International Trade and Wage Inequality: Evidence from Brazil[*]

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October 16, 2022

Abstract

We study the effect of the bilateral trade integration with China on wage inequality in Brazil. Previous studies have documented the contribution of trade opening to the decline in inequality since the 1990s, driven primarily by cross-firm pay differences. Using more recent data, we find a sharper reduction in wage inequality over the 2000s, parallel to China's accession to the WTO. Our reduced-form analysis of the China shock suggests that some firms are harmed by import competition, while others profit from increased exports and cheaper inputs. We rationalize these patterns by extending Helpman et al. (2017) to include sector heterogeneity in trade exposure and firm-level selection into imports. Our calibrated model indicates that the rise of China leads to a reduction in cross-firm wage inequality in Brazil since the cross-sectoral effect - which tends to benefit low-wage sectors and hurt high-wage sectors - dominates the within-sector - increase in inequality due to a rise in importing and exporting firms.

Keywords: Trade, Wage Inequality, Labor Markets, China, Brazil
JEL Classification: F16, J21, J31

[*]We thank Dan Bernhardt, Alexander Bartik, and Greg Howard for their continued support. We also thank Rafael Dix-Carneiro, Marc Muendler, Sergio Firpo, Andrew Garin, Jorge Lemus, Martin Perry, Kris Mitchener, Stefan Krasa, seminar participants at the University of Illinois, and the Midwest Economics Association 2021 Meeting for helpful comments. We acknowledge financial support from the Department of Economics at the University of Illinois. We thank Nereus-USP for providing access to the datasets. All errors are ours.

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1. Introduction

Studying the effects of international trade on labor markets has been a central topic in the theoretical and empirical international trade literature. Most recent literature has focused on the direct impacts of global trade liberalization, international demand, or supply shocks on labor market outcomes within trade partners, such as earnings and employment (E.g., Autor, Dorn, and Hanson (2013); Dix-Carneiro and Kovak (2017)). However, due to its industry-specific nature, international trade shocks have heterogeneous effects on firms and workers within a country. In particular, international trade shocks will disproportionately affect some sectors more than others. Therefore, it is natural to expect that these shocks will have reallocation consequences affecting the income distributions within each country (Muendler (2017); Adão, Carrillo, Costinot, Donaldson, and Pomeranz (2020)).

This paper investigates the relationship between international trade exposure and wage inequality in Brazil over the 2000s. During this period, bilateral trade between Brazil and China increased dramatically, driven by the rise of China as a prominent participant in global trade. Throughout the same period, Brazil (and other Latin American countries) experienced a significant decline in wage inequality (Messina and Silva, 2017; Ferreira et al., 2017), suggesting a possible causal relationship.

We exploit detailed information from the matched employer-employee administrative data, which contains the universe of formal employment in Brazil, the Relação Anual de Informações Sociais (RAIS), to determine how trade with China affected wage inequality and other economic outcomes. The data allows us to observe workers' earnings, occupations, and other characteristics while identifying the key features of their employers, such as their location, size, and industry. Our empirical strategy filters out all potential worker-specific characteristics that could affect wages to isolate the firm-specific component of the wage distribution.

We begin by establishing a series of stylized facts from the Brazilian matched employer-employee data about the evolution of wage dispersion. Using a standard log-wage variance decomposition, we observe that the between-firm-occupation component is the major contributor to the fall in wage inequality, explaining around 2/3 of the overall change in the wage variance. The evolution of the firm-component distribution reveals a significant decrease in the wage variance, especially coming from the bottom of the distribution.[1] Across sectors, the decline

[1] Recent works associate the decrease in wage variance to the increase in real minimum wages over the same period.

in the wage variance is proportional between- and within-sectors. Finally, we find positive and heterogeneous size premium and export and import premia across sectors. These facts suggest that firms' observables may explain between- and within-sector changes in the wage variance.

We then investigate the relationships between the exposure to international trade shocks and the changes in wages. Our industry-level measures of trade exposure are the changes in imports from China and exports to China between 2000 and 2008 per worker of 2000. We instrument these changes using the procedure proposed in Costa, Garred, and Pessoa (2016), which consists of the average shifts in imports and exports of other developing countries with China in the same period. Finally, we construct downstream and upstream exposure to the trade shocks using the input-output coefficients and build the instruments appropriately.

The reduced-form analysis estimates the impact of trade exposure to the China shock on firm wages, as measured by the firm wage component obtained in the previous decomposition. The results support a positive and significant impact of export exposure on wages and the adverse effects of import exposure on wages. In other words, export shocks cause a positive shift in the labor demand, whereas import shocks cause a negative shift in the labor demand. In addition, our results highlight the importance of indirect (or higher-level) exposure to trade shocks through industries' production networks to wages. The downstream export (import) exposure leads to an increase (decrease) in wages. Moreover, upstream import exposure increases wages, but upstream export exposure reduces wages. These results indicate that firms prosper when greater import exposure occurs in their input markets. In contrast, increases in upstream export exposure imply that firms will compete with the external demand for input supply, leading to a decline in wages.

Our preferred estimates, including upstream and downstream exposure, show statistical and economic relevance. The difference in changes in wages between the 90^{th} and 10^{th} percentiles of downstream export exposure is 3.5 percent, in line with the literature.[2] Downstream import exposure harms firm wages, and the difference in wage change between the 90^{th} and 10^{th} percentiles of exposure is around 10 percent. In contrast, upstream export exposure causes lower wages, and the difference in wages between the 90^{th} and 10^{th} percentiles of each shock's distribution is about 16 and 5 percent, respectively.

[2]For example, Adão (2016) studying the impact of commodity price shocks, which is highly related to the change in export exposure in our analysis. In the reduced form analysis, he also finds a positive relationship between commodity price shocks and commodity sector wages.

We do not find significant differential effects of trade exposure between importer/non-importer and exporter/non-exporter firms. Nonetheless, upstream import exposure positively impacts the probability that firms import, suggesting that firms benefit from imported inputs. In contrast, the positive shocks downstream of production (i.e., export exposure) increase firms' probabilities of exporting. Thus, the positive shift in the demand causes firms to supply their output in the external market.

Using those estimates, we find that the net effect of the China shock on the Agriculture/Mining sector is about a 1 percent increase in wages (1.8 percent increase from export exposure minus 0.9 due to import exposure).[3] The Low-Tech manufacturing sector suffers a net decrease in wages of about 0.6 percent on wages, primarily due to the downstream fall in demand through import exposure (about 1.6 percent, which more than offsets the positive effect of upstream exposure of around 0.5 percent). Finally, High-Tech manufacturing industries suffer a large 6 percent reduction in wages due to the China shock. Despite the cheaper and higher-quality inputs, which partially increment wages by 1.3 percent, the decline in demand from downstream import exposure implies larger negative effects on wages by almost 8 percent.

To account for these facts and the reduced-form results, we extend the model proposed in Helpman, Itskhoki, Muendler, and Redding (2017) (henceforth HIMR) and Helpman, Itskhoki, and Redding (2010) (henceforth HIR) to account for sector heterogeneity. We also incorporate within-sector firm selection into export and import markets as alternative mechanisms for trade shocks to affect the wage distribution. This model offers possibilities for the selection of firms into exporting and importing markets through market access and selection effects. The former establishes that exporter and importer firms pay higher wages and hire more workers, while the latter implies that high-productivity firms are more likely to engage in international trade activities by becoming exporters or importers. Moreover, sector heterogeneity means that firms in distinct sectors will pay different wages and be subject to different forces to select them into the exporting and importing markets. We estimate the model parameters using maximum likelihood (ML). We show that the estimated model provides a good fit for the empirical joint distribution of employment and wages and various measures of wage inequality. In particular, the model does a good job matching the observed trend in the fall of wage vari-

[3]We highlight that RAIS only contains formal employment. Especially for the Agriculture sector, which has a relatively higher informality rate and experienced higher growth in exports.

ance over time. Nonetheless, the model's predictions underestimate the share of employees and firms operating in the export and import markets.

The model presents two channels through which trade shocks may affect wages and employment. Import competition represents a negative shock on a firm's output demand, which leads to lower wages and lower demand for workers. Nonetheless, upstream import exposure represents a positive shock for firms by making inputs cheaper, which leads to higher labor demand and higher wages. Export exposure causes a positive shock on firms' output and enables firms to export. Moreover, due to downstream domestic increase in output demand, even non-exporter firms may benefit highly. Thus, direct and downstream export exposure leads to higher labor demand and higher wages. As a result, wage inequality arises within-sector firms taking advantage of trade shocks and selecting into imports or exports. Across sectors, import or export exposure changes the average wages for all firms and the composition of workers, which leads to between-sector changes in wage variance.

We use the model to perform counterfactual analyses. First, we construct two counterfactual scenarios in which we shut down one "side" of the trade integration shock, i.e., the import or export exposure. Then, using a strategy similar to Caliendo, Dvorkin, and Parro (2019), we calibrate the model's parameters to identify the partial effects of import and export exposure that we encountered in the reduced-form analysis for each sector. Our findings suggest that the China shock is responsible for a 5 percent decrease in the overall wage variance in Brazil between 2000 and 2008, mainly driven by the import exposure across sectors. In other words, the cross-sector effect tends to harm high-paying sectors relative to low-paying sectors, thus generating a decline in inequality and dominating the within-sector effect, which favors firms that select into imports or exports, thus increasing inequality.

We also consider counterfactual scenarios that combine the China shock with tariff reductions. We study whether trade liberalization can limit or amplify the effects on wage variance stemming from the China shock. The stronger effect will depend on whether the selection into imports (or exports) associated with the changes in the wage premium for importers or exporters is stronger than the import competition effect in the output market. For example, with a moderate import tariff reduction of around 10 percent, the negative impact of import exposure is moderated by the increase in the share of workers in importer and exporter firms. However, the reduction in wage dispersion would also be smaller.

Our findings are particularly relevant for policymakers who want to induce international demand shocks by promoting trade liberalization. Our empirical exercises suggest that tariff reduction under a situation of bilateral trade integration may reduce potentially harmful effects by inducing imports, which increase employment and wages. However, the weaker decline in average wages would come at higher wage variance, both between sectors (displacement of workers to the high-paying sector) and within sectors (enlarging the share of firms operating in external markets).

Despite our contributions to bilateral trade integration and trade liberalization in developing countries, our model does not explore all of the important trade and labor markets issues. For instance, our model does not address: i) welfare gains from trade due to higher trade and lower relative prices; ii) changes in the sectoral (and aggregated) productivity; iii) the relationship between formal and informal labor markets. Each of these questions is highly relevant for developing economies (Dix-Carneiro, Goldberg, Meghir, and Ulyssea (2021)) and can guide future research.

Literature and Contribution. This paper contributes to the extensive literature on the consequences of international trade on income inequality and labor market outcomes (e.g., Stolper and Samuelson (1941); Galle, Rodríguez-Clare, and Yi (2017); Adão, Carrillo, Costinot, Donaldson, and Pomeranz (2020)). Our analysis is most closely related to recent studies based on heterogeneous exposure to trade shocks and their consequences on labor market outcomes, especially to the literature exploring the effects of the so-called China shock (Autor, Dorn, and Hanson (2013); Autor, Dorn, Hanson, and Song (2014); Caliendo, Dvorkin, and Parro (2019); Bloom, Draca, and Van Reene (2016); Autor, Dorn, and Hanson (2016); Bloom, Kurmann, Handley, and Luck (2019)). Overall, these studies focus on the impact of import penetration on labor market outcomes, especially in manufacturing industries, for the United States and other developed economies. We complement these studies by including the export exposure side (e.g., Feenstra, Ma, and Xu (2019)) and by studying the impact in Brazil, a middle-income country (Costa, Garred, and Pessoa (2016); Attanasio, Goldberg, and Pavcnik (2004)). We also contribute by investigating the indirect effects through input-output linkages, which Acemoglu, Autor, Dorn, Hanson, and Price (2016) and Adão, Carrillo, Costinot, Donaldson, and Pomeranz (2020) have shown to play a significant role in the general equilibrium effects of trade.

By extending the model proposed by Helpman, Itskhoki, and Redding (2010) and Helpman, Itskhoki, Muendler, and Redding (2017), our paper also contributes to an extensive literature that incorporates firm and worker heterogeneity to explain wage variation across firms. Those differences may arise from assortative matching (as studied empirically in Abowd, Kramarz, and Margolis (1999) and Card, Cardoso, Heining, and Kline (2018)) or to labor market frictions (in the same line as search models, such as Burdett and Mortensen (1998)). In both settings, workers with the same characteristics can be paid different wages, and those differences are sustained in equilibrium. The empirical facts commonly stated in this type of model explain how firms sort into the exporting market and how larger firms pay higher wages than smaller firms (Melitz (2003); Amiti and Davis (2012)). Our empirical contribution also addresses those topics, approximating our work to Amiti and Davis (2012).

We also incorporate both firm and sector heterogeneity. In this sense, this paper also contributes to the literature that investigates structural changes in the economy, either due to trade shocks (Dix-Carneiro (2014); Cravino and Sotelo (2019)) or other factors (e.g., Bustos, Caprettini, and Ponticelli (2016); Rodrik (2013)). Moreover, our sector-heterogeneity model is associated with firm heterogeneity, explaining the change in inequality between and within-sector after a double-sided trade integration shock.

Finally, this paper discusses the puzzle of falling wage inequality in Latin America in recent decades,[4] with a particular interest in Brazil, which contrasts with the pattern in developed economies. For instance, the United States has experienced a great increase in wage (and income) inequality since the 1970s, which has fostered intense debate (see Acemoglu and Autor (2011), which makes an extensive analysis of this subject). In contrast, Brazil has experienced a sharp decline in wage inequality since the mid-1990s. Many studies relate this path to changes in international trade, such as trade opening (Dix-Carneiro (2014); Dix-Carneiro and Kovak (2017); Helpman, Itskhoki, Muendler, and Redding (2017)) and commodity price shocks (Adão (2016)). However, the most substantial effects suggested in the literature are the minimum wage policy since 1995 (Engbom and Moser (2021)) and the gender, race, education, and experience wage gaps (Nopo (2012); Messina and Silva (2017); Ferreira, Firpo, and Messina (2021)).

To the best of our knowledge, no work has tried to determine to which extent the China shock has influenced Brazil's (formal) wage inequality. Our analysis is most closely related to

[4] Although most countries experienced a fall in the Gini Index (except Costa Rica), the fall was not homogeneous. For example, some countries, such as Nicaragua and Bolivia, have a more drastic fall than Colombia (see Messina and Silva (2017)).

Costa, Garred, and Pessoa (2016), which studies the effects of China's rise on Brazil's local labor market outcomes, uncovering the existence of winners (where export exposure was high) and losers (where import exposure was high) that could impact wage inequality changes. In contrast to recent work, we focus on the impact of trade on the (formal) wage distribution and the potential mechanisms connected to it.

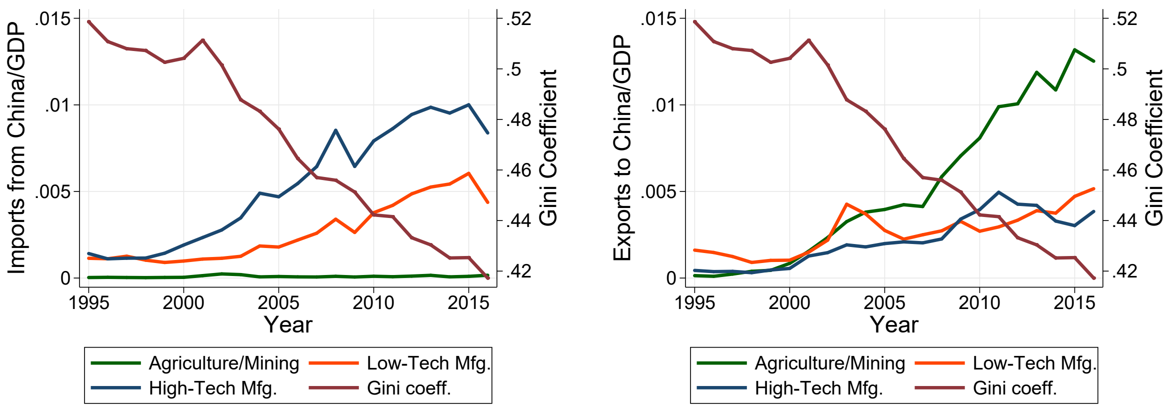
The paper proceeds as follows. Section 2 describes the context of the Brazilian economy over the 2000s, including the income inequality decrease and the increased economic integration with China over the same period. Section 3 describes the data and the instrumental variables. Section 4 presents and discusses the stylized facts and wage inequality trends in Brazil. Section 5 provides reduced-form analysis relating trade shocks to observable formal labor market characteristics. Section 6 describes the theoretical framework and the strategy to estimate the structural parameters. In Section 7, we estimate the structural model, present it fits the data, and perform counterfactuals. Section 8 concludes.

2. The rise of China and the Brazilian wage inequality reduction

As documented in Messina and Silva (2017), Latin American countries have experienced substantial decreases in earnings inequality. For instance, Latin America's average Gini coefficient for household income per capita fell by 5.9 points between 2002 and 2011. This fall is striking in light of that inequality increased during this period in most countries outside Latin America. Messina and Silva (2017) observed that many factors could be associated with this phenomenon, including changes in the labor supply (e.g., greater participation of women in the labor force) and changes in the composition of the labor skill supply. The case of Brazil is representative of the Latin American experience. Ferreira, Firpo, and Messina (2017) shows that the Gini coefficient of the country's distribution of household per capita income fell by 12 percent, from 0.59 in 1995 to 0.52 in 2012. While Brazil also has experienced changes in labor supply, Adão (2016) and Costa, Garred, and Pessoa (2016) highlight that the country faced significant international shocks on aggregate demand for labor that might have been particularly important to the wage inequality reduction. In this regard, the rise of the Chinese economy in the 2000s plays a central role.

Before China became a member of the World Trade Organization (WTO), the international trade volume between Brazil and China was modest, and the Chinese participation in Brazilian trade was tiny. Data from United Nations (2018) indicate that in 1999, China was the destination of 1.5% of total Brazilian exports, while 1.7% of Brazilian imports came from China. In sharp contrast, by 2010, China had become one of Brazil's largest international trade partners, accounting for 15.3% of its exports and 13.4% of its imports.

While Brazil and China dramatically increased their overall bilateral trade volume, there was considerable heterogeneity across sectors. Figure 1 illustrates the increase in bilateral trade between Brazil and China and the decrease in the Brazilian Gini coefficient. The figure depicts the imports (panel a) and exports (panel b) as a share of GDP for three main sectors of the economy, agriculture and mining (green line), high-technology manufacturing (blue line), and low-technology manufacturing (orange line). The brown line represents the Gini coefficient.



(a) Brazilian imports from China

(b) Brazilian exports to China

Figure 1. Trends in Brazil-China trade (relative to the Brazilian GDP) and wage inequality in Brazil. Imports (Panel A) and Export (Panel B) for Brazilian trade with China as a percentage of the GDP (left scale) and Gini Coefficient for the Brazilian formal labor market (right scale). Especially after the 2000s, Manufacturing industries showed the highest increase in imports as percentage of the GDP, whereas Agriculture and Mining industries showed the higher increase in exports as a percentage of the GDP. Wage inequality, measured by the Gini index, has a declining path, being steeper after 2001.

Figure 1 shows that the share of Brazilian spending on Chinese manufactured goods (both low-technology and high-technology) rose dramatically after 2001. In contrast, imports in agriculture and mining goods remained low. Panel (a) reveals a similar experience to other developing and developed economies. In contrast, Panel (b) shows another dimension to the economic integration with China, with a sharp rise in exports of agriculture and mining products and a significant increase in exports of some manufactured goods. Simultaneously, we observe a fall in the Gini coefficient over that period, particularly after 2002.

3. Data and Descriptive Statistics

3.1 Main Data Sets

Labor Markets and Firm Characteristics. One challenge in studying the consequences of international trade to wage inequality is the shortage of detailed data at the worker and firm levels that allow us to track firms over time. To address this challenge, we use labor market information from the Relação Anual de Informações Sociais (RAIS), a matched employer-employee administrative database collected by the Brazilian Ministry of Labor comprising the population of formal employment in Brazil from 1996 to 2012. It is a high-quality source of information regarding labor markets in Brazil because it contains rich details on wages and workers' characteristics such as educational attainment, gender, age, occupation, industry, and region.

We exclude observations with an invalid worker identification number (PIS) or firm identification number (CNPJ). Because a worker can have multiple entries each year, we adopt the standard procedure in the literature of selecting only the job with the highest average earning. We also exclude observations that either did not report wages or reported a null value. Levels of education and age are the mode declared for each job spell. Those issues are related to misreporting information, but they represent a small portion of the data (less than 1% of the total job spells each year). As Dix-Carneiro and Kovak (2017) and Dix-Carneiro (2014) noted, these aspects underscore the high quality of the dataset. To measure a firm's level of employment, we further restrict the data to include only workers with an employed status on December 31^{st} of each year.

We separate educational attainment into three categories: i) high-school dropouts; ii) high-school graduates; iii) at least some college. These definitions align with the literature and represent essential characteristics of the Brazilian economy. We restrict the analysis to workers aged 18 to 64.

Each year, RAIS reports average monthly wages in current values (Brazilian Reais - BRL) and in number of minimum wages. We follow other studies that have used RAIS and use the first measure to construct our main earning variables. Wages are inflated to values of 2016 using the average consumer price index (IPCA). Since 1995, RAIS also reports weekly hours in the contract, but not the number of hours the worker actually worked during a period. We assume that contracted hours are a good proxy for the effective number of hours worked. To calculate the total monthly hours worked, we multiply weekly hours by 4. Finally, we define the average monthly wage per hour by the ratio of those two measures.

Industries classification follows the Classificação Nacional de Atividades Econômicas (CNAE) version 2.0. We use the crosswalks provided by IBGE (Instituto Brasileiro de Geografia e Estatística) to match with previous versions. The primary definition of industry uses 4-digits, which comprises around 600 industries. To ease exposition, we aggregate those industries into broader sectors following Dix-Carneiro (2014): Agriculture/Mining, Low-Tech Manufacturing, High-Tech Manufacturing, and Non-Tradable. As Figure 1 shows, Agriculture/Mining is profoundly affected by growing exports, whereas Low- and High-Tech Manufacturing experience higher growth in imports.

In this paper, we follow the related literature and use industry-level shocks. We define a firm by a tuple firm-identifier-region.[5] We use IBGE's definition of microregions, which are roughly equivalent to counties in the United States, but immutable over time, comprising a set of municipalities. Henceforth, we will refer to them simply as regions.

Although a rich dataset for formal employment in Brazil, comprising a broad set of information about workers, RAIS has relatively few characteristics about firms. Hence, we cannot have information on revenues, profits, and input expenditures, among other firm characteristics. However, using the firm identifier and data provided by SECEX (Secretaria de Comércio Exterior), we can establish whether a firm f is an exporter or an importer (or both) in year t.

Census. The Brazilian Census data from 1991 through 2010 provides information on employment by industries and microregions. These datasets contain information necessary to build demographic control variables for our econometric specifications. Because RAIS is limited to formal employment, the Census data also allows us to control aggregate informal employment measures.

International Trade. We use data on bilateral trade flows of goods at the 4-digit Harmonized System between 1992 and 2016 from the U.N. Comtrade database United Nations (2018). In compiling the data, we give preference to the trade flows reported by the exporting country recorded fob (free on board). We determine the import flows by mirroring the bilateral export

[5] In this paper, we adopt the CNPJ (8 digits) as each firm identifier. A firm's identification number is the Cadastro Nacional da Pessoa Jurídica (CNPJ), an identification number issued to Brazilian companies by the Department of Federal Revenue of Brazil, which comprises 14 digits. The first 8 identify the firm, and the next 4 classify the establishment (headquarters are associated with a value 0001 while other numbers are associated with subsidiaries). The last two digits exist for validation purposes.

flows. The data is complemented by the reported import bilateral flows when the exporter's report is unavailable. Using a comprehensive crosswalk algorithm, we convert the international bilateral flows from the 4-digit Harmonized System product codes to the Brazilian industry codes from Classificação Nacional de Atividades Econômicas (CNAE) version 2.0.

3.2 Measuring the Import and Export shocks

Trade Shocks We use industry-level trade shocks,[6] measuring the exposure to international trade shocks using the change in trade with China in each industry per initial employment level in that industry. According to this measure, the shock is heterogeneous only at the sector level. Using a similar strategy as Autor, Dorn, Hanson, and Song (2014), Acemoglu, Autor, Dorn, Hanson, and Price (2016) and Feenstra, Ma, and Xu (2019), we measure the exposure of industry s to the trade shock by the change in the sector level trade between Brazil and China as follows:

$$IPW_{jt} = \frac{M_{jt} - M_{j2000}}{L_{j,2000}} \tag{3.1}$$

$$EPW_{jt} = \frac{E_{jt} - E_{j2000}}{L_{j,2000}}, \tag{3.2}$$

where IPW_{jt} is the import per worker, or import exposure in industry j and year t in Brazil from Chinese imports; EPW_{jt} is the Brazilian export per worker, or export exposure of industry j in year t to China; The numerators represent the difference between imports (M) in eq. (3.1) or exports (E) eq. (3.2) in year t with the base year of 2000. To normalize, we divide the differences in thousands of dollars by the total number of workers in industry j in 2000. These variables measure the increase in import and export exposure of each Brazilian industry j.

Indirect Trade Shocks The trade literature has extensively documented the various ways that trade shocks directly affect the firm's output demand. However, firms are not isolated in their production process. They buy and sell inputs with other firms, so trade shocks may also indirectly affect an industry through production chains. On the one hand, there is an *upstream effect* caused by *downstream exposure*: firms are indirectly affected if their customers are directly af-

[6] Alternatively, one could assume that trade shocks are related to local labor market changes. More recent works use regional-level shift-share designs to study the impact of the international economy on Brazilian labor markets. (Dix-Carneiro and Kovak, 2017; Adão, 2016; Costa et al., 2016).

fected by the shocks or firms downstream in the production chain. On the other hand, if positive (negative) demand shocks hit firms on their products, they will likely increase (decrease) their demand for inputs through the intermediate consumption channels (input-output linkages).

There is also a *downstream effect* caused by *upstream exposure*: firms are indirectly affected by trade shocks if their input suppliers are affected by those shocks or firms upstream in the production chain. Thus, the import exposure upstream in the production chain is likely to increase the supply of inputs (via price reductions or quality improvements), which reduces costs with potential transmission to increased wages. Conversely, export exposure upstream in the production leads to greater competition with external markets, with a potential increase in input prices and a decrease in wages. Therefore, breaks in the input-output relationship between firms caused by trade shocks may be harmful both upstream or downstream since they could destroy long-term relationships, specialization, and possible losses from terminated contracts. A valid extension to test these hypotheses can be done by studying transactions between firms.

Concerns about the indirect effects of trade shocks are increasing in the literature. For instance, Acemoglu, Autor, Dorn, Hanson, and Price (2016) documents that downstream exposure to import competition with China has a comparable effect on industry employment as the direct effect (or first-order) impact of import penetration.[7] More recently, Adão, Carrillo, Costinot, Donaldson, and Pomeranz (2020) have addressed indirect impacts of trade shocks in the Ecuadorian economy using a general equilibrium model. Other recent papers, such as Huneeus (2018) and Dhyne, Kikkawa, Mogstad, and Tintelnot (2021) have focused on using firm-to-firm transaction data to study the role of production networks in the transmission of international trade shocks through the economy.

Considering this potential propagation of shocks through the industries' production chains, we use an input-output matrix (Guilhoto and Sesso-Filho (2005, 2010)) to estimate how trade shocks disseminate to firms. The authors propose different methods to estimate yearly matrices using a flexible approach and preliminary data.[8] We propose four measures for the indirect exposure of a sector to the import and export shocks:

[7] In this paper, we use different terminology from Acemoglu, Autor, Dorn, Hanson, and Price (2016). They refer to downstream/upstream effects, which we refer to as upstream/downstream exposure.

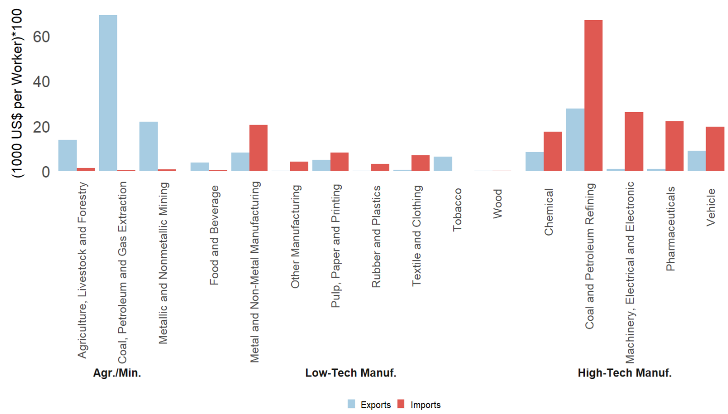
[8] Despite using a different methodology, their estimates do not differ from official input-output matrices from the Instituto Brasileiro de Geografia e Estatística - IBGE.

$$
\begin{aligned}
IPW_{jt}^{UP} &= \sum_{k \in J} \left(\omega_{kj,1995} IPW_{kt} \right) - IPW_{jt} \\
EPW_{jt}^{UP} &= \sum_{k \in J} \left(\omega_{kj,1995} EPW_{kt} \right) - EPW_{jt} \\
IPW_{jt}^{DOWN} &= \sum_{k \in J} \left(\omega_{jk,1995} IPW_{kt} \right) \\
EPW_{jt}^{DOWN} &= \sum_{k \in J} \left(\omega_{jk,1995} EPW_{kt} \right)
\end{aligned}
\tag{3.3}
$$

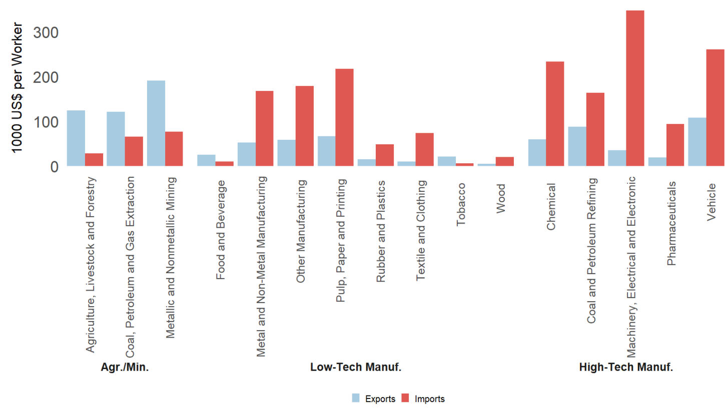
where $\omega_{jk,1995}$ is the $(j,k)^{th}$ entry in the Leontief-inverse matrix for the year 1995, normalized to sum 1 in the row or column depending on the direction from which we calculate the effect.[9] The superscripts *UP* and *DOWN* represent the indirect shock dimensions upstream and downstream, respectively. The shocks with no superscripts represent direct shocks to each industry, as defined in eq. (3.1) and eq. (3.2).

Figure 2 illustrates our exposure measures: direct exposure (panel a), indirect downstream exposure (panel b), and indirect upstream exposure (panel c). From panel (a), we note that Agriculture/Mining industries are relatively more exposed to the export shock. Low values are due to their size in the economy, represented by the number of employees. On the other hand, manufacturing industries show the highest values for import competition, especially those classified as High-Tech manufacturing.

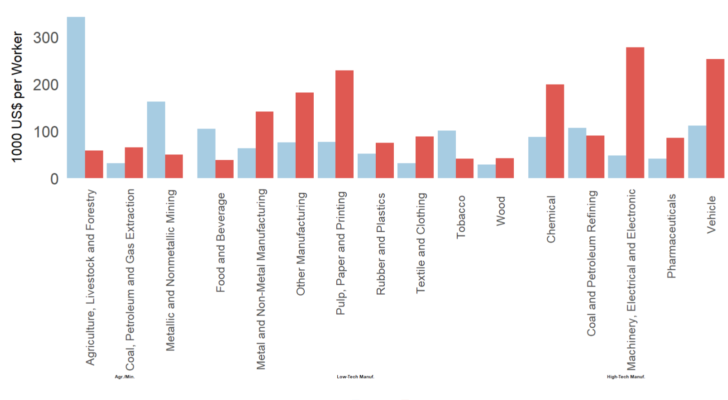
[9] We follow Acemoglu, Autor, Dorn, Hanson, and Price (2016) in using the Leontief-inverse matrix to obtain indirect effects. This way, we also capture the full chain of supply and demand triggered by trade shocks.



(a) Direct Exposure



(b) Downstream Exposure



(c) Upstream Exposure

Figure 2. Import and Export exposure to Trade Shocks between 2000 and 2008. The figures display the measures of direct and indirect import and export exposure. Each bar averages the exposure measures from the 4-digits to the 2-digit industry classification. We sort the columns according to our broad classification of sectors. Down and Upstream exposure are estimated using the Input-Output matrix (Guilhoto and Sesso-Filho (2005, 2010)). Panel (a) displays the direct shocks. Agriculture and Mining industries face higher levels export exposure. Contrarily, manufacturing industries are more highly exposed to import competition with China, especially the High-Tech Manufacturing industries. Panels (b) and (c) display the downstream and upstream exposure, respectively. Differently from the direct exposure, higher order exposure to trade shocks are relatively more sparse across industries. We highlight the impact on manufacturing industries, coming from their high up and downstream linkages.

