinot and Rodríguez-Clare (2014).

Using Eq (2.3):

$$P_{ij,s} = P_{j,s}\left(\frac{X_{ij,s}}{X_{j,s}}\right)^{\frac{1}{1-\sigma_s}},$$

and the expenditure share solution from Equation (2.7)

$$\lambda_{ij,s} = \frac{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}{\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}},$$

we obtain

$$P_{ij,s} = P_{j,s}\left(\frac{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}{\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}}.\right)^{\frac{1}{1-\sigma_s}}.$$

Now using the price index solution from Equation (2.6)

$$P_{j,s} = A_s[\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}]^{-\frac{1}{\theta_s}},$$

we get

$$P_{ij,s} = A_s[\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}]^{-\frac{1}{\theta_s}}\left(\frac{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}{\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}}\right)^{\frac{1}{1-\sigma_s}}.$$

Since $\frac{1}{\theta_s} + \frac{1}{1-\sigma_s} = -\frac{\eta_s}{\theta_s}$:

$$P_{ij,s} = \frac{A_s(\phi_{ij,s}c_{i,s})^{1+\eta_s}T_{i,s}^{\frac{1}{1-\sigma_s}}}{(\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s})^{-\frac{\eta_s}{\theta_s}}} \Leftrightarrow$$

$$P_{ij,s} = \frac{A_s(\phi_{ij,s}c_{i,s})^{1+\eta_s}T_{i,s}^{\frac{1}{1-\sigma_s}}}{A_s^{-\eta_s}A_s^{\eta_s}(\sum_l(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s})^{-\frac{\eta_s}{\theta_s}}} \Leftrightarrow$$

$$P_{ij,s} = \frac{(\phi_{ij,s}c_{i,s})^{1+\eta_s}A_s^{1+\eta_s}T_{i,s}^{\frac{1}{1-\sigma_s}}}{P_{j,s}^{\eta_s}}.$$

Appendix 2.C Tariff Revenues and Expenditure

This appendix presents a detailed derivation of the expression for the total expenditure. recall that tariff revenues are obtained from: $T_j = \sum_{i=1}^n \frac{t_{ij,k}}{1+t_{ij,k}}X_{ij,k}$. We plug in the expression

$X_{ij.k} = \lambda_{ij,k} E_{j,k}$, derived from the expenditure shares definition, and we substitute for the total expenditure definition given by Equation (2.4) to get

$$T_j = \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\beta_{j,k}(Y_j + T_j) + \sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right).$$

Isolating T_j, we obtain

$$T_j = \frac{\sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\beta_{j,k} Y_j + \sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}}. \tag{2.8}$$

Substituting for T_j into the expenditure expression given by Equation (2.4), we get

$$E_{j,l} = \beta_{j,l}(Y_j + \frac{\sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\beta_{j,k} Y_j + \sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}}) + \sum_{r=1}^{k} \alpha_{j,lr} R_{j,r} \Leftrightarrow$$

$$E_{j,l} = \beta_{j,l} Y_j + \frac{\beta_{j,l} \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\beta_{j,k} Y_j + \sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}}) + \sum_{r=1}^{k} \alpha_{j,lr} R_{j,r} \Leftrightarrow$$

$$E_{j,l} = \frac{\beta_{j,l} Y_j - \beta_{j,l} Y_j \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k} + \beta_{j,l} \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\beta_{j,k} Y_j + \sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}}) +$$

$$\sum_{r=1}^{k} \alpha_{j,lr} R_{j,r} \Leftrightarrow$$

$$E_{j,l} = \frac{\beta_{j,l} Y_j + \beta_{j,l} \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}}) + \sum_{r=1}^{k} \alpha_{j,lr} R_{j,r}.$$

Appendix 2.D Welfare

We can rewrite the expenditure share solution from Equation (2.7) in Appendix A as:

$$\lambda_{ij,s} = \frac{(\phi_{ij,s} c_{i,s})^{-\theta_s} \xi_{ij,s}^{1-\sigma_s}}{P_{j,s}^{-\theta_s}}$$

Using the fact that $\phi_{jj,s} = 1$, we get

$$P_{j,s} = \lambda_{jj,s}^{1/\theta_s} c_{j,s} \chi_{jj,s}^{-1/\theta_s},$$

where $\chi_{ij,s} = \xi_{ij,s}^{1-\sigma_s}$.

Substituting for the definition of $c_{i,s}$ in Equation (2.1):

$$P_{j,s} = \lambda_{jj,s}^{1/\theta_s} Y_j^{(1-\alpha_{j,s}-\alpha_{j,ks})} P_{j,k}^{\alpha_{j,ks}} \prod_{r=1}^{S} P_{j,r}^{\alpha_{j,rs}} \chi_{jj,s}^{-1/\theta_s}.$$

Taking logs yields

$$\ln P_{j,s} = \ln[\lambda_{jj,s}^{1/\theta_s} Y_j^{(1-\alpha_{j,s}-\alpha_{j,ks})} \chi_{jj,s}^{-1/\theta_s}] + \sum_{r=1}^{k} \alpha_{j,rs} \ln P_{j,r}$$

In matrix notation, this leads to the system of equations

$$(I - A_j) \ln \mathbf{P}_j = \ln \mathbf{B}_j,$$

where $A_j = \{\alpha_{j,sr}\}$, $\mathbf{P}_j$ and $\mathbf{B}_j$ are $S \times 1$ vectors with elements $P_{j,s}$ and $[\lambda_{jj,s}^{1/\theta_s} Y_j^{(1-\alpha_{j,s}-\alpha_{j,ks})} \chi_{jj,s}^{-1/\theta_s}]$, respectively. Inverting the system implies

$$\ln P_j = (Id - A_j)^{-1} \ln \mathbf{B}_j \Leftrightarrow$$

$$P_{j,s} = \prod_{r=1}^{k} [\lambda_{jj,r}^{1/\theta_r} Y_j^{(1-\alpha_{j,r}-\alpha_{j,kr})} \chi_{jj,r}^{-1/\theta_r}]^{a_{j,sr}},$$

where $a_{j,sr}$ is the (s,r) entry of the matrix $(I - A_j)^{-1}$, the Leontief inverse of the input-output matrix, including capital goods k. These technology parameters reflect the elasticity of the price index in sector s with respect to changes in the price index in sector r. Because $\sum_{r=1}^{k}(1 - \alpha_{j,r} - \alpha_{j,kr})a_{j,sr} = 1$, the expression simplifies to

$$P_{j,s} = Y_j \prod_{r=1}^{k} [\lambda_{jj,r}^{1/\theta_r} \chi_{jj,r}^{-1/\theta_r}]^{a_{j,sr}}.$$

Because we assume that the upper-level utility functions are Cobb-Douglas,

$$P_j = \prod_{s=1}^{k} P_{j,s}^{\beta_{j,s}},$$

and we get the final expression for the price index:

$$P_j = Y_j \prod_{s=1} \prod_{r=1} [\lambda_{jj,r}^{-1} \chi_{jj,r}]^{-\beta_{j,s} a_{j,sr}/\theta_r}.$$

Real consumption is given by $C_j = (Y_j + T_j)/P_j$. We substitute for the tax revenues expression obtained in Equation (2.8) and the price index we just found to get

$$C_j = (Y_j + \frac{\sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\beta_{j,k} Y_j + \sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}}) \times Y_j^{-1} \prod_{s=1} \prod_{r=1} [\lambda_{jj,r}^{-1} \chi_{jj,r}]^{\beta_{j,s} a_{j,sr}/\theta_r}.$$

Appendix 2.E Hat Algebra

The hat algebra is a tool for comparative static analysis. Dekle et al. (2008) argue that rather than estimating a model in terms of levels, we can specify the model in terms of changes from the current equilibrium, via elasticities and trade shares. We write $\hat{\nu} = \nu'/\nu$ for the proportional change in any variable ν between the initial and counterfactual equilibria. I then solve the linear system for an equilibrium after changing from policy t to policy t'.

Here I present the detailed derivation of the system of equations in relative changes, summarized in Table 1.

1. Cost of the input bundles:

$$c_{i,s} = Y_i^{1-\alpha_{i,s}-\alpha_{i,ks}} P_{i,k}^{\alpha_{i,ks}} \prod_{r=1}^{S} P_{i,r}^{\alpha_{i,rs}}$$

$$\frac{c'_{i,s}}{c_{i,s}} = \frac{Y_i'^{1-\alpha_{i,s}-\alpha_{i,ks}} P_{i,k}'^{\alpha_{i,ks}} \prod_{r=1}^{S} P_{i,r}'^{\alpha_{i,rs}}}{Y_i^{1-\alpha_{i,s}-\alpha_{i,ks}} P_{i,k}^{\alpha_{i,ks}} \prod_{r=1}^{S} P_{i,r}^{\alpha_{i,rs}}}$$

$$\hat{c}_{i,s} = \hat{Y}_i^{1-\alpha_{i,s}-\alpha_{i,ks}} \hat{P}_{i,k}^{\alpha_{i,ks}} \prod_{r=1}^{S} \hat{P}_{i,r}^{\alpha_{i,rs}}.$$

2. Price index of capital goods:

$$P_{i,k} = A_k[\sum_j (\phi_{ji,k} c_{j,k})^{-\theta_k} T_{j,k}]^{-\frac{1}{\theta_k}}$$

$$\frac{P'_{i,k}}{P_{i,k}} = \frac{A_k[\sum_j (\phi'_{ji,k} c'_{j,k})^{-\theta_k} T_{j,k}]^{-\frac{1}{\theta_k}}}{A_k[\sum_l (\phi_{li,k} c_{l,k})^{-\theta_k} T_{l,k}]^{-\frac{1}{\theta_k}}}$$

$$\frac{P'_{i,k}}{P_{i,k}} = \sum_j \frac{[(\phi'_{ji,k} c'_{j,k})^{-\theta_k} T_{j,k}]^{-\frac{1}{\theta_k}}}{[\sum_l (\phi_{li,k} c_{l,k})^{-\theta_k} T_{l,k}]^{-\frac{1}{\theta_k}}}$$

$$\hat{P}_{i,k} = \left(\sum_{j=1}^{n} \frac{(\phi_{ji,k} c_{j,k})^{-\theta_k} T_{j,k}}{\sum_l (\phi_{li,k} c_{l,k})^{-\theta_k} T_{l,k}} (\frac{\phi'_{ji,k}}{\phi_{ji,k}} \frac{c'_{j,k}}{c_{j,k}})^{-\theta_k} \right)^{-\frac{1}{\theta_k}}.$$

Using the expenditure share expression from Equation (2.7):

$$\hat{P}_{i,k} = \left(\sum_{j=1}^{n} \lambda_{ji,k} (\hat{\phi}_{ji,k} \hat{c}_{j,k})^{-\theta_k} \right)^{-\frac{1}{\theta_k}}.$$

3. Price indices for intermediate goods in sectors $r = 1, ..., S$:

$$P_{i,r} = A_r[\sum_j (\tau_{ji,r} c_{j,r})^{-\theta_r} T_{j,r}]^{-\frac{1}{\theta_r}}$$

$$\frac{P'_{i,r}}{P_{i,r}} = \frac{A_r[\sum_j (\tau'_{ji,r} c'_{j,r})^{-\theta_r} T_{j,r}]^{-\frac{1}{\theta_r}}}{A_r[\sum_l (\tau_{li,r} c_{l,r})^{-\theta_r} T_{l,r}]^{-\frac{1}{\theta_r}}}$$

$$\frac{P'_{i,r}}{P_{i,r}} = \sum_j \frac{[(\tau'_{ji,r} c'_{j,r})^{-\theta_r} T_{j,r}]^{-\frac{1}{\theta_r}}}{[\sum_l (\tau_{li,r} c_{l,r})^{-\theta_r} T_{l,r}]^{-\frac{1}{\theta_r}}}$$

$$\hat{P}_{i,r} = \left(\sum_{j=1}^{n} \frac{(\tau_{ji,r} c_{j,r})^{-\theta_r} T_{j,r}}{\sum_l (\tau_{li,r} c_{l,r})^{-\theta_r} T_{l,r}} (\frac{\tau'_{ji,r}}{\tau_{ji,r}} \frac{c'_{j,r}}{c_{j,r}})^{-\theta_r} \right)^{-\frac{1}{\theta_r}}.$$

Using the expenditure share expression from Equation (2.7):

$$\hat{P}_{i,r} = \left(\sum_{j=1}^{n} \lambda_{ji,r} (\hat{\tau}_{ji,r} \hat{c}_{j,r})^{-\theta_r} \right)^{-\frac{1}{\theta_r}}.$$

