Online Appendix

International Trade and Wage Inequality: Evidence from Brazil*

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Appendix A Data Details and Additional Empirical Results

A.1 Data cleaning procedure

As mentioned in the main text, we use labor market information from the Relação Anual de Informações Sociais (RAIS), the matched employer-employee administrative database collected by the Brazilian Ministry of Labor comprising the population of formal employment in Brazil from 1996 to 2012. We exclude observations with an invalid worker identification number (PIS) or firm identification number (CNPJ).[1] Because a worker can have multiple entries each year, we select only the job with the highest average earnings. We also exclude observations that either did not report wages or reported a null value.

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 31st of each year.

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[1] The Programa de Integração Social (PIS) represents a number that is unique for workers in Brazil and is associated with federal worker benefits programs. The Cadastro Nacional de Pessoas Jurídicas (CNPJ) is a national unique identifier for firms designated by the Brazilian tax authority.

Each year, RAIS reports average monthly wages in current values (Brazilian Reais - BRL) and in the 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). 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.

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. 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.

A.2 Additional Trends in Wage Inequality

Table A.1 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 bottom-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, 2022) and gender, race, education, and experience wage gaps (Nopo, 2012; Messina and Silva, 2017).

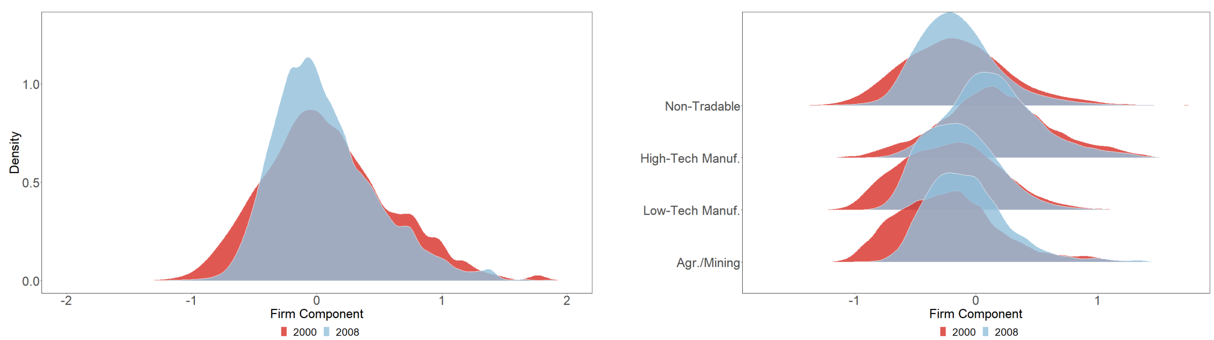
Table A.1. Firm Component Descriptive Statistics

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.

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-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.

Figure A.1 illustrates the distribution of $\hat{\psi}_{ft}$ in 2000 and 2008. The bottom of the distribution seems to have shifted faster relative to the top. Panel B in Figure A.1 illustrates the trend in the within-sector component. In general, the fall in inequality observed in Panel B follows a similar pattern across sectors, suggesting a concomitant and equivalent change in wage inequality (as measured by wage variances). 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.



(A) Overall Density

(B) Density by Sector

Figure A.1. 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. Panel (A) displays the density for the sample of all firms. In Panel (B), we separate the density by sectors.

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. But how are these changes associated with a firm's characteristics, like their size or exporter and importer status?