Table 1. Descriptive Statistics of Trade Shocks

Shock		Percentile 10	25	50	75	90	Std. Dev.	Mean Total	Agr./Min.	Low-Tech Manuf.	High-Tech Manuf.
Direct	Import	0.80	0.80	1.08	1.98	9.04	19.66	6.16	1.43	4.55	13.52
	Export	0.08	0.09	0.10	0.62	3.88	7.52	2.09	4.39	1.50	2.40
Downstream	Import	35.99	37.66	127.22	421.86	421.86	186.44	217.85	147.89	107.53	305.66
	Export	7.81	8.56	26.86	101.05	148.30	63.08	63.82	235.86	25.73	77.03
Upstream	Import	82.20	102.75	110.74	121.84	358.24	118.12	150.81	104.48	166.73	383.52
	Export	19.20	19.20	25.56	45.10	134.34	47.70	47.79	181.67	63.52	99.58

The results are based on the values reported in Figure 2. Values are displayed at US$ 1000 per worker.

In panels (b) and (c), we display the indirect exposure using the input-output linkages. Panel (b) presents the downstream influence of import and export shocks. Thus, it represents demand shocks on each industry's output. Even though increased exports primarily benefited agriculture/Mining in the 2000s and the commodity boom, they are not free from being negatively impacted by import shocks since those industries are important suppliers to other sectors.

Panel (c) displays the upstream import and export exposure. Thus, it represents the shocks in the supply of inputs to industries on the graphs' horizontal axis. Note that manufacturing industries, especially High-Tech, are largely affected by upstream and downstream shocks. That is caused by the high input-output linkages, up and downstream, in this sector. Low-tech manufacturing firms are also exposed to high up and downstream shocks, although with more variation across industries. Overall, upstream and downstream exposure show a high correlation. Table 1 presents the descriptive statistics in Figure 2.

3.2.1 Instruments for Import and Export Exposure

The measures of exposure to the China shock may be susceptible to endogeneity. The main concern is that the shock measures might be driven by factors other than the rise of the Chinese economy correlated with the Brazilian labor market outcomes. In other words, any Brazil-specific demand or supply shock in sectors that shared increased trade with China would bias our estimates. For example, the commodity boom in the 2000s, especially the soybean boom, led to a sharp increase in Brazilian exports in parallel to the increase in Chinese demand for soybeans.

To obtain consistent estimates of the parameters of interest, we use an identification strategy based on Costa, Garred, and Pessoa (2016). The authors use an instrumental variable strategy that eliminates endogeneity from Brazil-specific and world-level shocks. The procedure consists of two stages. In the first stage, we run auxiliary regressions to "filter" out the China shock in each sector using fixed effects. In the second stage, we use the estimated fixed-effects to construct the predicted trade changes with Brazil specific to the China shock and use them as instrumental variables.

Let $\widetilde{M}_{ijt}$ ($\widetilde{E}_{ist}$) denote the aggregate imports (exports) of country i in industry j in year t from (to) all countries other than Brazil. In the first stage, we run the following auxiliary regressions:

$$\frac{\widetilde{M}_{jt} - \widetilde{M}_{j,2000}}{\widetilde{M}_{ij,2000}} = \alpha_s + \theta_{jt,China} + \varepsilon_{ijt} \tag{3.4}$$

$$\frac{\widetilde{E}_{ijt} - \widetilde{E}_{ij,2000}}{\widetilde{E}_{ij,2000}} = \beta_s + \phi_{jt,China} + \mu_{ijt} \tag{3.5}$$

The left-hand sides of the equations are country's i growth rate of aggregate imports or exports between year t and 2000 in industry j; α_j and the β_j are sector fixed effects; $\theta_{st,China}$ and $\phi_{st,China}$ denote fixed effects for China in industry j; ε_{ijt} and μ_{ijt} are random terms. We weighted each auxiliary regression with the import and export volumes in 2000. We may interpret $\theta_{st,China}$ as China's demand change for imports in each industry j between year t and 2000. Similarly, $\phi_{jt,China}$ represents China's export supply change in industry j between year t and 2000. These coefficients capture the deviation of China's exports and imports in industry j from the average growth rate of exports and imports across countries.

In the second stage, we use the estimates $\hat{\theta}_{jt,China}$ and $\hat{\phi}_{jt,China}$ to construct the instrumental variables as follows:

$$IPW^*_{jt} = \frac{M_{j2000} \times \hat{\phi}_{jt,China}}{L_{j,2000}} \tag{3.6}$$

$$EPW^*_{jt} = \frac{E_{j2000} \times \hat{\theta}_{jt,China}}{L_{j,2000}} \tag{3.7}$$

The denominator of each measure combines the estimates from the first stage scaled by the 2000's imports or exports between Brazil and China (M_{j2000}, and E_{j2000} respectively). Note that since $\hat{\theta}_{jt,China}$ captures the supply (demand) shock from China in each industry j. $\hat{\phi}_{jt,China}$ captures the Chinese demand shock for Brazilian products in each industry j. The former is used to construct the instrumental variable for the import exposure and the latter for export exposure. To construct instruments for the indirect exposure, we simply substitute the measures in eq. (3.6) and eq. (3.7) into the formulas in eq. (3.3).

4. Stylized Facts and Trends in Wage Inequality

4.1 Log-Wage Variance Decomposition

To study the relationship between trade shocks and wage inequality at the firm level, we must find a consistent measure for the firm average wage. Therefore, based on Helpman, Itskhoki, Muendler, and Redding (2017) and Alvarez, Benguria, Engbom, and Moser (2018), we estimate the following model separately for each year in the period 1996-2012.

$$log(wage_{it}) = X'_{it}\Lambda_t + \psi_{oft} + \varepsilon_{i,t}, \tag{4.1}$$

where $log(wage_{it})$ is the natural logarithm of average hourly-wage of worker i in year t. X_{it} is a fully interacted set of workers' characteristics and sector-occupation-state pairs. Observable worker's characteristics include a dummy variable for females; educational attainment in three categories: i) high-school dropouts; ii) high-school graduates; iii) at least some college; dummy variable for age in five categories: 18-25, 26-34, 35-42, 43-50, 51-64 (these breaks roughly correspond to quintiles of the initial year of age distribution). Sector-occupation pairs interact with seven sectors (Agriculture/Mining, Low-Tech Manufacturing, High-Tech Manufacturing, Transportation/Communications, Construction, Trade, and Services), with five occupation definitions (blue-collar, skill-intensive blue-collar, white-collar, Technical and Supervisory, and Professional and Managerial), and 27 states. Λ_t is a vector of parameters that identifies the return to each category in X. Changes over time in the term $X'_{it}\Lambda_t$ represent the changes in the composition of the labor force in the economy. ψ_{oft} is an interaction of firm identifiers (CNPJ-region) with sector-occupation categories. This term captures the between firm-occupation components. Thus, eq. (4.1) decomposes wages into the labor market composition $X'_{it}\Lambda_t$ and between firm-occupation ψ_{oft} components. $\varepsilon_{i,t}$ is the idiosyncratic component. For the exposition, we present the decomposition of the variance of log wage for the years 2000 and 2008.

Our definition of sectors is derived from Dix-Carneiro (2014).[10] We split the tradable industries into three sectors: Agriculture-Mining, Low-Tech Manufacturing, and High-Tech Manufacturing. The first sector produces primary goods, which faced a large increase in exports over the first decade of the 2000s. Manufacturing industries are divided into Low- and High-Tech. Dix-Carneiro (2014) argues that the former is composed of industries for which Brazil has a greater comparative advantage. The latter comprises industries with comparative disadvantages.[11] Moreover, these two sectors also differ in terms of their input-output linkages: High-Tech industries are more linked with other industries upstream and downstream of the production network. Finally, we aggregate non-tradable sectors into one category.

Table 2 reports the variance decomposition of $log(wage_{it})$ estimated in Eq. (4.1).[12] The first line shows the change in overall wage variance between 2000 and 2008. Following the same pattern as the Gini coefficient in Figure 1, the wage variance fell almost 30 percent between 2000 and 2008. As documented by Helpman, Itskhoki, Muendler, and Redding (2017) and Alvarez, Benguria, Engbom, and Moser (2018), the between-firm fixed effects correspond to a large share of the total variance of log-wage, around 2/3. It also was the component with the highest decline over the period. As suggested in Alvarez, Benguria, Engbom, and Moser (2018), the fall in firm wage component is driven mainly by gains in productivity, being the main reason for the decreased inequality in the Brazilian formal labor market.

Table 2. Decomposition of Variance of Log-Wage per Hour

	2000		2008		Change (%)
	Level	(%)	Level	(%)	
$var(log(wage))$	0.663	100.0	0.489	100.0	–26.18
$var(\psi_{of})$	0.449	67.7	0.310	63.4	–30.82
$var(x'\beta)$	0.047	7.1	0.040	8.1	–15.09
$var(\varepsilon)$	0.105	15.9	0.089	18.1	–16.09
$2 \times cov$	0.062	9.3	0.051	10.3	–18.10

Results are based on estimates of Eq. (4.1). $log(wage)$ is the log of the wage per hour for every worker in our sample. ψ_{of} is a firm-occupation-sector component. $x'\beta$ as workers' observable characteristics. ε is the residual wage per hour. cov is the covariance between ψ_{of} and $x'\beta$.

[10] Dix-Carneiro (2014) approximately follows the sector definitions presented in Artuç, Chaudhuri, and McLaren (2010).

[11] In many aspects, High-Tech industries are also more protected by incentive laws and have access to higher public and private financing.

[12] The complete set of estimates are available upon request.

As a consequence of the more significant between-firm decline, within-firm wage variance increased to a greater share of the overall wage variance. In particular, we note an increase in the share of the residual component by over two percentage points. As studied in Helpman, Itskhoki, Muendler, and Redding (2017) and Alvarez, Benguria, Engbom, and Moser (2018), trade and productivity gains may explain a significant part of the faster decrease in cross-firm wage inequality.

One of the limitations of RAIS is that it only contains formal workers and firms. The literature documents that the informality rate in Brazil decreased almost 10 percentage points over the 1990s and 2000s, although the informal labor market still represented between 40 and 50 percent of the labor force by 2010.[13] Engbom et al. (2022) argues that the decline in the informality rate might be related to substantial effects on the overall wage variance through composition effects across the formal and informal sectors. Their analysis suggests that workers moving from the informal sector to the formal sector are concentrated at the bottom of the formal earnings distribution. However, a substantial share of workers locates at higher sections of the earnings distribution.[14] As a consequence, the wage decomposition in eq. (4.1) may suffer the influence of changes in the labor market composition between the formal and informal sectors.

We perform some exercises to account for the influence of the informality rate decline on the formal wage distribution. First, because we cannot observe workers outside the formal labor market, we assume that a share of workers entering the formal labor market between years $t-1$ and t is due to the decline in the informality rate in the period. We show that the pattern of new entries is similar to the observations in Engbom et al. (2022). In the most extreme scenario, we assume that all new entries are caused by the fall in the informality rate. Using the specification eq. (4.1), we include in X_{it} an indicator variable whether a worker entered the formal labor market between $t-1$ and t to control for the change in workers' composition caused by changes in the informal labor market in that period.

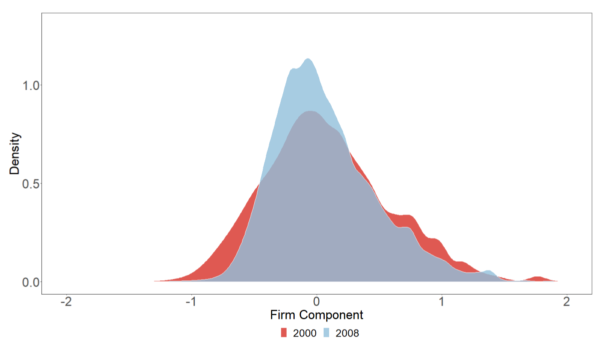
We are interested in the estimates of ψ_{oft} since it is the main component of the log wages, and we will use it throughout the paper. The results indicate that controlling for the informal labor market influence does not change significantly our estimates of ψ_{oft}. We report the results comparing both decompositions in Table 11 in the Appendix. In either specification, the variance of ψ_{oft} represents two-thirds of the overall log wage variance and accounts for most of its

[13]See Meghir et al. (2015), Engbom et al. (2022), Ulyssea (2018), and Ponczek and Ulyssea (2022) for reference.

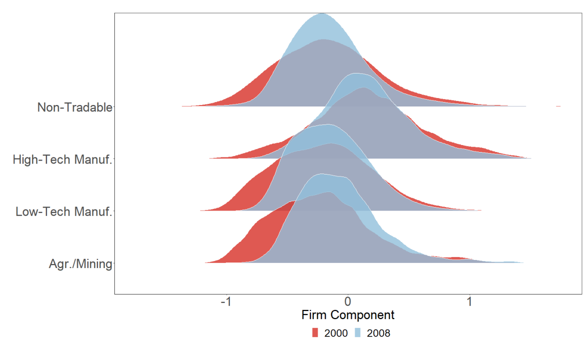
[14]This empirical pattern is consistent with the findings in Meghir et al. (2015) which suggest that although the workers' productivity is smaller in the informal labor market, the supports of the productivity distributions of formal and informal sectors largely overlap.

reduction between 2000 and 2008. The high correlation between the estimates of ψ_{oft} in eq. (4.1) with and without controlling for informality supports our original estimates of ψ_{oft}. Thus, we use the estimates summarized in Table 2 so our results are comparable to the relevant literature [Alvarez, Benguria, Engbom, and Moser (2018), Helpman, Itskhoki, Muendler, and Redding (2017)]. A full analysis of the effects of informality is in the Appendix.

Our analysis complements Alvarez, Benguria, Engbom, and Moser (2018) and Helpman, Itskhoki, Muendler, and Redding (2017) by focusing on the between-firm wage component evolution. We denote $\hat{\psi}_{ft}$ as the estimated between-firm wage component in Eq. (4.1). We obtain this term by averaging $\hat{\psi}_{oft}$ for each firm, weighting by the number of employees. Figure 3.a shows a detailed description of the distribution of $\hat{\psi}_{ft}$ in 2000 and 2008. As suggested previously, the bottom of the distribution seems to increase faster relative to the top. Table 3 shows the distributional statistics separately for 2000 and 2008. The growth in wages for firms at the bottom of the distribution exceeds the decrease for firms at the top: the first decile experienced an increase of 23 percent, while the decreases in the 75^{th} and 90^{th} percentiles are 26 and 18 percent, respectively. Consequently, there is a significant increase in the concentration of firms in the center of the distribution. Previous research suggests that much of the change at the bottom of the distribution is associated with a strong minimum wage policy (Engbom and Moser (2021)) and gender, race, education, and experience wage gaps (Nopo (2012), Messina and Silva (2017)).



(a) Overall Density



(b) Density by Sector

Figure 3. Density of Firm Component in 2000 and 2008. Notes: Densities of $\hat{\psi}_f$ are estimated using firm size as weights, separately for years 2000 and 2008. $\hat{\psi}_f$ is winsorized at the 98^{th} percentile, for each year. Graph (a) displays the density for the sample of all firms. In part (b), we separate the density by sectors.

The concentration of the wage distribution towards the center relates to a fall in the wage variance of 32 percent (from 0.38 to 0.26) between 2000 and 2008. The average nominal log-

Table 3. Firm Component Descriptive Statistics

Year	Percentile					Mean	Variance
	10	25	50	75	90		
2000	–0.73	–0.44	–0.07	0.37	0.93	0.01	0.38
2008	–0.56	–0.36	–0.09	0.27	0.77	0.01	0.26

This table includes descriptive statistics of the firm component, weighted by the number of employees in each firm.

wage mild decreases from 0.08 to 0.06. In the last two columns, we decompose the variance of $\hat{\psi}_{ft}$ into between- and within-sector-region components.

In both 2000 and 2008, the between-sector corresponds to 1/3 of the variance, whereas the within-sector corresponds to 2/3. In fact, there is a small increase in the within-sector component. Figure 3.b illustrates the trend in the within-sector component. In general, the fall in inequality observed in Figure 3.b follows a similar pattern across sectors, suggesting a concomitant and equivalent change in wage inequality (as measured by wage variances).

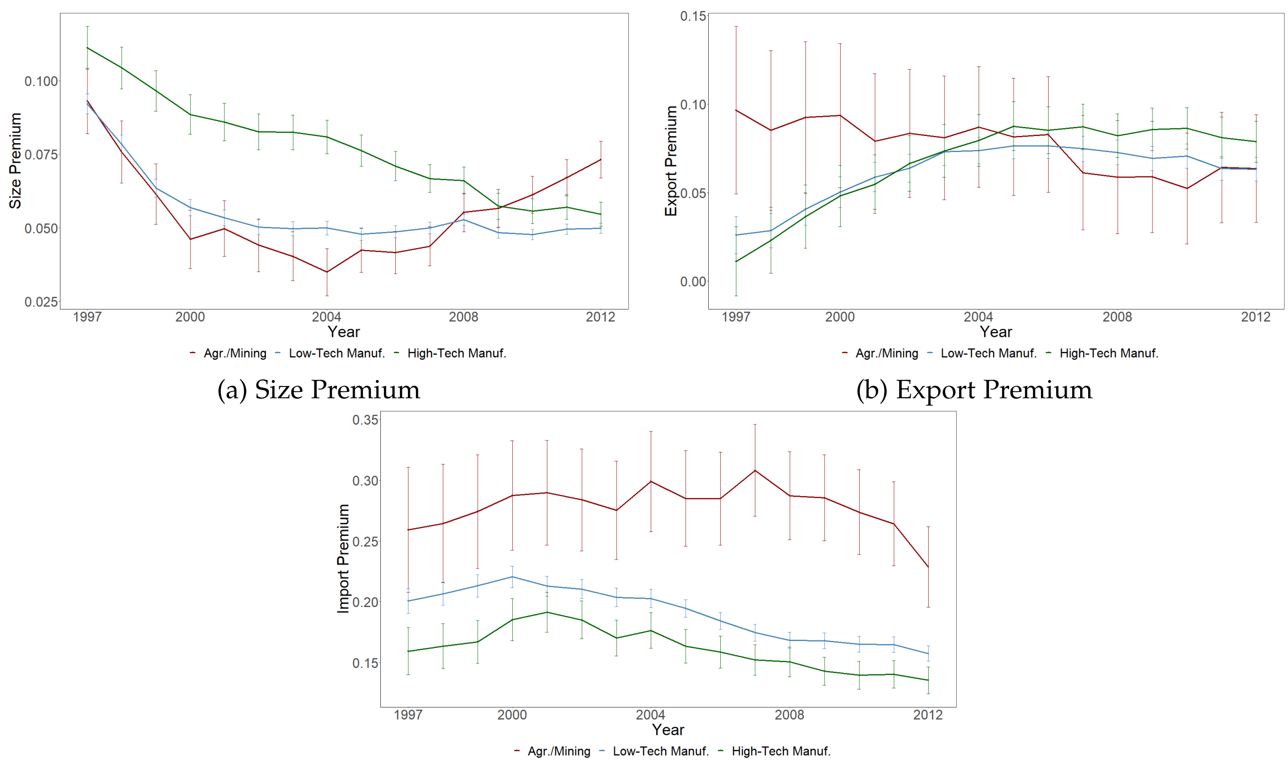
Based on the empirical evidence, we argue that the import/export exposure affects wage inequality in two ways. First, the between-sector component produces winning and losing sectors depending on the magnitude of their exposure to import and export shocks. Second, firms are heterogeneously affected through a within-sector component depending on some characteristics highlighted in the literature. We follow Melitz (2003), Amiti and Davis (2012), and Helpman, Itskhoki, Muendler, and Redding (2017), and analyze two aspects related to firms' wage components: log number of employees (firm-size) and exporter and importer status.

To understand how changes in $\hat{\psi}_{ft}$ relate to firms' characteristics and overall trends in the economy, we analyze the relationship between firm components and characteristics over time. We estimate the following specification:

$$\hat{\psi}_{ft} = \sum_{s} \beta_{1st}\mathbb{1}(s) log(size_{ft}) + \beta_{2st}\mathbb{1}(s) export_{ft} + \beta_{3st}\mathbb{1}(s) import_{ft} + \eta_{jrt} + \eta_t + \varepsilon_{f,t} \qquad (4.2)$$

$\hat{\psi}_{ft}$ is defined as above, $log(size)$ and $export$ are the log of number of employees and exporter status, respectively. $\mathbb{1}(s)$ is an indicator variable that assumes value 1 when the firm operates in sector s. The sectors in which we split the firms are defined previously into Agriculture/Mining, Low-Tech Manufacturing, and High-Tech manufacturing. Since $\hat{\psi}_{ft}$ is in logarithms form, one can interpret the size premium (β_{1st}) as the elasticity of the wage relative to the firm size in sector s. β_{2st} and β_{3st} are the semi-elasticity of export and import premia, respectively. η_{jrt} and η_t are sector-region and year fixed effects, respectively. We estimate eq. (4.2) separately for each year t.

The point estimates for β_{1st}, β_{2st}, and β_{3st} are reported in Figure 4. Consistent with the literature, such as Melitz (2003) and Helpman, Itskhoki, Muendler, and Redding (2017), the figures show that large exporters and importers pay higher wages on average since the parameters are positive and highly significant. Nonetheless, the strength of these relationships seems to have declined over time. Graph (a) shows an inelastic relationship between wage and firm's size (or size premium), with strong declining trends between 1997 and 2002. Afterward, the relationship stays stable over the interval between 0.03 and 0.10.



(a) Size Premium

(b) Export Premium

(c) Import Premium

Figure 4. Size, Export and Import Premia Across Sectors. The figures report size, export and import premia estimated using Eq. (4.2), separately for each year between 1997-2012. Graph (a) displays the coefficients β_{1s} of $log(size)$. Graph (b) displays the coefficients β_{2s} in the same exporter indicator. And Graph (c) displays the coefficients β_{3s} in the same importer indicator in the same specification.

Moreover, there is greater variability in size premium across sectors. The Manufacturing sectors have a continuous declining trend, whereas Agriculture/Mining has a U-shaped trend.

Because larger firms pay higher wages, these results suggest that a decrease in wage inequality may also be related to a potential downsizing in the average number of workers per firm.

The positive coefficients for export and import premia are also in line with the literature. Melitz (2003) predicts that exporting firms are more productive, which means that those firms would pay higher wages. Amiti and Davis (2012) provides evidence of a positive relationship between wages and import status. Differently from the size premia, eq. (4.2).b shows low heterogeneity of export premium across sectors and no trend over time. The coefficients range from 0.01 and 0.1.

In contrast, eq. (4.2).c shows higher and stable heterogeneity of import premium among sectors, ranging from 0.15 to 0.3 for the Agriculture/Mining sector. Thus, engaging in international trade, especially imports, has sizable effects on sector wage dispersion.

The positive coefficients on export and import status conceal two crucial components. First, the causal impact of exporting and importing on wages, or *market access*: firms that operate in the external market, either by exporting or importing, are more productive, have higher revenues (otherwise, they would only operate internally), and thus pay higher wages. Second, the selection into external supply/demand, or *market selection*: more productive firms self-select into importing and exporting. Because they are more productive, they are also more likely to pay higher wages.

In sum, the trends in wage inequality reveal the following facts:

1. After controlling for observables, the between-firm component is the major contributor to the fall in wage dispersion, accounting for 2/3 of the formal wage variance. Moreover, between 2000 and 2008, it is the component with the most significant decline.

2. Formal wage dispersion (measured by the weighted variance of between-firm wage component) declines proportionally between- and within sectors. The between/within ratio is roughly 1/2.

3. The relationship between firm wage-component and firm characteristics is heterogeneous across sectors. Furthermore, size, export, and import premia are associated with higher wages, consistent with the literature.

As Helpman, Itskhoki, and Redding (2010), Helpman, Itskhoki, Muendler, and Redding (2017) and Amiti and Davis (2012) note, trade shocks have heterogeneous impacts on firms. There are three main transmission mechanisms from trade shocks to wages. First, the direct impact on wages and employment causes firms to experience a shift along with the whole demand for their products. Second, changes in the export and import premia, as exporters and importers obtain higher gains than non-exporters and non-importers and transmit those gains to wages. Finally, changes in export or import costs, which incentive firms to selection into exporting or importing. As Helpman, Itskhoki, and Redding (2010) observe, trade opening removes barriers and allows more firms to select into the export market or import cheaper, better quality inputs.

5. Reduced-Form Evidence

Employment In this section, we study the effects of the China shock on employment, firm wages, firm size, and exporter and importer status. Following the literature investigating the effect of the China shock (Autor, Dorn, and Hanson (2013); Autor, Dorn, Hanson, and Song (2014); Acemoglu, Autor, Dorn, Hanson, and Price (2016); Pierce and Schott (2016)), we first aggregate our data to the industry level and estimate

$$\Delta y_{jt} = \sum_{k \in K} (\alpha_{I,k} IPW_j^k + \alpha_{E,k} EPW_j^k) + X_j'\delta + \eta_s + \varepsilon_j, \tag{5.1}$$

where Δy_{jt} is our industry-level dependent variable, which takes the difference between the levels in year t and 2000. In this specification, we use two measures for y_{jt}: $log(employment_{jt})$ and the weighted average of firm component ψ_{ft} for industry j. An industry is a 4-digit CNAE classification consisting of 306 industries in total. IPW_j^k and EPW_j^k are the measures of import and export exposure in industry j, with $k = \{UP, DOWN\}$. X_j includes pre-2000 exposure to Chinese imports and exports and industry-level controls in 2000: (unconditional) average wages, formality rate, share of high-educated workers, and the share of workers whose earnings are smaller than the minimum wage plus 10 percent. η_s are sector fixed effects. Thus, α_I and α_E capture the effect of import and export exposure within-sector. ε_j is an idiosyncratic error. We estimate eq. (5.1) using the instrumental variable approach discussed in Section 3, which we adapt from Costa, Garred, and Pessoa (2016). The results are reported in Table 4.

We expected $\alpha_I^{DOWN} < 0$ and $\alpha_E^{UP} < 0$ since they represent negative shocks in the labor demand. Downstream import exposure decreases a firm's output demand, whereas upstream export exposure increases competition in the input markets, meaning a negative shock to a firm's production. In contrast, we expect that $\alpha_I^{UP} > 0$ and $\alpha_E^{DOWN} > 0$, since they represent positive shocks in the labor demand. Upstream import exposure increases the availability of inputs for

Table 4. The Effect of Import and Export exposure on Log Employment and Average Wages

	(1)	(2)	(3)	(4)	(5)	(6)
		Employment			Average Frim Component	
	2002	2008	2012	2002	2008	2012
Downstream Import Exposure	–0.934**	–0.591	–0.522	–0.110	–0.586***	–0.689***
	(0.360)	(0.491)	(0.516)	(0.071)	(0.166)	(0.168)
Downstream Export Exposure	0.753*	2.043**	2.410***	–0.230	–0.267	–0.372
	(0.447)	(0.823)	(0.884)	(0.183)	(0.317)	(0.404)
Upstream Import Exposure	1.033**	0.629	0.447	0.303**	0.774***	0.921***
	(0.435)	(0.824)	(0.803)	(0.147)	(0.252)	(0.287)
Upstream Export Exposure	–0.125	–0.693	–0.889	–0.094	–0.049	–0.006
	(0.243)	(0.677)	(0.726)	(0.091)	(0.207)	(0.234)
Observations	306	306	306	306	306	306
R-squared	0.088	0.097	0.099	0.025	0.258	0.359
Controls	Yes	Yes	Yes	Yes	Yes	Yes
F statistic	1.570	2.170	2.081	3.989	8.231	17.22
Weak instruments (F-stat)	25.50	25.50	25.50	25.50	25.50	25.50

The dependent variable: change in log-employment between the year in column and 2000 (columns 1-3); change in the weighted average of the firm-component (ψ_{ft}) between the year in column and 2000. The industry definition is a 4-digit of the CNAE classification, for tradable sectors (N=306). All equations include sector fixed effects and pre-200 controls: (unconditional) average wages, formality rate, and share of workers whose earnings are smaller than minimum wage plus 10 percent. Specifications are estimates using the Instrumental variable approach described in the text. Regressions are weighted by the number of formal employees in 2000. Robust standard are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

firms, increasing their production. Downstream export exposure means a positive shock to a firm's output demand, leading to increased labor demand.

The results suggest that high downstream import exposure is associated with lower employment growth. That occurs mainly in the first periods after the shock and diminishes over time. The difference between the 90^{th} and 10^{th} percentile of downstream import exposure implies a reduction in employment by around 36 percent (-0.934×0.386) by 2002, with a lower 20 percent long-term impact percent (-0.5×0.386), although not significant. Likewise, upstream import exposure also has effects but only in the short-term, with a difference of 3 percent by 2002 (1.03×0.028) between the 90^{th} and 10^{th} percentile of exposure, becoming insignificant in the following years.

Downstream export exposure is related to an increase in aggregate employment over time. The magnitudes of the point estimates are relatively stable over time, and we find more significant results starting around 2008. This pattern indicates that the employment adjustment tends to take more time in those sectors, but with a considerable increase in the longer term. On average, by 2008, the industries in the 90^{th} percentile of the downstream export exposure experienced increased employment levels by 28 percent (2.04×0.140). In contrast, upstream export exposure has negative and insignificant point estimates.

Wages We further analyze the effect of the China shock in firm-level data. We restrict the analysis to firms operating between 1997 and 1998, so we can explore pre-trends in outcome variables. Then, we use the following model to test the impact of import and export exposure on the firm's wage component, ψ_{ft}. Our main model is

$$\Delta\psi_f = \rho\psi_{f,0} + \sum_{k\in K}(\alpha_{I,k} IPW_j^k + \alpha_{E,k} EPW_j^k) + X_f'\delta + \hat{\lambda}_f + \eta_{sr} + \varepsilon_f, \tag{5.2}$$

where $\Delta\psi_f$ is the difference in the firm component between the average over the period 2006-2010 and the average over the period 1997-2000 (pre-shock). $\psi_{f,0}$ is the average wage component of firm f over 1997-2000; IPW_j^k and EPW_j^k, for $k = \{DIRECT, UP, DOWN\}$ are the measures of import and export exposure in industry j, respectively, described in Section 3. Our instrumental variable approach uses the identification strategy proposed by Costa, Garred, and Pessoa (2016), which captures the changes in import and export exposure due to the rise in Chinese supply and demand for products from the Brazilian economy.

We follow the literature and include pre-2000 trends of each measure of import and export exposure included in the estimation to identify those terms consistently. η_{sr} are State-Sector fixed effects (27 States and 3 sectors). Therefore, the estimates for α_I and α_E refer to within-state-sector trade shocks.

X_f is a set of baseline (before 2000) controls that include firm characteristics, such as (log) number of employees, wage (firm component), the share of college-educated workers, and white-collar employment share. Industry controls include (unconditional) average wages, log of the number of employees, industry formality rate, and the share of workers whose earnings are below the minimum wages plus 10 percent. ε_f is an idiosyncratic shock.

We only use active firms to estimate eq. (5.2). Accordingly, we include $\hat{\lambda}_f$ to control for selection. As Olley and Pakes (1996) highlight, when estimating the production function parameters in firm-level data, the decision to exit the market is related to productivity: more productive firms are less likely to exit the market. Hence, selection may drive our estimates upward using only the observed firms. For instance, industries more affected by import competition shocks may lose more unproductive firms. As a result, the point estimates associated with trade shocks will be higher (or less negative for positive shocks). Following Amiti and Davis (2012), we first round up the panel to include all the firms that appear in the sample at least once and create an indicator variable that assumes a value of 1 if the firm is active. Then, we apply the selection procedure as proposed in Heckman (1979). For that, we need exclusion restrictions in the first stage. We rely on three excluded variables that influence changes in firm wages only through the probability that a firm will operate in a given year: i) firm's age; ii) cost of opening a firm; and iii) indicator of belonging to a "priority" sector.

The seminal model in the firm dynamic literature Hopenhayn (1992) suggests that older firms are less likely to drop out of the market. Analogously, Bergin and Bernhardt (2008) allows firms to draw their productivity from a stochastically better distribution over time, implying a learning-by-doing process, so that older firms tend to be more productive and are less likely to exit. However, they also argue that firms that require specialized resources are in a weak position to liquidate their assets and shut down.[15] As a result, firms tend to be larger and less productive in sectors with more specialized inputs. We measure a firm's age as the difference between the current year and the opening date (or the first time they appear in the data set).