4. Expenditure shares:

$$\lambda_{ij,s} = \frac{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}{\sum_l (\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}}$$

$$\frac{\lambda'_{ij,s}}{\lambda_{ij,s}} = \frac{(\phi'_{ij,s}c'_{i,s})^{-\theta_s}T_{i,s}}{\sum_l (\phi'_{lj,s}c'_{l,s})^{-\theta_s}T_{l,s}} \frac{\sum_h (\phi_{hj,s}c_{h,s})^{-\theta_s}T_{h,s}}{(\phi_{ij,s}c_{i,s})^{-\theta_s}T_{i,s}}$$

$$\hat{\lambda}_{ij,s} = \frac{(\hat{\phi}_{ij,s}\hat{c}_{i,s})^{-\theta_s}}{\sum_l \frac{(\phi_{lj,s}c_{l,s})^{-\theta_s}T_{l,s}}{\sum_h (\phi_{hj,s}c_{h,s})^{-\theta_s}T_{h,s}} (\frac{\phi'_{lj,s}}{\phi_{lj,s}} \frac{c'_{l,s}}{c_{l,s}})^{-\theta_s}}$$

$$\hat{\lambda}_{ij,s} = \frac{(\hat{\phi}_{ij,s}\hat{c}_{i,s})^{-\theta_s}}{\sum_l \lambda_{lj,s}(\hat{\phi}_{lj,s}\hat{c}_{l,s})^{-\theta_s}}.$$

5. Total expenditure in country j and sector s:

$$E_{j,s} = \frac{\beta_{j,s}Y_j + \beta_{j,s}\sum_{i=1}^n \frac{t_{ij,k}}{1+t_{ij,k}}\lambda_{ij,k}\left(\sum_{r=1}^k \alpha_{j,kr}R_{j,r}\right)}{1-\sum_{i=1}^n \frac{t_{ij,k}}{1+t_{ij,k}}\lambda_{ij,k}\beta_{j,k}}) + \sum_{r=1}^k \alpha_{j,sr}R_{j,r}$$

$$\frac{E'_{j,s}}{E_{j,s}}E_{j,s} = \frac{\beta_{j,s}\left(\frac{Y'_j}{Y_j}Y_j + \sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\frac{\lambda'_{ij,k}}{\lambda_{ij,k}}\lambda_{ij,k}\sum_{r=1}^k \alpha_{j,kr}\frac{R'_{j,r}}{R_{j,r}}R_{j,r}\right)}{1-\sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\frac{\lambda'_{ij,k}}{\lambda_{ij,k}}\lambda_{ij,k}\beta_{j,k}} + \sum_{r=1}^k \alpha_{j,sr}\frac{R'_{j,r}}{R_{j,r}}R_{j,r}.$$

The expression for the relative change in total expenditure is

$$\hat{E}_{j,s}E_{j,s} = \frac{\beta_{j,s}\left(\hat{Y}_jY_j + \sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\hat{\lambda}_{ij,k}\lambda_{ij,k}\sum_{r=1}^k \alpha_{j,kr}\hat{R}_{j,r}R_{j,r}\right)}{1-\sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\hat{\lambda}_{ij,k}\lambda_{ij,k}\beta_{j,k}} + \sum_{r=1}^k \alpha_{j,sr}\hat{R}_{j,r}R_{j,r}.$$

Let

$$(\widehat{Y_j+T_j}) = \frac{1}{Y_j+T_j} \times \left(\hat{Y}_jY_j + \frac{\sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\hat{\lambda}_{ij,k}\lambda_{ij,k}(\beta_{j,k}\hat{Y}_jY_j + \sum_{r=1}^k \alpha_{j,kr}\hat{R}_{j,r}R_{j,r})}{1-\sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\hat{\lambda}_{ij,k}\lambda_{ij,k}\beta_{j,k}}\right) \Leftrightarrow$$

$$(\widehat{Y_j+T_j}) = \frac{1}{Y_j+T_j} \times \left(\frac{\hat{Y}_jY_j + \sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\hat{\lambda}_{ij,k}\lambda_{ij,k}(\sum_{r=1}^k \alpha_{j,kr}\hat{R}_{j,r}R_{j,r})}{1-\sum_{i=1}^n \frac{t'_{ij,k}}{1+t'_{ij,k}}\hat{\lambda}_{ij,k}\lambda_{ij,k}\beta_{j,k}}\right).$$

Then we can further simplify the expenditure expression as

$$\hat{E}_{j,s}E_{j,s} = \beta_{j,s}(\widehat{Y_j+T_j})(Y_j+T_j) + \sum_{r=1}^k \alpha_{j,sr}\hat{R}_{j,r}R_{j,r}.$$

6. Revenues:

$$R_{i,s} = \sum_{j=1}^{n} \frac{\lambda_{ij,s}}{1+t_{ij,s}} E_{j,s}$$

$$\frac{R'_{i,s}}{R_{i,s}} R_{i,s} = \sum_{j=1}^{n} \frac{\frac{\lambda'_{ij,s}}{\lambda_{ij,s}} \lambda_{ij,s}}{1+t'_{ij,s}} \frac{E'_{j,s}}{E_{j,s}} E_{j,s}$$

$$\hat{R}_{i,s} R_{i,s} = \sum_{j=1}^{n} \frac{\hat{\lambda}_{ij,s} \lambda_{ij,s}}{1+t'_{ij,s}} \hat{E}_{j,s} E_{j,s}.$$

7. Total income:

$$Y_i = \sum_{s=1}^{k} (1 - \alpha_{i,s} - \alpha_{i,ks}) R_{i,s}$$

$$\frac{Y'_i}{Y_i} Y_i = \sum_{s=1}^{k} (1 - \alpha_{i,s} - \alpha_{i,ks}) \frac{R'_{i,s}}{R_{i,s}} R_{i,s}$$

$$\hat{Y}_i Y_i = \sum_{s=1}^{k} (1 - \alpha_{i,s} - \alpha_{i,ks}) \hat{R}_{i,s} R_{i,s}.$$

8. Real consumption:

$$C_j = \frac{Y_j + T_j}{Y_j} \times \prod_{s=1} \prod_{r=1} [\lambda_{jj,r}^{-1} \chi_{jj,r}]^{\beta_{j,s} a_{j,sr}/\theta_r}$$

where

$$T_j = \frac{\sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\beta_{j,k} Y_j + \sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}}.$$

$$C_j = \left(\frac{Y_j + \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \left(\sum_{r=1}^{k} \alpha_{j,kr} R_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t_{ij,k}}{1+t_{ij,k}} \lambda_{ij,k} \beta_{j,k}} \right) \times Y_j^{-1} \prod_{s=1} \prod_{r=1} [\lambda_{jj,r}^{-1} \chi_{jj,r}]^{\beta_{j,s} a_{j,sr}/\theta_r}$$

$$\frac{C'_j}{C_j} = \left(\frac{Y'_j + \sum_{i=1}^{n} \frac{t'_{ij,k}}{1+t'_{ij,k}} \lambda'_{ij,k} \left(\sum_{r=1}^{k} \alpha_{j,kr} R'_{j,r} \right)}{1 - \sum_{i=1}^{n} \frac{t'_{ij,k}}{1+t'_{ij,k}} \lambda'_{ij,k} \beta_{j,k}} \right) \times Y_j^{\prime -1} \prod_{s=1} \prod_{r=1} [\lambda_{jj,r}^{\prime -1} \chi_{jj,r}]^{\beta_{j,s} a_{j,sr}/\theta_r}$$

$$\times \frac{Y_j}{(Y_j + T_j)} \times \prod_{s=1} \prod_{r=1} [\lambda_{jj,r}^{-1} \chi_{jj,r}]^{-\beta_{j,s} a_{j,sr}/\theta_r}$$

$$\hat{C}_j = \frac{\widehat{(Y_j + T_j)}}{\hat{Y}_j} \times \prod_{s=1} \prod_{r=1} [\hat{\lambda}_{jj,r}^{-1}]^{\beta_{j,s} a_{j,sr}/\theta_r}, \tag{2.9}$$

where

$$\widehat{(Y_j + T_j)} = \frac{Y_j' + T_j'}{Y_j + T_j}.$$

That is,

$$\widehat{(Y_j + T_j)} = \frac{1}{Y_j + T_j} \times \left(\frac{\hat{Y}_j Y_j + \sum_{i=1}^{n} \frac{t'_{ij,k}}{1+t'_{ij,k}} \hat{\lambda}_{ij,k} \lambda_{ij,k} (\sum_{r=1}^{k} \alpha_{j,kr} \hat{R}_{j,r} R_{j,r})}{1 - \sum_{i=1}^{n} \frac{t'_{ij,k}}{1+t'_{ij,k}} \hat{\lambda}_{ij,k} \lambda_{ij,k} \beta_{j,k}} \right).$$

Chapter 3

Technological Diffusion: Does Multinational Presence Encourage the Adoption of New Technology?

3.1 Introduction

The diffusion of technological innovation across firms and across international borders has proven to be fundamental for productivity growth. For most countries, foreign sources of technology are estimated to account for 90% or more of domestic productivity growth (Keller, 2010). Most of the world's innovation effort occurs in only a few of developed countries. The pattern of worldwide technical change is thus determined in large part by international technology diffusion.

Good data on diffusion have been difficult to observe, though. Evidence on the adoption patterns of new technologies across countries is rarely collected. Past research has thus relied on a collection of indirect evidence. Since data are available on investments in tangible capital, some studies consider the technologies that are embodied in capital goods. This also allows one to investigate international diffusion, as capital goods are highly traded. Thus, equipment imports are a natural starting point for thinking about how a country can acquire technology from abroad. Indeed, for developing countries, a large fraction of their total investment in producer equipment consists of imported goods coming from advanced countries. Although there are good data on the source and type of the equipment, the lack of detailed data on the specific technologies embodied in capital goods has limited previous research from observing actual arrival and penetration rates. In this paper, I aim to fill the detailed data gap in the literature by taking advantage of a trade in capital goods dataset that contains narrowly defined products. This allows me to identify the first firm to adopt a technology and to track subsequent adoptions.

Another channel for thinking about the international diffusion of technology is foreign direct investment (FDI) activity. The majority of business research and development is performed by multinational companies. In 2010, for example, 71% of the R&D in the United States were performed by U.S. multinational parent companies (NSF, 2016). Empirical evidence shows that multinationals use more advanced technologies than domestic firms, for both developed and developing economies (survey in Alfaro et al. (2004)). Given their higher innovation productivity, the potential for technological learning from foreign firms is thus higher than for learning from the average domestic firm. Therefore, FDI can be a source of valuable productivity externalities for developing countries.

The main goal of this study is to contribute to the understanding of the determinants of technology diffusion and the role of multinationals in this process. To make progress on these challenges, I bring together rich datasets. I employ a register database, which covers the universe of trade transactions by firm, product and destination. Second, I obtain detailed information on the imports of capital goods in Brazil under a special tariff regime, which contains the full description of the technology. This nice feature allows me to follow the adoption of specific technologies by different firms over time and across space within Brazil.

I find evidence of important spillovers from multinationals: they are importers of new technology later followed by other firms. This implies that the presence of foreign competitors encourages investment in new technologies by local firms. Regarding the determinants of the adoption lag, I show that equipment of higher value, imported by multinationals and by larger firms, take longer to be diffused. I also report that first adopters experience a very large increase in their export growth following the investment in the foreign capital (23 percentage points), while follower firms can still get an important benefit from the import too (6 percentage points). The gains for followers of multinationals are higher (10.7 percentage points) than the average of followers. This finding has important implications for capital policy. As foreign investment is liberalized, negative effects due to competitor entry are counter-balanced by positive effects on exports. Finally, I show that the type of technology adopted varies greaty across the country and is correlated with local factor availability.

This work builds on a large literature modeling innovation and diffusion of technologies. Looking for precise measures of diffusion, some studies have focused on tracking a small number of innovations. Stokey (2020) reviews micro data analyses on adoption patterns and rates in the U.S. and across international boundaries of specific technologies. Caselli and Coleman (2001) presents a case study of the diffusion of computer technology over the period 1970-1990. In particular, they identify variables that predict the adoption of computers in a panel of countries. They find that computer adoption is associated with high levels of human capital, manufacturing trade openness, property-rights protection, high rates of investment per worker, and a small share of agriculture in GDP. There is also some evidence for a negative role of the size of government. Different from these papers, I do not focus on a single technology.

Other studies of cross-country diffusion have asked what country characteristics explain faster adoption. In the last step of the empirical analysis, I follow the nine categories of capital equipment identified by Caselli and Wilson (2004), who document large cross-country differences in import shares across categories. The authors construct stocks of equipment in each sector by combining share data on capital goods imports and data on aggregate investment.