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

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

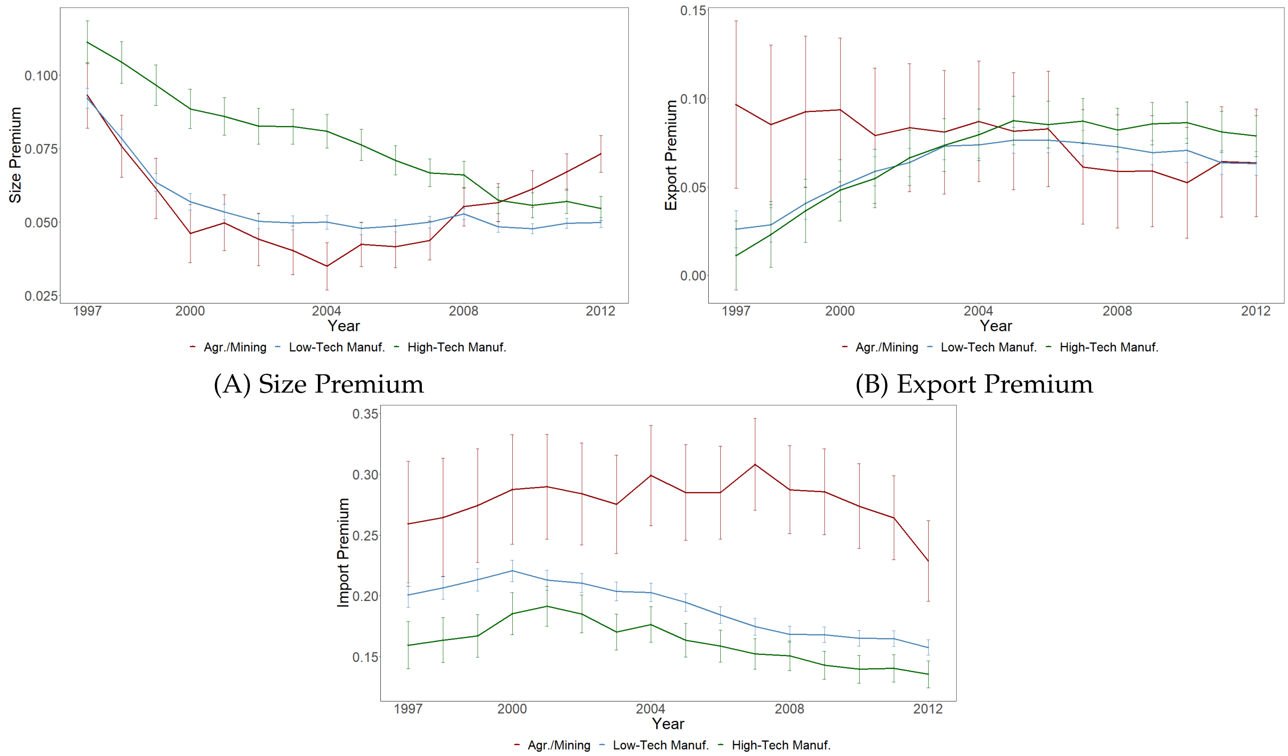
$\hat{\psi}_{ft}$ is defined as above, $log(size)$ and $export$ are the log of number of employees and exporter status, respectively. $\mathbb{1}(s)$ is an indicator variable that assumes value 1 when the firm operates in sector s (Agriculture/Mining, Low-Tech Manufacturing, and High-Tech Manufacturing). 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. (A.1) separately for each year t.

The point estimates for β_{1st}, β_{2st}, and β_{3st} are reported in Figure A.2. Consistent with the literature, the figures show that large exporters and importers pay higher wages on average since the parameters are positive and highly statistically significant (Melitz, 2003; Helpman et al., 2017). Nonetheless, the strength of these relationships seems to have declined over time. Panel (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.

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.

Panel (B) of eq. (A.1) shows low heterogeneity of export premium across sectors and no trend over time. The coefficients range from 0.01 and 0.1. In contrast, Panel (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



(A) Size Premium

(B) Export Premium

(C) Import Premium

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

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.

Our findings about the trends in wage inequality can be summarized as follows:

1. After controlling for observables, the between-firm component is the major contributor to the fall in the 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) declined 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.