Our second excluded variable is the (log) cost of opening a firm multiplied by the average time to open those firms in the same circumstances. This variable is heterogeneous across Brazilian states and manufacturing and services sectors. We then divide the resulting value by the (pre-exposure) average number of employees in that state and sector, obtaining the average opening cost per worker.[16]

Finally, we include an indicator variable that assigns the value 1 to industries considered Priority. This strategy is based on Carvalho (2014), who argues that under a federal law dating back to the 1960s, a firm in priority industries has preferences in government connections, access to credit (public and private), and tax benefits. Our identification strategy in the first stage of Heckman's procedure requires that conditional on pre-exposure levels of employment and wages (which are our measures for size and productivity), age, average opening cost, and preferential access to credit only affect future wages and employment through their effect on the probability of firms staying in the market. The details on the selection problem specification and the estimates for the first stage are presented in Table 13 in the Appendix. The

[15]Because those firms would be in a disadvantaged bargaining position with potential entrants that would acquire their assets, they would rationally choose to hold on to the market for longer.

[16]Values from Firjan, The Federation of Manufacturing Industries of Rio de Janeiro (FIRJAN (2010)) for 2010 and are time-invariant.

Inverse-Mills ratio (up to third-order polynomial), as suggested in Heckman (1979), is estimated using the predicted values of column 7 in the Appendix.

Because import exposure shifts the demand for a firm's variety downward, we expect $\alpha_{I,DIRECT} < 0$. Analogously, we expect $\alpha_{E,DIRECT} > 0$. Moreover, because upstream exposure may also influence firm wages, we expect that $\alpha_{I,UP} > 0$, so that higher availability of imported inputs is beneficial to the firm. $\alpha_{E,UP} < 0$ reflects the increased external demand on a firm's input market, and so a potential negative impact on wages. On the other hand, we expect that $\alpha_{E,DOWN} > 0$, so that firms improve their gains when exposed to a positive output demand shock. An import competition shock downstream in production should reduce the demand for a product, so we might expect that $\alpha_{I,DOWN} < 0$.

The estimates are reported on Table 5. Column 1 displays the OLS (endogenous) regression of firm wages on the trade shocks. The other columns present the instrumental variable estimates. The first row in each specification shows the baseline average wages, which has a negative sign and is highly significant in every specification, indicating the convergence in wages across firms, i.e., high-paying firms tend to have lower wage growth.

The OLS estimates show that the effects of import and export exposure are consistent with the findings in the literature: positive shocks in the output market lead to higher wages, while negative shocks lead to lower wages. In the input market, the logic is reversed: negative shocks are related to higher wages, and positive shocks are linked to lower wages. In Table 5, columns 2 to 9 present instrumental variable estimates with different assumptions over controls, dependent variables, and clustered standard errors. The IV procedure increased the magnitudes of most estimates (except for downstream export shocks). The inclusion of controls does not significantly change the direction and magnitude of our estimates, although it makes them more precise.

Because we observe heterogeneous input demand and output supply across industries, the upstream and downstream exposure measures are also heterogeneous. Similar to the duality of import-export exposure, identification of indirect exposure relies on this heterogeneity in the composition of input-output linkages to capture the partial causal impact.

The estimates suggest that upstream import exposure and downstream export exposure positively relate to firm wages. Higher upstream import exposure in the production structure means a more extensive input variety at lower prices. Similarly, higher downstream export exposure in the production leads to a positive shift in the demand for a firm's outputs and increased

Table 5. Impact of Import and Export Shocks on Firm Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dep. Var. Average Firm Wage								
	2006-2010						2007-2009	2006-2008	2008
	OLS	IV	IV	IV	IV	IV-Clust. 2d	IV-Clust. 2d	IV-Clust. 2d	IV-Clust. 2d
Lagged-Wage	–0.410***	–0.322***	–0.350***	–0.415***	–0.409***	–0.409***	–0.411***	–0.389***	0.590***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.015)	(0.015)	(0.015)	(0.015)
Downstream Import Exposure	–0.080	–0.174	–0.190**	–0.259***	–0.280***	–0.280**	–0.275**	–0.266**	–0.261**
	(0.068)	(0.114)	(0.091)	(0.091)	(0.096)	(0.111)	(0.114)	(0.106)	(0.117)
Downstream Export Exposure	0.327***	0.187	0.077	0.194*	0.250**	0.250*	0.245*	0.238*	0.246*
	(0.098)	(0.127)	(0.125)	(0.117)	(0.115)	(0.132)	(0.133)	(0.136)	(0.139)
Upstream Import Exposure	0.177**	0.482***	0.370***	0.472***	0.508***	0.508***	0.508***	0.483***	0.492***
	(0.088)	(0.182)	(0.126)	(0.121)	(0.127)	(0.141)	(0.144)	(0.132)	(0.146)
Upstream Export Exposure	–0.233***	–0.383**	–0.334***	–0.361***	–0.421***	–0.421***	–0.418***	–0.392***	–0.417***
	(0.074)	(0.149)	(0.092)	(0.081)	(0.082)	(0.090)	(0.088)	(0.086)	(0.087)
Observations	50,325	50,327	50,327	50,327	50,325	50,325	50,325	50,325	50,325
R-squared	0.481	0.331	0.349	0.381	0.382	0.382	0.370	0.349	0.691
Firm Controls	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection Controls	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	154.8	139.3	89.92	148.6	159.9	637.6	717.6	511.1	2423
Clusters	304	304	304	304	304	32	32	32	32
Weak instruments (F-stat)		56.48	53.57	53.13	53.35	63.98	63.98	63.98	63.98

The dependent variable is the difference in the average firm component estimated in Eq. (4.1) for the average in 1997-2000. The models are estimated from Eq. (5.2). The first column shows the OLS (endogenous) specification. Columns 2 to 8 display the Instrumental Variables specifications of 3 columns show the results for the whole sample of firms under different specifications. All regressions include State-Sector fixed effects and pre-2000 levels of exposure to Chinese imports and exports. Industry controls (baseline, 2000): log of employees, (unconditional) average wages, formality rate, and share of workers whose earnings are smaller than minimum wage plus 10 percent. Firm controls (baseline, 2000): log wages, log-firm size, the share of high-educated workers, and white-collar workers. Selection controls the third-order polynomial of Inverse-Mills term for the probability of a firm to operate. Robust standard errors are clustered at the industry level, with 4 or 2 digits. *** p<0.01, ** p<0.05, * p<0.1.

wages. These results are similar to those found by Acemoglu, Autor, Dorn, Hanson, and Price (2016) and aligned our hypotheses $\alpha_{I,UP} > 0$ and $\alpha_{E,DOWN} > 0$.

In contrast, downstream import exposure and upstream export exposure industries negatively relate to firm wages and are robust to different specifications. Higher downstream import exposure decreases the demand for a firm's output and thus represents a negative shift in the demand with a decrease in wages. Higher upstream export exposure increases the competition with the external market, which increases input prices, meaning a downward shift in the firm's demand for labor. Again, these estimates align with our hypotheses $\alpha_{I,DOWN} < 0$ and $\alpha_{E,UP} < 0$.

Using values in Table 5 column 5, the difference in changes in wages between the 90^{th} and 10^{th} percentiles of downstream import exposure reflects a decrease of 10 percent in the average per hour (-0.280×0.386). Downstream export exposure is related to a 3.5 percent increase in the average wage per hour (0.250×0.140). In contrast, the difference in changes in firm wages between the 90^{th} and 10^{th} percentiles of upstream import exposure is about 16 percent (0.588×0.276). For upstream export exposure, the difference is 5 percent (-0.421×0.115).

In sum, by including direct and indirect exposure, we move from a mild impact of trade shocks to much broader changes in wages. Overall, import exposure (including direct, upstream, and downstream) has a negative net effect in every economic sector, particularly in the High-Tech manufacturing sector due to the intense competition with Chinese products in the output market. Contrarily, the net impact of export exposure shocks is related to moderate increases in wages, especially for the firms in the Agriculture/Mining sector that experience an upward shift in the output's demand. Nonetheless, the negative impacts from import exposure are attenuated for surviving firms because that makes inputs cheaper for the surviving firms, which is partially passed through to wages. Likewise, upstream export exposure makes firms compete with exports in the input markets, increasing those prices and decreasing wages.

Firm-Level Employment Previously, we observed that downstream import exposure reduced employment at the industry-level. Now, we study the effects of the China shock on firm-level employment. The results are reported in Table 6.

Columns 1 and 2 estimate Eq. (5.2) with the wage component $\hat{\psi}_f$ as the dependent variable (column 1) and log-employment (column 2). In column 1, we draw the same conclusions as before, i.e., downstream import exposure and upstream export exposure cause a decrease in

Table 6. The Effects of Import and Export Exposure on Firm-Level Employment

	(1)	(2)	(3)	(4)	(5)
	Cross-Section		Unbalanced		
Variable	Wage-Comp.	Log-Emp.	Wage Comp.	Log-Emp.	Active
Downstream Import Exposure	–0.233**	–0.134	–0.186	–0.225	–0.157
	(0.093)	(0.361)	(0.150)	(0.236)	(0.170)
Downstream Export Exposure	0.129	0.134	0.107	0.123	0.344
	(0.121)	(0.527)	(0.218)	(0.433)	(0.256)
Upstream Import Exposure	0.436***	0.259	0.045	0.339	0.389
	(0.126)	(0.490)	(0.204)	(0.309)	(0.248)
Upstream Export Exposure	–0.298***	–0.019	–0.216	–0.126	–0.217
	(0.081)	(0.385)	(0.139)	(0.196)	(0.151)
Observations	50,325	50,325	257,617	257,618	599,724
R-squared	0.690	0.635	0.371	0.105	0.004
Firm Controls	Yes	Yes	Yes	Yes	No
Industry Controls	Yes	Yes	Yes	Yes	Yes
Selection Controls	Yes	Yes	Yes	Yes	No
F statistic	895.5	942	123.3	71.71	7.738
Weak instruments (F-stat)	53.51	53.37	30.27	29.99	30.17
Clusters	304	304	307	307	307

The dependent variables are the firm wage component (columns 1 and 3), the log of the number of employees (columns 2 and 4) and the indicator that the firm is active (column 5). Models 1 and 2 include state-sector fixed-effects. Models 3 to 5 include regressions include state-sector-year fixed effects. All models include pre-2000 levels of exposure to Chinese imports and exports, baseline industry, and firm controls. Industry controls: log of employees, (unconditional) average wages, formality rate, and share of workers whose earnings are smaller than minimum wage plus 10 percent. Firm controls: log wages, log-firm size, the share of high-educated workers, and white-collar workers. Selection controls: third-order polynomial of Inverse-Mills term for the probability of a firm to operate. Robust standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

wages, and upstream import exposure and downstream export exposure cause an increase in wages. However, estimates in column 2 for firm-level employment are not as precise, being not significant at the usual statistical levels. However, the point estimates have the same direction as the estimates for the wage component. These results support the earlier estimates in this section when we found sizable effects of the China shock on industry-level employment.

To understand how the trade shocks are related to firm-level employment, we estimate

$$y_{ft} = \sum_{k \in K} \mathbb{1}_{t>2000}(\beta_{I,k} IPW_j^k + \beta_{E,k} EPW_j^k) + \sum_{k \in K}(\alpha_{I,k} IPW_j^k + \alpha_{E,k} EPW_j^k) + X'_{ft}\delta + +\eta_{srt} + \varepsilon_{ft}, \quad (5.3)$$

where y_{ft} is the dependent variable for firm f in year t. The trade exposure variables IPW_j^k and EPW_j^k are the same as before. $\mathbb{1}_{t>2000}$ has a value 1 if $t > 0$, or the post-shock period, and 0 otherwise. β's measure the impact of the trade shocks after China entered into the

WTO, thus our parameters of interest. η_{srt} are sector-region-year fixed effects. X_{ft} includes firm and industry-level controls. The firm-level controls are the share of high-educated workers, the share of white-collar employees, and an indicator of an incumbent firm, i.e., that the firm operated before 2000. The industry-level controls are (unconditional) average wages, log of the number of employees, industry formality rate, and the share of workers whose earnings are below the minimum wages plus 10 percent.

We report the results in columns 3 to 5 in Table 6. In the estimates, we use $t \in \{2000, 2008\}$. In columns 3 and 4, we include all active firms in 2000 and 2008. In column 3, the dependent variable is the wage component $\hat{\psi}_f$, and in column 4, the dependent variable is the log-employment. In column 5, the specification includes all active firms either in 2000 or 2008. Thus, we estimate a linear probability model in which the dependent assigns a value of 1 if the firm is active in year t and 0 otherwise. We use the same instrumental variables approach presented before. This specification is similar to Amiti and Davis (2012).

Most estimates for the impact of trade shocks are in the expected directions. Downstream import exposure and upstream export exposure are related to a decrease in wages, a smaller firm size, a lower probability of being active, and thus, a higher probability for a firm to exit. In contrast, downstream export exposure and upstream import exposure are related to higher wages, a greater firm size, a higher probability of being active, and thus, a lower probability for a firm to exit. Therefore, these estimates corroborate the findings for employment, wages, and the selection of firms into importing and exporting. However, the estimates are not significant at usual levels.

Therefore, the results suggest that the employment decline in manufacturing is driven by the exit of firms and the downsizing of existing or entrant firms in industries more exposed to downstream import competition. The upstream import exposure effect is related to a higher probability of firms being active, but this effect is not strong enough to compensate for the losses due to the downstream import exposure effect. As we observed before, downstream export exposure is related to increased employment due to the higher output demand.

Probability of Import and Export To further assess the heterogeneous consequences for importer/non-importer and exporter/non-exporter firms within industries, we adapt the estimates in eq. (5.2) to two possibilities. Firstly, we use the probability of export or import as the dependent variables. We estimate eq. (5.2) using a Probit.[17] Moreover, we also estimate eq. (5.2) separately for importer and exporter firms.[18] Note that those groups may overlap. Results are reported on Table 7. Each column reproduces the same specification of column 8 on Table 5.

Table 7. Probability of Import and Export and Heterogeneous Effects

	(1)	(2)	(3)	(4)	(5)	(6)
			Average Firm Wage 2006-2008			
Depedent Variable	Prob. Importer	Prob. Exporter	Non-Importer	Importer	Non-Exporter	Exporter
Lagged-Wage	0.641***	0.358***	–0.412***	–0.338***	–0.406***	–0.342***
	(0.051)	(0.054)	(0.011)	(0.012)	(0.011)	(0.012)
Downstream Import Exposure	0.594	–1.535	–0.277***	–0.256**	–0.344***	–0.155
	(0.815)	(1.280)	(0.098)	(0.103)	(0.099)	(0.097)
Downstream Export Exposure	0.492	4.357***	0.283**	0.250*	0.319**	0.232
	(1.174)	(1.588)	(0.132)	(0.146)	(0.134)	(0.150)
Upstream Import Exposure	2.900**	3.519*	0.519***	0.407***	0.578***	0.299**
	(1.361)	(1.802)	(0.132)	(0.129)	(0.128)	(0.122)
Upstream Export Exposure	–0.679***	–0.667***	–0.336***	–0.448***	–0.352***	–0.421***
	(0.149)	(0.166)	(0.087)	(0.111)	(0.083)	(0.119)
Observations	50,024	50,090	38,261	12,061	39,573	10,748
R-squared/Pseudo R-squared	0.350	0.301	0.369	0.294	0.368	0.297
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Selection Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	304	303	300	290	299	287
F statistic			122.7	99.44	127.1	102.2
Weak instruments (F-stat)			50.80	44.18	57.22	40.87

The dependent variables are the indicator of importer (column 1), the indicator of exporter (columns 2), and the change in the firm wage component (columns 3-6). The models are analogous to Eq. (5.2), except for the dependent variable in columns 1-2. All regressions include State-Sector fixed effects and pre-2000 levels of exposure to Chinese imports and exports, baseline industry, and firm controls. Industry controls (baseline, 2000): log of employees, (unconditional) average wages, formality rate, and share of workers whose earnings are smaller than minimum wage plus 10 percent. Firm controls (baseline, 2000): log wages, log-firm size, the share of high-educated workers, and white-collar workers. Selection controls: third-order polynomial of Inverse-Mills term for the probability of a firm to operate. Robust standard errors are clustered at the industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The first two columns report the estimates of Probit models with Import and Export status as dependent variables. The estimates for upstream and downstream shocks affect the probability of firms selecting into imports or exports. In column 1, the coefficient for upstream import exposure is positive and significant at a 5 percent level. Thus, when an import shock affects the input market, firms are more likely to become importers to take advantage of lower input prices from the external market. In column 2, the coefficients for downstream export exposure

[17] Other specifications, such as Logit and Poisson, are presented in the Appendix.

[18] We separate firms into importers/non-importers or exporter/non-exporter using an indicator whether the firm imported or exported anytime in the period 1997-2012. Estimates for other definitions of importer and exporter firms are presented in Appendix.

are particularly relevant in that they are positive and statistically significant at a 1 percent level. Thus, firms are more likely to export when facing a positive shift in their output's demand.[19]

The models in columns 3 to 6 are estimated separately for each group, importer/non-importer and exporter/non-exporter. Note that the coefficients are similar across groups and also similar to the findings on Table 5. Indeed, the point estimates for those groups suggest that importers and exporters are less sensitive to trade shocks than non-importers and non-exporters. Nonetheless, the estimates' distributions overlap, so we cannot imply a statistical difference.

Within-Firm-Group Wage Dispersion The literature on heterogeneous firms and trade liberalization focuses mainly on the between-firm components of wage inequality. Few papers include within-firm wage variance as an underlying component of wage dispersion. Helpman, Itskhoki, and Redding (2010) presents an extension to their theoretical model with observable ex-ante heterogeneity so that workers of different groups perform different tasks or occupations. However, these are not the main characteristics in the subsequent empirical work Helpman, Itskhoki, Muendler, and Redding (2017). In Verhoogen (2008), within-firm wage inequality arises because identical co-workers may receive different wages when employed in different production lines. In Georgiev and Henriksen (2020), firms hire different types of workers and, within each type, wage bargaining induces pay differentials to more productive workers.

A notable example in models of heterogeneous firms in the same line as Melitz (2003) is Pupato (2017). It includes within-firm wage inequality due to optimal performance pay contracts, which generates wage dispersion among co-workers. Wage contracts arise from a moral hazard problem where firms generate an incentive to induce workers to higher performance conditional on the worker's constraints. Moreover, because the performance pay increases with productivity, more productive firms pay higher wages and have more dispersed wages. The caveat of this model is that firm-level wages and variance do not depend on the trade costs and the export status.

To investigate whether the China shock significantly impacts the within-firm-group wage dispersion, we will estimate eq. (5.2) using firm-level measures of wage inequality as dependent variables. We define our main measure as the firm-level $var(\varepsilon_{it})$ resulting

[19] Note that the coefficient for upstream import exposure is also significant in column 2. That is because there is a positive relationship between import and export status. The coefficients for upstream export exposure are negative and significant in both specifications, indicating that a negative shift in output's demand decreases firms' probability of engaging in international trade.

from Eq. (4.1), where ε_{it} is the residual wage conditional on occupation-firm fixed-effects and workers' observable characteristics. As widely discussed in the literature, this variation may arise from search frictions, matching between employer and employee, and worker-level bargaining. Because workers' and firms' characteristics do not fully capture those labor market idiosyncrasies, they are captured in ε_{it}.

The second source of within-firm-group wage dispersion derives from heterogeneous labor inputs. In Helpman, Itskhoki, and Redding (2010), there is only one type of labor, and differentiation across workers is due to their ability level $a \sim G(a)$. Alternatively, as proposed in Verhoogen (2008) and Georgiev and Henriksen (2020), the firm's final production function may use heterogeneous types of workers, such as low- and high-skill, white- and blue-collar, and different product lines within a plant. We use the estimates of ψ_{oft}, denoted $\hat{\psi}_{oft}$, to separate workers into two mutually exclusive groups.[20]

First, we separate $\hat{\psi}_{oft}$ into white- and blue-collar occupations. Second, we separate them into low- and high-skilled workers (high-school dropouts versus high-school graduates). For each firm f, we have a measure $\hat{\psi}^{u}_{ft}$ that gives the average $\hat{\psi}_{oft}$ for group $u = \{\text{White,Blue,Low,High}\}$. We measure the within-firm inequality as $\hat{\psi}^{White}_{ft} - \hat{\psi}^{Blue}_{ft}$ (or the firm-level occupation premium) for occupation and $\hat{\psi}^{High}_{ft} - \hat{\psi}^{Low}_{ft}$ for education (or the firm-level education premium or skill premium).[21]

The results are presented in Table 8. Each column displays the estimates of Eq. (5.2) for a different dependent variables. Columns 1 and 2 use the between-firm component $\hat{\psi}_{ft}$, as we study in the main text. Columns 3 and 4 use the $var(\varepsilon_{it})$. Columns 5 and 6 use the occupation wage-gap $\hat{\psi}^{White}_{ft} - \hat{\psi}^{Blue}_{ft}$. Columns 7 and 8 use the education wage-gap $\hat{\psi}^{High}_{ft} - \hat{\psi}^{Low}_{ft}$. The sample size differs from the main analysis because it is restricted to the firms we can measure those indicators.

Results in columns 1 and 2 align with the between-firm discussed before. Columns 3 and 4 show that the within-firm wage variance is not as unresponsive to trade shocks as the between-firm wage component. Indeed, upstream import exposure shows statistically significant estimates, suggesting that importers are more likely to pay differential wages to workers than non-importers. Combined with the results in columns 1 and 2, those firms pay higher wages to some

[20]Our definition of occupation is education-sector specific. Thus, we can aggregate $\hat{\psi}_{oft}$ into different categories within a firm.

[21]Note that, because some of these groups may not be present in every firm, we might incur a loss of observations in this part of the analysis.

Table 8. Effects of Trade Shocks on Within-Firm-Group Wage Dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Between-Firm		Variance		White-Blue		High-Low Education	
	2006-2008	2008	2006-2008	2008	2006-2008	2008	2006-2008	2008
Downstream Import Exposure	–0.243**	–0.228**	–0.060*	–0.037	0.207*	0.216	–0.081	–0.057
	(0.098)	(0.109)	(0.031)	(0.025)	(0.122)	(0.133)	(0.082)	(0.096)
Downstream Export Exposure	0.174	0.202	–0.015	–0.004	–0.761***	–0.893***	–0.579***	–0.735***
	(0.148)	(0.155)	(0.043)	(0.034)	(0.228)	(0.239)	(0.148)	(0.166)
Upstream Import Exposure	0.474***	0.491***	0.152***	0.112***	–0.238	–0.276	0.139	0.130
	(0.127)	(0.142)	(0.045)	(0.035)	(0.171)	(0.192)	(0.122)	(0.146)
Upstream Export Exposure	–0.314***	–0.358***	0.025	0.013	0.011	0.024	0.118	0.119
	(0.090)	(0.095)	(0.034)	(0.025)	(0.193)	(0.200)	(0.130)	(0.139)
Observations	22,180	22,180	22,180	22,180	18,416	17,721	16,898	16,146
R-squared	0.721	0.685	0.276	0.287	0.193	0.158	0.137	0.103
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F statistics	690.9	621.5	120.2	171	83.94	81.03	56.54	39.72
Weak instruments (F-stat)	47.52	47.52	47.52	47.58	45.51	45.33	42.15	42.13
Clusters	297	297	297	297	296	295	296	296

The table presents the results of estimates based in Eq. (5.2). Each column displays a dependent variable derived from decomposition in Eq. (4.1); $\hat{\psi}_{ft}$ in columns 1 and 2, $var(\hat{\varepsilon}_{i,t})$ in columns 3 and 4, $\hat{\psi}_{ft}^{White} - \hat{\psi}_{ft}^{Blue}$ in columns 5 and 6, and $\hat{\psi}_{ft}^{High} - \hat{\psi}_{ft}^{Low}$ in columns 7 and 8. All regressions include State-Sector fixed effects and pre-2000 levels of exposure to Chinese imports and exports, baseline industry, and firm controls. Industry controls (baseline, 2000): log of employees, (unconditional) average wages, formality rate, and share of workers whose earnings are smaller than minimum wage plus 10 percent. Firm controls (baseline, 2000): log wages, log-firm size, the share of high-educated workers, and white-collar workers. Selection controls: third-order polynomial of Inverse-Mills term for the probability of a firm to operate. Robust standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

workers than others. Arguably, high-ability workers may benefit more from the import wage premium. Other sources of trade shocks are not significant at usual statistical levels.

In contrast, columns 5 to 8 show statistically significant results only for downstream export exposure. Firms highly exposed to this shock reduce the distance between white- and blue-collar occupations and between high- and low-skill workers. Thus, the positive output demand shock may also decrease the wage variance for the economy.

In the Appendix, we further study the relationship between within-firm wage dispersion and firm productivity (as measured by the between-firm wage component and the number of employees). However, our reduced-form estimates show that the impacts of the China shock on within-firm wage variance are of secondary interest. Indeed, as we have shown previously, most of the impact of trade shocks is transmitted to the between-firm wage component and the incentives to firms for becoming importers and exporters. This conclusion emphasizes our primary interest in the impacts of the China shock across sectors and firms.

Effects by Sector We may interpret the coefficients in Table 4, Table 5, and Table 7 on their economic magnitude under the input-output structure. For instance, High-Tech Manufacturing industries are highly impacted by a positive upstream import competition exposure, leading to greater changes in wages. However, upstream export exposure may also have a high impact, implying a larger decrease in wages or employment. The net effect may be positive or negative depending on the composition of the trade shocks. Thus, we use the sector averages presented in Table 1 to interpret the economic meaning of these estimates. For that, we decompose the total change in employment, wages, and the probability of importing and exporting for each sector in Figure 5 and Figure 6.

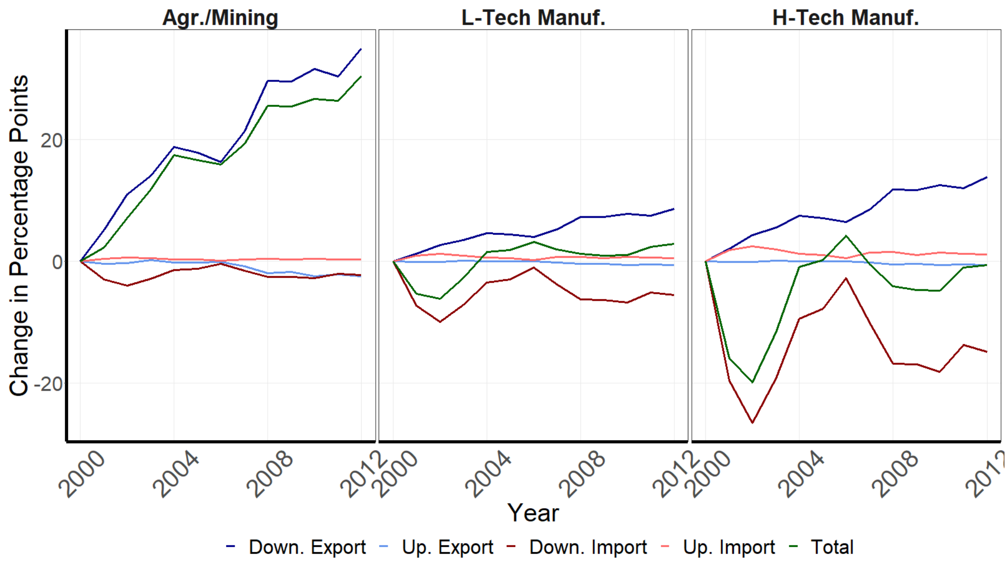
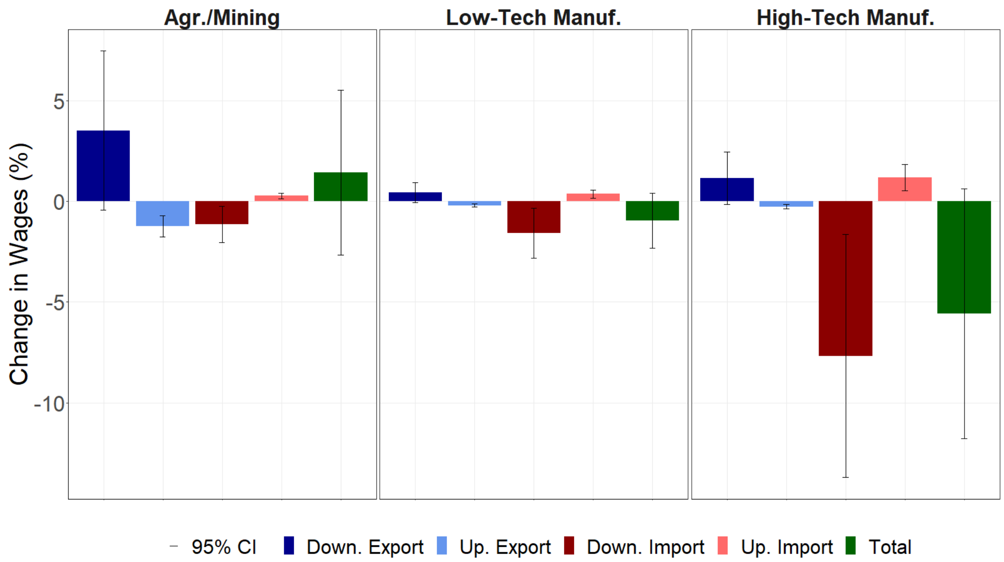
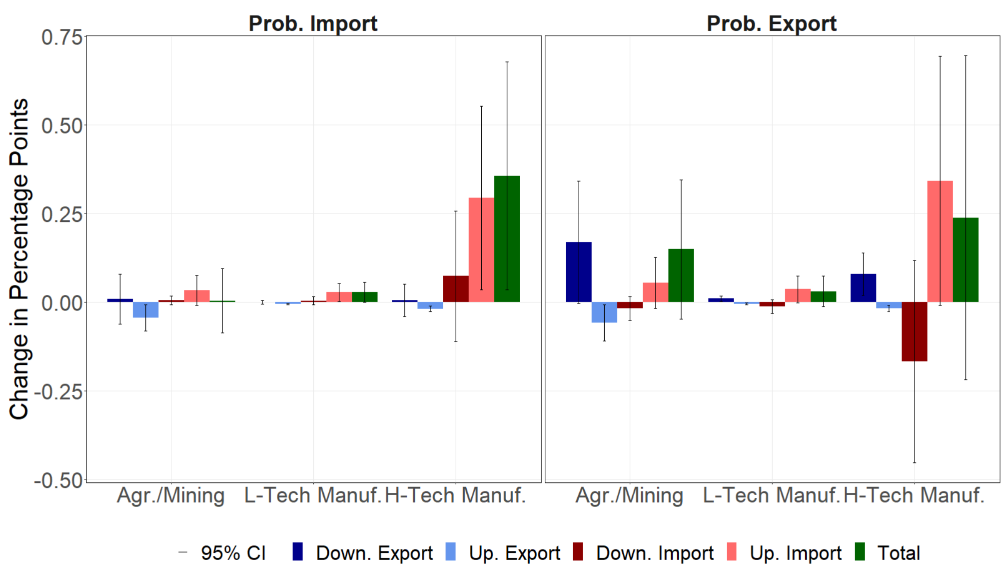


Figure 5. Predicted Impact of the China Shock on the Employment Growth Over Time. The Figures display the predicted impact of the China Shock on employment for each sector. The values are based on the point-estimates of Eq. (5.1). The lines decompose the partial impact of Upstream/Downstream import and export exposure per sector and the total for the economy. For clarity in the visualization, we omit confidence intervals. Note that Agriculture and Mining industries highly benefit from (downstream) export exposure by increasing employment. Contrarily, Manufacturing industries (especially High-Tech) suffer sharp decrease in employment as a consequence of import competition in years subsequent the China shock, but such effect vanishes over time.



(a) Average Wages



(b) Probability of Import and Export

Figure 6. Predicted Impact of the China Shock on the Changes in Averages Wage and on the Probability of Import or Export. The Figures display the predicted impact of the China Shock on wages and probability of import or export. The values are based on estimates in column 5 of Table 5 and columns 1 and 2 of Table 7. The bars decomposed the partial impact of Upstream/Downstream import and export exposure per sector and total for the economy. Vertical, black lines represent the 95% confidence intervals.

In Figure 6, we display the change in employment over time for an average firm in each sector. Values are based on point estimates in columns 1 to 5 of Table 4 and average upstream and downstream exposure for each industry. We omit confidence intervals for clarity in visualization.

Note that Agriculture and Mining industries benefit highly from downstream export exposure, with an increase in employment over time after the most significant effects of the China shock. This is because those industries are not heavily affected by import competition.

In contrast, downstream import exposure leads to a sharp decrease in employment in Manufacturing industries years after the entry of China into the WTO, with a relative stabilization in employment growth after 2004. The partial impact of import exposure reduces employment growth by almost 10 percent in Low-Tech Manufacturing industries and around 20 percent in High-Tech Manufacturing industries. Oppositely, upstream import exposure is related to a slight increase in employment growth around 2001 and 2002 for High-Tech Manufacturing industries, although with a much smaller magnitude. Thus, import competition in a firm's input market attenuates the negative impact of import competition in the output market.

In Figure 6.a we present the predicted changes in the average wage per sector. An average firm within the Agriculture/Mining sector experiences an overall increase of 1 percent in their wages: export exposure increases wages by 1.7 percent, whereas import exposure decreases wages by 0.9 percent. Most of their gains come from downstream export exposure (which contributed to about a 3 percent increase). On the other hand, downstream import exposure leads to a decrease of approximately 1.3. Competition with imported inputs (upstream export exposure) leads to a decline of 1.2 percent.