Comin and Hobijn (2004) build a dataset that spans two centuries and examine the diffusion of 25 technologies across 23 countries. The authors document the common patterns observed in the diffusion: most technologies originate in advanced economies, get adopted there first, and, subsequently, diffuse to countries that lag economically; the most important determinants of the speed at which a country adopts technologies are the country's human capital endowment, type of government, degree of openness to trade, and adoption of predecessor technologies; the overall rate of diffusion has increased markedly over time because of the convergence in these variables across countries.

Using a sample of 139 countries, Comin and Mestieri (2018) estimate an average adoption lag of 42 years and an average intensity of adoption twice as large in Western countries. They find that differences in the evolution of technology diffusion are responsible for 75 percent of the increase in the income gap between countries during the period of 1820 to 2000. This paper complements the previous studies by looking at more detailed technology data and by linking adoption patterns to local economic characteristics, at the state level.

The literature also studies alternative channels of technology transfers. Santacreu (2020) focuses on technology transfer that takes place through licensing of intellectual property, recorded in the balance of payments of a country as a trade in services. Another channel is the knowledge spillover from international trade. According to this argument, accelerating the cross-country transfer of new technologies can also boost domestic innovation. Trade models that incorporate technology diffusion predict higher gains from liberalization relative to a model without diffusion. For example, Buera and Oberfield (2020) model innovation as a process involving the combination of new ideas with insights from other industries or countries. Trade openness affects the creation and diffusion of ideas by determining the distribution from which producers draw their insights. It also affects the quality of the insights drawn by producers because it determines the set of sellers to a country and the set of technologies used domestically. As a country opens up to trade the set of domestic producers improves as the unproductive technologies are selected out. This raises the quality of insights drawn and increases the growth rate of the stock of knowledge. They find that both gains from trade and the fraction of variation of TFP growth accounted for by changes in trade more than double relative to a model without diffusion. Keller (2010) surveys empirical studies that find evidence for technology spillovers from both international trade and the activity of multinational enterprises.

This work is also related to the strand of the literature that focuses on finding evidence of externalities from the presence of multinational corporations in a country or sector by exploring whether they are associated with increases in the productivity of local firms in that country or sector or in upstream sectors. My focus differs from these studies in that I measure spillovers from multinational presence on technology adoption and export growth.

Harrison and Rodriguez-Clare (2010) and Kose et al. (2010) report mixed evidence in their overviews of the literature on the relationship between FDI, productivity, and economic growth. While some of the surveyed studies conclude that nations with greater openness to multinational production have been shown to exhibit, on average, higher aggregate productivity and faster economic growth, others tend to find that other complementary policies need to be in place to maximize the gains from inward foreign investment. Harrison and Rodriguez-Clare (2010) find evidence that multinational firms conduct more product and process innovation, adopting new machines and foreign technologies, leading to higher productivity. Arnold and Javorcik (2009) show evidence that the productivity boost is achieved partly through massive investments in machinery.

The empirical results seem to depend on the measures of equity market liberalization, the sample period, industry or country coverage and choice of empirical methodology. Keller and Yeaple (2009), for example, find that productivity gains are particularly strong in high-tech sectors, whereas they are largely absent in low-tech sectors. Also, small firms with low productivity benefit more from FDI spillovers than firms with more productivity do. Javorcik (2004) finds spillovers associated with projects with shared domestic and foreign ownership but not with fully owned foreign investments.

Although the aggregate growth benefits of FDI flows are hard to document, reassessments of the mechanisms through which technological spillovers from FDI inflows occur have begun to show more positive evidence of such productivity externalities. Among the mechanisms often highlighted for these externalities are production linkages, sharing common inputs, and labor mobility.

The multinational affiliate might generate technological learning spillovers to domestic firms in the industry through its business operations. The literature refers to these within-industry effects as horizontal FDI spillovers. The work of Keller and Yeaple (2009) is one example of empirical horizontal spillovers estimate, which finds significant evidence of within-industry positive spillover in the United States.

One mechanism of such spillover depends on the flow of workers out of multinational corporations. For example, multinational corporations may devote more resources to labor training than domestic firms. Given that a large part of this labor training is not paid for by the workers and constitutes knowledge that is not completely firm specific, this constitutes a positive externality that leads to increased wages for these workers and raises the productivity of firms that hire these workers after they leave the multinationals. These labor training externalities would show up as horizontal knowledge spillovers, in the sense that they would benefit other firms in the same sector as the multinationals. Similar effects can happen if workers increase their knowledge not through formal labor training, but through on-the-job training, or learning by doing. Poole (2013) estimates wage spillovers from an employer-employee dataset for Brazil. Specifically, she finds that workers in establishments with a higher proportion of workers with some experience at a multinational firm earn higher wages, consistent with the idea that there are knowledge transfers from multinational to domestic firms workers.

Other mechanisms that could give rise to positive externalities can arise through vertical backward linkages and the provision of specialized inputs. They arise when the multinational affiliate provides technology to its inputs supplier at a price that is below its market value.

Domestic firms may also become more productive as a result of gaining access to new, improved, or less costly intermediate inputs produced by multinationals. This is the case of vertical forward effects, where the technology would diffuse from the multinational affiliate to downstream firms. Javorcik (2004) focuses on these effects operating across industries. The results, based on firm-level data from Lithuania, provide evidence consistent with positive productivity spillovers from FDI taking place through contacts between foreign affiliates and their local suppliers in upstream sectors. The author does not find robust evidence of spillovers occurring through either the horizontal or the forward linkage channel.

Carluccio and Fally (2013) account for the possibility that technologies used by multinational firms require different intermediate goods to those used by domestic firms. They show that entry by foreign firms induces changes in the supply chain to obtain inputs compatible with the foreign technology. Technological incompatibilities can thus generate complex interactions between vertical linkages and technology adoption decisions.

Finally, multinational entry often leads to a higher degree of competition, which may induce firms to reduce inefficiencies, and thus increase productivity. Domestic incumbents may also respond through resource reallocation within the firm by changing product composition and reallocating resources to focus on core-advantage goods. Alfaro and Chen (2018) show that new multinational entry leads to a significant increase in domestic firms patenting activities, and find that domestic firms, especially those with the lowest productivity, are more likely to drop products after facing foreign multinational entry. They emphasize an explanation centering on selection and market reallocation of resources from less productive to more productive firms after increased competition. Similar to that study, I also document a competition effect, but through a different channel: domestic firms adopt new technologies trying to keep their competitiveness against multinational firms.

The rest of the paper is organized as follows. Section 3.2.1 describes the data and section 3.2.2 discusses conceptual and measurement issues. Section 3.3 presents stylized facts on technology diffusion. Section 3.4 states the estimation strategies for the following analyses: 3.4.1 investigates the determinants of adoption, section 3.4.2 quantifies the effect of the technology adoption on exports growth, while section 3.4.3 is concerned with technology diffusion at the state-level. Section 3.5 presents the results and section 3.6 concludes.

3.2 Data and Measurement

3.2.1 Data Sources

The starting point is a dataset that comprehends the firm-level imports of equipment under a special tariff exemption regime between 2000 and 2018, provided by the Ministry of Economy of Brazil. The exemption program, called Ex-tarifário, was established in 1990 with the goal of stimulating national production investment, by temporarily reducing the import tariff on varieties of capital goods that are not domestically produced. Note that this last feature is crucial for interpreting the data as imports of new technologies, not available in the country.

Each exemption refers to a specific equipment, described in detail, and not to a whole Harmonized System code. This is the main advantage of the dataset, compared to the traditional trade data employed in previous literature, and it allows us to follow the adoption of specific technologies by different firms over time. In order to highlight the granulatity level of the dataset, here are two examples of such exemption descriptions compared to the respective HS code descriptions:

1) **Ex-tarifário description:** *Tools used for hot forming of automotive parts, with punches and dies with internal channels for the passage of liquid for cooling and uniform tempering throughout the entire structure of parts, both at the bottom (punch) and at the top (matrix); 1 inlet piping system and 1 coolant outlet piping system with connection pipes from the connections to the punch and the independent die; 2 24-pin electrical connectors for input and output of electrical pulses of data communication with system; pressure gauges to indicate pressures in nitrogen chambers.*

HS description: *Tools for pressing, stamping or punching, and parts thereof, of base metal.*

2) **Ex-tarifário description:** *Automatic wet polishing machines for stainless steel sheets, width 2.100mm, with automatic pressure control of the sandpaper on the material, electronic control via a programmable logic controller (PLC), exhaust filter for mist recovery, two motors 90kW controlled by two speed inverters, tank to collect the lubricating and cooling liquid, two sanding tensioners, two rollers to move the abrasive sandpaper, centralized lubrication pipe with electric pump, plate temperature gauge, devices of pressing at the entrance and exit of rubberized rollers.*

HS description: *Machines for carrying out other finishing operations on metals or cermets by means of grinding wheels, abrasives or polishing products.*

I combine this information with transaction-level exports data, also from the Ministry of Economy, covering 2000 to 2019. This second dataset also contains firm-level variables that

I explore: identifier, address and industry.

I then merge the resulting trade dataset with employer-employee data from the Brazilian Ministry of Labor and Employment, from 2000 to 2017. Labor data come from the survey Relação Anual de Informações (RAIS), which contains information of all tax-registered firms in the country. The datasets include a time-invariant firm identifier that allows for the merge.

The fourth dataset is publicly released by the Brazilian Revenue Service and includes firms' ownership information for every firm ever registered in Brazil. Fortunately, it includes the same firm identifier found in the trade data, allowing for a simple merge of both. In 2019, Brazil was the world's sixth-largest destination for FDI, with inflows of $72 billion, according to the World Investment Report (UNCTAD, 2020).

Finally, for the last section of the empirical analysis I complement the above datasets with state-level data. Real GDP and sectoral shares of GDP (services, government and manufacturing) data come from the Regional Account System, by the Brazilian census bureau, IBGE. State-level FDI data are publicly provided by the Central Bank of Brazil. The source for the share of population by years of education is the Annual Continuous National Household Survey, from IBGE.

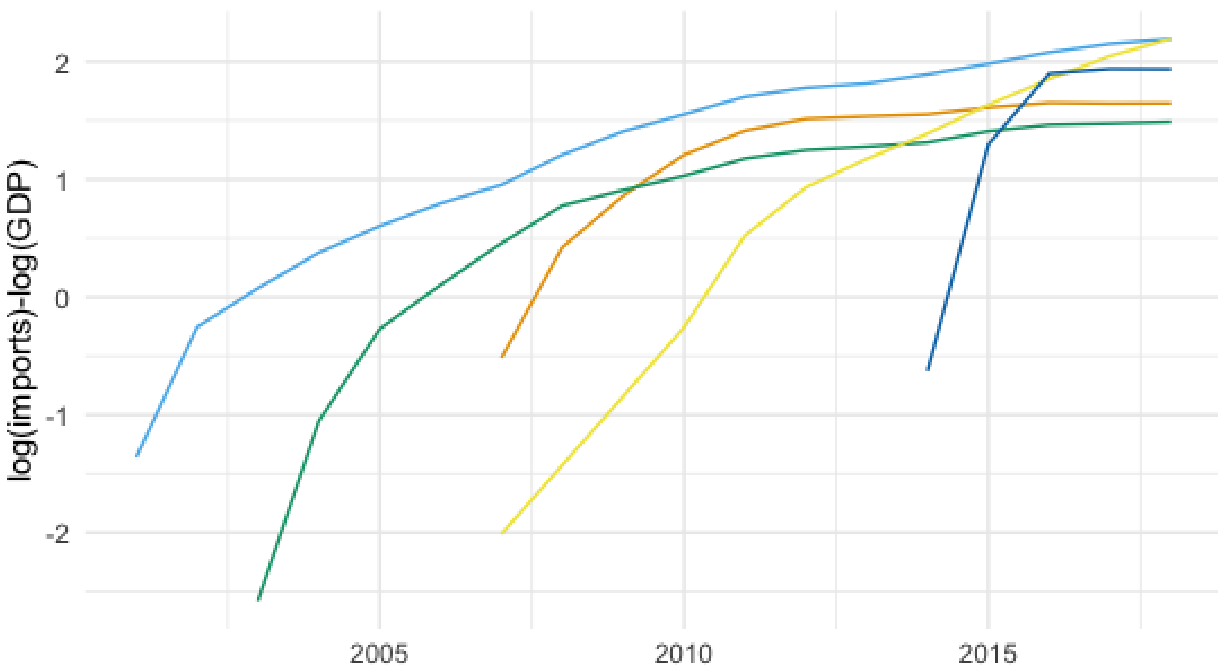
3.2.2 Conceptual and Measurement Discussion

Technology Diffusion: previous literature has employed different measures of technology diffusion. One possibility, the Solow residual, in addition to technology, also captures the variation in capacity utilization, labor productivity and the inefficiencies of the economy (Comin et al., 2006). Another alternative involves measuring the share of potential adopters that have adopted a given technology. But this approach neglects the intensive margin and the measure of the number of potential adopters is not always available.