One of the limitations of RAIS is that it only contains formal workers and firms. One natural concern is the role of informality in the trends we discuss above. The literature documents that the informality rate in Brazil decreased by almost ten percentage points over the 1990s and 2000s. However, the informal labor market still represented between 40 and 50 percent of the labor force by 2010.[2]

In Appendix B, we perform a series of tests to account for the influence of the informality rate decline on the formal wage distribution. The results corroborate our findings and suggest that the trends discussed above did not change significantly after controlling for the informal labor market influence. A full analysis of the effects of informality is in the Appendix B.

Appendix B 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. (2.4). But, more importantly, we want to understand whether different assumptions on the effect of informality impact our conclusions from Table 1 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

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

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

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

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 et al. (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 et al. (2015), which suggests that there is a significant overlapping area between the productivity distributions of both markets. Figure B.1.A plots the share of entry workers in the total workers per quartile of the formal wage distribution. Figure B.1.B plots the share of entry workers in the total number of entry workers each year per quartile 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. (B.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^2_{st} is a within-groups change in the volatility for a given workforce composition.[3] The second sum on the right-hand side of eq. (B.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. (B.1) in Figure B.2. We assume different probabilities for a worker entering the formal

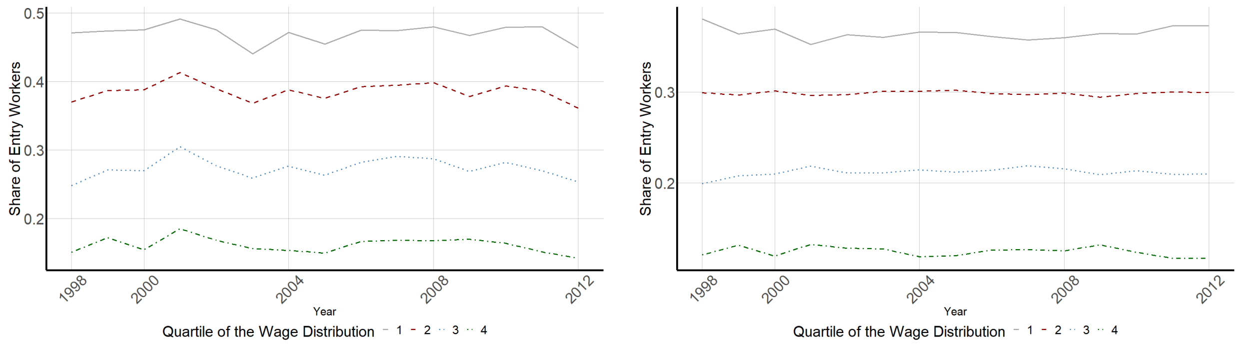
[3]The decomposition and terminology are similar to Engbom et al. (2022).

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 B.3 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. (2.4) 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 to capture the upper-bound effect of informality on formal wage inequality. The results are presented in Table B.1.

The first two columns repeat the decomposition in Table 1. 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. (2.4), which is more common in the literature [Helpman et al. (2017)]. Figure B.4 shows the relationship between the two measures for ψ_{of} for each decile of the log wage distribution in 2000 and 2008.



(A) Share in the Total (B) Share in the Entry Workers

Figure B.1. Entry Workers and the Formal Wage Distribution. Figure (A) shows the evolution in the share of entry workers in the total number of workers in each quartile of the formal wage distribution. Figure (B) shows the share of entry workers in the total number of entry workers per year workers in each quartile of the formal wage distribution.