Likewise, an average firm in the Low-Tech manufacturing sector faces a decline in their wages by around 1 percent. Most of this decline is driven by the competition with Chinese products in the output market (i.e., downstream import competition), contributing to a decrease of around 1.6 percent in the average wages. Nonetheless, import competition affecting the input markets is highly beneficial to those firms: upstream import exposure is related to an almost 0.5 percent increase in wages.

Finally, an average firm in the High-Tech manufacturing sector experiences a negative net effect on wages derived from the bilateral trade integration with China of around 6 percent. Although those firms largely benefit from cheaper imported goods, they mainly demand inputs from other manufacturing sectors, and upstream import exposure leads to a 1.3 percent increase in wages. Nonetheless, because the main destination of their production is other manufacturing industries, losses due to import competition downstream in production also have a sizable effect on wages (almost 8 percent fall).

Using the estimated coefficients from columns 1 and 2 of Table 7, we also estimate the predicted changes in the probabilities of import and export for each sector. The results are presented in Figure 6. The overall impact of the China shock increases the firm's probability to import by 5 percentage points, mainly for firms in High-Tech manufacturing, which are highly exposed to import competition shocks. On the other hand, the firm's probability of exporting increases by about 6 percentage points (statistically insignificant) driven by the export exposure in the Agriculture/Mining (11 percentage points) and the High-Tech manufacturing (6 percentage points) sectors.

These results reveal some interesting facts, which we can connect to our findings in section Section 4. First, trade shocks tend to push firms into operating or not in the external market, either as importers or exporters.[22] The positive coefficients for lagged wages also suggest that high-paying firms (thus, more likely, high-productivity firms) also have higher probabilities of import/export. Nonetheless, trade shocks do not seem to change the export/import premium for incumbent firms, which is consistent with the stable import and export premia on Figure 4.

Discussion. The reduced-form results show that direct and indirect trade shocks significantly impact wages and firm size, especially shocks coming from upstream and downstream in the production. We analyze the heterogeneous impacts by comparing importers with non-importers and exporters with non-exporters firms. Our findings suggest that firms operating in the external markets are susceptible to indirect shocks. Specifically, firms tend to pay higher wages when import shocks are stronger upstream of the production structure. On the other hand, workers largely benefit from export exposure downstream in the production structure.

In the big picture, the results agree with Costa, Garred, and Pessoa (2016), who found a negative impact of import exposure and the reverse for export exposure on local wages and employment. Moreover, as suggested by Acemoglu, Autor, Dorn, Hanson, and Price (2016), we also show that indirect shocks based on the input-output linkages strongly impact firm wages and size. Thus, because we evaluate the heterogeneous impact on firms within sectors, direct and indirect trade shocks may induce firms into importing inputs or exporting their output, which would imply a wage premium for their workers and firm expansion (in terms of the number of employees).

[22] Our results apply mainly to incumbent firms, for which we restrict our analysis. These firms may benefit from experience in operating and higher productivity compared to entrants.

Our results show that the China shock significantly impacts labor market outcomes. Nonetheless, the reduced-form analysis is limited in two crucial aspects. Firstly, it does not provide evidence on the mechanisms through which the shock impacts labor markets. Secondly, it does not enable us to perform any credible counterfactual analysis. Based on the empirical evidence we presented in the last two sections, we will introduce and estimate a structural model highlighting the mechanisms through which the China shock may influence Brazilian firms. The model provides the relevant parameters to perform the counterfactual analysis.

6. Structural Model

In this section, we develop a theoretical framework based on the models of Helpman, Itskhoki, Muendler, and Redding (2017), henceforward HIMR, and Helpman, Itskhoki, and Redding (2010), which accounts for the stylized facts presented in Section 4 and the reduced-form estimates in Section 5. Similar to HIMR, we develop a static model to explain steady-state patterns. In addition, the model incorporates firm selection into import markets and heterogeneous sectors as alternative mechanisms through which trade shocks may affect the earnings distribution.[23] We use this model to conduct counterfactual exercises in which we compare the steady-state distributions of wages and employment in two scenarios: i) if there is only import exposure, and ii) if there is only export exposure.

6.1 Theoretical Framework

The world consists of two countries (Home and Foreign) and S sectors. Home is a small economy with no influence on external prices. Each sector is indexed as s. Each country has a continuum of workers who are ex-ante identical. The goods in each sector are differentiated and produced by a primary factor, labor. Workers are endowed with one unit of labor supplied inelastically with zero disutility.

The home country has a representative consumer with Cobb-Douglas utility over goods produced by each sector $s \in S$

$$U = \prod_{s \in S} U_s^{v_s},$$

[23] We choose this model because it provides a clear, straightforward interpretation of the mechanisms through which trade affect earnings inequality. Moreover, the model delivers intuitive structural equations that are simple to estimate compared to more sophisticated general equilibrium models in the literature.

where $\upsilon_s > 0\ \forall s$ is the share of sector s in the total expenditure, so that we normalize $\sum_{s\in S}^{S}$. Consumers first choose between domestic and imported goods Q_s and Q_s^*, respectively, with constant elasticity of substitution $1/(1-\epsilon)$. Moreover, nested within domestic and imported goods, consumers choose between varieties. There is a continuum of monopolistically competitive firms in each sector, each supplying a distinct, horizontally differentiated variety, represented by $q(j)$, for $j \in J_s$. Firms in the import market are represented analogously. The quantity index for goods in sector s is given by

$$U_s = \left[\left(\int_{j\in J_s} q(j)^{\beta} dj\right)^{\epsilon/\beta} + \left(\int_{j\in J_s^*} q^*(j)^{\beta} dj\right)^{\epsilon/\beta}\right]^{1/\epsilon}, \quad 0 < \beta < 1,$$

where $\epsilon \in (0,1)$ determines the elasticity between domestic and imported goods $1/(1-\epsilon) > 1$. $\beta \in (0,1)$ controls the elasticity of substitution between varieties equal to $1/(1-\beta) > 1$.[24]

To import goods, consumers face an iceberg cost $\tau_m > 1$, which gives the relative cost between imported exported varieties. So for every imported unit, consumers must pay τ_m to acquire the same quantity. Additionally, we assume there are further barrier terms that determine the relationship between countries, so that prices of foreign goods are given by $P^* = A/A^* \tau_m P$, where P^* and P are the price indexes for foreign and domestic goods, respectively, A/A^* is the non-tariff shifter in the barriers between the two countries. In this case, we assume that the entrance of China into the WTO decreases A/A^*, so that foreign goods become relatively cheaper compared to domestic goods.

By solving the domestic consumer's problem, we get the following relationship for the revenues of firms operating in the domestic market [25]

$$R_j = A_d q_j^{\beta}, \tag{6.1}$$

where

$$A_d = \bar{A}_{sd}\left(1 + \left(A^*/A\right)^{1/(1-\epsilon)} \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)}, \tag{6.2}$$

and $\bar{A}_{sd}$ is a sector-specific constant.

[24]This specification of preferences are largely assumed in empirical works. We base our theoretical approach in Demidova and Rodríguez-Clare (2009), who also assume that domestic and imported varieties are substitutes under a constant elasticity of substitution.

[25]Detailed derivation is presented in the Appendix.

Notice that domestic revenues are negatively related to domestic consumption relative price shifter for imported goods ${}^{A^*}/{}_{A}$. So an exogenous increase in preferences for domestic goods decreases the demand for domestic varieties, leading to a decrease in revenues. Moreover, domestic revenues are positively related to import tariffs τ_m. Hence, an increase in import tariffs makes imported varieties more expensive, which increases the relative demand for domestic goods, and increases revenues.

Firms can decide to allocate the production between domestic and imported technologies, which we interchangeably refer to as importing. When importing, a firm has a technology (or demand) shifter of $A_m > A_d$. Contrarily, if producing only internally, the sole demand constant is A_d. Moreover, firms may also decide to sell part of their production in the external market, for which the firm faces a demand shifter $A_x > A_d$. As a result, we can represent a firm's revenue in market/technology j in terms of its output supplied to this market (Y_j) and a demand shifter (A_j):

$$R_j = A_j Y_j^{\beta}, \quad j \in \{d, x, m\}, \tag{6.3}$$

where d denotes the domestic market, x the export market, and m the import market. The demand shifter (A_j) measures product market competition, increasing sectoral expenditure and decreasing the sectoral price index. Since every firm is small relative to the sector, the firm takes this demand shifter as given.

To export, a firm has to incur a fixed cost $e^{\varepsilon_x} C_{x,s}$ where ε_x is a firm-specific random draw and $C_{x,s}$ is common to all firms in the sector s. In addition, there is an iceberg transportation cost $\tau_x > 1$ for shipping products across the two countries. This iceberg cost means that for every unit of output the firm sells abroad, it must produce an amount τ_x. The exporting firm's problem is to maximize its revenue by allocating its production between the domestic and export markets.

Analogously, to import, a firm incurs a cost $e^{\varepsilon_m} C_{m,s}$, a firm-specific random draw ε_m and common import cost $C_{m,s}$. By having access to a wider variety of inputs at potentially lower prices, importing firms can improve their production quality, which increases their productivity from A_d to A_m. Amiti and Davis (2012) calls the "import globalization" effect. In other words, those firms that can afford higher quality/quantity inputs will get higher revenues for their output. However, imports are also subject to an iceberg cost $\tau_m > 1$, which gives the relative cost between imported exported inputs. So for every unit of imported input, an importer firm must pay τ_m.

We can write a firm's total revenue as:

$$R = \left[1 + \iota_x \left(\Upsilon_x - 1\right)\right]^{1-\beta} \left[1 + \iota_m \left(\Upsilon_m - 1\right)\right]^{1-\beta} A_d Y^{\beta}, \tag{6.4}$$

with

$$\Upsilon_x = 1 + \tau_x^{\frac{-\beta}{1-\beta}} \left(\frac{A_x}{A_d}\right)^{\frac{1}{1-\beta}} > 1 \quad \text{and} \quad \Upsilon_m = 1 + \tau_m^{\frac{-\beta}{1-\beta}} \left(\frac{A_m}{A_d}\right)^{\frac{1}{1-\beta}} > 1.$$

I these equations, ι_x (ι_m) is an indicator variable, equal to one when the firm exports (imports) and equal to zero otherwise. $\Upsilon_x^{1-\beta}$ is the firm revenue premium from exporting, which is decreasing in the bilateral trade cost parameter (τ_x) and increasing in the foreign demand shifter relative to the domestic demand shifter (A_x/A_d). Similarly to HIMR, firms face a decreasing demand schedule. Likewise, the revenue premium for importing is increasing in the input supply shifter (A_m/A_d) and decreasing in the importing trade cost parameter (τ_m).

Each firm hires a measure H of workers. Following Helpman, Itskhoki, and Redding (2010), each worker has an ability level, a, which firms have an incentive to screen. With heterogeneous screening costs added to the model, à la Helpman, Itskhoki, Muendler, and Redding (2017), the production technology is

$$Y = e^{\theta} H^{\gamma} \bar{a}, \quad 0 < \gamma < 1, \tag{6.5}$$

where $\bar{a}$ represents the average ability of the hired workers, γ is the elasticity of employed workers. Following Helpman, Itskhoki, Muendler, and Redding (2017), workers choose a sector in which to search for employment, where each firm bears the search cost bN to match with N workers randomly. The hiring cost b is exogenously determined by the labor market tightness and taken as given by each firm. In the econometric model, labor market tightness and the product market demand shifters are absorbed in the sector fixed-effects.

The timing of decisions is as follows. There is a mass of potential entrant firms J in the economy. In the first stage, firms draw a cost of operating in each sector of the economy $C_{\pi,s}$ from a sector-specific distribution G_{C_s}. For simplicity, we assume that the draws are independent across sectors and firms. Based on the expected profit from operating in each sector, the firms decide which sector to operate. For simplicity, we also assume that firms can operate at most in one single sector, which we can interpret as having a random draw for a potential product variety or innovation that gives differential expected profits when applied in different sectors. Once they decide to produce, firms then draw their idiosyncratic productivity θ, the firm-specific screening cost term η, and the firm-specific export fixed cost term ε. Given this triplet, each firm chooses whether to serve only the domestic market or export or import. Each firm pays the search costs and matches its chosen number of workers. After matching, each firm chooses its screening threshold and hires workers with abilities above this threshold. After the firm has paid all the fixed costs for search, screening, and exporting, it engages in multilateral bargaining with its H workers over wages, as in Helpman, Itskhoki, Muendler, and Redding (2017). The authors show that each firm that searched for N workers and chose the ability cutoff a_c hires $H = N\left[1 - G\left(a_c\right)\right] = N a_c^{-k}$ workers whose expected ability is $\bar{a} = \mathbb{E}\left\{a \mid a \geq a_c\right\} = \frac{k}{k-1} a_c$. The outcome of the bargaining game is the following common wage for all workers within the firm:

$$W = \frac{\beta\gamma}{1+\beta\gamma} \frac{R}{H} \tag{6.6}$$

Regardless of its sector, a firm vector of random components $(\theta, \eta, \varepsilon_x, \varepsilon_m)$ operating in a sector s solves the following problem (we omit firm and sector subscripts for simplification):

$$\Pi(\theta,\eta,\varepsilon) = \max_{N, a_c, \iota_x, \iota_m \in \{0,1\}} \left\{ \frac{1}{1+\beta\gamma} R\left(N, a_c, \iota; \theta\right) - bN - e^{-\eta} \frac{C}{\delta} \left(a_c\right)^{\delta} - \iota_x e^{\varepsilon_x} C_x - \iota_m e^{\varepsilon_m} C_m \right\}, \tag{6.7}$$

where the revenue $R\left(N, a_c, \iota; \theta\right)$ is defined by eq. (6.4), eq. (6.5), and the functions that determine the workers hired and their expected ability. The solution to the firm's profit maximization problem yields:

$$R = \kappa_r \left[1 + \iota_x \left(\Upsilon_x - 1\right)\right]^{\frac{1-\beta}{\Gamma}} \left[1 + \iota_m \left(\Upsilon_m - 1\right)\right]^{\frac{1-\beta}{\Gamma}} \left(A_d\right)^{\frac{1}{\Gamma}} \left(e^{\theta}\right)^{\frac{\beta}{\Gamma}} \left(e^{\eta}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}}, \tag{6.8}$$

$$H = \kappa_h \left[1 + \iota_x \left(\Upsilon_x - 1\right)\right]^{\frac{(1-\beta)(1-k/\delta)}{\Gamma}} \left[1 + \iota_m \left(\Upsilon_m - 1\right)\right]^{\frac{(1-\beta)(1-k/\delta)}{\Gamma}} \left(A_d\right)^{\frac{(1-k/\delta)}{\Gamma}} \left(e^{\theta}\right)^{\frac{\beta(1-k/\delta)}{\Gamma}} \left(e^{\eta}\right)^{-\frac{k-\beta}{\delta\Gamma}} \tag{6.9}$$

$$W = \kappa_w \left[1 + \iota_x \left(\Upsilon_x - 1\right)\right]^{\frac{k(1-\beta)}{\delta\Gamma}} \left[1 + \iota_m \left(\Upsilon_m - 1\right)\right]^{\frac{k(1-\beta)}{\delta\Gamma}} \left(A_d\right)^{\frac{k}{\delta\Gamma}} \left(e^{\theta}\right)^{\frac{\beta k}{\delta\Gamma}} \left(e^{\eta}\right)^{\frac{k(1-\beta\gamma)}{\delta\Gamma}}, \tag{6.10}$$

Eq. (6.8) to eq. (6.10) are sufficient to determine a firm's profits. Thus, we also find sufficient conditions for firms to export or import given by

$$\kappa_\pi \left(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1\right) \left(e^{\theta}\right)^{\frac{\beta}{\Gamma}} \left(e^{\eta}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} \geq C_x e^{\varepsilon_x} \tag{6.11}$$

and

$$\kappa_\pi \left(\Upsilon_m^{\frac{1-\beta}{\Gamma}} - 1 \right) \left(e^{\theta} \right)^{\frac{\beta}{\Gamma}} \left(e^{\eta} \right)^{\frac{\beta(1-\gamma k)}{\delta \Gamma}} \geq C_m e^{\varepsilon_m}. \tag{6.12}$$

Eq. (6.8) to eq. (6.12) are the equilibrium firm-level variables within each sector. κ_r, κ_h, κ_w, and Γ are constants that depend only the model's parameters. Eq. (6.8), eq. (6.9) and eq. (6.10) show that exporting firms increase revenues, employment, and wages by a shift of size Υ_x. Analogously, importing firms increase revenues, employment, and wages by Υ_m. Eq. (6.11) establishes a sufficient condition for the firm to become an exporter, whereas eq. (6.12) presents the sufficient condition for the firm to become an importer. Within sectors, firm heterogeneity is drawn from the idiosyncratic components $(\theta, \eta, \varepsilon)$ and their decision to become exporters.

Eq. (6.9) and eq. (6.10) establish the relationship between productivity and firm size and wages, respectively. More productive firms, those with higher draws of θ and η, are larger and pay higher wages. The first term, θ, is the production productivity, whereas the second term, η, is the human resources management productivity, which gives higher screening efficiency to firms. As a consequence, it also characterizes the positive correlation between firm size and wages, extensively addressed in the literature and corroborated in Section 4.[26] As suggested in HIMR and other models that followed Melitz (2003), this is the first source of firm heterogeneity.

The second source of heterogeneity is related to the selection of firms into exporting and importing. Eq. (6.11) and eq. (6.12) imply that only high productivity firms can afford the trading costs c_x and c_m to engage in the international market. By exporting their output to foreign markets or importing higher quality/lower price inputs from abroad, firms are enabled to pay higher wages and employing more workers, as determined in eq. (6.9) and eq. (6.10). This is consistent with our findings in Section 5 and other papers in the literature. HIMR calls the mechanism derived from eq. (6.11) and eq. (6.12) as *selection effect* and the premia implied in eq. (6.9) and eq. (6.10) as *market access*. Amiti and Davis (2012) calls the combination of such effects as *import globalization* and *export globalization*.

6.2 Econometric Model and Estimation

By taking logs and rearranging the terms of eq. (6.9)-eq. (6.11), we obtain the following reduced-form equations from the structural model:

[26] We assess this correlation using other measures for size and productivity, such as profits, revenues, and value-added. In general, controlling for industry characteristics, those variables are related to a higher number of employees.

$$
\begin{aligned}
h_s &= \alpha_{hs} + \mu_{h,xs}\iota_{xs} + \mu_{h,ms}\iota_{ms} + u \\
w_s &= \alpha_{ws} + \mu_{w,xs}\iota_{xs} + \mu_{w,ms}\iota_{ms} + \zeta u + v \\
\iota_{xs} &= \mathbb{1}\{z_x > c_{x,s}\} \\
\iota_{ms} &= \mathbb{1}\{z_m > c_{m,s}\}
\end{aligned}
\tag{6.13}
$$

where $\mathbb{1}$ denotes an indicator function. $x = (h, w, \iota_x, \iota_m, s)$ is the vector of observable variables: log of employees, firm wages (we use the firm's wage component Ψ estimated in Section 4), ι_x is an indicator of exporter status, ι_m is an indicator of exporter status, and s is the firm's sector choice. (u,v,z_x,z_m) are the reduced-form shocks, which are linear transformations of the structural shocks $(\theta, \eta, \varepsilon_x, \varepsilon_m)$ defined from the structural eq. (6.9)-eq. (6.11). Firms learn those shocks after they chose their sector of activity, but they have prior knowledge about the distribution of those shocks.

These equations highlight the main characteristics in HIMR's model we incorporate into our model. In those, $\mu_{h,xs}$ and $\mu_{w,xs}$ are the market access parameters to supplying in the external markets for sector s, and $\mu_{h,ms}$ and $\mu_{w,ms}$ are the market access parameters to external inputs. Those terms capture important characteristics observed in the data: exporter and importer firms are larger and pay higher wages. $c_{x,s}$ and $c_{m,s}$ are the selection effects, which capture the fact that exporting and importing firms are more productive than non-exporters/non-importers. Based on our findings in section 5, we argue that these terms vary across sectors and are potentially affected by bilateral trade shocks.

We assume that the joint distribution of shocks u, v, z_x, and z_m is common across firms, regardless of their sector. Therefore, their joint distribution drives the overall trends in inequality. In addition, firms' selection into exporting and importing markets drive within-sector inequality, generating employment and wage premia (μ_h and μ_w).[27] Because we include sector heterogeneity, cross-sector wage inequality is determined by the intercept levels of employment and wage levels, α_h and α_w, which capture labor market tightness and competition that affects all firms within a sector. Moreover, the gains of engaging in international trade, with consequent employment and wage premium (μ_h and μ_w) and the selection terms, determine within-sector wage inequality derived from international trade.

[27] Another possible source of heterogeneity to incorporate is regional differences, which we can derive from the quality of the local labor market where the firm operates.

Following HIMR, we also impose that the reduced form of the structural shocks is jointly normally distributed.

$$(u, v, z_x, z_m) \sim N(0, \Sigma) \qquad with \qquad \Sigma = \begin{pmatrix} \sigma_u^2 & 0 & \rho_{ux}\sigma_u & \rho_{um}\sigma_u \\ 0 & \sigma_v^2 & \rho_{vx}\sigma_v & \rho_{vm}\sigma_v \\ \rho_{ux}\sigma_u & \rho_{vx}\sigma_v & 1 & \rho_{xm} \\ \rho_{um}\sigma_u & \rho_{vm}\sigma_v & \rho_{xm} & 1 \end{pmatrix} \tag{6.14}$$

Note that we construct the variance-covariance matrix so that u and v are independent. The variances of z_x and z_m are equal to 1.[28] The error structure in eq. (6.14) implies that the probability distribution of x_f given the set of parameters Θ is given by

$$\begin{aligned} P(x_f|\Theta) = \frac{1}{\sigma_u}\phi(\bar{u}_f)\frac{1}{\sigma_v}\phi(\bar{v}_f)\left[\Phi(\bar{z}_x, \bar{z}_m)\right]^{(1-\iota_{x,f})(1-\iota_{m,f})}\left[\Phi(-\bar{z}_x, \bar{z}_m)\right]^{\iota_{x,f}(1-\iota_{m,f})} \\ \left[\Phi(\bar{z}_x, -\bar{z}_m)\right]^{(1-\iota_{x,f})\iota_{m,f}}\left[\Phi(-\bar{z}_x, -\bar{z}_m)\right]^{\iota_{x,f}\iota_{m,f}} \end{aligned} \tag{6.15}$$

where the variables are indicated as above. ι_x is an indicator for exporting firms, and ι_m is an indicator for importing firms.

ϕ is the density from a standard normal distribution. Φ is the cumulative distribution of a bivariate standard normal. $(\bar{z}_x, \bar{z}_m)' = \bar{\Sigma}_{xm}^{-1}(c_x - \bar{m}_x, c_m - \bar{m}_m)'$ is the transformed vector of shocks that determine the exporting/importing decisions. $(\bar{m}_x, \bar{m}_m)$ is the vector of means and $\bar{\Sigma}_{xm}$ is the joint variance-covariance matrix of the conditional distribution $\{z_x, z_m|u, v\}$.

Given this structure for the probability of the data conditional on parameters, $P(x_f|\Theta)$, we obtain estimates for Θ by solving the likelihood problem

$$\hat{\Theta} \ = \ argmax_{\Theta} \quad \prod_f P(x_f|\Theta). \tag{6.16}$$

We estimate eq. (6.16) by Maximum Likelihood (ML). Identification of the parameters in Θ relies on some assumptions. As discussed in HIMR, to construct the structural restriction, we reconcile the theoretical and the econometric models given by eq. (6.13) and eq. (6.14). Firstly,

[28] In HIMR as well as in the online appendix, we show the proofs that imply the structure of the variance-covariance matrix, which makes it more tractable and reduce the number of parameters we estimate.

the assumptions that unconditional variance of z_x and z_m equal one, which are derived from eq. (6.11) and eq. (6.12). Moreover, the assumption that the structural error terms θ and η are unrelated, which implies that u and v are also unrelated, and hence the bounds for the exporting and importing market access $\mu_{w,xs}/\mu_{h,xs}$ and $\mu_{w,ms}/\mu_{h,ms}$ leads to[29]

$$\zeta \;\leq\; \frac{\mu_{w,xs}}{\mu_{h,xs}}, \frac{\mu_{w,ms}}{\mu_{h,ms}} \;\leq\; \frac{\sigma_v^2}{(1+\zeta)\sigma_u^2}, \tag{6.17}$$

and

$$\mu_{w,xs}, \mu_{h,xs}, \mu_{w,ms}, \mu_{h,ms} \;>\; 0. \tag{6.18}$$

Additionally, we also need to certify that the conditional variance-covariance matrix $\bar{\Sigma}$ is positive definite, and thus invertible. For that, the sufficient condition is that the determinant of $\bar{\Sigma}$ be positive, so

$$(1-\rho_{ux}^2-\rho_{vx}^2)(1-\rho_{um}^2-\rho_{vm}^2)-(\rho_{xm}-\rho_{ux}\rho_{um}-\rho_{um}\rho_{vm})^2 \;>\; 0. \tag{6.19}$$

Therefore, the ML estimator maximizes eq. (6.16) subject to constraints eq. (6.17), eq. (6.18), and eq. (6.19).[30] HIMR argue that those constraints are essential to identify separately the parameters the selection and market access effects. More specifically, the terms $\mu = (\mu_{hx}, \mu_{wx}, \mu_{hm}, \mu_{wm})$ and $\rho = (\rho_{ux}, \rho_{vx}, \rho_{um}, \rho_{vm}, \rho_{xm})$. Note that the ML problem for identification of μ and ρ follows a conditional bivariate Probit.

The parameters $\alpha = (\alpha_{hs}, \alpha_{ws})$ absorb sector-level market tightness and competition in the input/output markets. In our setting, the increase in trade integration with China during the 2000s may have impacted such terms, i.e., affected non-exporters/non-importers due to import competition (or competition with Chinese demand on the input market) or an increase on the output demand induced by input-output linkages.

[29]We omit the formal derivation of those terms but can provide them upon request. Nonetheless, they do not fundamentally differ from Helpman, Itskhoki, and Redding (2010), Helpman, Itskhoki, Muendler, and Redding (2017) and their respective online appendices.

[30]An additional constraint is $\rho_{xm} > 0$, which accounts for the abstraction in the implied by the sufficient conditions imposed in eq. (6.11) and eq. (6.12), as well as the empirical fact that there is a positive relationship between exporter and importer status. Another way to put it is through the positive relationship between export and import costs drawn from ε_x and ε_m. We do not impose this restriction during estimation but observe their validity after the estimation.

7. Results and Counterfactual

7.1 Results and Model Fit

We estimate the model represented in eq. (6.16)-eq. (6.19) separately for each year between 1997-2012. The observation unit is a firm f in each period t. We expect that the parameters may change over time to reflect the changes in the Brazilian economy in that period. Figure 17 and Figure 18, in the Appendix, present the detailed estimated coefficients, i.e., $(\alpha, \mu, c, \sigma_u^2, \sigma_v^2, \rho, \zeta)$ along with the 95% confidence intervals.[31]

We next examine the model fit. For each year between 1997 and 20012, we use the aggregated statistics constructed from the parameters in Figure 17 and Figure 18 along with the predicted probabilities of sector choice to simulate an artificial data set and recover the first and second-order statistics that describe the data. We are particularly interested in matching the first and second moments of the distribution of wages and employment, conditional moments on sector choice, and exporter/importer status. More importantly, to evaluate the trends in the Brazilian economy after the China shock, it is desired that the model also approximate trends observed in the data. We present detailed results for the first moments in Figure 19. For simplicity, Table 9 and Table 14 compare model and data for years 2000 and 2008 (our benchmark scenarios before and after the China shock, respectively).

Table 9. Model vs. Data: Shares of Firms and Workers per Sector (2000)

		Agr./Min.		Low-Tech Manuf.		High-Tech Manuf.	
		Data	Model	Data	Model	Data	Model
Fraction in Total	Workers	0.09	0.08	0.71	0.75	0.20	0.17
	Firms	0.08	0.08	0.77	0.80	0.14	0.13
Fraction of Workers in the Sector	Exporters	0.15	0.07	0.27	0.15	0.47	0.39
	Importers	0.15	0.07	0.29	0.17	0.54	0.42
	Exporters-Importers	0.09	0.03	0.19	0.10	0.41	0.29
Fraction of Firms in the Sector	Exporters	0.05	0.02	0.07	0.03	0.18	0.14
	Importers	0.04	0.02	0.07	0.03	0.23	0.16
	Exporters-Importers	0.02	0.01	0.03	0.01	0.13	0.08

Comparison between Model and Data for 2000.

Overall, the model approximates well most of the observed statistics from the data. For the average log-employment per firm (a) and the average wage per firm (b), our model over-

[31] We use robust standard errors (sandwich-form) to construct the confidence intervals. We apply the delta method to obtain the standard errors for the aggregated coefficients.

estimates the statistics from the data by a narrow margin. In contrast, the dispersion of employment and wages (measured by the standard deviation) is slightly underestimated (employment dispersion is more pronounced, at around 17 percent). The shift upward in employment and wages also rises the correlation between them. Nonetheless, although the model does not predict the data with perfection, it accurately represents the trends for the relevant measures. Table 9 and Table 14 display the values for firms in 2000.

In Figure 20, we report the comparison between the simulated and actual data in terms of dispersion statistics. In particular, we are interested in the variance, Gini coefficient, 90-10 ratio, 90-50 ratio, and 50-10 ratio, which will provide information on overall inequality and inequality in the top and bottom of the wage distribution. Table 10 displays the same statistics in 2000 using firm size as weight.[32]

Table 10. Model vs. Data: Worker Moments (2000)

	All Firms		Agr./Min.		Low-Tech Manuf.		High-Tech Manuf.	
	Data	Model	Data	Model	Data	Model	Data	Model
Mean w	–0.12	–0.18	–0.33	–0.35	–0.21	–0.26	0.34	0.27
Var w	0.28	0.25	0.28	0.20	0.23	0.21	0.22	0.21
Perc. 90	0.66	0.48	0.44	0.22	0.44	0.33	0.94	0.86
Perc. 50	–0.15	–0.19	–0.39	–0.35	–0.24	–0.27	0.37	0.27
Perc. 10	–0.81	–0.82	–0.97	–0.92	–0.83	–0.85	–0.30	–0.32

Comparison between Model and Data for 2000.

Our model also performs well in replicating the observed aggregated measures of dispersion. For variance and the Gini coefficients, the model slightly underestimates the changes in observable values. For the Gini, which differs more significantly, the difference compared to the observed data is less than 10 percent. As for the previous statistics, the model precisely represents the time trends of wage inequality, as we documented in Section 4 and Section 5.

Looking at the $90^{th} - 10^{th}$ percentile ratio as a measure of inequality, the model has an impressive accuracy in replicating the data. However, the inequality in the top and bottom of the distribution does not seem to be precise. Indeed, as expected, underestimating the variance and Gini coefficient, the model overestimates the $50^{th} - 10^{th}$ percentile ratio and underestimates the $90^{th} - 50^{th}$ percentile ratio. These patterns suggest that the generated data tend to be more

[32] We assume that firms pay the same wage for each worker. In other words, we calculate the aggregated statistics by weighting observations with the number of employees in the firm. In the Appendix, we derive and estimate a simple model where workers may have different wages within a firm. The overall conclusions are unchanged.

concentrated around the median wage than the observed data. Nonetheless, as for the other measures of centrality and dispersion, the trends over time are well represented.

As anticipated in HIMR, the difficulty separating market access and selection effects is the main challenge in identifying the model type. In Table 9, we display the statistics for the share of firms and workers across sectors. Although we can approximate the total share of firms and workers well, the same shares for exporters, importers, and exporter-importer firms underestimate the observed shares in the data by a significant margin. Nonetheless, the observed and simulated size premium and import and export premia are remarkably closer.

7.2 Counterfactuals

In this section, we use the estimated model to perform counterfactual analyses. This paper is interested in assessing the impact of the China shock, both import and export exposure, on the between-firm wage dispersion. Thus, we propose two scenarios to separate the effects of each side of the trade integration with China.

1. Imports: the partial effect of import exposure. Imports change to levels between 2000 and 2008, whereas Exports remain at the levels of 2000.

2. Exports: the partial effect of export exposure. Exports change to levels between 2000 and 2008, whereas Imports remain at the levels of 2000.

Our benchmark economy is based on the estimated parameters using data for 2000, right before China joined as a member of the WTO. Thus, changes in the economic environment driven by China will be measured relative to the simulated economy in 2000.

The changes from import and export exposure affect the demand/supply shifters presented in Section 6: A_s^*/A_s, A_{xs}/A_{ds}, and A_{ms}/A_{ds}, where s indexes sector. The first term, A_s^*/A_s, incorporates the competition relationship between domestic and external markets for the firm's output. The export and import shocks impact A_s^*/A_s through downstream and direct exposure. On the one hand, import competition increases A_s^*/A_s because of the rise in competition with Chinese products, which leads to a decrease in wages and employment. These assumptions are supported by our reduced form results and several papers in the literature investigating import competition shocks [Autor, Dorn, and Hanson (2013); Autor, Dorn, Hanson, and Song (2014); Bloom, Draca, and Van Reene (2016); Bloom, Kurmann, Handley, and Luck (2019); Costa, Garred, and Pessoa (2016)].