Some technologies take the form of new production techniques, in which case, the diffusion of the technology is measured by the share of output produced with the technique (Comin and Mestieri, 2018). Since technology is often embodied in capital and ICT goods, the authors also rely on the units of capital per capita. I follow their view and consider technology diffusion as encompassing both the intensive and the extensive margins. Thus, I take into account the number of imports of machinery and the dollar value of the imports per capita.

Adoption: As mentioned before, I rely on the fact that the tariff exemption only applies to capital goods that are not domestically produced in order to define the adoption of new technologies. This special feature allows me to consider the imports under the regime as new technologies, since they are not yet available in the country. I denote the first importing firm of each technology by *First Adopter*. Firms responsible for the next imports of such technology are denoted as *Followers*, as long as they are not the same firm from the first import. However, one caveat is in order: I cannot rule out that the same firm, or a different one, has imported a given machinery before, outside the regime. In this case, the true first import is not recorded in my dataset. Because I focus on the comparison of the average behavior of firms across different characteristics, I do not believe this to significantly affect my results. Furthermore, when measuring growth effects following the adoption of new technologies, I argue that the potential missing observations would lead to attenuation bias. I discuss this in further detail in the Results section. Finally, I explore whether the adoption patterns in the dataset resemble those repeatedly found by Comin et al. (2006), Comin and Hobijn (2010) and Comin and Mestieri (2018). Following their approach, I calculate the

Figure 3.1: Diffusion curves



Notes: Diffusion curves of five capital goods in Brazil, following the approach of Comin and Mestieri (2018). The curves refer to the five most adopted capital goods under the exemption of tariff program in Brazil, between 2000 and 2018. I omit their code for reasons of confidentiality. Each line shows the logarithm of the number of adoptions (imports) of the technology divided by the country real GDP.

logarithm of the number of adoptions of a technology divided by the country real GDP. In Figure 3.1, I show the five most adopted technologies in the dataset, for which there are enough data in order to plot the yearly observations. The adoption curves follow closely the pattern described in the literature.

Multinational: A multinational is an enterprise that engages in foreign direct investment and owns or, in some way, controls value-added activities in more than one country. The choice of the threshold at which a firm is deemed to become a multinational is bound to be arbitrary, though. Past research has set the limit at different levels: for example, Alfaro et al. (2004) and Alfaro and Chen (2018) consider a 50% or higher share of foreign equity, Arnold and Javorcik (2009) set at 20%, and Alfaro-Urena et al. (2019) and Poole (2013) consider foreign capital of any amount. I define a firm as a multinational if it has at least one foreign owner (direct foreign owner) or if it is a subsidiary of a parent company with at least one foreign owner (indirect foreign owner).

3.3 Descriptive Statistics and Stylized Facts

There are 16,511 firms in the dataset of capital goods imports under the exemption regime, between 2000 and 2018. The average shipment value is US$608,551, and the 25, 50 and 75 percentiles are US$37,120, US$128,245, US$418,010, respectively. The majority of technologies, 56% of them, are adopted by one firm only, while 27% of technologies are adopted by 3 or more firms, 15% by 5 or more, and 6.5% by 10 or more.

Table 3.1 presents the shares of capital goods that are imported by domestic and multinational firms. The first column considers all import transactions of equipment under the exemption regime while the second column focuses on capital goods that are being imported for the first time in the country. I denote this last group by First Adoption of the new technologies. Domestic firms are responsible for 66.5% of all transactions and for 59.5% of new technologies. Multinationals import 33.5% and 40.5%, respectively. This means that although domestic firms are still the main importers of new technologies in absolute terms, multinationals are first adopters more often, relatively to their number of imports (28.5%

versus 21.1% for domestic firms).

The last column in Table 3.1 considers the ownership of the firms that imported a new equipment which was later also imported by other firms (followers). This statistic highlights the role of multinationals as early adopters in the technology diffusion process: while only 40.5% of the new technologies were imported by multinationals, 44.5% of the repeated technologies (second, third, and so on, import of the same capital good) followed imports by multinationals.

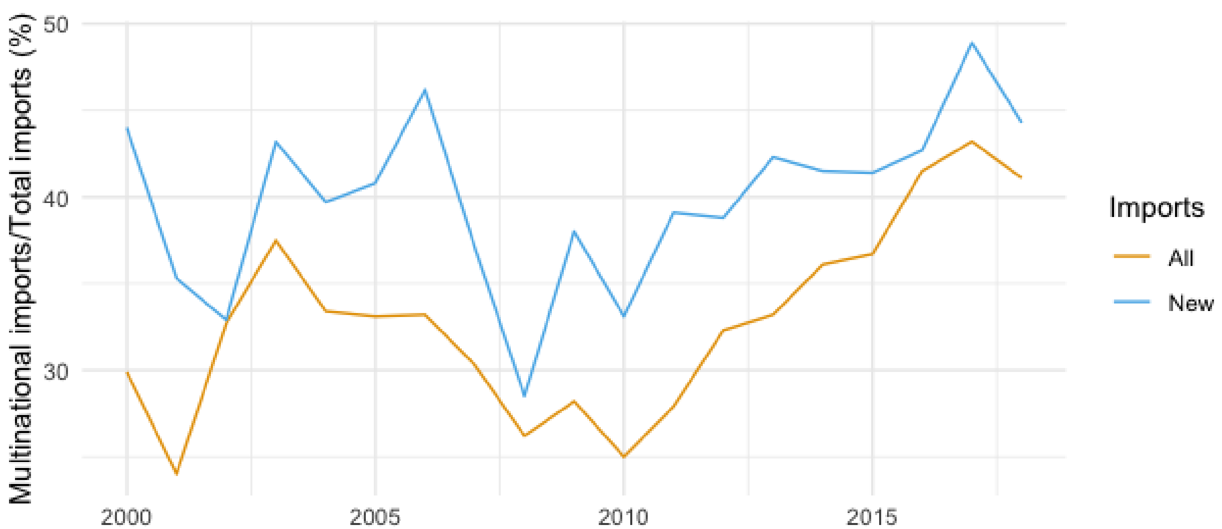
Table 3.1: Share of Capital Goods Imports by Domestic and Multinational Firms

	All Imports	**First Adopter**	**Follower from**
Domestic	66.5%	59.5%	55.5%
Multinational	33.5%	40.5%	44.5%
Other outcome shares for comparison			
	Exports	**Manuf Labor**	**Imports**
Domestic	75.2%	81.8%	62.1%
Multinational	24.8%	18.2%	37.9%

Notes: The capital goods imports refer to the imports under the exemption of tariff program in Brazil, between 2000 and 2018. The table presents the shares of imports made by domestic and multinational firms relative to all import transactions in the dataset (column 1), to transactions regarding the first adoption of the technologies only (column 2), and shares of late adoption imports, following an import made by domestic versus multinational firms (column 3).

In Figure 3.2, I plot how the share of technologies imports by multinationals varies across time. We notice that the share considering all imports under the exemption regime (orange line) has increased during the past decade, as expected from the stronger foreign capital flow observed globally. We also find from the plot that a higher share of multinationals as first adopters of new technologies (blue line), when compared to all transactions, is observed not only on average, but in every year of the available data.

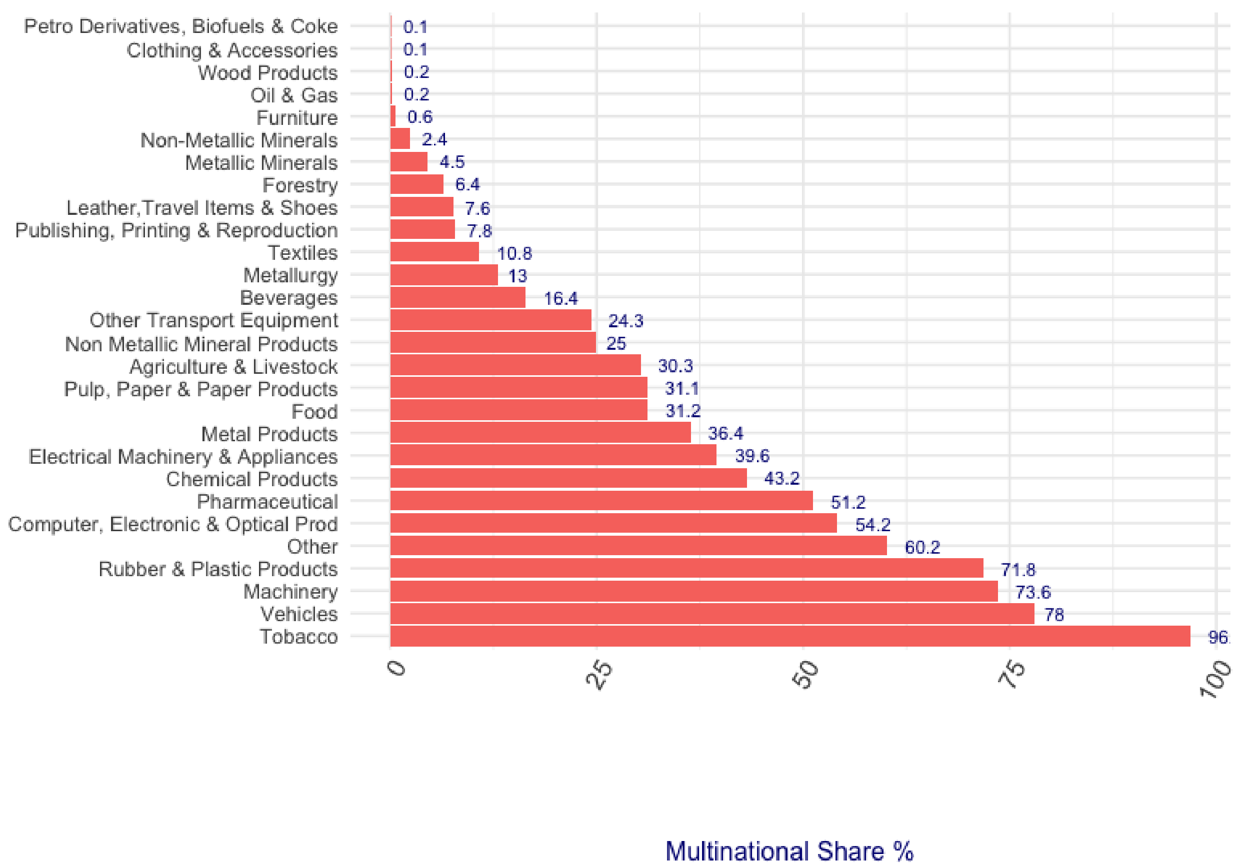
Figure 3.2: Share of equipment imports by multinational firms



Notes: The imports refer to the capital goods imports under the exemption of tariff program in Brazil, between 2000 and 2018. The orange line shows the share of imports made by multinationals relative to all import transactions in the dataset. The blue line presents the share of imports made by multinationals relative to import transactions regarding the first adoption of the technologies only.

Next, I turn to the industry-level statistics. Figure 3.3 shows the concentration of multinationals among the imports of capital goods under analysis. We notice a large variation on the share of multinational imports across industries: among the highest are tobacco, vehicles and machinery sectors and among the lowest shares are petro derivatives, clothing, oil & gas and wood products. The petro derivatives and oil & gas shares are related to strong government presence and regulation. The vehicles and tobacco large shares are related to fiscal incentives for local production, which encouraged multinationals to invest in new production capability in Brazil rather than serving the market by export. In order to check whether the results are driven by this variation, in the empirical section I estimate both average effects and heterogeneous effects, by industry.

Figure 3.3: Percentage of equipment imports by multinational firms across industries



Notes: The imports refer to the capital goods imports under the exemption of tariff program in Brazil, between 2000 and 2018. The graph shows the share of imports made by multinationals relative to the import transactions made by all firms in each industry.

In order to study the time for adoption in the diffusion process, I track the imports of each specific technology and calculate the number of days between the first and the second imports. I find that it takes 481 days on average for the second import of a new technology when it was first imported by a domestic firm, and 564 days when a multinational was the first adopter. I explore more of the determinants of the diffusion lag in the empirical section.

I now investigate whether first adopters and followers diverge in terms of firm size. To do so, I use the number of employees variable from the RAIS survey. Table 3.2 shows that first adopters are larger than followers on average: (i) for domestic firms, first adopters have 715 employees on average, while followers have 373; (ii) for multinational firms, first adopters and followers have 732 and 562 employees, respectively. We also notice that multinational firms are larger than domestic firms, as expected.

Table 3.2: Firm Size by Rank of Adoption.

	Adoption	Employees
Domestic	First	715
	Follower	373
Multinational	First	732
	Follower	562

Notes: The table presents the average number of employees of domestic and multinational firms, that adopted a new technology for the first time (*First*) or that adopted a technology previously imported by a different firm (*Follower*). There are 16,511 firms in the exemption regime sample.

The result above could reflect industry, rather than position in the industry. In order to further investigate this, in Figure 3.4 I show the average number of employees of domestic and multinational firms, split between first adopters and followers, for each industry, separetely.

The graph ranks the industries in order of the size difference between first adopters and followers. First adopters are larger than followers for the majority of sectors, but not for all of them.

Figure 3.4: Percentage of equipment imports by multinational firms across industries

Notes: The graph shows the average number of employees of domestic and multinational firms (MNC), that adopted a new technology for the first time (*First*) or that adopted a technology previously imported by a different firm (*Follower*) in each industry.

Which firms copy the new technology imported by multinationals and domestic firms? We have seen that follower firms are on average smaller than early adopters. Now I focus on the geography aspect of how diffusion takes place.

First, I plot the number of occurrences of imports of new technologies during the sample period, by county. Figure 3.5 shows the progressive spread in the adoption of new equipments: the first map shows the number of machinery imported for the first time, and then the following maps add up to the second, forth and eigth imports of the same technologies. We notice that diffusion takes place in nearby counties, rarely spreading to farther counties. However, from this graph, we cannot know if the spread to neighboring counties concerns the same technology.

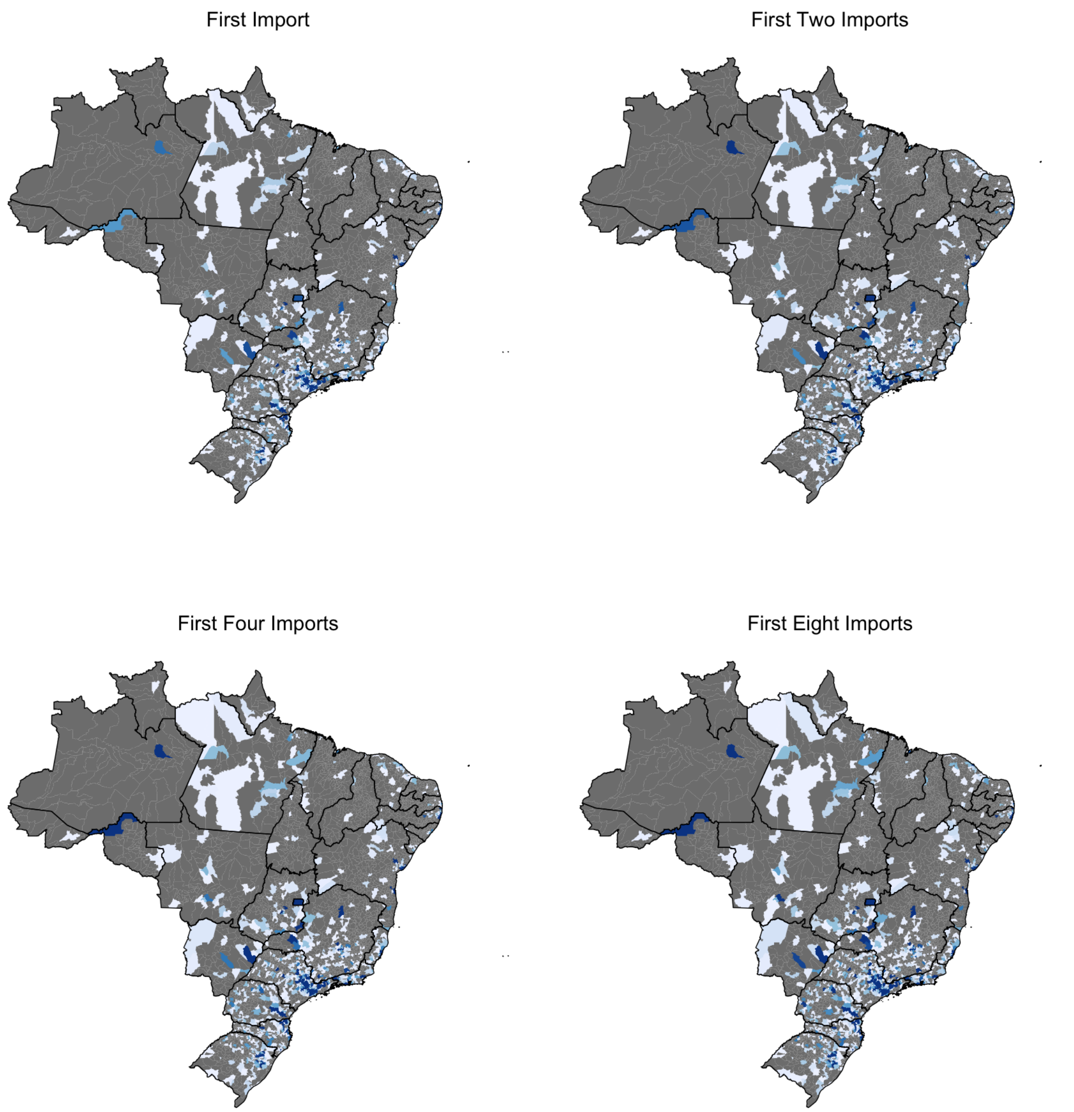
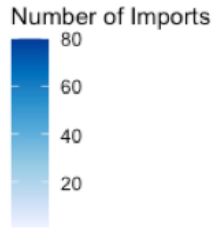


Figure 3.5: Continues on the next page.



Notes: The graph plots the number of occurrences of imports of new technologies, by county. The first map shows the number of machinery imported for the first time, and then the following maps add up to the second, forth and eigth imports of the same technologies.

So next, I analyze whether the follower firms are found in the same county or in the same state as the leading firm. The first three rows of Table 3.3 consider the state level and the last three rows consider the county level. We see that 36.9% of the imports occur in the same state as the first import of the technology and 12.3%, in the same county. When the diffusion takes place in the same state or in the same county, it is more likely that the first equipment was imported by a multinational than a domestic firm: 20.7% for multinational versus 16.2% for domestic in the state level and 6.3% for multinational versus 6% for domestic in the county level.

Table 3.3: Geography aspect of Technology Diffusion

	First Multinational	First Domestic	Total
Same State	20.7%	16.2%	36.9%
Different State	23.8%	39.3%	63.1%
Total	44.5%	55.5%	100%
Same County	6.3%	6.0%	12.3%
Different County	38.2%	49.5%	87.7%
Total	44.5%	55.5%	100%

Notes: The table considers all imports of capital goods under the exemption of tariff program in Brazil, between 2000 and 2018. The table presents in the *Total* column the shares of the imports that occur in the same/different state or county as the first import of the technology. In the first two columns the table disaggregates these shares to also account for the ownership of the firm that first imported the technology.

3.4 Estimation strategy

For the empirical analysis, I investigate whether this new dataset corroborates the predictions from different theoretical frameworks in the literature, regarding technological diffusion and the role of multinationals in this process.

3.4.1 Determinants of adoption at the firm level

As shown in a large volume of empirical literature, foreign multinational entry could generate positive productivity spillover to domestic firms through production linkages, sharing common inputs, and labor mobility. Alfaro and Chen (2018) argue that the entry of foreign multinational firms can also affect the productivity level of domestic firms by motivating the firms to raise R&D, alter product composition and adopt better technologies, to increase their competitiveness. The authors present evidence on the first two effects: multinational entry leads to an increase in patenting activities and in the reallocation of resources towards more efficient products. I aim to collect evidence on the last effect, that is, the motivation for technology adoption.

Vishwasrao and Bosshardt (2001) point out that foreign-held companies might have some advantages in the technology adoption process: easier access to technology from the parent company, greater capital resources with which to purchase technology, or access to the R&D facilities of the parent company, which facilitates the adaptation of the technology to host country needs. Even when the technology is purchased from an unaffiliated foreign firm, the transaction costs may be lower between two foreign firms. I follow their model based on the theoretical framework developed by Katz and Shapiro (1987), in which firms compete to adopt innovations and introduce them into the market. The probability of a firm adopting new technology is hypothesized to depend on firm and industry characteristics. The model suggests that a firm is more likely to adopt new technology if it is larger and has a lower initial cost of adoption, which is expected to be lower for foreign multinationals. Besides potential lower trade costs, Blonigen (1997) suggests another reason for this: multinationals can benefit from scale economies when using a technology in multiple countries. I estimate the following probit model:

$$Pr(FirstAdoption_i) = \Phi(\alpha + \beta_0 Multinational_i + \beta_1 Employees_i + Year + Industry),$$

where $FirstAdoption_i$ is a dummy with a value of 1 if the import transaction i refers to a technology being imported for the first time in the country and 0 otherwise, $\Phi(\dot{})$ is the cumulative distribution function of the standard normal distribution, $Multinational_i$ is a dummy for the ownership of the firm importing the technology, with a value of 1 for multinationals and 0 for domestic firms, $Employees_i$ is the number of employees of the firm in the year of the import, in hundreds, and $Year$ and $Industry$ are year and industry fixed effects. Then, I also estimate the probit model above for each industry, to check whether the results are driven by differences in the ownership and size composition of industries, as discussed in the Stylized Facts Section.

The sample for this first specification includes the imports of capital goods under the exemption regime, between 2000 and 2018. There were 22,734 shipments registered in the dataset in this period.

Next, I investigate the factors that influence the magnitude of the lag between the first and second import of each specific new technology. I am interested in determining which elements facilitate the diffusion across firms and which factors delay the widespread adoption. I run the following regression:

$$Days_j = \alpha + \beta_0 CGValue_j + \beta_1 Multinational_j + \beta_2 Employees_j +$$

$$\beta_3 Multinational1st_j + \beta_2 Employees1st_j + Industry + Year + \varepsilon_j,$$

where $Days_j$ is the number of days elapsed between the first two imports (made by two different firms) of a capital good j, $CGValue_j$ is value of the equipment shipment in the second import, measured in million dolars, $Multinational_j$ is a dummy for the ownership of the follower firm, with a value of 1 for multinationals and 0 for domestic firms, $Multinational1st_j$ is a dummy for the ownership of the leading firm, with a value of 1 for multinationals and 0 for domestic firms, $Employees_j$ and $Employees1st_j$ are the number of employees, in hundreds, of the follower and leading firms at the time of the import of machinery, respectively. The sample includes the imports under the exemption regime, between 2000 and 2018, of technologies that are being imported for the second time. There were 6,999 second imports registered in the dataset in this period.

3.4.2 Growth following diffusion

Past research has showed that most of cross-country productivity differences are due to the delayed adoption of new technologies by countries that lag behind (Comin and Hobijn, 2010; Comin and Mestieri, 2018). This section explores firm-level productivity, looking at whether first adopters and followers of new technologies experience a better performance in their export outcomes. The goal is to compare the results between the two groups of firms and determine if followers can benefit as much as early adopters.

In this section, I do not interpret the results as a causal relantionship, since the investment decision of the firm might be correlated to some demand shock that boosts exports, for example. Instead, I consider the technology investment to be a mechanism that allows the firm to meet such potential increased demand. I am interested in distinguishing the effect between first adopter and follower firms and studying whether follower firms are also able to employ the technology and expand their sales. To do so, I estimate the following regressions:

$$\%\Delta Exports_{f,t} = \alpha + \beta_0 FirstAdopter_{f,t-1} + \beta_1 Multinational_f +$$

$$\beta_2 Multinational_f * Adopter_{f,t-1} + Year + \varepsilon_{f,t}$$

$$\%\Delta Exports_{f,t} = \alpha + \beta_0 Follower_{f,t-1} + \beta_1 Multinational_f +$$

$$\beta_2 Multinational_f * Adopter_{f,t-1} + Year + \varepsilon_{f,t},$$

where $Exports_{f,t}$ is the average base exports growth (%) of firm f in year t,[1] $FirstAdopter_{f,t-1}$ is a dummy with a value of 1 if the firm f is the first to import a technology in year $t-1$ and 0 if it did not import technologies, $Follower_{f,t-1}$ is a dummy with a value of 1 if the firm f has only imported technologies in year $t-1$ that have been imported before by a different firm, and 0 if it did not import technologies, $Multinational_f$ is a dummy for the ownership of the firm, with a value of 1 for multinationals and 0 for domestic firms, and $Year$ are time fixed effects. The unbalanced panel sample includes firms that imported capital goods at least once (including imports outside the exemption regime), between 2000 and 2018, for the years in which it is feasible to measure percentage exports growth.