On the other hand, the ${}^{A_s^*}/{}_{A_s}$ decreases due to direct and downstream export exposure, which induces higher demand for firms' output, leading to an increase in wages and employment.[33]

The term ${}^{A_{xs}}/{}_{A_{ds}}$ affects the export shifter Y_x, which increases the firm's wage and size through $\mu_{hx,s}$ and $\mu_{wx,s}$ (market access) and decreases the fixed export cost c_x, implying a higher probability of a firm to become an exporter (selection) given its productivity draws. Here, we assume that the increase in A_x surpasses the increase on A_d, so that export exposure leads to more firms exporting and a higher export premium. Therefore, the export exposure due to the China shock may affect firms by inducing them to operate in the external market and increase the wage premium.

Finally, the term ${}^{A_{ms}}/{}_{A_{ds}}$ affects the import shifter Y_m, impacting firms through two channels. First, through an increase in the import premium μ_{hm} and μ_{wm} (market access). Second, a fall in the fixed importing cost c_m reduces the productivity threshold for firms to import and raises the probability of importing given its productivity draws. Again, we assume that the increase of A_m is greater than the increase of A_d, so that (upstream) import exposure creates incentives for firms to import. Hence, import exposure to Chinese products may harm firms within a sector due to competition with foreign markets but benefit importer firms by reducing import costs and increasing the import premium for their workers.

Changes in ${}^{A_s^*}/{}_{A_s}$, ${}^{A_{xs}}/{}_{A_{ds}}$, and ${}^{A_{ms}}/{}_{A_{ds}}$ imply changes in the relevant parameters α_{hs}, α_{ws}, $\mu_{hx,s}$, $\mu_{wx,s}$, $\mu_{hm,s}$, $\mu_{wm,s}$, $c_{x,s}$, and $c_{m,s}$, depending on the counterfactual, keeping the remaining ones (ζ, σ_u, σ_v, ρ_{ux}, ρ_{vx}, ρ_{um}, ρ_{vm}, and ρ_{xm}) constant at the baseline values of 2000. With a new set of modified parameters, we simulate the model to extract summary statistics of the data.

For simulations, we draw 10 million observations, each representing a firm, selected with a random shock from the distribution of (u, v, z_x, z_m) in eq. (6.14). Because we are not modeling the selection of firms into production, we keep the distribution of firms constant across sectors. Therefore, adjustment to trade shocks happens only through wages and employment, not on firms' creation and destruction.

The first step of our counterfactual strategy is similar to Caliendo, Dvorkin, and Parro (2019):[34] we calibrate the changes in parameters ${}^{A_s^*}/{}_{A_s}$, ${}^{A_{xs}}/{}_{A_{ds}}$, and ${}^{A_{ms}}/{}_{A_{ds}}$ that replicate

[33]For instance, Costa, Garred, and Pessoa (2016) and Feenstra, Ma, and Xu (2017). In the discussion on the impact of trade opening on models derived from Melitz (2003), it is common for authors to consider potential impacts on fixed costs for firms to enter into the domestic market (or the productivity cutoff for firms to produce), even though it is not necessarily related to trade. In those models, trade opening increases the production cutoff, displacing unproductive firms out of the market.

[34]Caliendo, Dvorkin, and Parro (2019) using the average changes in manufacturing wages found in Autor, Dorn, and Hanson (2013) to obtain the respective changes in the productivity parameters that imply the same change in the

our reduced-form findings. For each sector, we set a range from 0 to 100 for percentage changes in α_h, α_w, μ_x and μ_m, from which we can obtain changes in c_x and c_m. Because we only match the changes in the average wages, we restrict the relative variation on α and μ proportionally to the relative downstream and upstream exposure.

Downstream import exposure decreases α_h and α_w. Upstream import exposure increases μ_m and decreases c_m. Downstream export exposure increases α_h, α_w, and μ_x, and decreases c_x. Across sectors, those changes in the parameters are proportional to their level of import or export exposure relative to the Agriculture/Mining sector, which we consider as benchmark.[35] In each interaction over percentage changes in the range 0-100, we recover the change in the model's predictions for average wages for each sector relative to their benchmark value. We compare these values with the point estimates of average wages predicted by the reduced-form on Figure 6. We select the percentage variation in the parameters that minimize the average squared difference between these statistics, weighted by the number of employees in each sector in 2000.

To obtain the updated values for c_x and c_m, we use the structural equations in the model, as proposed in HIMR. Based on the values for μ_x and μ_m, we have

$$\tilde{Y}_{js} = \exp[\mu_{hj,s} + \mu_{wj,s}],$$

and then

$$c_{js} = \frac{1}{\sigma_j}(-\alpha_\pi + \log(C_{js}) - \log[\tilde{Y}_{js} - 1]),$$

where $j \in \{x, m\}$.

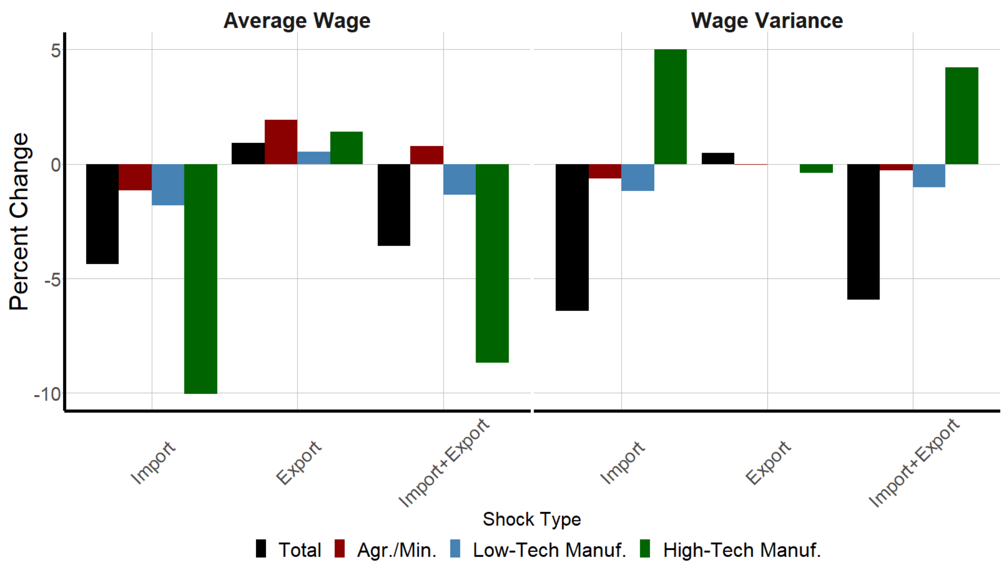
We summarize the changes in the parameters for each sector and type of shock in the Appendix. For the remaining parameters in the model, we use the values in HIMR.

Figure 7 presents the main results on the impact of the China shock. Figure 7.a shows that the import exposure reduces the average wages substantially, especially for the High-Tech manufacturing industries. In contrast, export exposure has a positive effect on the average wages. For Agriculture and Mining industries, the effect of export exposure is higher, leading to an overall

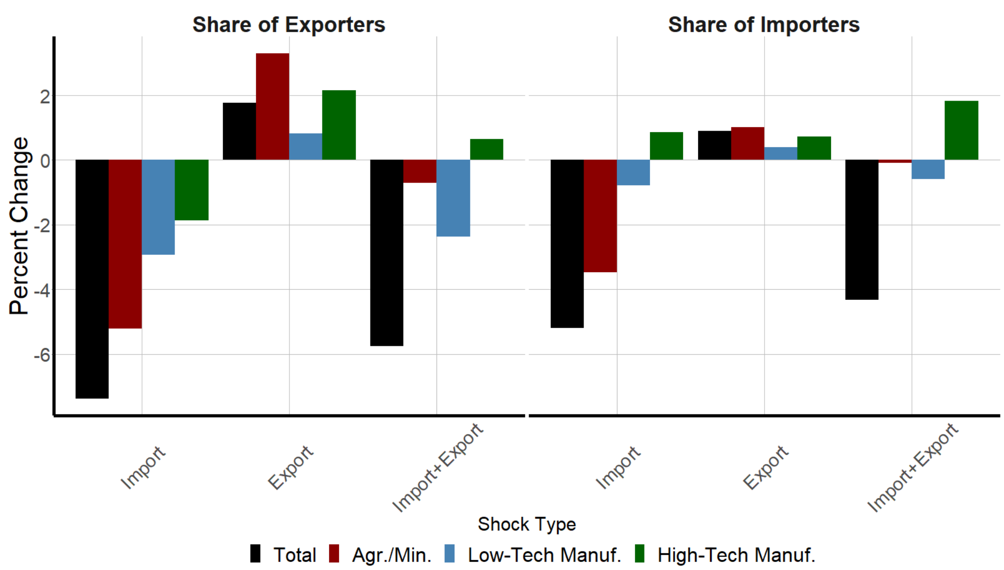
average wage predicted in their model. Then, they use that variation in productivity to conduct their counterfactual analysis.

[35] For example, a one percent decrease in α_w for the Agriculture/Mining sector due to import exposure represents a $I\bar{P}W_{High-Tech}/I\bar{P}W_{Agr./Min.}$ percent decrease in α_w for the High-Tech Manufacturing sector, where $I\bar{P}W_s$ is the average import exposure for sector s. Because we showed that $I\bar{P}W_{High-Tech} > I\bar{P}W_{Agr./Min.}$, since the High-Tech manufacturing sector has higher import exposure, that decrease $\alpha_w^{High-Tech}$ is greater than the decrease in $\alpha_w^{Agr./Min.}$. We proceed similarly with all parameters.

increase in wages. For manufacturing sectors, the positive impact of export exposure does not compensate for the negative import exposure, leading to a net negative impact. Overall, the China shock decreases the average (nominal) wages for the whole economy by around 4 percent.



(a) Average Wage



(b) Wage Variance

Figure 7. Impact of the China Shock on Average Wages, Wage Variance and the Share of Workers on Exporter and Importer Firms. Figures (a) displays the changes in average wage and wage variance across sectors and for the whole economy relative to the model's predictions in 2000. Figure (b) displays the changes in the share of workers in exporter and importer firms relative to the model's predictions in 2000. The horizontal axis displays the shock type: "Import" refers to import exposure only. "Export" refers to export exposure only. "Import+Export" refers to both import and export exposure.

Nonetheless, the higher import exposure is associated with higher wage variance. For the High-Tech Manufacturing sector, wage variances increase by about 5 percent due to the import exposure. As in Figure 7.b, this happens because import exposure decreases importing costs for firms while increasing the import premium. Thus, although there is a net negative effect on wages, this effect is partially compensated by the benefit to importers. However, this effect is not associated with the selection of firms (and workers) into the exporting market. In the other sectors, import exposure reduces the share of workers in exporter and importers firms, suggesting that competition with imports is the dominant force. Export exposure is favorable to the Agriculture and Mining industries, which increases the share of workers in exporter firms by more than 2 percent. However, the overall impact is slightly negative.

7.3 China Shock and Trade Opening

Inspired by Dix-Carneiro, Goldberg, Meghir, and Ulyssea (2021), we continue our counterfactual analysis by examining the impact of tariff reduction on labor market outcomes. The Brazilian economy went through a rapid trade opening between 1990 and 1994. During that period, industries faced a unilateral fall in importing tariffs. The average tariff fell from 30.5% to 12.8% [Dix-Carneiro and Kovak (2017), Dix-Carneiro and Kovak (2019)]. This generates an interesting natural experiment that the international trade literature has extensively exploited.

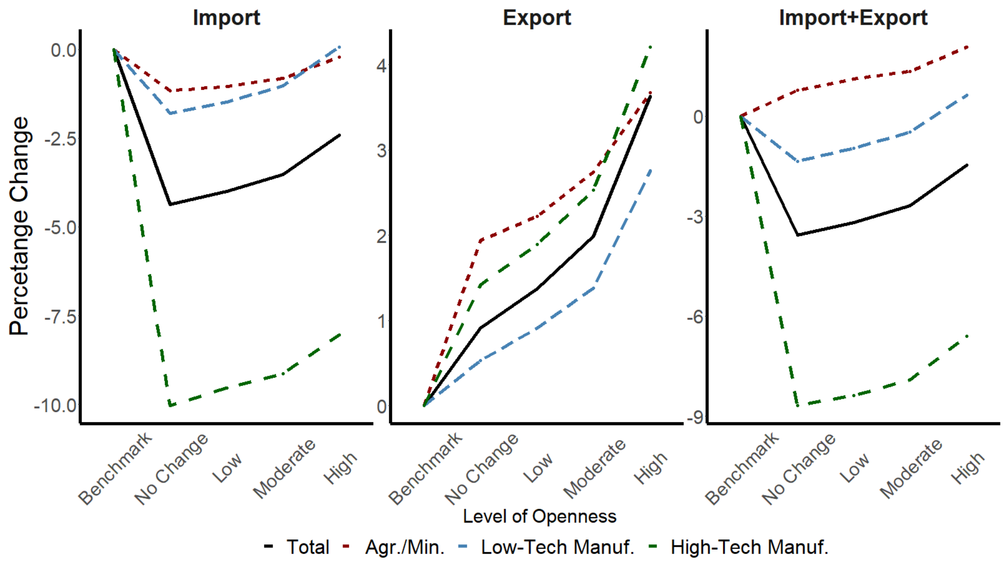
Despite the substantial decrease in tariffs, it is arguable that the Brazilian economy is still considerably closed. According to the World Bank, the total volume of trade in Brazil as a share of GDP during the 1980s and 1990s ranged between 14.9% and 21.5%. By 2012, the share was 25.11%. These numbers illustrate that the share of trade in the Brazilian GDP is relatively modest compared to other similar countries. For instance, the total trade over GDP for middle-income countries grew from 27.5% in 1980 to 50% in 2000. In contrast, high-income countries experienced a growth in trade over GDP between 38.5% and 46.9% during the same period. Furthermore, in 2000, the average tariffs in the bilateral trade Brazil-China were around 15% and remained between 10% and 15% until 2012.

The impact of the China shock on the Brazilian labor market could be amplified by another change in importing tariffs. So a question we pose here is: if Brazil implemented an additional round of tariff reduction, what would be the impact of the China shock on the Brazilian economy? On the one hand, a decrease in importing tariffs increases the competition with imported products, leading to a fall in wages and employment in higher exposed sectors. This happens through a decrease in A_{ds}, and then α_{ws} and α_{hw}, which affects all firms. On the other hand, a decrease in importing tariffs increases market access ($\mu_{wm,s}$ and $\mu_{hm,s}$) and selection into import (c_{sm}), implying an increase in Y_{ms} and in the share of workers in importing firms. Note that because of the positive relationship between selection into imports and exports, we may also expect an increase in the share of workers in exporting firms. The overall impact on average wages is ambiguous, depending on which effect is stronger. However, we can expect that: i) sectors facing higher competition may decrease in size (measured by the number of employees); and that ii) within-sectors, larger differences between importers and non-importers (or exporter and non-exporters), which will increase within-sector wage dispersion.[36]

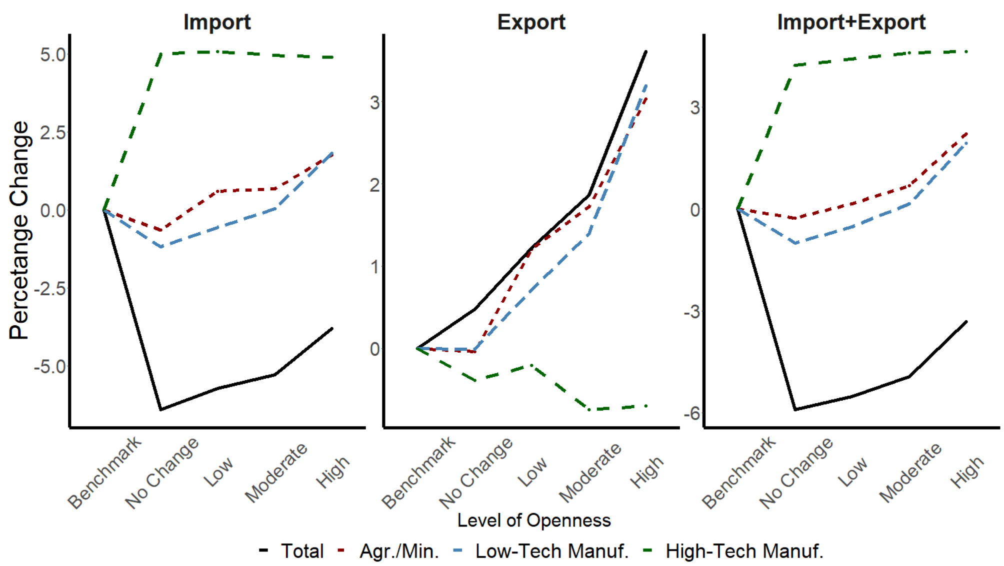
Under our theoretical framework, the predominant effect depends on the relative elasticities of substitution between domestic and imported goods (also referred to as Armington's elasticity), determined by ϵ (see Section 6), and between domestic varieties within the composite domestic good, which is determined by β (see Section 6). HIMR does not include the former and assumes a value for $\beta = 3/4$, which gives an elasticity of substitution among domestic varieties of 4. Feenstra, Luck, Obstfeld, and Russ (2018) estimates both the Armington's elasticity substitution (which they name macro elasticity) and the elasticity of substitution between domestic varieties (which they call micro elasticity). The estimates suggest a significant heterogeneity across products, with many showing no statistical difference. However, the findings support the claim that the macro elasticity is smaller than (or the most equal to) the micro elasticity. On average, the macro elasticity is about half the size of the micro elasticity. Hence, we use $\epsilon = 1/2$, which implies an elasticity of substitution between domestic and imported varieties of 2. We also test scenarios where $\epsilon = 1/4$ and $\epsilon = 3/4$, which leads to elasticities of substitution equal to 1.33 and 4, respectively. Finally, we summarize the comparison between elasticities in the Appendix.

To study the effect of the China shock under different tariff regimes, we simulate the model separately for each reduction level. Based on Dix-Carneiro, Goldberg, Meghir, and Ulyssea (2021), we elaborate on 3 scenarios of tariff reduction: i) low decrease in tariffs of 5%; ii) moderate decrease in tariffs of 10%; iii) high decrease in tariffs of 20%. We then use the same changes on ${}^{A_s^*}/{}_{A_s}$, ${}^{A_x}/{}_{A_d}$, and ${}^{A_m}/{}_{A_d}$ calibrated for the China shocks, separating them into export exposure, import exposure, and export-import exposure. The main results are presented on Figure 8 (average and variance of wages) and Figure 9 (share of workers in exporter and importer firms).

[36]That may happen for a low reduction in tariffs, which pushes firms into the exporting markets. For higher reductions, which implies low tariffs, most firms will select into imports, which drives wage dispersion down.

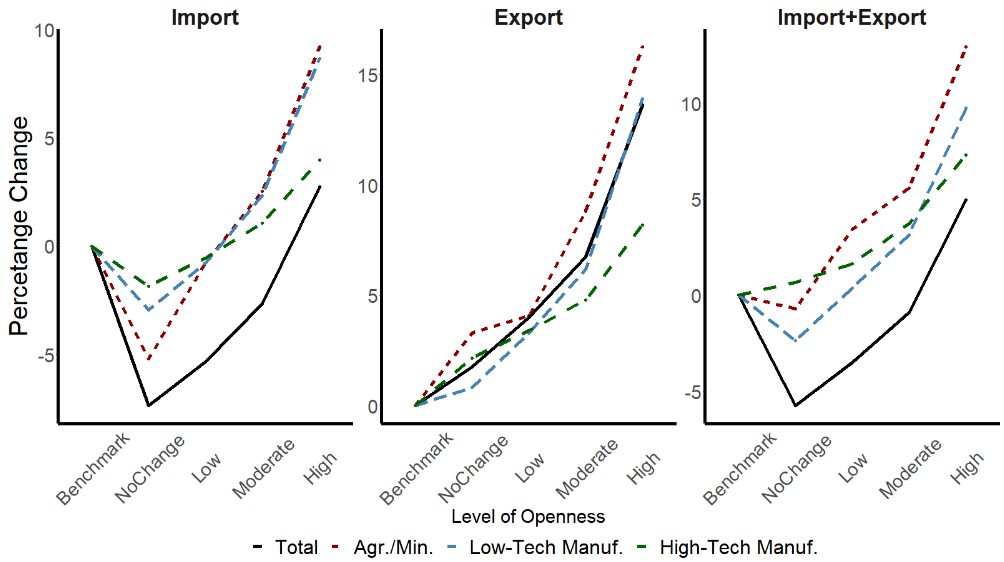


(a) Average Wage

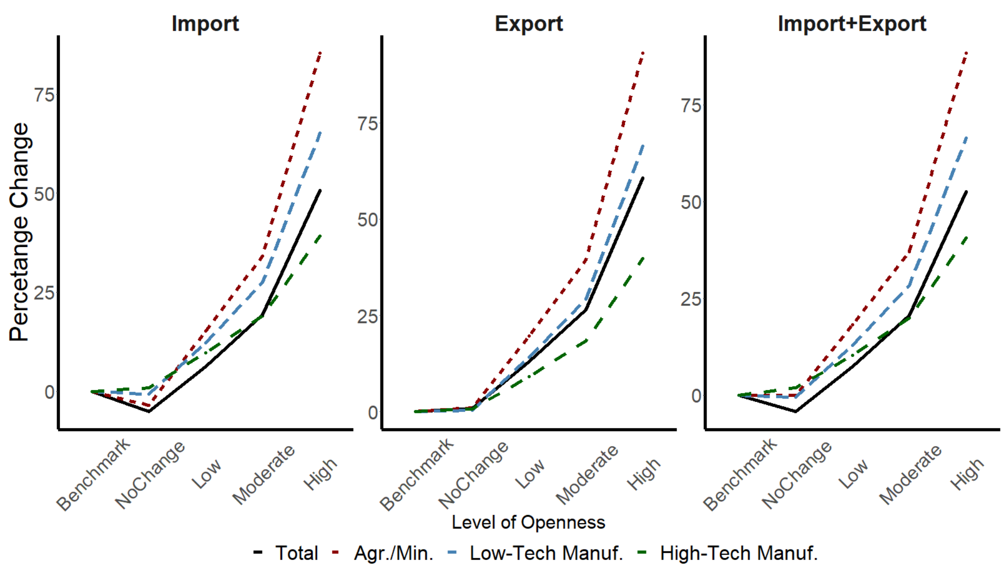


(b) Wage Variance

Figure 8. Impact of Trade Exposure and Openness on Wages. The figures compare the average wages and wage variance for different exposure to trade shocks and levels of openness. "Import" refers to import exposure only. "Export" refers to export exposure only. "Import+Export" refers to both import and export exposure. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "No Change" are the model predictions under trade exposure and no change in tariffs; "Low", "Moderate", and "High" refer to different assumptions on tariff reduction: 5%, 10%, and 20%, respectively.



(a) Share of Workers in Exporter Firms



(b) Share of Workers in Importer Firms

Figure 9. Impact of Trade Exposure and Openness on the Share of Workers in Exporter and Importer Firms. The figures compare the average wages and wage variance for different exposure to trade shocks and levels of openness. "Import" refers to import exposure only. "Export" refers to export exposure only. "Import+Export" refers to both import and export exposure. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "No Change" are the model predictions under trade exposure and no change in tariffs; "Low", "Moderate", and "High" refer to different assumptions on tariff reduction: 5%, 10%, and 20%, respectively.

In the figures, "Benchmark" (normalized to 1) are the model predictions for the year 2000. "No Change" refers to the model with parameters that simulate the China shock and no tariff reduction. "Low", "Moderate", and "High" refer to the China Shock associated with changes in tariffs by 5%, 10%, and 20%, respectively. Each graph decomposes the shocks into the import exposure, export exposure, and both. Average wages and variance are weighted by the firm's number of employees. As argued in HIMR and the theoretical model presented in Section 6, it is implicitly assumed that each worker within a firm receives the same wage.

Panel (a) displays the changes in average wages, both total and for each sector. As expected, changes in import exposure are followed by a fall in average wages, especially for the high-exposed High-Tech Manufacturing sector. However, higher levels of openness tend to buffer this effect since trade liberalization influences firms to import higher-quality inputs with a consequent increase in productivity and wages (as argued by Amiti and Davis (2012)). Export exposure increases wages for every sector, as found in our reduced-form results. Moreover, trade opening also amplifies the positive shock by enabling firms to export. Overall, import exposure dominates export exposure for manufacturing sectors.

Panel (b) depicts the total changes in the overall wage variance and the wage variance within-sectors. Note that the China shock alone leads to a decrease of almost 5 percent in the overall wage variance (black, solid line). However, trade openness slightly reduces this magnitude due to the increase in the within-sector variance. As suggested in the previous Figure, this is mainly due to changes in the between-sector component. Import exposure decreases the average wage for the high-paying sector (High-Tech Manufacturing), and imports and exports increase the average wage in the low-paying sector (Agriculture/Mining). In addition, the reduction in tariffs leads to a substantial increase in the overall variance. The slight increase in variance due to the tariff reduction is a consequence of lower trade barriers that enable firms to operate as importers or exporters in the external markets.

Note that the relationship between openness and inequality may not be monotonic for the High-Tech Manufacturing sector. This result is shown in HIMR. In autarky (where high tariffs are prohibitive to international trade), no firm will import/export, so the within-sector variance is equal to zero. In a perfect open economy (no tariffs on international trade), every firm becomes an exporter (or importer, in our case), leading to zero within-sector variance.

Figure 9 shows that the share of workers in exporting and importing firms is increasing with trade openness. In particular, firms would grow substantially under lower import tariff scenarios. For example, a reduction in tariffs of 20 percent leads to an increase in the participation of importing firms in the labor market by around 20 percentage points, even for the relatively lower exposed Agriculture/Mining and Low-Tech Manufacturing sectors. Similarly, the share of workers in exporting firms increases by 5 percentage points, following the positive correlation between importer and exporter status. In contrast, the same change in tariffs favors the Agriculture/Mining sector under export exposure. Figure 10 shows that the economy's employment adjustment displaces workers from Agriculture/Mining sectors, especially in the High-Tech Manufacturing sector, which is the sector that obtains the highest gains from trade openness. However, the import competition effect is dominant when we put shocks together, leading to a reduction in the share of the High-Tech Manufacturing sector by more than 15 percent.

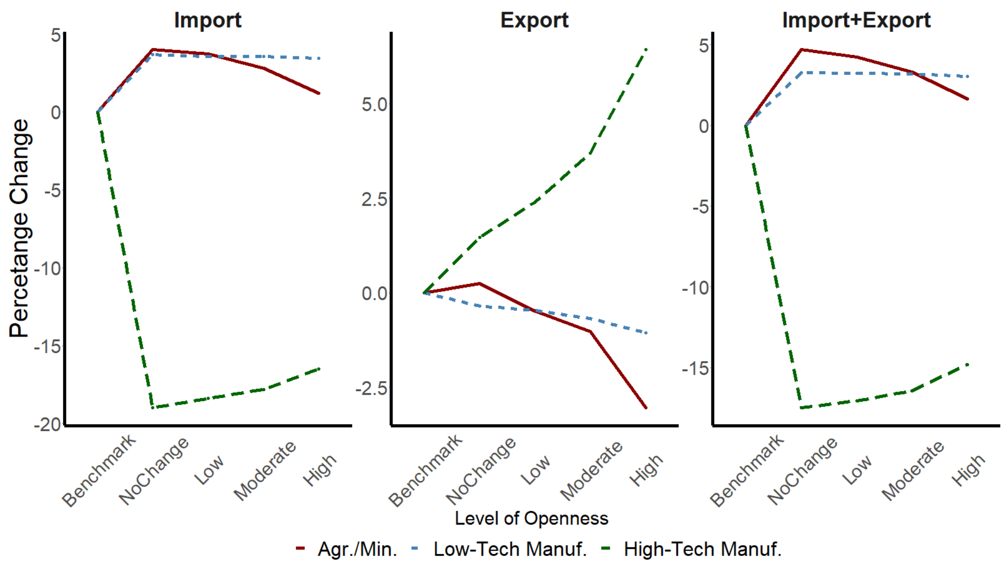


Figure 10. Impact of Trade Exposure and Openness on the Share of Workers per Sector. The figures compare the change on the share of workers across sectors. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "No Change" are the model predictions under trade exposure and no change in tariffs; "Low", "Moderate", and "High" refer to different assumptions on tariff reduction: 5%, 10%, and 20%, respectively.

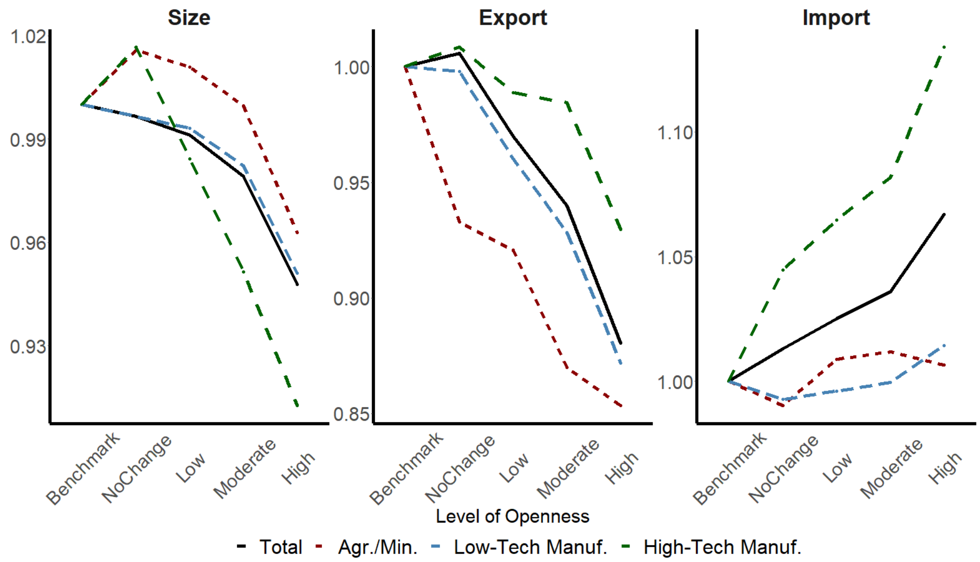


Figure 11. Impact of Trade Exposure and Openness on Size, Export and Import Premia. The figures compare the change on size, export, and import premia. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "No Change" are the model predictions under trade exposure and no change in tariffs; "Low", "Moderate", and "High" refer to different assumptions on tariff reduction: 5%, 10%, and 20%, respectively.

Finally, Figure 11 complements the analysis by showing the changes in size (log-employees) and the export and import premia. With tariff reductions, the share of importers and exporters increases, meaning that more unproductive firms participate in the international trade. Hence, we observe these decreasing trends, particularly for the size premium. Following a different path, export and import premia for the High-Tech Manufacturing sector increase.