I also investigate a potential interaction effect between the adoption of a technology and the ownerhip of the early adopter firm. That is, I want to study whether technologies that are brought in the country by multinationals have a different impact on firm performance than technologies employed by domestic firms.

I run the following model:

$$\%\Delta Exports_{f,t} = \alpha + \beta_0 FollowerMultinational_f + Year + \varepsilon_{f,t},$$

[1] Average base growth is calculated as: $\frac{Exports_{f,t} - Exports_{f,t-1}}{(Exports_{f,t} + Exports_{f,t-1})/2} * 100$

where $FollowerMultinational_{f,t-1}$ is a dummy with a value of 1 if the firm has imported technologies that have been imported before by a multinational firm, and 0 if it did not import technologies.

3.4.3 State-level analysis

In this last exercise, I follow Caselli and Wilson (2004) and look at disaggregated imports of various types of equipment. They develop a model of investment in heterogenous types of capital that suggests that a capital-type share in total investment depends on its intrinsic efficiency (reflecting embodied technology), as well as on the degree to which it is complementary with other inputs whose abundance may vary across countries. For example, computers may be more complementary with human capital than other types of capital, leading to the prediction that human-capital abundant countries will devote a larger share of their investment to computers. According to their model, the composition of capital has the potential to account for some of the large observed differences in TFP across countries. I aim to test whether their predictions are consistent with differences across states in the composition of equipment investment. Their relative imports equation is based on the premise that the types of imported equipment cannot be produced domestically by most countries. Due to the design of the exemption regime, I am able to work confidently under this premise.

The main focus of the empirical analysis is the equation below, where $RI_{s,p,t}$ is the relative imports, that is, the share of capital of type p in state s over total capital, in year t. I conjecture that $RI_{s,p,t}$ depends on a series of state characteristics: $z_{s,c,t}$ is the value of characteristic c in state s and year t relative to the average value for the country. It captures the abundance or scarcity of characteristic c in state s. I estimate the non-linear model:

$$RI_{s,p,t} = \beta_p \Pi_c (z_{s,c,t})^{\beta_{p,c}} \varepsilon_{s,p,t}.$$

The types of capital p are: fabricated metal products, non-electrical equipment, computing and accounting machinery, electrical equipment, communication equipment, motor vehicles, other transportation equipment, aircraft and professional goods. The first state characteristic is human capital, measured in two different ways: as the share of population with 11 or more years of education (high-school graduated) and the share of population with 15 or more years of education (bachelor degree). Other possible characteristics that may complement different capital types differently are: inward foreign direct investment (FDI) as a share of GDP, where a high correlation would denote a comparative advantage by foreign corporations in importing and installing this type of capital; the share of government in GDP, where a high correlation signals that the government has a comparative advantage in operating this type of capital, or a unique demand for this capital; the shares of manufacturing and services, which allows for sector-specificity of the capital types p. In addition, I control for real per-capita income.

3.5 Results

3.5.1 Determinants of adoption at the firm level

I begin with the results from the probit estimation, in which the probability of a firm adopting new technology is hypothesized to depend on firm and industry characteristics. Table 3.4 shows the estimated average marginal effects, considering ownership, number of employees, year and industry fixed effects. As predicted by the theoretical model in Vishwasrao and Bosshardt (2001), multinational firms are more likely to adopt new technology: they have an average likelihood 3.8% to 5.8% higher than domestic firms. This likely reflects the lower costs of import and investment for multinationals. The firm size coefficient is statistically significant, but shows a small impact: larger firms (by 100 employees) are around 0.23% more likely to adopt new technology.

Table 3.4: Probit Average Marginal Effects

Dependent variable: Probability of being a First Adopter				
	(1)	(2)	(3)	(4)
Multinational	0.058***	0.052***	0.058***	0.038***
	(0.005)	(0.005)	(0.006)	(0.006)
Employees		0.0023***	0.0026***	0.0011***
		(0.0002)	(0.0002)	(0.0002)
Year FE			✓	✓
Industry FE				✓
Observations	22,734	22,734	22,734	22,734

Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Table shows average marginal effects from the probit estimation. *Multinational* is a dummy for the ownership of the firm, with a value of 1 for multinationals and 0 for domestic firms. *Employees* is the number of employees of the firm, in hundreds. The sample includes the imports of capital goods under the exemption regime, between 2000 and 2018. There were 22,734 shipments registered in the dataset in this period.

Next, I estimate the probit model above for each industry, to check whether the results are driven by differences in the ownership and size composition of industries. Unfortunately, due to the small number of imports observed in some sectors, the regression can only be estimated for 14 out of 28 industries. Table 3.5 shows that multinationals are more likely to adopt a technology for the first time in six industries: food, chemical products, plastic products, computer & electronic products and electrical machinery. The two sectors with negatives estimates, wood products and vehicles, are found at the two opposite extremes of multinational shares in Figure 3.3. Thus, these estimates are based on a very small sample of multinationals (for the wood sector) or of domestic firms (for the vehicles sector) and should be taken with caution. Firm size seems to be significant only for the pharmaceutical, metal products, electrical machinery and transport equipment industries.

Table 3.5: Determinants of adoption at the firm level, by industry.

Dependent variable: Probability of being a First Adopter					
	Multinational	Std. Error	Employees	Std. Error	N
Wood Products	-0.070***	(0.015)	0.001	(0.005)	286
Food	0.549***	(0.133)	-0.006	(0.009)	76
Paper Products	0.008	(0.023)	-0.003	(0.002)	703
Printing	-0.051	(0.082)	0.014	(0.008)	123
Chemical Products	0.145*	(0.081)	0.015	(0,010)	156
Pharmaceutical	0.102	(0.094)	0.048***	(0.012)	71
Plastic Products	0.201***	(0.065)	-0.004	(0003)	315
Metallurgy	0.419***	(0.060)	0.002	(0.001)	567
Metal Products	0.077	(0.079)	0.015*	(0.008)	153
Computer, Electronic	0.057***	(0.014)	0.001	(0.001)	3,000
Electrical Machinery	0.134***	(0.040)	0.004***	(0.001)	512

Machinery	0.002	(0.014)	0.001	(0.001)	3,389
Vehicles	-0.121***	(0.031)	-0.001	(0.001)	1,582
Transport Equip	0.006	(0.108)	0.007**	(0.003)	167

Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Table shows average marginal effects from the probit estimation. *Multinational* is a dummy for the ownership of the firm, with a value of 1 for multinationals and 0 for domestic firms. *Employees* is the number of employees of the firm, in hundreds. The sample includes the imports of capital goods under the exemption regime, between 2000 and 2018. N shows the number of observations in each industry: shipments registered in the dataset in this period.

After the first adoption, a question that arises is how fast the technology spreads in the country. The estimates of the coefficients in the adoption lag regression are presented in Table 3.6. I test for a number of different specifications of the regression model: (1) the first column considers the capital goods value and the multinational control; (2) the second column adds firm size, proxied by the number of employees, in hundreds; (3) the third column considers ownwerhip and size of the first adopter of the technology; and (4) the fourth column includes all controls.

Table 3.6: Estimates of the determinants of adoption lags.

Dependent variable: Days until second import				
	(1)	(2)	(3)	(4)
CG Value $1mi	18.090***	13.060***	18.610***	14.030***

	(4.911)	(4.872)	(4.364)	(4.563)
Multinational	116.500***	81.600***		71.800***
	(28.580)	(27.200)		(26.080)
Employees		2.770***		2.332***
		(0.800)		(0.827)
Multinational 1st			56.730***	46.280**
			(24.010)	(24.310)
Employees 1st			-1.004	-1.365
			(0.829)	(0.832)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	6,999	6,999	6,999	6,999
R^2	0.088	0.084	0.076	0.078

Notes: Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: days between first and second import of given technology. $CGValue$ is value of the equipment shipment in the second import, measured in million dolars, $Multinational$ is a dummy for the ownership of the follower firm, with a value of 1 for multinationals and 0 for domestic firms, *Multinational 1st* is a dummy for the ownership of the leading firm, with a value of 1 for multinationals and 0 for domestic firms, *Employees* and *Employees 1st* are the number of employees, in hundreds, of the follower and leading firms at the time of the import of machinery, respectively. The sample includes the imports under the exemption regime, between 2000 and 2018, of technologies that are being imported for the second time.

The value of the equipment imported has a positive and significant effect on the adoption lag across all specifications. Therefore, more costly technologies take longer to spread across firms: each \$ 1 million increase in the value of the shipment of machineries is correlated to around 13 to 19 more days before a second adoption. The ownership of the second adopter is consistently significant: equipments that are copied by a multinational take between 72 to 116 more days to be adopted for the second time. The ownership of the first adopter is also significant: equipments that were first imported by a multinational take between 46 to 56 more days to be adopted for the second time. This can be interpreted in a different number of ways: (i) multinationals might be better in hiding their business strategy from competitors; (ii) multinationals might be importing more exclusive equipment, which is of harder access; or (iii) multinationals might be ahead of domestic firms in terms of the capacity to learn about and adopt the new technology. Finally, the size of the follower firm also matters for diffusion: technologies that are copied by larger firms (with 100 more employees) are expected to take 3 more days to be adopted for the second time. Therefore, technologies adopted by larger firms seem to be harder to copy.

Table 3.7 show the results for the industry regressions. I focus on the ownership of the leading firm, the first adopter, and on the value of the technology. Out of the 19 industries for which there were enough observations to run the regression, 9 show a slower diffusion for technologies first adopted by multinationals, and 3 a faster diffusion. These later industries present a high share of multinational presence in the country, such that there are few observations from domestic firms in the sample. Technology price does not seem to affect diffusion in a consistent manner across industries.

Table 3.7: Estimates of the determinants of adoption lags by industry.

Dependent variable: Days until second import					
	Multinational 1st	SE	CG Value $1mi	SE	N
Wood Products	170	(258)	134***	(39)	102
Metallic Minerals	476**	(223)	-12*	(16)	62
Food	318***	(132)	65	(49)	334
Beverages	83	(175)	323***	(67)	58
Textiles	274	(185)	15	(125)	142
Leather & Shoes	401**	(174)	-12	(169)	76
Paper Products	338**	(132)	53***	(19)	231
Printing	356**	(140)	39	(84)	82
Chemical Products	50	(144)	29	(30)	190
Pharmaceutical	390***	(149)	12	(65)	119
Plastic Products	183**	(76)	-29	(46)	394
Non-Metallic Min Prod	333**	(140)	27	(38)	261
Metallurgy	496***	(132)	27***	(6)	257
Metal Products	51	(84)	76	(52)	365
Computer, Electronic	-230***	(82)	-96	(65)	281
Electrical Machinery	51	(135)	-43	(86)	242
Machinery	-195***	(67)	-12	(23)	534
Vehicles	-312***	(86)	16	(32)	589
Furniture	-185	(149)	53	(216)	144

Notes: Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: days between first and second import of given technology. $CGValue$ is value of the equipment shipment in the second import, measured in million dolars, *Multinational 1st* is a dummy for the ownership of the leading firm, with a value of 1 for multinationals and 0 for domestic firms. The sample includes the imports under the exemption regime, between 2000 and 2018, of technologies that are being imported for the second time. N shows the number of observations in each industry: shipments registered in the dataset in this period.

3.5.2 Growth following diffusion

The next estimates exploit how the adoption of technologies affect exports growth. Table 3.8 reports the parameter estimates and standard errors for the different specifications. In the first and second columns I compare the growth effect observed for first adopters and followers. I find that both groups of firms experience a higher growth rate than firms that did not import new technologies embodied in capital goods. However, I do observe that the growth for first adopters is estimated to be much higher than the growth for followers: the former group is expected to grow by 23 percentage points more than non importers, while the later is expected to grow by 6.3 percentage points more.

In columns (3) and (4) I present the results for the interaction between adoption and ownership regression. I still find a positive and significant effect of adoption on exports growth one year later, but with a stronger effect for domestic firms. Adopting a technology for the first time is correlated with a 30 percentage points higher growth rate for domestic firms and 11 percentage points for multinationals.[2] Adopting a technology as a follower is

[2] 30.899 - 19.503 = 11.396

correlated with a 7 percentage points higher growth rate for domestic firms and 3 percentage points for multinationals.[3] Multinationals are also found to grow faster, by 3.27 percentage points, on average. Finally, I find evidence that technologies first imported by multinationals have a different impact than those first imported by domestic firms. The last column shows that followers of multinationals experienced higher growth in their exports, relative to non-adopters, by 10 percentage points on average, in contrast to the full sample of followers average of 6 percentage points.