7.4 Within-Firm Inequality

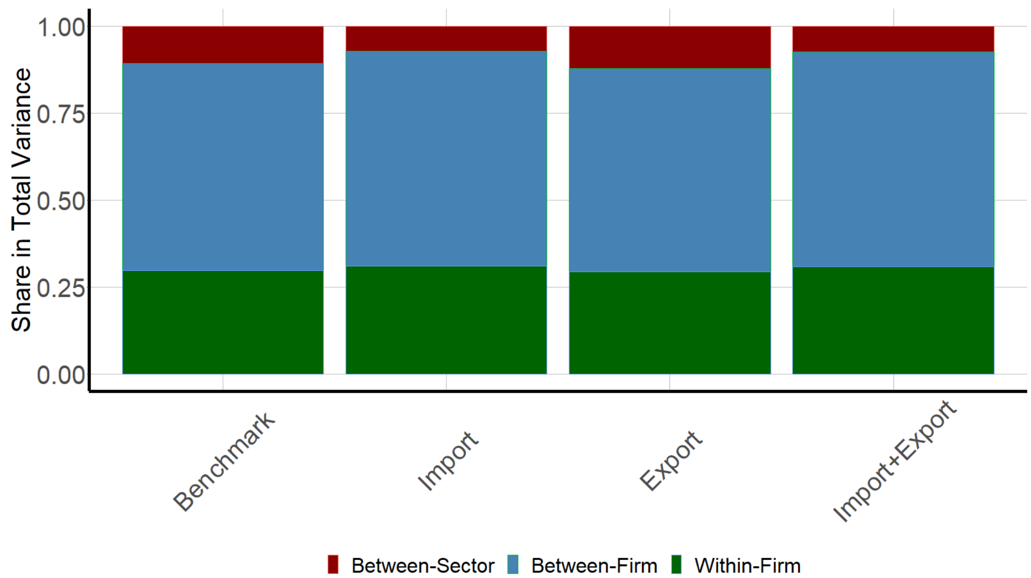
In this section, we include within-firm wage dispersion into the model to simulate the effects of the China shock. We include more details on this discussion in the Appendix. Based on theoretical findings [see the Appendix and Pupato (2017)] and the empirical relationship between within-firm and the firm wage component ψ_{ft} [see Appendix], we update the structural model to account for a within-firm variance in wages to

$$
\begin{aligned}
h_s &= \alpha_{hs} + \mu_{h,xs}\iota_{xs} + \mu_{h,ms}\iota_{ms} + u \\
w_s &= \alpha_{ws} + \mu_{w,xs}\iota_{xs} + \mu_{w,ms}\iota_{ms} + \zeta u + v \\
\iota_{xs} &= \mathbb{1}\{z_x > c_{x,s}\} \\
\iota_{ms} &= \mathbb{1}\{z_m > c_{m,s}\} \\
var(w_s) &= f(w_s) + v_\varepsilon
\end{aligned} \tag{7.1}
$$

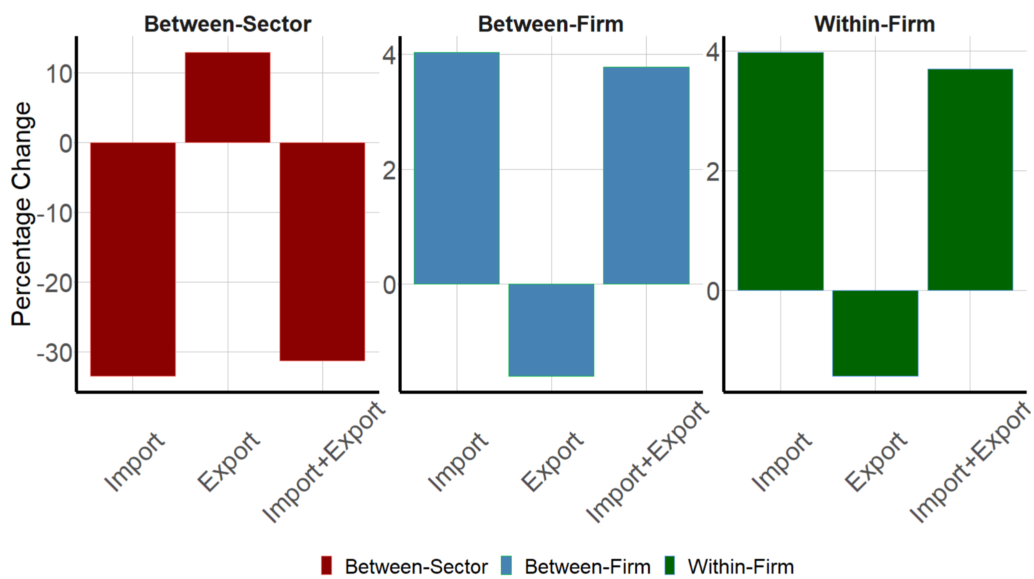
where f is a polynomial function, and η_{ft} is the idiosyncratic component. We assume that the error term v_ε is independent of the error structure in the model eq. (6.13). This assumption aligns with Pupato (2017) and our theoretical motivation in the Appendix. Note that in this way, we do not obtain the closed-form solution for the variance of log wages and neither need to assume values for other parameters in the model. The reaming terms eq. (7.1) are identical to eq. (6.13).

In eq. (7.1), we estimate the first 4 equations using the same procedure described in Section 6. Separately, we estimate f using the observed variance of ε_f in the left-hand side and the wage component ψ_f in the right-hand side using f as constant and a a second-order polynomial in w_s.

To simulate the models in our counterfactual analysis, we proceed similarly. First, we use the estimated parameters to obtain simulated values for (w, h, ι_x, ι_m). Then, we obtain the within-firm wage variance by fitting the polynomial f in the simulated w. We present the main results in Figure 12.



(a) Model vs. Counterfactual



(b) Change in the Variance Component

Figure 12. Variance Composition with Within-Firm Dispersion. In Figure (a), "Benchmark" presents the model simulations in 2000, "Import" presents the model simulations under import exposure only, "Export" presents the model simulations under export exposure only, and "Import+Exports" presents the model simulation under both import and exposure. Figure (b) displays the percentage changes between the components showed in (b) and the benchmark model.

The results in Figure 12.a show that the decrease in the wage variance due to the China shock is mainly related to the between-sector component. Figure 12.b shows that the between-sector component reduces by more than 30 percent as a consequence of the

China shock, mainly due to the import competition effect. The export exposure causes an increase in the between-sector wage variance of almost 15 percent but is compensated by the negative impact in the variance given by the import competition.

In contrast, the increase in the within-firm wage variance follows the increase in the between-firm wage variance implied by the last equation in eq. (7.1). The increase is primarily due to the import exposure effect, which incentives firms to become importers and exporters, increasing the wage variance across firms in the same sector. Consequently, the within-firm variance also increases due to the positive relationship between average and variance within a firm. Both between-firm and within-firm variance increase by almost 4 percent due to import and export exposure to China.

However, the import competition effect is stronger than the export exposure effect and the upstream import exposure effect. As a result, the cross-sector effect still dominates the between-firm and the within-firm effects on the wage variance. As a consequence, the overall variance falls by almost 4 percent. Note that by including the within-firm wage component into the model, we attenuate the overall impact of the China shock on the formal wage inequality in Brazil by 2 percentage points. This happens because the changes in the within-firm wage variance follow the same direction as the changes in the between-firm wage variance.

8. Conclusion

This paper provides empirical evidence of the China shock's role in the observed fall of wage inequality in Brazil in the 2000s. Unlike the literature in this field, which focuses on the impact of import competition on manufacturing industries, we focus on the two-sided effect of China on the Brazilian economy by adding export exposure. Essentially, we argue that those shocks have a differential impact on industries. Furthermore, inspired by Acemoglu, Autor, Dorn, Hanson, and Price (2016), we also include indirect shocks given by input-output linkages.

We gather facts to understand how bilateral trade integration, such as the China shock, may affect wage dispersion. First, we decompose the log hourly wage into a firm wage component, composition components, and the residual wage. The decomposition results in three empirical facts: 1) the between-firm term accounts for two-thirds of the wage variance; 2) inequality falls for every sector and proportionally in the between- and within-sector components; 3) size premium and export and import premia are positive, with significant heterogeneity across sectors and persistent over time.

Second, we use an instrumental variable approach to estimate the effect of the China shock on employment and wages. Our findings suggest that downstream import exposure decreases employment and wages, whereas downstream export exposure increases employment and wages. Nonetheless, upstream import exposure is related to higher wages and higher probabilities of importing. Firms also respond positively to downstream export shocks by entering the export markets. Hence, firms may also benefit from a rise in trade integration through better importing and exporting conditions.

To address these facts, we adapted the model proposed by Helpman, Itskhoki, and Redding (2010) and Helpman, Itskhoki, Muendler, and Redding (2017) to a multi-sector setting and selection into exporting and importing markets through two terms. First, sector heterogeneity means that firms in distinct sectors will have different responses to trade shocks in terms of wages and employment. Second, selection into importing and exporting enables firms to increase revenues (and thus employment and wages) by entering the import and export markets to respond to trade shocks.

We use the model to study the effects of two counterfactual scenarios when shocks occur only in imports or only in exports. We also experiment with these scenarios under different importing tariff regimes. In the model, we have an ambiguous effect of import exposure and import tariffs. While import exposure has adverse labor market effects of increasing competition, it also has the positive effect of enabling firms to access imported inputs. Our results suggest that the China shock had an overall negative impact on average wages and is associated with a 5 percent decrease in the formal wage inequality between 2000 and 2008. Moreover, under some conditions in the model's elasticities, tariff reduction may attenuate the harmful effects of import exposure.

This work contributes to the literature by measuring the impact of the China shock in a medium-income country. We highlight the potential gains from trade, even under negative demand shocks, with significant policy implications for removing trade barriers.

Nonetheless, we acknowledge several possible improvements in our analysis. A straightforward possibility is to add regional heterogeneity. In this sense, our work could be compared to Autor, Dorn, and Hanson (2013) and Dix-Carneiro and Kovak (2017), who study the trade shock consequences on local labor markets. This extension would not require significant modifications to the model. However, the biggest challenge is the increased number of estimated parameters, which could harm their identification.

We point to several possible extensions for the model to encompass the recent concerns in the literature about the impact of international trade. First, one could extend the model to include the welfare impacts of trade shocks and tariff reduction. One possibility is to use a general equilibrium model. One may also add within-firm heterogeneity. A straightforward, exogenous way would be to assume different bargaining power for high- and low-skilled workers. In this sense, trade shocks could disproportionately affect different types of workers, which could address the changes in the skilled/unskilled composition of the labor force.

Following Coşar, Guner, and Tybout (2016), one could include firm dynamics and the firm's entry or exit decision. Helpman, Itskhoki, Muendler, and Redding (2017) partially addresses the first, showing that their results would be similar. However, Helpman, Itskhoki, Muendler, and Redding (2017) is based on Melitz (2003) and requires additional assumptions over the error structure in our econometric estimation.

Finally, Dix-Carneiro and Kovak (2019) documents a significant displacement of workers to the informal sector after the Brazilian trade opening in 1990-1994. Dix-Carneiro, Goldberg, Meghir, and Ulyssea (2021) calibrate a model similar to Coşar, Guner, and Tybout (2016) that that includes the informal sector. They find that the informal sector acts as a buffer for welfare losses from trade. Furthermore, they argue that stricter enforcement of regulations against informality decreases welfare loss.

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Appendix A Wage Decomposition and Informality

The informality rate in the Brazilian labor market declined in parallel to the fall in the formal wage variance during the 1990s and 2000s. A recent study, Engbom et al. (2022) shows that the significant decrease in the economy-wide earnings variance is driven mainly by the within-sector evolution of earnings rather than the changes in the composition of formal and informal labor markets.

In this section, we perform an exercise to determine to which extent the decline in the informality rate in Brazil impacts our log wage decomposition in eq. (4.1). But, more importantly, we want to understand whether different assumptions on the effect of informality impact our conclusions from Table 2 and our estimates for ψ_{oft}, which is our relevant measure for the firm wage component ψ_{ft}.

To address the effects of informality on the formal log wage variance, we first perform a variance decomposition. The log wage variance in year t can be decomposed as

$$var(w)_t = \underbrace{\sum_{s=1}^{S} \overbrace{\frac{N_{st}}{N_t}}^{\text{Composition}} \overbrace{\sigma_{st}^2}^{\text{Return}}}_{\text{Within-Group}} + \underbrace{\sum_{s=1}^{S} \frac{N_{st}}{N_t} (\bar{w}_{st} - \bar{w}_t)^2}_{\text{Between-Group}}, \tag{A.1}$$

where $S \in \{formal, informal\}$. $formal$ are the workers in the formal labor market between $t-1$ and t, or workers who entered the formal labor force independently of changes in the informal labor market. $informal$ denotes workers who entered the formal labor due to the changes that led to the fall in the informality rate.

Similarly to Engbom, Gonzaga, Moser, and Olivieri (2022), we assume that workers who moved into the formal labor market between years $t-1$ and t are potentially moving as a consequence of the changes in the Brazilian economy that led to a reduction in the informality rate. Because we cannot observe a worker's employment outside of the formal workforce, in practice, those workers may come from unemployment or just starting their first job. Then, we assume probabilities for workers entering the formal labor market due to the reduction in the informality rate. For example, we assume that 20 percent of new entrants into the formal labor market between years $t-1$ and t is due to the decline in the informality rate.

This assumption is not unreasonable. There are similar patterns of workers' movements into the formal labor market from the informal sector or due to other reasons. Generally, those workers tend to represent a higher share of workers at the bottom of the wage distribution than at the top. As argued in Engbom et al. (2022), because informal workers are, on average, less productive than formal workers, a large share of workers coming from the informal to the formal labor market lies at the bottom of the formal earnings distribution. This share declines for higher levels of the formal earnings, although positive across the whole distribution. These findings are supported by Meghir, Narita, and Robin (2015), which suggests that there is a significant overlapping area between the productivity distributions of both markets. Figure 13.a plots the share of entry workers in the total workers per quartiles of the formal wage distribution. Figure 13.b plots the share of entry workers in the total number of entry workers each year per quartiles of the formal wage distribution. Note that entry workers tend to concentrate in the first quartile of the wage distribution, although they still represent about 10 percent of workers in the fourth quartile.

Back to eq. (A.1), the first term on the right-hand side measures the within-group effect on the wage variance. N_{st}/N_t is the composition channel, which measures the changes in the formal wage variance due to higher participation of former informal workers. σ_{st}^2 is a within-groups change in the volatility for a given workforce composition.[37] The second sum on the right-hand side of eq. (A.1) is the between-group term, which measures changes in the overall wage variance as a consequence of different average wages across groups.

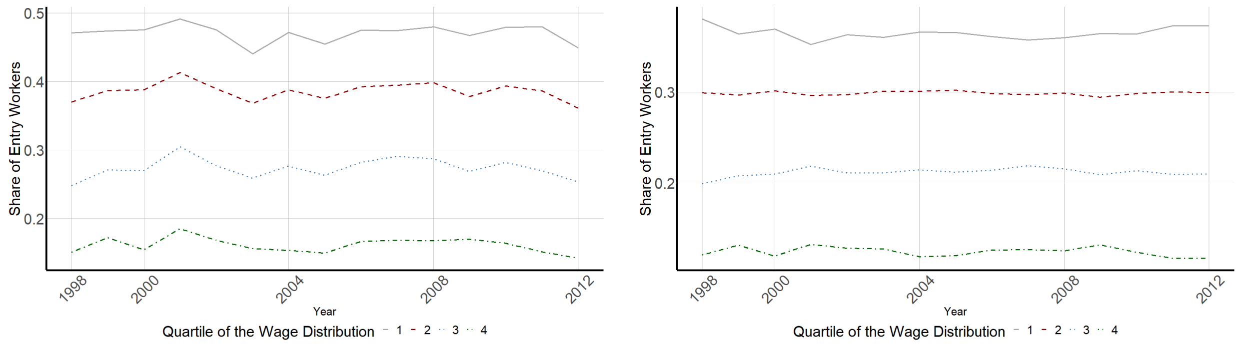
We plot the variance decomposition into between and within components according to eq. (A.1) in Figure 14. We assume different probabilities for a worker entering the formal labor market because of informality reduction: 20, 30, 50, and 100 (i.e., all the new entries are due to changes in the informal labor market). The within-group component represents the highest share of the total log wage variance. Differentials between the group average and the total log wage average respond to a small fraction of the overall variance and do not significantly contribute to the wage variance's decline.

Following Engbom et al. (2022), we use a shift-share approach to understand the determinants of the within-group wage variance. More specifically, we first fix the composition of workers N_{st}/N_t in the 1997 level and let the returns σ^2_{st} to change. Then, we fix the returns σ^2_{st} in the 1997 levels and let the composition term N_{st}/N_t to change. Figure 15 displays these results for the different definitions of informal workers. Because we are interested in the changes in the formal wage variance due to the composition of formal and informal workers, the second part is more relevant to us. Note that when we consider that all entry workers are due to the changes in the informality, the composition effect is stronger.

To estimate the effects of informality on our estimates of ψ_{oft}, we re-estimate eq. (4.1) with a different specification. First, we use the strongest definition for the effect of informality in the formal labor market, i.e., that all entries of workers into the formal labor market between years $t-1$ and t are due to the fall in the informality rate. Then, we include an indicator variable that assumes a value of 1 if worker i entered into the formal labor market between years $t-1$ and t and 0 otherwise. This variable is included in X_{it}, fully interacted with the other covariates in the model. By doing so, we aim at capturing the upper bound effect of informality on the formal wage inequality. The results are presented in Table 11.

The first two columns repeat the decomposition in Table 2. The following two columns present the variance decomposition considering the effects of informality. Note that taking into account the effects of informality in the formal wage does not significantly change the results. Still, the between-occupation-firm wage component explains about two-thirds of the overall wage variance, and it is the main responsible for the decline in the wage variance between 2000 and 2008. The last column displays the correlation between the estimated components of each specification. Note that there is a high correlation in the occupation-firm wage component ψ_{oft} between the models. This term represents most of the decline in the wage variance, and it is our main measure of firm wages. The high correlation supports our wage decomposition in eq. (4.1), which is more common in the literature [Helpman, Itskhoki, Muendler, and Redding (2017)]. Figure 16 shows the relationship between the two measures for ψ_{of} for each decile of the log wage distribution in 2000 and 2008.

[37] The decomposition and terminology are similar to Engbom et al. (2022).



(a) Share in the Total (b) Share in the Entry Workers

Figure 13. Entry Workers and the Formal Wage Distribution. Figure (a) shows the evolution in the share of entry workers in total number of workers in each quartile of the formal wage distribution. Figure (b) shows in the share of entry workers in total number of entry workers per year workers in each quartile of the formal wage distribution.

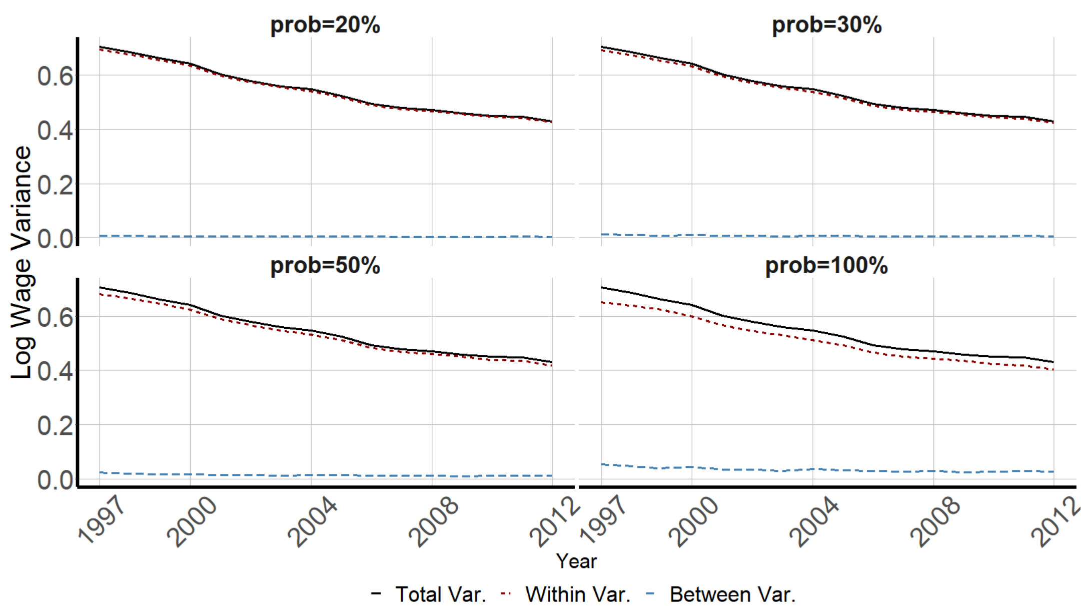


Figure 14. Formal Wage Variance Decomposition and the Effect of Informality. The figures display the decomposition of the formal log wage variance following Eq. (A.1). Each graph has a definition regarding the groups of workers who entered the formal labor market as a consequence of the change in the informal labor market. Prob=P%, for $P \in \{20, 30, 50, 100\}$ means that P percent of new entries are due to the informality rate decline.

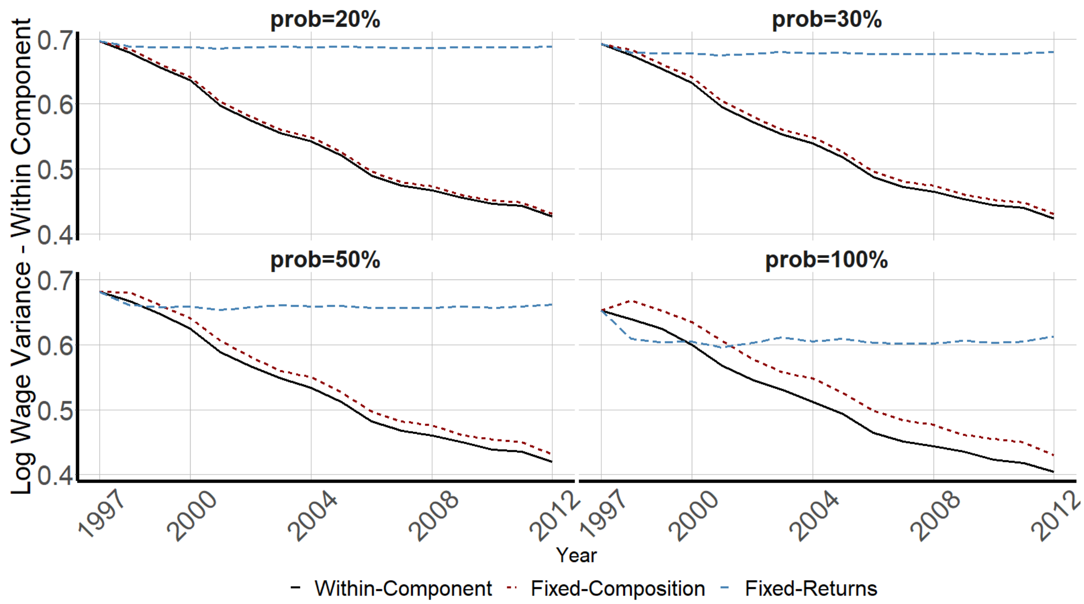


Figure 15. Decomposition of the Within Component. The figures display the decomposition of the formal log wage variance following Eq. (A.1). Each graph has a definition regarding the groups of workers who entered the formal labor market as a consequence of the change in the informal labor market. Prob=P%, for $P \in \{20, 30, 50, 100\}$ means that P percent of new entries are due to the informality rate decline.

Table 11. Decomposition of Variance of Log-Wage per Hour

	Original				Control For Informality				Correlation	
	2000		2008		2000		2008		2000	2008
	Level	(%)	Level	(%)	Level	(%)	Level	(%)		
$var(log(wage))$	0.663	100.0	0.489	100.0	0.663	100.0	0.489	100.0	1.00	1.00
$var(\psi_{of})$	0.449	67.7	0.310	63.4	0.444	67.0	0.308	63.0	1.00	1.00
$var(x'\beta)$	0.047	7.1	0.040	8.1	0.052	7.9	0.044	8.9	0.96	0.96
$var(\varepsilon)$	0.105	15.9	0.089	18.1	0.098	14.8	0.083	17.0	0.98	0.99
$2 * cov$	0.062	9.3	0.051	10.3	0.068	10.3	0.054	11.1		

Results are based on estimates of Eq. (4.1). $log(wage)$ is the log of the wage per hour for every worker in our sample. ψ_{of} is a firm-occupation-sector component. $x'\beta$ as workers' observable characteristics. ε is the residual wage per hour. cov is the covariance between ψ_{of} and $x'\beta$. "Original" refers to the decomposition in Table 2. "Control For Informality" refers to the decomposition controlling for the effects of informality. The last columns shows the correlation between the components in each specification.

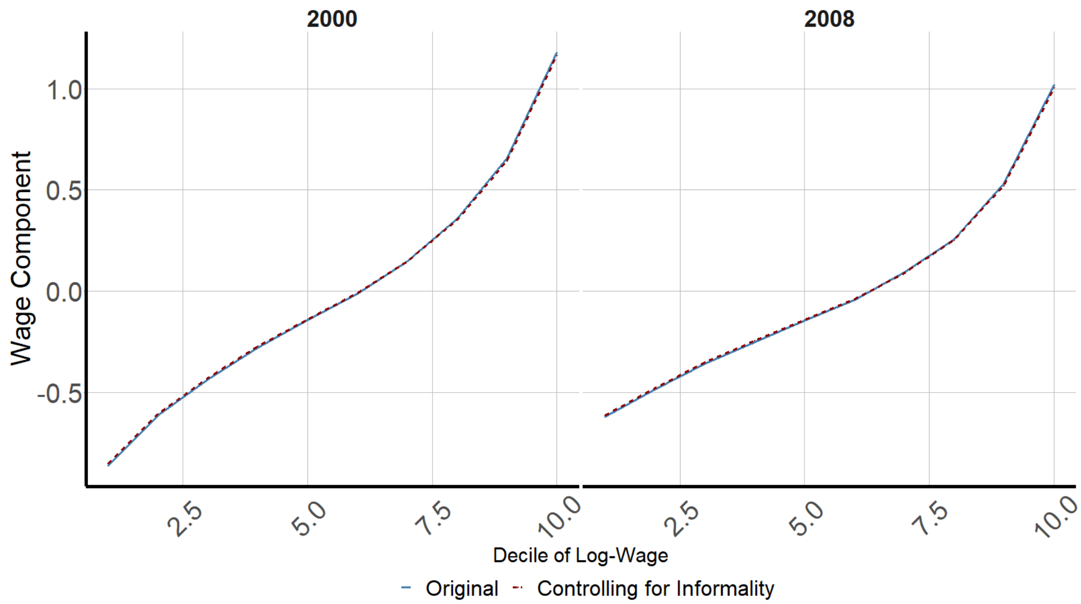


Figure 16. Estimates of the Occupation-Firm Wage Component by Deciles of the Log Wage Distribution. The figures display the average estimated values of ψ_{of} in the original model based on Eq. (4.1) and controlling by the influence of the fall in the informality rate. The horizontal axis presents the deciles of the log wage distribution in each year.

Appendix B First Stage Results: Import/Export Exposure on Instruments

In this section, we present the first stage results.

Table 12. First Stage Regressions: Trade Exposure vs. Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
	Direct		Downstream		Upstream	
	Import	Export	Import	Export	Import	Export
Inst. Import	2.881***	0.124				
	(0.248)	(0.192)				
Inst. Export	0.819	6.984***				
	(0.502)	(0.910)				
Inst. Downstream Import			1.098**	0.197	-1.565***	0.012
			(0.456)	(0.188)	(0.281)	(0.151)
Inst. Downstream Export			5.497***	6.595***	3.663***	-1.824***
			(0.815)	(0.399)	(0.800)	(0.240)
Inst. Upstream Import			2.291***	-0.361*	4.938***	0.036
			(0.424)	(0.187)	(0.357)	(0.225)
Inst. Upstream Export			1.603***	-0.391	2.376***	8.340***
			(0.545)	(0.346)	(0.682)	(0.322)
Observations	50,327	50,327	50,327	50,327	50,327	50,327
R-squared	0.824	0.761	0.935	0.828	0.924	0.909
F statistics	92.48	15.71	269.9	180.3	217.6	1548
Clusters	32	32	32	32	32	32
Firm Controls				Yes	Yes	Yes
Industry Controls				Yes	Yes	Yes
Selection Controls				Yes	Yes	Yes

The models present the first stage of Eq. (5.2). All regressions include State-Sector fixed effects and pre-2000 levels of exposure to Chinese imports and exports. Industry controls (baseline, 2000): log of employees, (unconditional) average wages, formality rate, and share of workers whose earnings are smaller than minimum wage plus 10 percent. Firm controls (baseline, 2000): log wages, log-firm size, the share of high-educated workers, and white-collar workers. Selection controls the third-order polynomial of Inverse-Mills term for the probability of a firm to operate. Robust standard errors are clustered at the industry level, 2 digits. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C Selection in the Reduced-Form Estimates

To control for selection of active firms in the main reduced-form specification, we estimate the model:

$$Prob(active_f) = \gamma_I IPW_s + \gamma_E EPW_s + X_f'\delta + \eta_s + \eta_r + \eta_t + \varepsilon_{ft}, \tag{C.1}$$

where $Prob(active_f)$ is an indicator of whether firm f is active anytime in the period 2006-2010 (we centered the intervals around 2008, which we consider our reference post-exposure period). IPW_s and EPW_s are the import and export exposure as describe in Section 3. We use the change in exposure between 2000 and 2008 (before the crisis showed the highest effects in Brazil) as our baseline for the exposure measures. X_f is a set of firm and industry baseline (before 2000) controls. The firm's characteristics include the log number of employees, wage (firm component), the share of college-educated workers, and white-collar employment. Industry characteristics include (unconditional) average wages, log of the number of employees, pre-2000 import and export exposure trends, and industry's formality rate. η_{rs} are State-sector fixed-effects. Thus, γ_I and γ_E give the impact of import and export exposure on the probability of firm f being active after the shock. If import exposure is a negative downward shift in the firm's demand for output, then we should expect that more exposed firms are more likely to drop out of the market, those $\gamma_I < 0$. Conversely, if export exposure is an upward shift in the firm's demand, then $\gamma_E > 0$. We use several specifications of eq. (C.1). Our preferred one is a Probit model. The results are reported in Table 13.

Estimates in columns 1-4 suggest that the impact of import and export exposure is positive, although not robust or significant under different specifications. Note that the inclusion of firm and industry controls in column 3 makes those estimates insignificant at the usual levels. The parameters of lagged wages are positive and highly significant in every specification. Considering the relationship between productivity and wages widely studied in the literature, we may infer that more productive firms are more likely to stay open after the shocks. In columns 4 and 6, we include a full interaction among the excluded controls variables discussed in the text. Under the inclusion of those excluded variables, the influence of import exposure shocks becomes positive and significant. The same happens with export exposure shocks. Thus, firms more exposed to trade shocks tend to keep the door open, conditional on operating in priority sectors.

Columns 5 and 6 include upstream and downstream exposure to trade shocks, as constructed in Section 3. Again, estimates for indirect exposure are robust to the inclusion of excluded variables. In general, both upstream import exposure and downstream export exposure are positively related to the probability of being active after the shocks.

Thus, we estimate a Probit using these two variables and their interaction and lagged trade exposure to China, sector, and state fixed-effects in the first stage. Results are reported in columns 5-7 of Table 13. In general, they do not change the previous estimates for trade exposure. Moreover, we also observe that opening costs lower probability, which is our proxy for fixed operating costs. Also, older firms are more likely to be active, which further supports selecting more productive firms.

Table 13. Trade Exposure and Probability of Active (2006-2010)

	Dep. Variable: Active = 1 if firm is active					
Specification	Probit	Probit	Probit	Probit	Probit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline Wages	0.154***	0.152***	0.078***	0.064***	0.334***	0.244***
	(0.010)	(0.011)	(0.013)	(0.013)	(0.040)	(0.042)
Import Shock	0.015	0.547	0.686**	0.651	1.084***	1.147***
	(0.333)	(0.338)	(0.341)	(0.409)	(0.349)	(0.415)
Export Shock	4.509***	2.421**	1.159	2.004**	0.559	1.690*
	(0.962)	(0.976)	(0.987)	(1.015)	(0.989)	(1.016)
Import Shock Upstream				1.799***		1.261***
				(0.428)		(0.437)
Export Shock Upstream				–3.806***		–3.523***
				(0.696)		(0.700)
Import Shock Downstream				–1.944***		–1.410***
				(0.428)		(0.437)
Export Shock Downstream				3.842***		3.253***
				(0.653)		(0.665)
Observations	104,603	104,603	104,603	104,603	104,603	104,603
Operating Costs-Age-Priority Sector	No	No	No	No	Yes	Yes
Firm Control	No	No	Yes	Yes	Yes	Yes
Industry Control	No	Yes	Yes	Yes	Yes	Yes
State-Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Models are estimated by Probit regression. The dependent variable assigns value 1 if a firm operates between 2006 and 2010 and 0 if it closed. Data is restricted to firms that were operating anytime in the period 1997-1998. Estimates are based on a pooled cross-section on the period 2006-2010. Results are restricted to tradable firms (Agriculture/Mining, Low-Tech Manufacturing, and High-Tech Manufacturing). All regressions include sector-state fixed effects. Baseline firm controls (log) number of employees, wage (firm component), the share of college-educated workers, and white-collar employees. Baseline industry controls: pre-2000 levels of exposure to Chinese imports and exports, log of the number of employees, (unconditional) average wages in 2000, the share of high-educated workers, formality rate. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix D Model

D.1 Demand

The economy has a representative consumer with Cobb-Douglas utility function over sectors indexed by $s \in S$.

$$U = \prod_{s \in S} U_s^{v_s},$$

with $v_s > 0$ and $\sum_{s \in S} v_s = 1$. By the properties of the Cobb-Douglas production function, v_s is the share of expenditure in goods produced by sector s. Each term U_s is composed of a basket of domestic and foreign products, denoted by q and q^*, respectively. Within any sector s, each basket nest a C.E.S. utility function for domestic and imported goods indexed by j:

$$U_s = \left[\left(\int_{j \in J_s} q(j)^\beta dj \right)^{\epsilon/\beta} + \left(\int_{j \in J_s^*} q^*(j)^\beta dj \right)^{\epsilon/\beta} \right]^{1/\epsilon}, \quad 0 < \beta < 1,$$

where j indexes varieties, J_s is the set of domestic varieties produced in sector s, J_s^* is the set of imported varieties in sector s, and $q(j)$ is the consumption of variety j. β determines the elasticity of substitution between varieties. ϵ determines the elasticity of substitution between (aggregated) domestic and imported baskets, also known as Armington elasticity, that define national product differentiation. Such specification is commonly used in applied works.[38]

The comprehensive price index for U_s is given by

$$P_s = \left(\int_{j \in J_s} p(j)^{-\beta/(1-\beta)} dj \right)^{-(1-\beta)/\beta},$$

where $p(j)$ is the price of variety j. We define the price index for imported varieties analogously. As it is well known for the CES properties, we can solve for prices to obtain the demand curve for domestic variety j as

$$p(j) = \left(E_s^{dom} \right)^{1-\beta} P_s^\beta q(j)^{-(1-\beta)},$$

where E_s^{dom} is the total expenditure in domestic varieties in sector s. Let $\tau_m > 1$ be the standard iceberg trade cost of importing one unit of the foreign good.

For simplicity, let's assume

$$P_s^* = \frac{A}{A^*} \tau_m P_s, \tag{D.1}$$

so that there is no arbitrage between domestic and imported varieties. A/A^* is a term that represents supply shocks on domestic and foreign products that are not related to trade barriers such as tariffs and other non-tariff barriers included on τ_m. In our case, the China shock represents a shift in the relative supply of Chinese products in the Brazilian economy after 2001. Thus, we can solve the total domestic expenditure in varieties in sector s:

$$E_s^{dom} = \left(1 + \left(A^*/A \right)^{1/(1-\epsilon)} \tau_m^{-\epsilon/(1-\epsilon)} \right)^{-1} E_s,$$

[38] Feenstra, Luck, Obstfeld, and Russ (2018) provides a good summary of the use of Armington's elasticity and the challenges to its estimation.

where E_s is the total expenditure in varieties (domestic and imported) of sector s.

By the properties of the Cobb-Douglas utility, the total domestic expenditure in sector s, is

$$E_s = v_s E,$$

where E is the total expenditure. Putting all the results together, we can finally obtain the demand curve for a domestic variety s as

$$p(j) = \left(1 + \left({}^{A^*}/_{A}\right)^{1/(1-\epsilon)} \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)} (v_s E)^{1-\beta} P_s^{\beta} q(j)^{-(1-\beta)}. \tag{D.2}$$

Finally, we can obtain a firm's revenue by multiplying prices and quantities for a domestic variety j

$$r(j) = p(j)q(j) = \left(1 + \left({}^{A^*}/_{A}\right)^{1/(1-\epsilon)} \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)} (v_s E)^{1-\beta} P_s^{\beta} q(j)^{\beta}. \tag{D.3}$$

The revenue equation above delivers two main properties. i) the revenues for domestic variety j are negatively related to the relative preferences for imports ${}^{A^*}/_{A}$, so that increase in preferences for imported varieties (or an increase in relative productivity on the production of imported goods), displaces demand from domestic to imported varieties. ii) revenues of domestic firms are positively related to import trade costs and the relative demand shifters between imported and domestic goods. Thus, an increase in trade barriers, such as tariffs, make imported goods more expensive relative to domestic goods, leading to a higher demand for outputs of domestic firms. A reduction in tariffs increases the competition with imported goods, decreasing the domestic firm's revenues. We can simplify eq. (D.3) by writing

$$r(j) = A_d q(j)^{\beta}, \tag{D.4}$$

where A_d is the domestic demand shifter. Differently from HIMR, we may allow for the changes in external conditions (i.e., relative prices between domestic and imported goods and importing tariffs) to affect non-importing firms. For example, an import competition shock decreases r through a decrease in ${}^{A^*}/_{A}$, thus in A_d.

D.2 Firm Revenues

Unlike the model in HIMR, we propose that firms also select into the import market. Upon profit maximization, firms may choose between domestic and imported inputs in a constant return to scale function. The usage of inputs is represented by a shift in the demand for inputs. We begin by assuming that the demand and supply for a firm's variety are equal:

$$q = IY,$$

where q is the demand for the output's variety, IY is the total production, with I being the intermediate input usage, and Y being a function of other inputs (labor, in our case). The amount of intermediate inputs used by a firm follows:

$$I = (B_d I_d^{\epsilon} + B_m I_m^{\epsilon})^{1/\epsilon},$$

where I_d and I_m represent domestic and foreign input demands, respectively, B_d and B_m are the relative productivity of intermediate inputs and ϵ determines the elasticity of substitution between them.

A firm is a price-taker in the input market. The optimal demand for inputs follows from the maximization of such expression conditional on prices given by eq. (D.1). The solution leads to

$$I \;=\; B_d^{1/\epsilon} I_d \left(1 + \left({}^{B_m}/{}_{B_d}\right)^{1/(1-\epsilon)} \left({}^{A^*}/{}_{A}\right)^{\epsilon/(1-\epsilon)} \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)},$$

which we simplify to

$$I \;=\; B_d^{1/\epsilon} I_d \left(1 + A_m \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)}. \tag{D.5}$$

The shifter A_m depends on the import competition term in the final consumer decision and the relative intermediate input productivity. We assume that under an import competition shock, the increase on A_m is higher than the loss implied on ${}^{A^*}/{}_{A}$ on eq. (D.4). A non-importer firm has an output shifter of $B_d^{1/\epsilon} I_d$, whereas an importer shifter may increase its production because the reminder expression on eq. (D.5) makes it bigger than 1. We also incorporate the constant term $B_d^{1/\epsilon} I_d$ into A_d, the constant multiplying the firm's revenue, which will not make a difference in our results.

Firms also select into exporting. In this case, it follows directly from HIMR. An exporter firm decides to allocate part of its production to the internal market and the rest to the external market by choosing Y_d to maximize

$$A_d Y_d^{\beta} \;+\; A_x \left[\frac{1}{\tau_x}\left(Y - Y_d\right)\right]^{\beta}.$$

That yields the revenue for an exporter

$$R \;=\; A_d Y^{\beta} \left(1 + \tau_x^{\frac{-\beta}{1-\beta}} \left(\frac{A_x}{A_d}\right)^{\frac{1}{1-\beta}}\right).$$

Together, the conditions for importer/non-importer or exporter/non-exporter firm leads to the revenue on eq. (6.4).

To simplify the model and account for the fact that we observe a positive relationship between a firm being an importer and exporter, we assume that export and import selection costs are positively related through the selection cost. In other words, $cov(\varepsilon_x, \varepsilon_m) > 0$, which will also imply a positive correlation in the reduced-form errors in the econometric framework.

Appendix E Econometric Framework

E.1 Likelihood Function and Constraints

The derivation from the theoretical to the econometric model follows directly from HIMR. However, the inclusion of selection into imports modifies the likelihood function. That will also impose additional constraints on the parameters. We can write the distribution of (u, v, z_x, z_m) are

$$f(u, v, z_x, z_m) = f(z_x, z_m|u, v)f(u, v) = f(z_x, z_m|u, v)f(u)f(v), \tag{E.1}$$

because u and v are not correlated as assumed in eq. (6.14).

We have

$$u \sim N(0, \sigma_u^2) \quad , \quad v \sim N(0, \sigma_v^2). \quad \text{, and} \quad z_x, z_m|u, v \sim N((\bar{m}_x, \bar{m}_m), \bar{\Sigma}_{xm}),$$

where $(\bar{m}_x, \bar{m}_m) = \bar{\Sigma}_{12}\bar{\Sigma}_{11}^{-1}(u, v)$ and $\bar{\Sigma}_{xm} = \bar{\Sigma}_{11} - \bar{\Sigma}_{21}\bar{\Sigma}_{22}^{-1}\bar{\Sigma}_{12}$. And variance-covariance matrices are

$$\bar{\Sigma}_{12} = \begin{bmatrix} \rho_{ux}\sigma_u & \rho_{vx}\sigma_v \\ \rho_{um}\sigma_u & \rho_{vm}\sigma_v \end{bmatrix},$$

$$\bar{\Sigma}_{11} = \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix},$$

and

$$\bar{\Sigma}_{22} = \begin{bmatrix} 1 & \rho_{xm} \\ \rho_{xm} & 1 \end{bmatrix}.$$

Solving for $\bar{\Sigma}_{xm}$, we get

$$\bar{\Sigma}_{xm} = \begin{bmatrix} 1 - \rho_{ux}^2 - \rho_{vx}^2 & \rho_{xm} - \rho_{ux}\rho_{um} - \rho_{um}\rho_{vm} \\ \rho_{xm} - \rho_{ux}\rho_{um} - \rho_{um}\rho_{vm} & 1 - \rho_{um}^2 - \rho_{vm}^2 \end{bmatrix}.$$

As we mentioned in the text, we need this matrix to be positive definite so it can be inverted. Thus, the constraint in the determinant as expressed in eq. (6.19). Using the distributions for $(z_x, z_m|u, v)$, u, and v, we can transform the distribution for the likelihood functions in eq. (6.15).

Constraints eq. (6.17) and eq. (6.18) are straight from the model, as showed by HIMR (see Lemma S.1 in the online appendix).

We estimate eq. (6.16) by Maximum Likelihood (ML). Identification of the parameters in Θ relies on some assumptions. As discussed in HIMR, to construct the structural restriction, we reconcile the theoretical and the econometric models given by eq. (6.13) and eq. (6.14). Firstly, the assumptions that unconditional variance of z_x and z_m equal one, which are derived from eq. (6.11) and eq. (6.12). Moreover, the assumption that the structural error terms θ and η are unrelated, which implies that u and v are also unrelated, and hence the bounds for the exporting and importing market access $\mu_{w,xs}/\mu_{h,xs}$ and $\mu_{w,ms}/\mu_{h,ms}$ leads to[39]

$$\zeta \leq \frac{\mu_{w,xs}}{\mu_{h,xs}}, \frac{\mu_{w,ms}}{\mu_{h,ms}} \leq \frac{\sigma_v^2}{(1+\zeta)\sigma_u^2}, \tag{E.2}$$

[39]We omit the formal derivation of those terms but can provide them upon request. Nonetheless, they do not fundamentally differ from Helpman, Itskhoki, and Redding (2010), Helpman, Itskhoki, Muendler, and Redding (2017) and their respective online appendices.

and

$$\mu_{w,xs}, \mu_{h,xs}, \mu_{w,ms}, \mu_{h,ms} \ > \ 0 \tag{E.3}$$

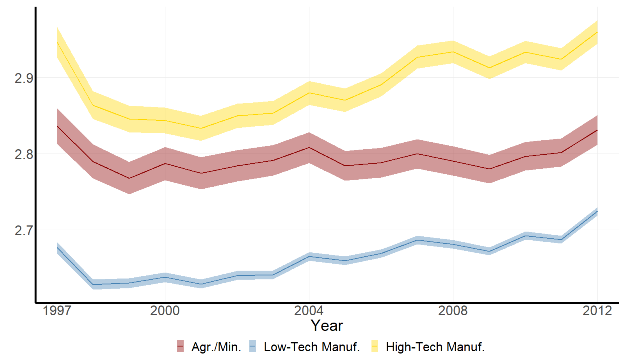
Additionally, we also need to certify that the conditional variance-covariance matrix $\bar{\Sigma}$ is positive definite and thus invertible. For that, the sufficient condition is that the determinant of $\bar{\Sigma}$ be positive, so

$$(1-\rho_{ux}^2-\rho_{vx}^2)(1-\rho_{um}^2-\rho_{vm}^2)-(\rho_{xm}-\rho_{ux}\rho_{um}-\rho_{um}\rho_{vm})^2 \ > \ 0 \tag{E.4}$$

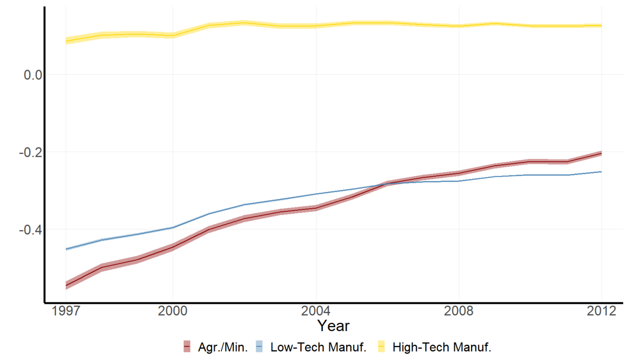
Therefore, the ML estimator maximizes eq. (6.16) subject to constraints eq. (E.2), eq. (E.3), and eq. (E.4).[40] HIMR argue that those constraints are essential to identify separately the parameters the selection and market access effects. More specifically, the terms $\mu = (\mu_{hx}, \mu_{wx}, \mu_{hm}, \mu_{wm})$ and $\rho = (\rho_{ux}, \rho_{vx}, \rho_{um}, \rho_{vm}, \rho_{xm})$. The parameters α_{hs}, α_{ws} absorb sector-level market tightness and competition in the input/output markets. In our setting, the increase in trade integration with China during the 2000s may have impacted such terms, i.e., affected non-exporters/non-importers due to import competition (or competition with Chinese demand on the input market) or an increase on the output's demand induced by input-output linkages.

[40] An additional constraint is $\rho_{xm} > 0$, which accounts for the abstraction in the implied by the sufficient conditions imposed in eq. (6.11) and eq. (6.12), as well as the empirical fact that there is a positive relationship between exporter and importer status. Another way to put it is through the positive relationship between export and import costs drawn from ε_x and ε_m. We do not impose this restriction during estimation but observe their validity after the estimation.

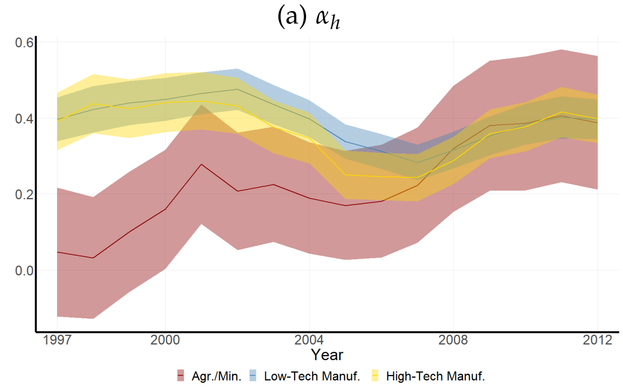
Appendix F Estimated Structural Parameters and Model Fit



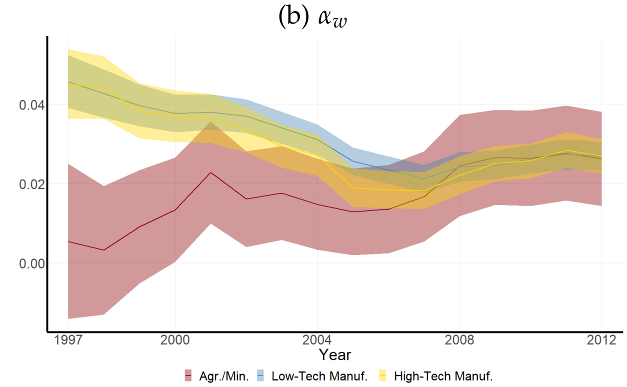
(a) α_h



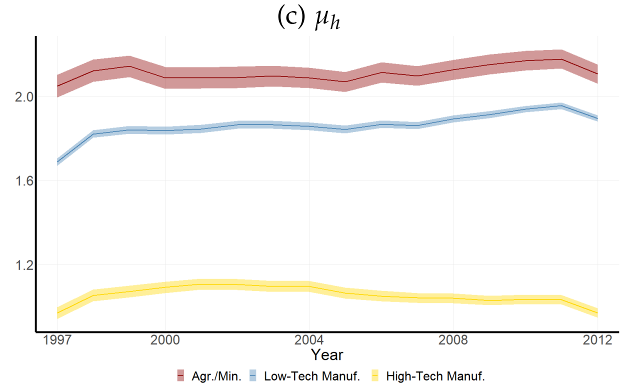
(b) α_w



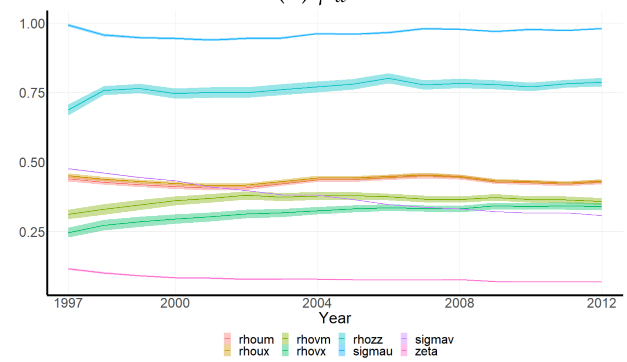
(c) μ_h



(d) μ_w



(e) c_x



(f) Σ

Figure 17. Model Estimates: Aggregate Estimates and Confidence Interval by Sector and Year. The figures display the point estimates and confidence intervals for the aggregate parameters in the structural model in Eq. (6.13). Shaded areas represent 95% confidence intervals for the parameters.

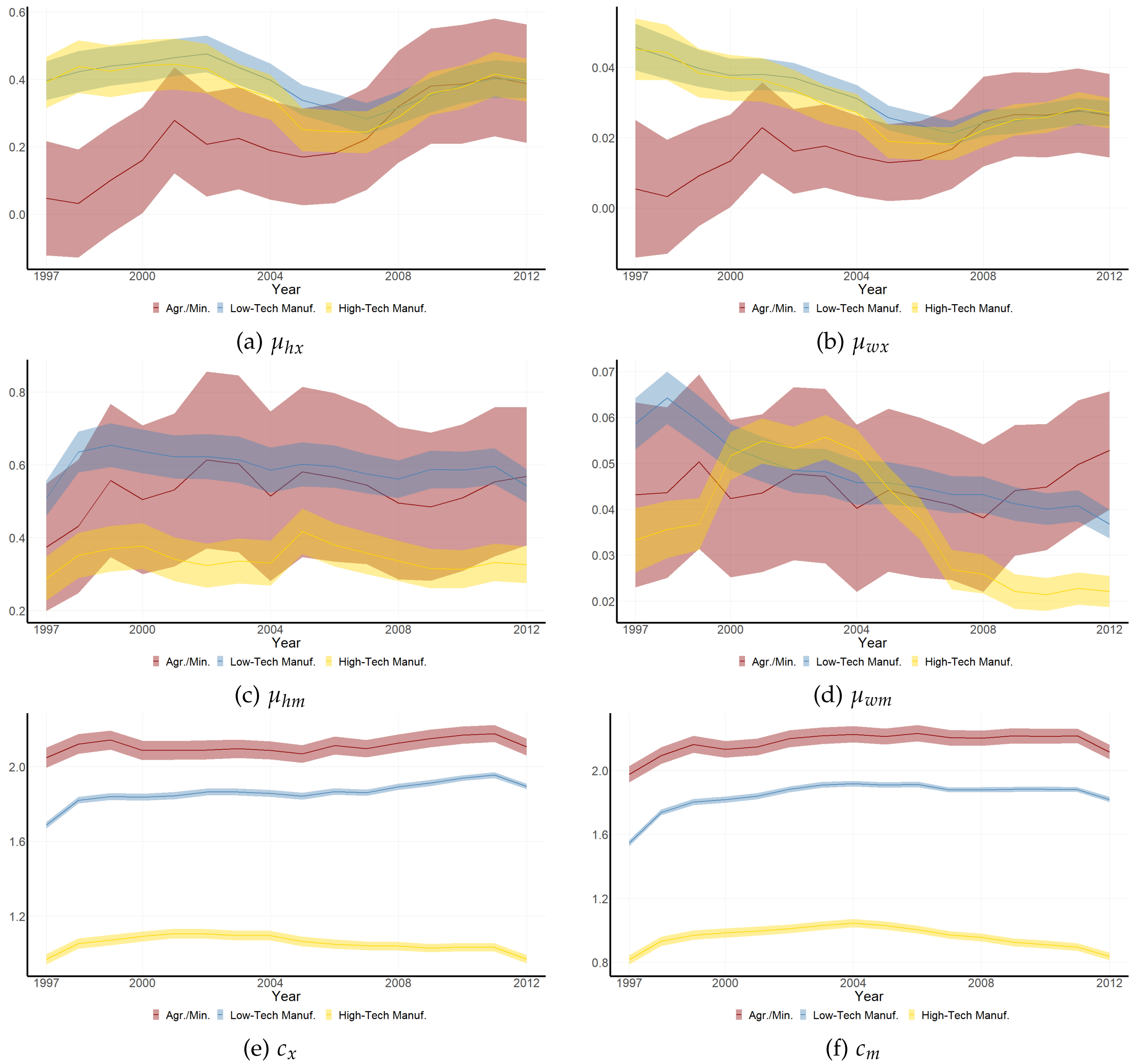
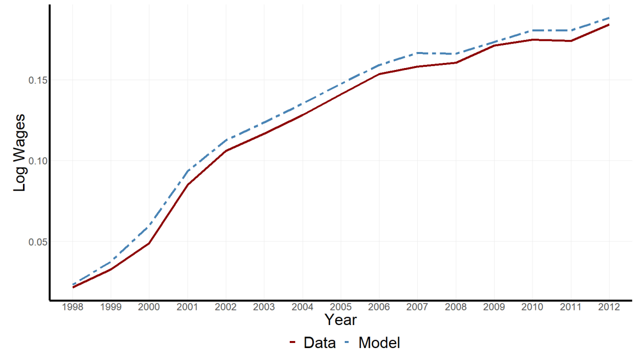
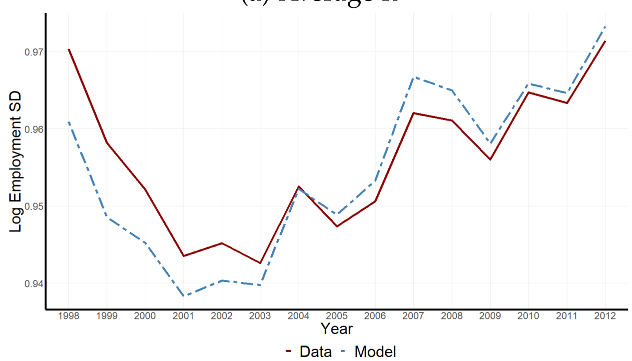


Figure 18. Model Estimates: Aggregate Estimates and Confidence Interval by Sector and Year. The figures display the point estimates and confidence intervals for the aggregate parameters in the structural model in equation Eq. (6.13). Shaded areas represent 95% confidence intervals for the parameters.

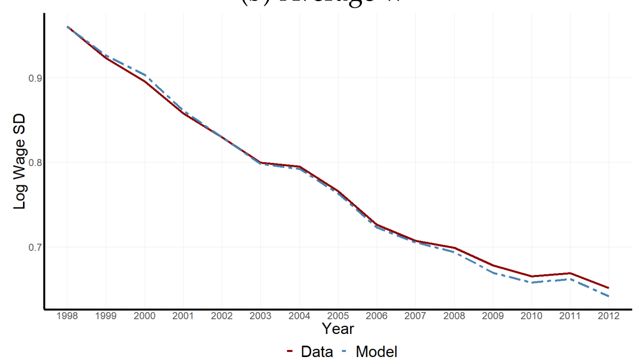
(a) Average h



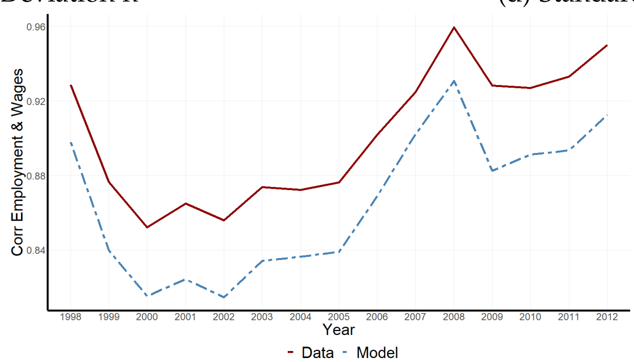
(b) Average w



(c) Standard Deviation h

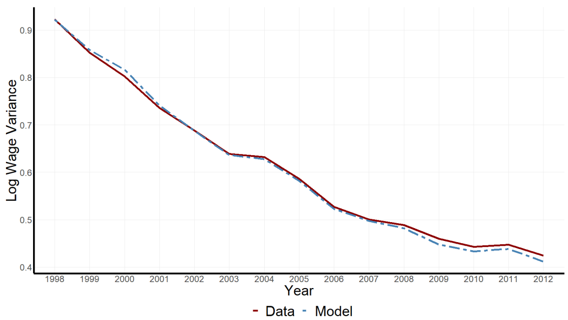


(d) Standard Deviation w

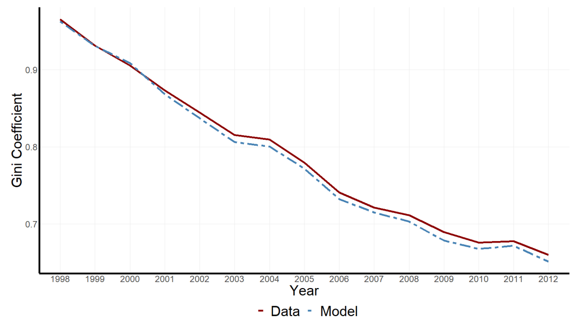


(e) Correlation h and w

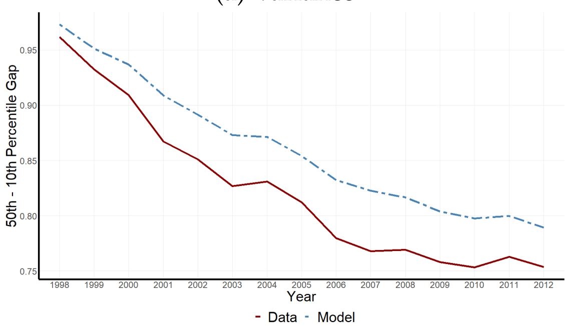
Figure 19. Model Fit: Wages and Employment. The figures compare dispersion statistics for firm wages. The model statistics are displayed in red, solid lines. The model predictions are displayed in blue dashed lines. The data in the model was simulated with 10 million draws using the estimated parameters in the respective year.



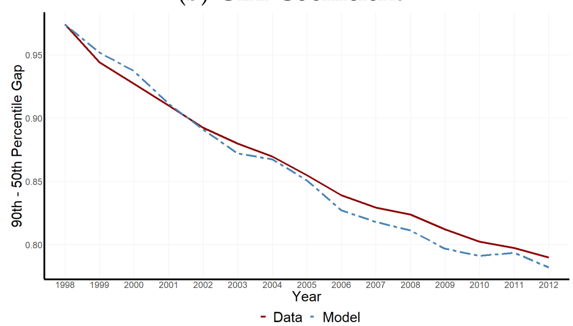
(a) Variance



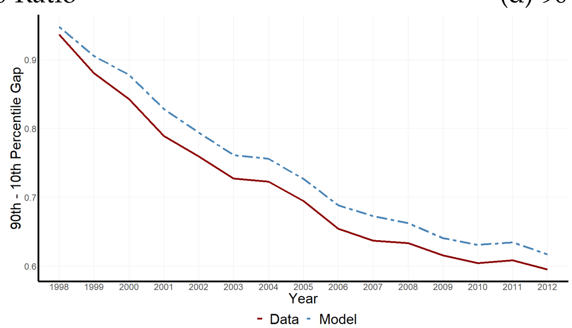
(b) Gini Coefficient



(c) 50-10 Ratio



(d) 90-50 Ratio



(e) 90-10 Ratio

Figure 20. Model Fit: Dispersion Statistics For Wages. The figures compare dispersion statistics for firm wages. The model statistics are displayed in red, solid lines. The model predictions are displayed in blue dashed lines. The data in the model was simulated with 10 million draws using the estimated parameters in the respective year.

Table 14. Model vs. Data: Firm Moments (2000)

	All Firms		Agr./Min.		Low-Tech Manuf.		High-Tech Manuf.	
	Data	Model	Data	Model	Data	Model	Data	Model
Average h	2.75	2.72	2.80	2.80	2.70	2.67	2.98	2.96
Average w	–0.32	–0.33	–0.45	–0.45	–0.39	–0.39	0.11	0.11
Sd h	0.99	1.00	1.02	0.96	0.96	0.99	1.11	1.05
Sd w	0.48	0.48	0.48	0.44	0.43	0.44	0.49	0.45
Corr(h,w)	0.26	0.24	0.14	0.19	0.24	0.21	0.32	0.26
Corr(x,m)	0.51	0.43	0.42	0.34	0.47	0.38	0.55	0.48

Comparison between Model and Data for 2000.

Appendix G Counterfactuals

G.1 Constructing the Conterfactuals

Our first exercise simulates the impact of the China shock on the Brazilian economy separately, i.e., we isolate the impact of import and export exposure. Then, we put them together to evaluate the total impact of the bilateral trade integration on the average wages and the wage variance.

In our model, import and export exposure affect firm wages and employment firstly in the constants α_{ws} and α_{hs}. Changes in the internal demand due to China alter A_s^*/A_s. Import penetration decreases the demand from a firm output favoring import products. Thus, it represents an increase in A_s^*/A_s. Contrarily, downstream exposure to exports to China (also considering the level change in exposure, hence the total impact on the firm's output demand) increases the internal demand for the firm's output. Thus, it represents an decrease in A_s^*/A_s.

We can write α_{ws} and α_{hs} as

$$\begin{aligned}
\exp(\alpha_{ws}) &= \bar{\alpha}_w \bar{\alpha}_{ws} \left(1 + \left(A_s^*/A_s\right)^{\frac{-1}{1-\epsilon}} \tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{\frac{-(1-\beta)k}{\delta\Gamma}} \\
\exp(\alpha_{hs}) &= \bar{\alpha}_h \bar{\alpha}_{hs} \left(1 + \left(A_s^*/A_s\right)^{\frac{-1}{1-\epsilon}} \tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{\frac{-(1-\beta)(1-k/\delta)}{\Gamma}},
\end{aligned}$$

where $\bar{\alpha}_w$ and $\bar{\alpha}_h$, are constant for all firms, $\bar{\alpha}_{ws}$ and $\bar{\alpha}_{hs}$ are constants for all firms in sector s. We symmetric countries before the shock, so that the initial level of A^*/A is equal to one. We also assume that changes due to the China shock only impact on A^*/A.

Given the changes in α_{ws} and α_{hs} and that replicate the findings in the reduced-form analysis, we may obtain A_s^*/A_s. Using the expressions for α_{ws} and α_{hs}, we can represent the change in α_{ws} and α_{hs} due to the China shock as

$$\begin{aligned}
\exp(\Delta\alpha_{ws}) &= \frac{\left(1+\left(A_s^*/A_s\right)^{\frac{1}{1-\epsilon}} \tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)k}{\delta\Gamma}}}{\left(1+\tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)k}{\delta\Gamma}}} \\
\exp(\Delta\alpha_{hs}) &= \frac{\left(1+\left(A_s^*/A_s\right)^{\frac{1}{1-\epsilon}} \tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)(1-k/\delta)}{\Gamma}}}{\left(1+\tau_m^{-\frac{\epsilon}{1-\epsilon}}\right)^{\frac{-(1-\beta)(1-k/\delta)}{\Gamma}}},
\end{aligned}$$

where $\Delta\alpha_{ws}$ and $\Delta\alpha_{hs}$ represent the difference between α_{ws} and α_{ws}, respectively, before and after the China shock happened. By multiplying the expressions for $\Delta\alpha_{ws}$ and $\Delta\alpha_{hs}$, we get

$$\exp(\Delta\alpha_{ws} + \Delta\alpha_{hs}) \left(1 + \tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)}{\Gamma}} = \left(1 + \left(A_s^*/A_s\right)^{\frac{1}{1-\epsilon}} \tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)}{\Gamma}}.$$

Then, we can obtain the corresponding changes in A^*/A that imply the effects of import and export exposure on α_{ws} and α_{hs} by

$$\left(\frac{A_s^*}{A_s}\right)^{\frac{1}{1-\epsilon}} = \left[\exp(\Delta\alpha_{ws} + \Delta\alpha_{hs})^{-\frac{\Gamma}{(1-\beta)}} \left(1 + \tau_m^{\frac{-\epsilon}{1-\epsilon}}\right) - 1\right] \tau_m^{\frac{\epsilon}{1-\epsilon}}. \tag{G.1}$$

Throughout our counterfactual exercises of the impact of a tariff change, we keep constant the term $\left({}^{A_s^*}/{}_{A_s}\right)^{\frac{1}{1-\epsilon}}$, so that we evaluate the impact of a same-sized import and export shocks under different tariff regimes.

As found in our reduced-form estimates, the China shock also stimulates firms to import and export. More specifically, upstream import exposure increases the availability of external inputs and reduces their prices. Contrarily, upstream export exposure increases competition in the input markets, which reduces wages. However, our findings suggest that upstream export exposure has low economic relevance. Thus, upstream import exposure increases $\mu_{wm,s}$ and $\mu_{hm,s}$, and reduces c_{ms}. Analogously, downstream export exposure (total impact on output's demand) stimulates firms to export. Thus, it increases $\mu_{wx,s}$ and $\mu_{hx,s}$, and reduces c_{xs}.

Because the China shock occurs with no reduction in trade tariffs, we assume that all it is a result of shifts in ${}^{A_m}/{}_{A_d}$ and ${}^{A_x}/{}_{A_d}$, greater than the change in A_d we calibrated previously. Finding those changes is similar to the procedure in HIMR. Using the structural equations in the model, we first find the values for ${}^{A_m}/{}_{A_d}$ and ${}^{A_x}/{}_{A_d}$ in the benchmark model, which consists of the estimated parameters for the year 2000.