Table 3.8: Estimates of the effect of technology adoption on exports growth.

Dependent variable: Exports Growth (%)					
	(1)	(2)	(3)	(4)	(5)
First Adopter	23.704***		30.899***		
	(1.453)		(1.867)		
Follower		6.348***		7.388***	
		(1.151)		(1.388)	
Multinational			3.299***	3.277***	
			(0.695)	(0.694)	
Multinational * Adoption			-19.503***	-4.436*	
			(2.979)	(2.477)	
Follower of Multinational					10.575***
					(1.834)
Year FE	✓	✓	✓	✓	✓

[3] 7.388 - 4.436 = 2.952

Observations	235,719	241,548	235,719	241,548	217,414
R^2	0.009	0.008	0.009	0.008	0.007

Notes: Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *FirstAdopter* is a dummy with a value of 1 if the firm is the first to import a technology and 0 if it did not import technologies, *Follower* is a dummy with a value of 1 if the firm has only imported technologies that have been imported before by a different firm, and 0 if it did not import technologies. *Follower of Multinational* is a dummy with a value of 1 if the firm has imported technologies that have been imported before by a multinational firm, and 0 if it did not import technologies. The unbalanced panel sample includes firms that imported capital goods at least once, between 2000 and 2018, for the years in which it is feasible to measure percentage exports growth.

What if some of the imports registered as first adoption are actually related to technologies that were imported before, but did not participate in the regime for some reason, as discussed in section 2.2? I argue that this would cause an attenuation bias in the estimates. First, if we expect the growth effect to be higher for first adopters, having second or third adopters in the sample by mistake, would drive the estimates down. Second, firms might avoid participating in the exemption regime because they fear a negative competition effect from spreading the information about a new technology available. In this case, the estimates are also lower than what we would expect under normal technology diffusion, outside the regime, when the knowledge takes longer to spread.

As a robustness check of the results I also estimate growth effects whithin industry samples. Tables 3.9 shows that the effect for first adopters is positive for all sectors and significant for 18 out of 25 sectors. The result for followers is driven by fewer industries: mettalic and non-mettalic minerals, food, leather & shoes, paper products, mineral products, metal products and furniture. The remaining industries present positive coefficients, but with lower significance levels, with the exception of tobacco and computer. This might be explained by the much lower number of observations, compared to the main regression. Another reason could be that some industries are not export oriented in Brazil, such that exports are not a perfect measure for productivity gains in those sectors.

Table 3.9: Estimates of the effect of technology adoption on exports growth by industry.

Dependent variable: Exports Growth (%)						
	First Adopter	SE	N	Follower	SE	N
Agriculture	39.816**	(18.848)	3,161	14.010	(15.922)	3,177
Forestry	58.192	(42.899)	380	51.298	(37.331)	383
Wood Products	23.314**	(9.989)	3,911	7.266	(6.787)	4,042
Metallic Minerals	57.624***	(12.960)	1,074	19.041*	(10.324)	1,151
Non-Metallic Min	5.301	(24.059)	1,052	53.018**	(26.895)	1,059
Food	15.193***	(5.391)	14,057	11.015**	(5.587)	14,016
Beverages	17.901	(18.602)	1,647	7.841	(15,496)	1,674
Tobacco	3.575	(19.942)	532	-4.152	(34.935)	512
Textiles	28.109***	(9.340)	7,876	6.240	(6.193)	8,118
Clothing	131.090***	(23.655)	3,602	8.330	(9.381)	3,799
Leather & Shoes	33.180***	(9.856)	6,246	11.193**	(5.516)	6,552
Paper Products	30.638***	(7.470)	3,964	14.838**	(6.275)	4,119

Printing	62.124***	(15.757)	1,372	4.040	(11.595)	1,485
Chemical Products	8.464	(5.729)	15,245	4.793	(5,270)	15,320
Pharmaceutical	10.453	(8.748)	2,886	7.984	(9.012)	2,870
Plastic Products	15.398***	(5.087)	15,139	2.945	(5.015)	15,171
Mineral Products	26.477***	(6.805)	6,729	16.009***	(5.382)	6,907
Metallurgy	10.964*	(6.184)	4,529	4.909	(5.927)	4,566
Metal Products	20.968***	(6.277)	10,685	10.883**	(5.057)	10,965
Computer, Electronic	20.656***	(8.044)	10,017	-5.230	(4.785)	10,666
Electrical Machinery	13.326**	(7.079)	9,023	6.357	(5.679)	9,228
Machinery	12.000***	(4.122)	28,552	0.222	(3.259)	29,242
Vehicles	9.685***	(3.830)	12,381	2.396	(3.318)	12,735
Transport Equip	16.310	(16.960)	1,794	6.906	(15,228)	1,812
Furniture	30.685***	(9.793)	5,484	13.348***	(5.240)	5,917

Notes: Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *First Adopter* is a dummy with a value of 1 if the firm is the first to import a technology and 0 if it did not import technologies, *Follower* is a dummy with a value of 1 if the firm has only imported technologies that have been imported before by a different firm, and 0 if it did not import technologies. The unbalanced panel sample includes firms that imported capital goods at least once, between 2000 and 2018, for the years in which it is feasible to measure percentage exports growth.

Different Estimation Lags

Next, I investigate whether the growth effect is experienced by firms during the following year only, or whether it lasts for a longer time. Table 3.10 presents the estimates for first adopters, followers and followers of multinationals, from one to four years after the adoption. First adopters see an export gain for up to three years after the investment, although smaller than the first year. For follower firms, the gains of the first year are now offset by negative effects three and four years later. This result might be driven by late adoptions of technologies that are close to being replaced, such that firms can only take advantage of the boost in productivity for a short period. Followers of multinationals, on the other hand, experience export growth for the three years following adoption.

Table 3.10: Estimates of the effect of technology adoption on exports growth at different lags.

Dependent variable: Exports Growth (%)				
	t+1	t+2	t+3	t+4
First Adopter	30.899***	8.543***	7.999***	2.901
	(1.867)	(1.841)	(1.870)	(1.912)
Observations	235,719	227,347	218,204	208,398
Follower	7.388***	-0.867	-2.738*	-4.416***
	(1.388)	(1.424)	(1.474)	(1.531)
Observations	241,5484	232,505	222,782	212,415
Follower of Multinational	10.207***	6.276***	4.448***	0.453
	(1.495)	(1.544)	(1.585)	(1.653)

Observations	217,414	187,278	163,944	143,168

Notes: Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The columns show the estimated growth effects one, two, three and four years later. *First Adopter* is a dummy with a value of 1 if the firm is the first to import a technology and 0 if it did not import technologies, $Follower$ is a dummy with a value of 1 if the firm has only imported technologies that have been imported before by a different firm, and 0 if it did not import technologies. *Follower of Multinational* is a dummy with a value of 1 if the firm has imported technologies that have been imported before by a multinational firm, and 0 if it did not import technologies. The unbalanced panel sample includes firms that imported capital goods at least once, between 2000 and 2018, for the years in which it is feasible to measure percentage exports growth.

3.5.3 State-level analysis

I begin this section with basic statistics about the equipment import shares. The means and standard deviations, by capital-type, of the capital import shares are shown in Table 3.11, with the correlations between each equipment types import share and real GDP per capita. Consistent with the results in Caselli and Wilson (2004), I document large differences in investment composition among states: the standard deviations of investment shares are always large relative to the cross-state means. That is, different types of equipment constitute widely varying fractions of the overall capital stock across states, which might be correlated to productivity differences.

Looking at the correlations with per-capita income, I also find a similar pattern to their study: it appears that poorer states capital stocks tend to have larger shares of fabricated metal products, non-electrical equipment and vehicles. Rich states investments, instead, are more skewed towards computing and accounting machinery, communication equipment, aircraft and professional goods. The results only diverge for electrical equipment and other transportation equipment.

Table 3.11: Capital-type import shares statistics

	Metal prod	Non-elec	Computers	Elec eep	Comm eep	Other transp	Vehicles	Aircraft	Prof goods
Import share mean	0.607	62.794	0.374	6.559	4.915	7.443	3.393	0.001	10.209
Std. deviation	1.325	33.722	0.834	19.120	18.780	13.692	11.247	0.002	21.015
min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
max	6.080	100.000	2.899	94.189	97.119	52.104	55.355	0.006	100.000
corr. w/ income pc	-0.101	-0.169	0.235	-0.129	0.168	0.093	-0.142	0.335	0.357

Next, I focus on the question of what explains cross-state differences in the shares of investment devoted to different types of equipment. The goal is to investigate whether the results in Caselli and Wilson (2004) can also be observed under a different setting: first, I look at within-country variation instead of cross-country; second, I observe a much shorter and more recent time period; third, I consider the adoption of very specific technologies by firms. The regression results by capital-type are presented in Table 3.12.

Caselli and Wilson (2004) find a negative correlation between inward FDI and the import share of all equipment types. I also find negative effect for communication equipments and professional goods. Different from them, I find a positive correlation for non-electrical and electrical equipments, and vehicles. A high correlation denotes a comparative advantage by foreign corporations in importing and installing this type of capital. One reason for this difference might be related to the focus on firms in my data, and not on general adoption.

They report that government consumption share in GDP is negatively associated with electrical equipment, while I find significant and positive correlations for the majority of capital types, with the exception of other transportation equipment. The share of industry in GDP predicts relatively more non-electrical equipment investment in both studies, although I also find a significant impact on computers, communication equipment and vehicles. Similar to their results, I also find that services' share of GDP is associated with less investment in communication equipment, and with more investment in motor vehicles. Finally, both analyses document that human capital is complementary with computers, communication equipment and motor vehicles (regarding the share of population with eleven or more years of education). As opposed to their results, I find a negative correlation for electrical equipment and professional goods.

Table 3.12: Capital-type estimates of the determinants of technology adoption at the state-level

	Dependent variable: Relative imports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-elec eqp	Computers	Elec eqp	Comm eqp	Other transp	Vehicles	Aircraft	Prof goods
Intercept	4.084***	1.064***	1.358***	1.085***	-0.007	-1.205***	-8.615	1.341***
Time trend	0.005***	-0.070***	-0.056***	0.082***	-0.027***	0.182***	-0.006	0.067***
FDI/GDP	0.052***	0.126	0.651***	-0.431***	-0.083	0.322***	-1.218	-0.103***
Government share	-0.008	1.922***	1.126***	2.339***	-4.981***	-0.141	-4.553	0.616***
Industrial share	0.042**	1.071***	0.597***	2.203***	-1.265***	0.633***	0.167	0.087
Services share	1.006***	5.357***	4.477***	-2.538***	-2.601***	2.144***	-4.534	1.550***
Education 15+	0.292***	-2.329***	-0.810***	-1.639***	-0.302*	0.979***	3.762	1.091***
Education 11+	-0.998***	2.222***	-2.278***	1.627***	1.613***	2.173***	12.623	-1.680***
Income per capita	0.097**	1.071***	0.777***	2.098***	-2.620***	-1.580***	-6.795	0.937***
Observations	459	459	459	459	459	459	459	459

3.6 Conclusion

This research offers a number of important contributions to the literature on multinational knowledge spillovers and technology diffusion, in large part due to the depth of a novel capital goods database from Brazil.

I find evidence of important spillovers from multinationals: they are importers of new technology, later followed by other firms, relatively more often than domestic firms. This implies that the presence of foreign competitors encourages investment in new technologies by local firms. Regarding the determinants of the adoption lag, I show that equipment of higher value, imported by multinationals and by larger firms, take longer to be diffused. I also report that first adopters experience a very large increase in their exports growth following the investment in the foreign capital (23 percentage points), while follower firms can still get an important benefit from the import too (6 percentage points). This finding has important implications for capital policy. As foreign investment is liberalized, negative effects due to competitor entry are counter-balanced by positive effects on exports.

References

Adao, Rodrigo, Arnaud Costinot, and Dave Donaldson, "Nonparametric counterfactual predictions in neoclassical models of international trade," *American Economic Review*, 2017, *107* (3), 633–89.

Alfaro, Laura and Maggie X Chen, "Selection and market reallocation: Productivity gains from multinational production," *American Economic Journal: Economic Policy*, 2018, *10* (2), 1–38.

_ **, Andrés Rodríguez-Clare, Gordon H Hanson, and Claudio Bravo-Ortega**, "Multinationals and linkages: an empirical investigation [with Comments]," *Economia*, 2004, *4* (2), 113–169.