Let $j \in \{x, m\}$. Given the estimates for $\mu_{wj,s}$ and $\mu_{hj,s}$, we obtain Y_j by

$$Y_{js}^{\frac{1-\beta}{\Gamma}} = \exp[\mu_{hj,s} + \mu_{wj,s}],$$

where s indexes sector and Y_{js} is defined as in the text for each sector. Thus, given Y_{js}, we pin down the value for the entry cost into j market as

$$c_{js} = \frac{1}{\sigma_{js}}(-\alpha_\pi + \log(C_j s) - \log[Y_{js}^{\frac{1-\beta}{\Gamma}} - 1]).$$

As suggested in HIMR, we also assume a value for σ_{js} equal to...

After calibrating the values for ${}^{A^*}/{}_{A}$, ${}^{A_m}/{}_{A_d}$, and ${}^{A_x}/{}_{A_d}$ to match our findings in the reduced-form results, we can use those values to perform counterfactual analysis on the impact of the China shock under different tariff regimes. For that, we fix ${}^{A^*}/{}_{A}$, ${}^{A_m}/{}_{A_d}$, and ${}^{A_x}/{}_{A_d}$, and change only the import tariffs τ_m. This exercise would represent another round of trade opening in the Brazilian economy, widely studied in the international trade literature.

G.2 Substitution between Domestic and Imported Products

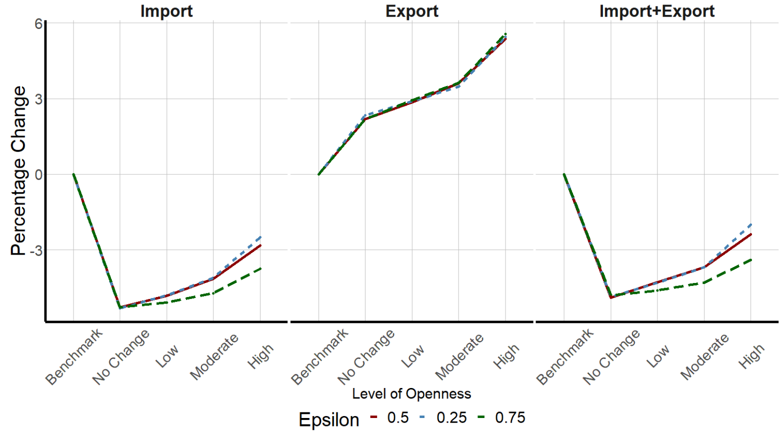
In the text, we follow Feenstra, Luck, Obstfeld, and Russ (2018) and that the elasticity of substitution between domestic and imported varieties (also known as Armington's or macro elasticity) is at most equal to the elasticity of substitution between domestic varieties (also known as micro elasticity). Moreover, Feenstra, Luck, Obstfeld, and Russ (2018) supports the claim that the macro elasticity is around half the size of the micro elasticity. The relationship between those two parameters is crucial to evaluate which effect is dominant in tariff reduction, import competition, or selection into imports. The macro elasticity determines how likely consumers are to replace domestic with imported products, whereas the macro elasticity also determines a firm's choice to become an importer.

In our model, the macro elasticity is determined by the parameter ϵ (see Section 6), whereas the micro elasticity is determined by the parameter β. To make our results comparable, we use the same value as HIMR and set $\beta = 3/4$. To keep a $1/2$ relationship between macro and micro elasticity implies $\epsilon = 1/2$. This Appendix shows that our results remain approximately the same under different assumptions over ϵ. More specifically, we test $\epsilon = 1/4$ (which implies a macro elasticity equal to 1.33) and $\epsilon = 3/4$ (which implies a macro elasticity equal to 4).

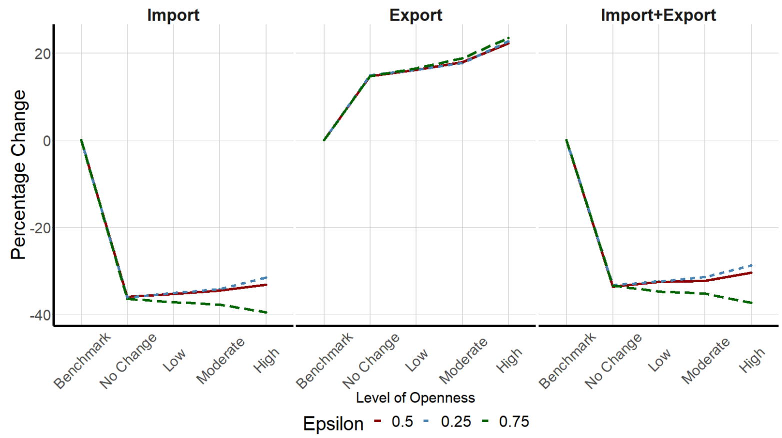
Because different assumptions over the macro elasticity reflect mainly on the import competition effect of trade shocks, we must expect that different values for this parameter will mainly reflect the variance across sectors and the null effect within the sector. In our model, import competition has heterogeneous effects across sectors but equally impacts all firms within a sector. Thus, it does not influence on firm's decision to import.

Figure 21 reports a summary of these results. We restrict the analysis to comparisons in the overall, between-sectors, and within-sector wage variance (weighted by sector size) across difference trade shocks, tariff reduction scenarios, and values for ϵ.

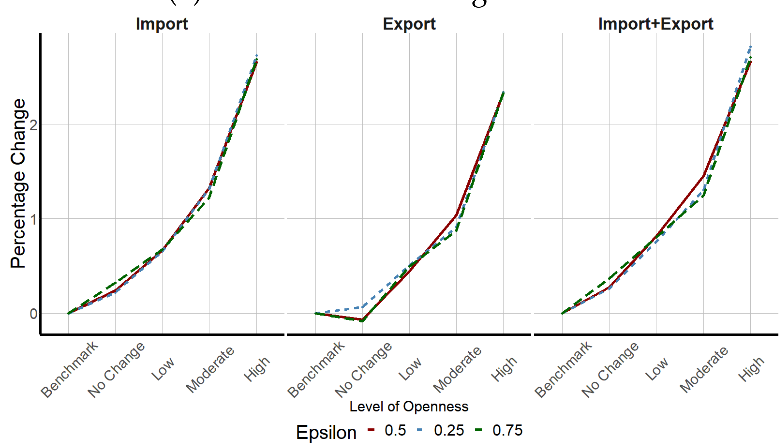
There are slight differences for each assumption on values for ϵ, mainly in the between-sector wage variance and virtually none in the within-sector wage variance. It is important to highlight the negative effect of import competition with Chinese products on wage variance. As in the main text, we documented that this is a result of the dominance of import competition (variance reduction effect) over selection into imports (variance increase effect). Under a tariff reduction scenario, selection into imports attenuates the import competition so that the cross-sector effects are not as strong. However, when there is high substitutability between domestic and imported, the attenuation effect of selection into imports is not strong enough, so tariff reduction leads to a higher decrease in the between-sector wage variance.



(a) Overall Wage Variance



(b) Between-Sectors Wage Variance



(c) Within-Sectors Wage Variance

Figure 21. Changes Overall, Between-Sector, and Within-Sector for Assumptions on Macro Elasticity. The figures compare the percentage changes in the wage variance components. "Import" refers to import exposure only. "Export" refers to export exposure only. "Import+Export" refers to both import and export exposure. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "No Change" are the model predictions under trade exposure and no change in tariffs; "Low", "Moderate", and "High" refer to different assumptions on tariff reduction: 5%, 10%, and 20%, respectively. Line colors and shapes vary according the values of parameter ϵ: 0.5 (our benchmark in the text), 0.25, and 0.75.

Appendix H Wages and Within-Firm Dispersion

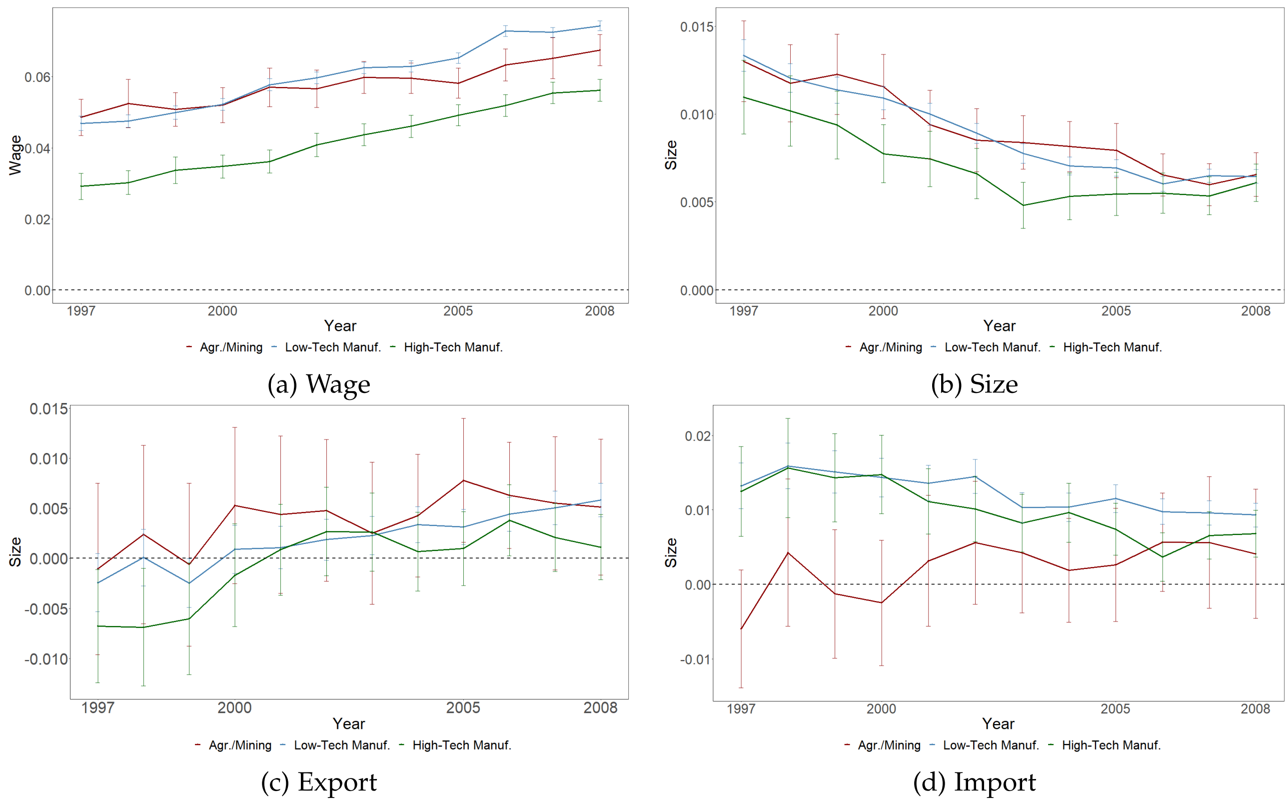
H.1 Empirical Patterns in Within-Firm Dispersion

Our main empirical approach uses the wage decomposition in eq. (4.1), from which we derive an observed within-firm-occupation component ($X_{it}'\Lambda_t$), a between firm-occupation (ψ_{oft}) component, and the residual wage ($\varepsilon_{i,t}$).

Following the terminology in the literature, we refer to $\hat{\psi}_{ft}$ (the estimated firm-level average of ψ_{ft}) as the between-firm wage component. As in HIMR, this is the term that we use to measure the firm-level wage-premium, or simply firm component. $X_{it}'\hat{\Lambda}_t$ measures the participation of workers' observable characteristics in the wage composition. This term is common to all firms and reflects an economy-wide change in labor market conditions and compositional effects. $\hat{\varepsilon}_{i,t}$ is the residual wage or within-firm wage component. This term incorporates the non-observable wages variations within a firm, which may reflect matching, search frictions, and firm-worker bilateral bargaining.

This section aims to understand the relationship between within-firm wage dispersion and the firm's number of employees, and the wage component ψ_{ft}. We measure the within-firm wage dispersion with the variance of $\varepsilon_{i,t}$ for each firm. Figure 22 shows the coefficients of a regression of $var(\varepsilon_{ft})$ on $\hat{\psi}_{ft}$ (Graph a) and $log(employment_{ft})$ (Graph b). The evidence shows that within-firm wage variance is positively related to firm size and average firm wage. Bigger firms tend to pay higher wages and to present a high wage dispersion across co-workers, even when controlled by observable workers' characteristics and occupation-education fixed effects. Graphs (c) and (d) show the relationship between within-firm variance and the indicators of exporter and importer, respectively. The estimates suggest that exporter firms may have higher within-firm variance but only in the Agriculture and Mining sectors. In contrast, importer firms may present higher within-firm variance only in the manufacturing industries.

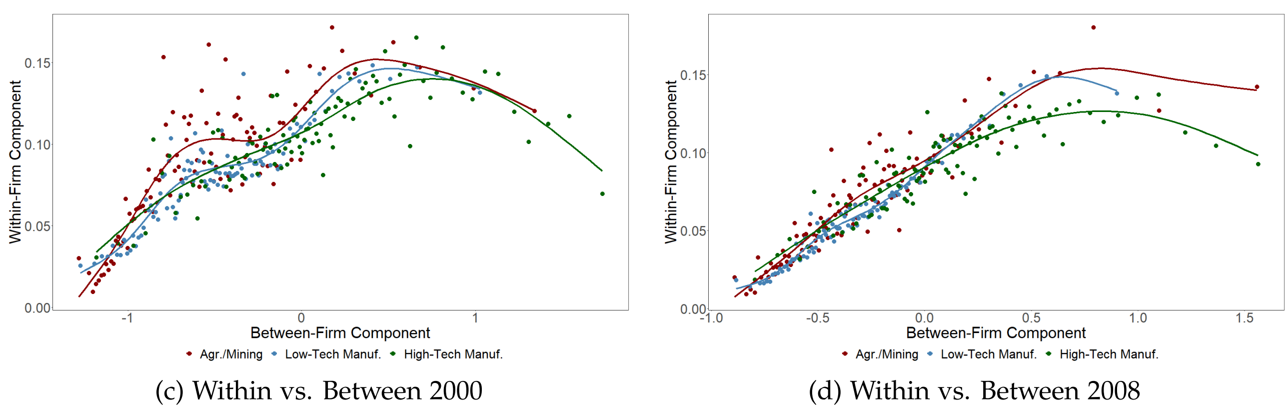
We further assess the relationship between within- and between-firm components in Figure 23. These graphs display the binned scatter relationship between $var(\varepsilon_{ft})$ on the vertical axis and $\hat{\psi}_{ft}$ on the horizontal axis, separately for 2000 and 2008. Note that there is a strong, positive relationship between the mean and the variance of wages for low-paying firms, which is relatively similar across sectors and years. These patterns corroborate the findings of graphs (a) and (b) in Figure 22, suggesting a high within-firm wage dispersion for more productive firms. However, this relationship is not monotonic; within-firm dispersion declines as we approximate for firms at the top of the wage distribution.



(a) Wage (b) Size

(c) Export (d) Import

Figure 22. Within-Firm Variance and Firm Observables. The Figures report the correlation of within-firm wage variance and average wage (firm component $\hat{psi}_{ft}$) in Graph (a), firm size (log of number of employees) in Graph (b), export indicator in Graph (c), and import indicator in Graph (c). Each point represents the estimate and 95% Confidence Interval of a regression of wage variance against firm component and log firm size separately for each year.



(c) Within vs. Between 2000 (d) Within vs. Between 2008

Figure 23. Within-Firm Variance and Firm-Component. The Figures plot the within-firm variance (vertical axis) and the between-firm component (horizontal axis). Each point is a binned average based on values of the between-firm component. The lines represent a polynomial fit. The bin-plot weights observations by firm size.

H.2 Theoretical Motivation

In HIMR, a firm drafts an amount n of potential employees, and then screens only those workers with a minimum ability threshold a_C, with $a \sim G(a)$, at a cost $\frac{C}{\delta}a_C^{\delta}$, with $C > 0$ and $\delta > 0$. The firm pays the screening cost but only observes whether the workers are above or below the minimum ability level a_C. The firm does not observe each worker's ability. After screening only workers with a minimum ability a_C, the firm hires an amount $h = [1 - G(a_C)]$ of workers.

HIMR assumes the following production function for a firm with productivity θ

$$y = \theta \left(\frac{1}{h}\right)^{1-\gamma} \left(\int_0^h a_i d_i\right) = \theta h^{\gamma} \bar{a},$$

where θ is a firm-specific productivity, h is the number of employees hired, a_i is the ability of employee i, $0 < \gamma < 1$ is a parameter. $\bar{a}$ is the average ability hired by the firm, or $\bar{a} = \bar{a}(a_C) = E[a|a \geq a_C]$. HIRM interprets this production function as the following:

"A manager with productivity θ has one unit of time, which he allocates equally among his employees. Thus, the manager allocates $1/h$ of his time to each worker, and as a result, a worker with ability a can contribute $\theta(1/h)^{1-\gamma}a$ to the total output of the firm, where $(1-\gamma)$ measures the importance of managerial time input." Helpman, Itskhoki, and Redding (2010).

As a result of the consumer's problem, in equilibrium, a firm's revenue is given by

$$R = Ay^{\beta},$$

where A is a revenue shifter and $0 < \beta < 1$ is a parameter.

The marginal product of hiring worker h with ability ability a_h is

$$\frac{\partial y(a_h|\theta)}{\partial h} = \theta h^{-(1-\gamma)} \left[a_h - (1-\gamma)\bar{a}(a_h)\right].$$

Likewise, we can write the marginal revenue of a worker as

$$\frac{\partial r(a_h|\theta)}{\partial h} = \beta\theta h^{-(1-\gamma)} \left[a_h - (1-\gamma)\bar{a}(a_h)\right] \frac{r(a_h|\theta)}{y(a_h|\theta)}. \tag{H.1}$$

Note that the marginal product of adding another worker with ability a_h depends on the number of employees and the average ability of her co-workers. The average ability will decrease because a_h pushes the ability boundary down. Thus, the marginal revenue may be negative if $a_h < (1-\gamma)\bar{a}(a_h)$. In words, if the ability of the marginal worker is smaller than a fraction of the average ability hired by the firm, the marginal workers will have a negative marginal revenue.

For example, from HIMR, suppose that $G(a) = 1 - a^{-k}$, with $k > 1$. In this case,

$$\bar{a} = \frac{k}{k-1}a_C,$$

and

$$h = na_C^{-k},$$

which implies that the production function is

$$y = \theta \left(\frac{k}{k-1}\right) n^{\gamma} a_C^{1-\gamma k}.$$

The marginal product of a worker with ability a_h depends on its ability, the number of employees, and the average ability.

The production function is increasing in a_C if $\gamma k < 1$. Replacing the definition of the marginal product, we have

$$\frac{\partial y(a_h|\theta)}{\partial h} = -\theta h^{-(1-\gamma)} \frac{1-\gamma k}{k-1} a_C,$$

which is negative for all values of a_C when $\gamma k < 1$. That also implies that the marginal revenue for any cutoff a_C will be negative.

Note that there is an interval $[a_c, \hat{a})$, with $\bar{a} = (1-\gamma)\bar{a}$ with negative marginal revenue.[41]

To include within-firm wage dispersion into the model simply, we need to add some modifications to the model. In HIMR, the firm does not know ex-ante the ability level of each worker. However, it can learn the worker's ability after production and propose a payment schedule based on their performance. To incentive the worker reveals their actual ability level, the payment schedule must minimize the distance between the worker's marginal revenue and their wage. However, the firm must follow two institutional constraints: 1) the least productive worker must receive, at least, its outside option; 2) the average wage must be at least as high as the bargained ex-ante average wage.

We assume that workers are risk-neutral, and the outside option of any worker is equal to zero, regardless of her ability level a. Thus, the firm solves

$$w(a) = argmin_w \int_{a_C}^{\infty} \left[\tilde{w} MR(a) - w\right]^2 \frac{g(a)}{1-G(a_C)} da$$

subject to

$$\begin{aligned} w(a_C) &\geq 0 \\ w(\bar{a}) &= \bar{W} \\ w'(a) &> 0 \\ \int_{a_C}^{\infty} w(a) \frac{g(a)}{1-G(a_C)} da &= \bar{W}. \end{aligned}$$

where $MR(a)$ is the marginal revenue with ability a. The first constraint determines that the marginal worker must receive at least the outside option equal to zero. The second constraint determines that the worker with the average ability $\bar{a}$ will receive the average wage $\bar{W}$. The third constraint determines that the wage schedule $w(a)$ is an increasing function of a. And the last is the institutional constraint that determines that the average wage schedule $w(a)$ must be equal to the average wage bargained between the firm and the workers before the production.

The first-order condition for this problem results in

$$w(a) = \tilde{w}[MR(a) - MR(a')] + w(a'),$$

for any $a, a' \in [a_C, \infty]$. Particularly, using $a' = \bar{a}$ and the second optimization constraint, we get

$$w(a) = \tilde{w}[MR(a) - \bar{MR}] + \bar{w},$$

[41] We also tested some specifications with $log(a) \sim N(\mu, \sigma^2)$, which may not have an explicit closed form. For any cutoff ability a_C, the marginal product is also negative.

where $\bar{MR}$ is the average marginal revenue hired by the firm. As shown in HIR and in the second constraint, this is also the marginal revenue of a worker with ability $\bar{a}$.

Finally, by replacing a with a_C in the last equation and applying the first constraint in the optimization problem, we get

$$\tilde{w} = \frac{\bar{w}}{[\bar{MR} - MR(a_C)]}.$$

Replacing it into the wage equation, we get

$$w(a) = \frac{MR(a) - \bar{MR}}{\bar{MR} - MR(a_C)}\bar{w} + \bar{w},$$

or

$$w(a) = \frac{MR(a) - MR(a_C)}{\bar{MR} - MR(a_C)}\bar{w}.$$

Using the formulas for the marginal revenue in eq. (H.1) and the Pareto distribution for a, we can simplify this expression to

$$w(a) = \frac{(k-1)(a-a_C)}{a_C}\bar{w}.$$

Thus, if $k > 1$, the wage for a worker with ability a is an increasing function on a, which satisfies the third optimization constraint.

We can obtain the firm-level wage variance with

$$var(w) = \int_{a_C}^{\infty}\left[\frac{(k-1)(a-a_C)}{a_C}\bar{w} - \bar{w}\right]^2 \frac{g(a)}{1-G(a_C)},$$

which yields

$$var(w) = \frac{k}{k-2}\bar{w}^2.$$

Therefore, we require that $k > 2$ (unlike $k > 1$ in HIR) evaluate the within-firm wage variance. Moreover, because $\bar{W}$ is an increasing function of the firm's productivity, so is $var(w)$. Therefore, more productive firms are larger, pay higher wages, and have more wage dispersion across their employees. Finally, note that $var(w)$ does not depend directly on selection into exports or imports, except through their effects on $\bar{W}$, a result also shared with Pupato (2017).

H.3 Simulated Impact of the China Shock

The theoretical motivation in the previous section shows an increasing relationship between wage variance and average wages. Thus, more productive firms are larger, pay higher wages, and pay more dispersed wages for co-workers. This result is similar to Pupato (2017), which finds an increasing relationship between the variance of log wages and firm productivity and, as a consequence, an increasing relationship between the variance of average log wages. Based on these theoretical results and our empirical findings, we update the structural model to account for a within-firm variance in wages to

$$
\begin{aligned}
h_s &= \alpha_{hs} + \mu_{h,xs}\iota_{xs} + \mu_{h,ms}\iota_{ms} + u \\
w_s &= \alpha_{ws} + \mu_{w,xs}\iota_{xs} + \mu_{w,ms}\iota_{ms} + \zeta u + v \\
\iota_{xs} &= \mathbb{1}\{z_x > c_{x,s}\} \\
\iota_{ms} &= \mathbb{1}\{z_m > c_{m,s}\} \\
var(w_s) &= f(w_s) + v_\varepsilon.
\end{aligned} \tag{H.2}
$$

f is a second-order polynomial fit, and η_{ft} is the idiosyncratic component. The reaming terms are identical to eq. (6.13). We simplify the model by assuming that the error term v_ε is independent of the error structure in the model eq. (6.13). Note that in this way, we do not obtain the closed form solution for the variance of log-wages and neither need to assume a value for k.

In eq. (H.2), we estimate the first 4 equations using the same procedure described in Section 6. Separately, we estimate f using the observed variance of ε_f in the left-hand side and the wage component ψ_f in the right-hand side using f as constant and a a second-order polynomial in w_s.

To simulate the models in out counterfactual analysis, we proceed similarly First, we use the estimated parameters to obtain simulated values for (w, h, ι_x, ι_m). Then, we obtain the within-firm wage variance by fitting the polynomial f in the simulated w from our structural econometric model in Section 6.

We plot the comparison between the observed data and the simulated data in Figure 24. We estimate this model separately for each year between 1997 and 2008.

The horizontal axis displays the percentiles of the observed and simulated between-firm component (ψ_{ft}). The vertical axis displays the average within-firm variance for each percentile of ψ_{ft}. The model represents well the patterns in wage dispersion across the sectors. Following Pupato (2017), there is a positive relationship between the within- and between-firm terms. The model is also consistent across years. Between 2000 and 2008, the curves fall for all sectors, following the declining trend in the wage variance, without a significant change in their shape.

H.4 Additional Counterfactual Analysis

The main analysis is in Section 7. Here we show additional results on the effects of the China shock on the within-firm wage variance. Results are presented in Figure 25. Analogously to the impact on sector-level average wages, the decline of the within-firm wage dispersion is higher for the High-Tech Manufacturing sector under the import exposure shock. Moreover, firms at the bottom of the wage distribution experience the greatest decrease of around 15 percent. Because of the relationship between firm wages and within-firm wage variance due to performance pay contracts, low-paying firms are more harmed by the import competition, bearing a higher decrease in the average paying and, consequently, in the payment variance. High-paying firms benefit from the China shock by becoming importers or exporters. Thus, they face lower average losses and a lower decrease in dispersion.

Figure 26 provides additional comparisons between the data, the model predictions, and the model simulations. Note that the fitted and simulated models replicate reasonably well the data. Nonetheless, our model overestimates the share of the within-firm component by around 4 percentage points and underestimates the share of the between-sector component by almost 6 percentage points.

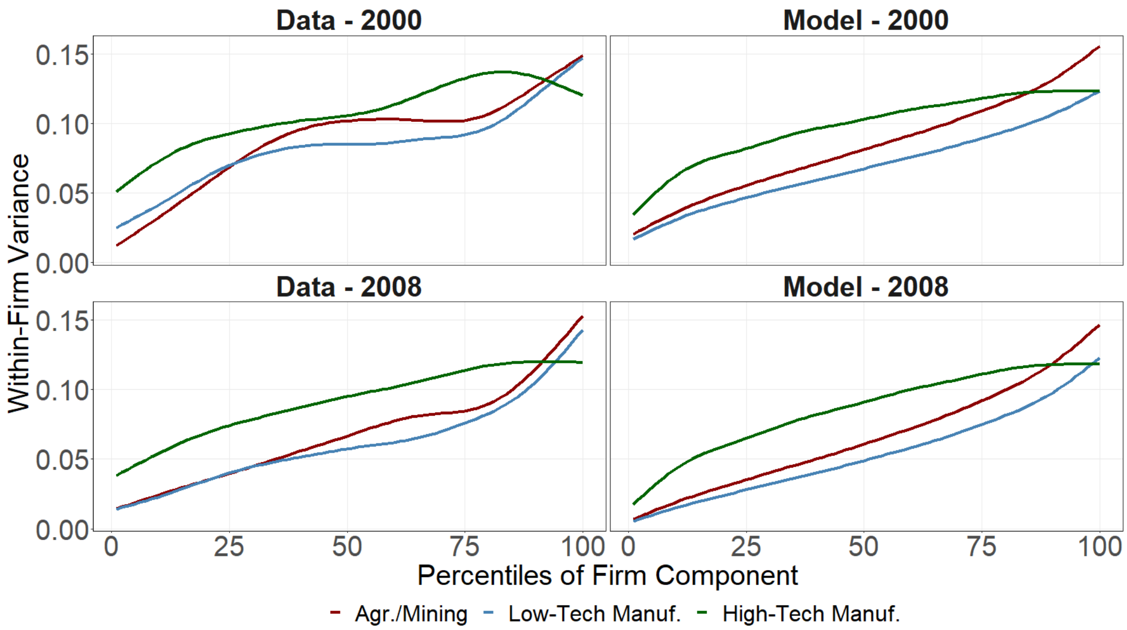


Figure 24. **Within-Firm Variance and Firm-Component.** The horizontal axis displays the percentiles of the between-firm component ψ_{ft} (Data) and the simulated ψ_{ft} (Model). The vertical axis displays the average within-firm variance for each percentile of ψ_{ft}.

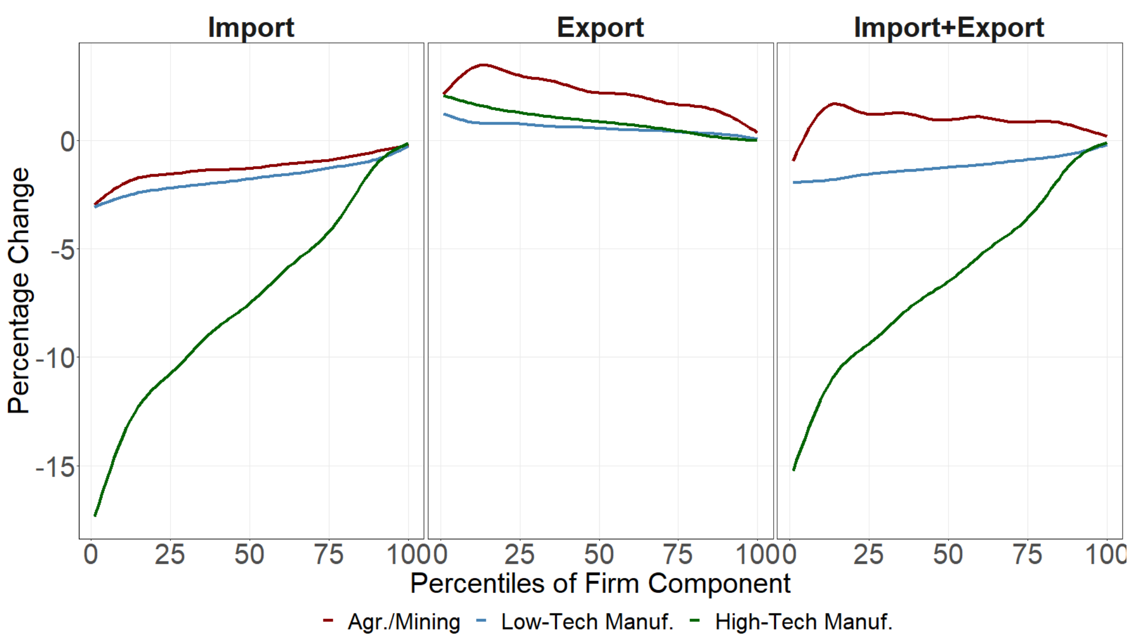


Figure 25. **Impact of the China Shock on the Within-Firm Wage Dispersion.** The Figures depict the change in within-firm wage dispersion due to the China shock relative to the model predictions in 2000. The horizontal axis displays the percentiles of the between-firm component ψ_{ft} (Data) and the simulated ψ_{ft} (Model). The vertical axis displays the percentage change of the average variance within each percentile of the ψ_{ft} distribution.

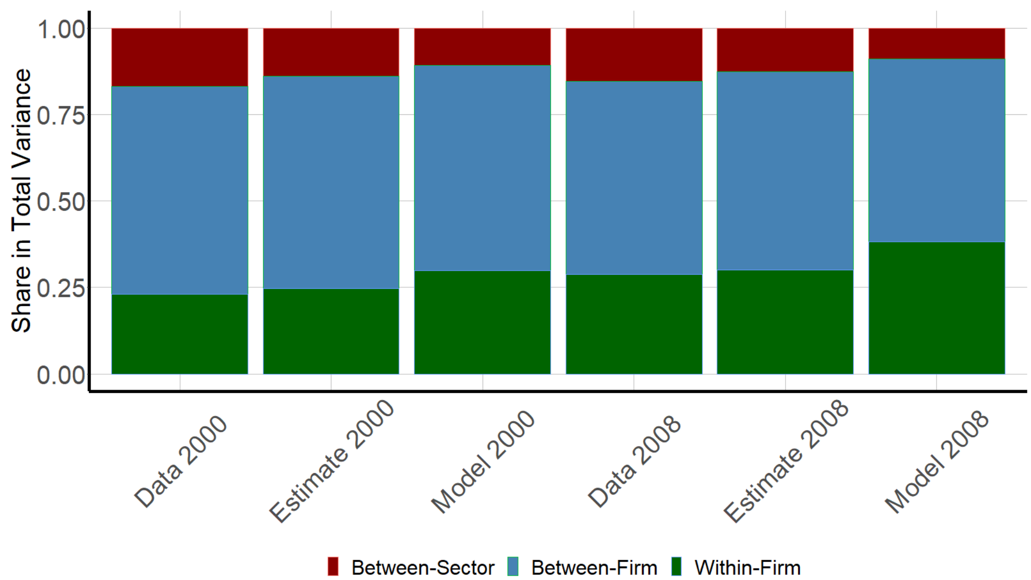


Figure 26. Comparison of Variance Composition Across Models. The Figure displays the variance composition for the different models. “Data” presents the observed composition in the data, "Estimate" presents the fitted model in the observed data, and “Model” presents the model simulations.