Alfaro-Urena, Alonso, Isabela Manelici, and Jose P Vasquez, "The effects of joining multinational supply chains: New evidence from firm-to-firm linkages," *Working Paper*, 2019.

Allen, Treb, Costas Arkolakis, and Yuta Takahashi, "Universal gravity," *Journal of Political Economy*, 2020, *128* (2), 393–433.

Amiti, Mary and Jozef Konings, "Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia," *American Economic Review*, 2007, *97* (5), 1611–1638.

Anderson, James E, "A theoretical foundation for the gravity equation," *The American economic review*, 1979, *69* (1), 106–116.

— **and Eric Van Wincoop**, "Gravity with gravitas: A solution to the border puzzle," *American economic review*, 2003, *93* (1), 170–192.

— **and** — , "Trade costs," *Journal of Economic literature*, 2004, *42* (3), 691–751.

Arkolakis, Costas, Arnaud Costinot, and Andrés Rodríguez-Clare, "New trade models, same old gains?," *American Economic Review*, 2012, *102* (1), 94–130.

Arnold, Jens Matthias and Beata S Javorcik, "Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia," *Journal of International Economics*, 2009, *79* (1), 42–53.

Bas, Maria, Thierry Mayer, and Mathias Thoenig, "From micro to macro: Demand, supply, and heterogeneity in the trade elasticity," *Journal of International Economics*, 2017, *108*, 1–19.

Bastos, Paulo, Joana Silva, and Eric Verhoogen, "Export destinations and input prices," *American Economic Review*, 2018, *108* (2), 353–92.

Bernard, Andrew B and J Bradford Jensen, "Exceptional exporter performance: cause, effect, or both?," *Journal of international economics*, 1999, *47* (1), 1–25.

Blonigen, Bruce A, "Firm-specific assets and the link between exchange rates and foreign direct investment," *The American Economic Review*, 1997, pp. 447–465.

Buera, Francisco J and Ezra Oberfield, "The global diffusion of ideas," *Econometrica*, 2020, *88* (1), 83–114.

Burstein, Ariel, Javier Cravino, and Jonathan Vogel, "Importing skill-biased technology," *American Economic Journal: Macroeconomics*, 2013, *5* (2), 32–71.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 2015, *82* (1), 1–44.

Carluccio, Juan and Thibault Fally, "Foreign entry and spillovers with technological incompatibilities in the supply chain," *Journal of International Economics*, 2013, *90* (1), 123–135.

Caselli, Francesco and Daniel J Wilson, "Importing technology," *Journal of monetary Economics*, 2004, *51* (1), 1–32.

_ **and Wilbur John Coleman**, "Cross-country technology diffusion: The case of computers," *American Economic Review*, 2001, *91* (2), 328–335.

Caselli, Mauro, "Do all imports matter for productivity? Intermediate inputs vs capital goods," *Economia Politica*, 2018, *35* (2), 285–311.

Casler, Stephen D, "Why Growth Rates? Which Growth Rate? Specification and Measurement Issues in Estimating Elasticity Values," *The American Economist*, 2015, *60* (2), 142–161.

Cavallo, Michele and Anthony Landry, "The Quantitative Role of Capital Goods Imports in US Growth," *American Economic Review*, 2010, *100* (2), 78–82.

_ **and** _ , "Capital-Goods Imports and U.S. Growth," *Unpublished manuscript*, 2018.

Comin, Diego and Bart Hobijn, "Cross-country technology adoption: making the theories face the facts," *Journal of monetary Economics*, 2004, *51* (1), 39–83.

_ **and** _ , "An exploration of technology diffusion," *American economic review*, 2010, *100* (5), 2031–59.

_ **and Martí Mestieri**, "If technology has arrived everywhere, why has income diverged?," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 137–78.

_ **, Bart Hobijn, and Emilie Rovito**, "Five facts you need to know about technology diffusion," Technical Report, National Bureau of Economic Research Working Paper 2006.

Costinot, Arnaud and Andrés Rodríguez-Clare, "Trade theory with numbers: Quantifying the consequences of globalization," in "Handbook of international economics," Vol. 4, Elsevier, 2014, pp. 197–261.

Davis, Steven J and John Haltiwanger, "Gross job flows," *Handbook of labor economics*, 1999, *3*, 2711–2805.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum, "Global rebalancing with gravity: Measuring the burden of adjustment," *IMF Staff Papers*, 2008, *55* (3), 511–540.

Delgado, Miguel A, Jose C Farinas, and Sonia Ruano, "Firm productivity and export markets: a non-parametric approach," *Journal of international Economics*, 2002, *57* (2), 397–422.

Eaton, Jonathan and Samuel Kortum, "Trade in capital goods," *European Economic Review*, 2001, *45* (7), 1195–1235.

_ **and** _ , "Technology, geography, and trade," *Econometrica*, 2002, *70* (5), 1741–1779.

Estevadeordal, Antoni and Alan M Taylor, "Is the Washington consensus dead? Growth, openness, and the great liberalization, 1970s–2000s," *Review of Economics and Statistics*, 2013, *95* (5), 1669–1690.

Fan, Haichao, Yao Amber Li, and Stephen R Yeaple, "Trade liberalization, quality, and export prices," *Review of Economics and Statistics*, 2015, *97* (5), 1033–1051.

Feenstra, Robert C, James R Markusen, and William Zeile, "Accounting for Growth with New Inputs: Theory and Evidence," *The American Economic Review*, 1992, *82* (2), 415–421.

_ **, Philip Luck, Maurice Obstfeld, and Katheryn N Russ**, "In search of the Armington elasticity," *Review of Economics and Statistics*, 2018, *100* (1), 135–150.

Feng, Ling, Zhiyuan Li, and Deborah L Swenson, "The connection between imported intermediate inputs and exports: Evidence from Chinese firms," *Journal of International Economics*, 2016, *101*, 86–101.

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova, "Imported intermediate inputs and domestic product growth: Evidence from India," *The Quarterly journal of economics*, 2010, *125* (4), 1727–1767.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, "Long-run implications of investment-specific technological change," *The American Economic Review*, 1997, *87* (3), 342.

Harrison, Ann and Andres Rodriguez-Clare, "Trade, Foreign Investment, and Industrial Policy for Developing Countries*," in Dani Rodrik and Mark Rosenzweig, eds., *Handbooks in Economics*, Vol. 5 of *Handbook of Development Economics*, Elsevier, 2010, pp. 4039 – 4214.

Helpman, Elhanan, Marc J Melitz, and Stephen R Yeaple, "Export versus FDI with heterogeneous firms," *American economic review*, 2004, *94* (1), 300–316.

i Martin, Xavier Sala, Gernot Doppelhofer, and Ronald I Miller, "Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach," *American economic review*, 2004, pp. 813–835.

Imbs, Jean and Isabelle Mejean, "Trade elasticities," *Review of International Economics*, 2017, *25* (2), 383–402.

Javorcik, Beata, "Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages," *American economic review*, 2004, *94* (3), 605–627.

Jordà, Òscar, "Estimation and inference of impulse responses by local projections," *American economic review*, 2005, *95* (1), 161–182.

Kandilov, Ivan T, Aslı Leblebicioğlu, and Ruchita Manghnani, "Trade Liberalization and Investment in Foreign Capital Goods: A Look at the Intensive Margin," *Emerging Markets Finance and Trade*, 2019, pp. 1–24.

Katz, Michael L and Carl Shapiro, "R and D rivalry with licensing or imitation," *The American Economic Review*, 1987, pp. 402–420.

Keller, Wolfgang, "International technology diffusion," *Journal of economic literature*, 2004, *42* (3), 752–782.

_ , "International trade, foreign direct investment, and technology spillovers," in "Handbook of the Economics of Innovation," Vol. 2, Elsevier, 2010, pp. 793–829.

_ **and Stephen R Yeaple**, "Multinational enterprises, international trade, and productivity growth: firm-level evidence from the United States," *The Review of Economics and Statistics*, 2009, *91* (4), 821–831.

Kose, M Ayhan, Eswar Prasad, Kenneth Rogoff, and Shang-Jin Wei, "Financial globalization and economic policies," in "Handbook of development economics," Vol. 5, Elsevier, 2010, pp. 4283–4359.

Lian, Weicheng, Natalija Novta, Evgenia Pugacheva, Yannick Timmer, and Petia B Topalova, "The Price of Capital Goods: A Driver of Investment Under Threat," *Chapter 3 in World Economic Outlook, IMF*, 2019.

Long, J Bradford De and Lawrence H Summers, "Equipment investment and economic growth," *The Quarterly Journal of Economics*, 1991, *106* (2), 445–502.

Meleshchuk, Sergii and Yannick Timmer, "Trade Liberalization and Firm Investment: Evidence from Colombia," *Unpublished working paper*, 2019.

Melitz, Marc J, "The impact of trade on intra-industry reallocations and aggregate industry productivity," *econometrica*, 2003, *71* (6), 1695–1725.

Ministry of Economy of Brazil, "Estatisticas sobre pleitos de concessao ou renovacao de Ex-Tarifarios," *Retrieved from: http://www.mdic.gov.br/index.php/competitividade-industrial/acoes-e-programas-13/estatisticas-dados-abertos*, 2019.

Mobarak, Ahmed Mushfiq and Denni Puspa Purbasari, "Corrupt protection for sale to firms: evidence from Indonesia," *Unpublished working paper*, 2006.

Muendler, Marc-Andreas, "Trade, technology and productivity: A study of Brazilian manufacturers 1986-1998," 2004.

Mutreja, Piyusha, B Ravikumar, and Michael Sposi, "Capital goods trade, relative prices, and economic development," *Review of Economic Dynamics*, 2018, *27*, 101–122.

NSF, "International Investment and R&D Data Link: 2008-10," *National Science Foundation - National Center for Science and Engineering Statistics. Available at http://www.nsf.gov/statistics/2016/nsf16306/*, 2016.

Ossa, Ralph, "Why trade matters after all," *Journal of International Economics*, 2015, *97* (2), 266–277.

Parro, Fernando, "Capital-skill complementarity and the skill premium in a quantitative model of trade," *American Economic Journal: Macroeconomics*, 2013, *5* (2), 72–117.

Poole, Jennifer P, "Knowledge transfers from multinational to domestic firms: Evidence from worker mobility," *Review of Economics and Statistics*, 2013, *95* (2), 393–406.

Rodriguez-Clare, Andres, "The role of trade in technology diffusion," *Federak Reserve Bank of Minneapolis Discussion Paper*, 1996, (114).

Santacreu, Ana Maria, "International Technology Diffusion A Gravity Approach," *Federal Reserve Bank of St. Louis Working Paper*, 2020.

Schor, Adriana, "Heterogeneous productivity response to tariff reduction. Evidence from Brazilian manufacturing firms," *Journal of Development Economics*, 2004, *75* (2), 373–396.

Shikher, Serge, "Predicting the effects of NAFTA: Now we can do it better!," *Journal of International and Global Economic Studies*, 2012, *5* (2), 32–59.

_ , "Putting industries into the Eaton–Kortum model," *The Journal of International Trade & Economic Development*, 2012, *21* (6), 807–837.

Simonovska, Ina and Michael E Waugh, "The elasticity of trade: Estimates and evidence," *Journal of international Economics*, 2014, *92* (1), 34–50.

Soderbery, Anson, "Trade elasticities, heterogeneity, and optimal tariffs," *Journal of International Economics*, 2018, *114*, 44–62.

Solow, Robert M, "Investment and technical progress," *Mathematical methods in the social sciences*, 1960, *1*, 48–93.

Stokey, Nancy L, "Technology diffusion," *Review of Economic Dynamics*, 2020.

The Growth Lab at Harvard University, "Growth Projections and Complexity Rankings, V2, [Data set]," 2019. https://doi.org/10.7910/dvn/xtaqmc.

Timmer, Marcel P, Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J De Vries, "An illustrated user guide to the world input–output database:

the case of global automotive production," *Review of International Economics*, 2015, *23* (3), 575–605.

UNCTAD, "World Investment Report," *United Nations*, 2020.

Vishwasrao, Sharmila and William Bosshardt, "Foreign ownership and technology adoption: evidence from Indian firms," *Journal of development economics*, 2001, *65* (2), 367–387.

Xu, Bin and Jianmao Wang, "Capital goods trade and R&D spillovers in the OECD," *Canadian Journal of Economics*, 1999, pp. 1258–1274.

Yilmazkuday, Hakan, "Estimating the trade elasticity over time," *Economics Letters*, 2019, *183*, 108579.

Yotov, Yoto V, Roberta Piermartini, José-Antonio Monteiro, and Mario Larch, *An advanced guide to trade policy analysis: The structural gravity model*, World Trade Organization Geneva, 2016.