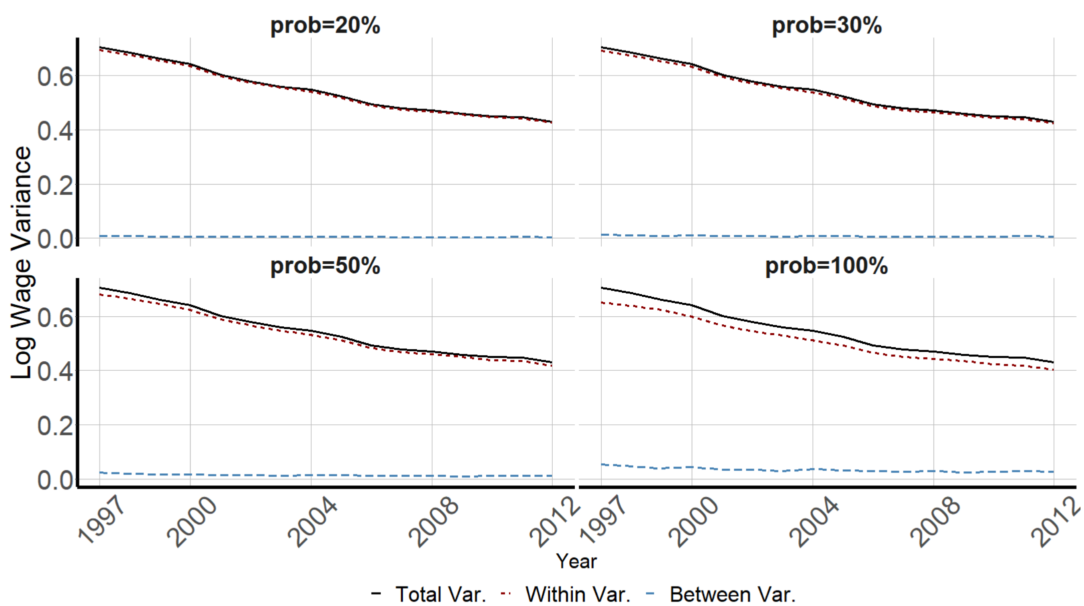


Figure B.2. Formal Wage Variance Decomposition and the Effect of Informality. The figures display the decomposition of the formal log wage variance following Eq. (B.1). Each graph has a definition regarding the groups of workers who entered the formal labor market as a consequence of the change in the 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.

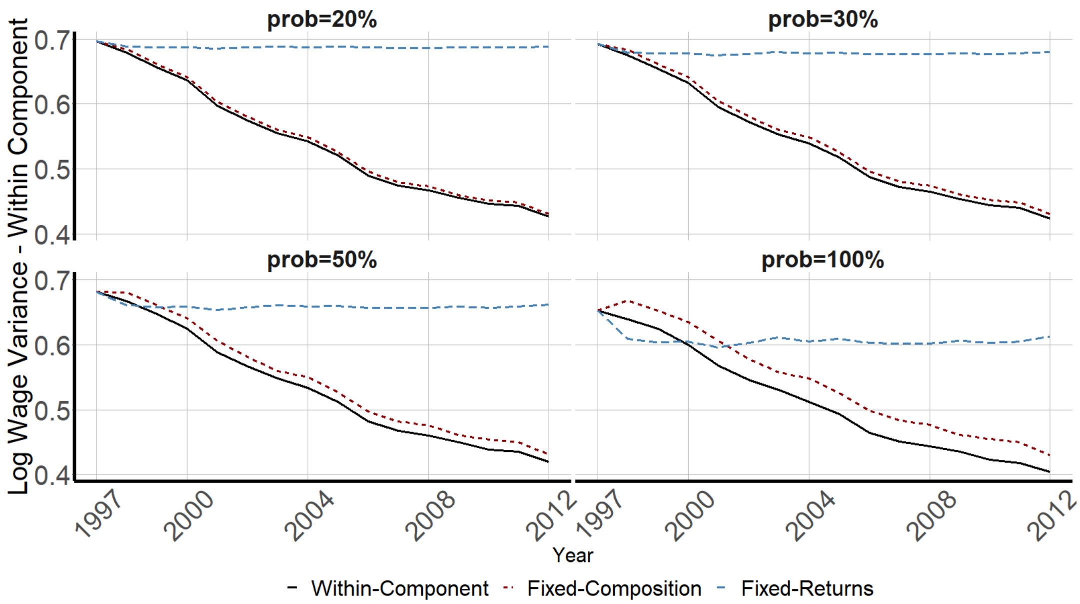


Figure B.3. Decomposition of the Within Component. The figures display the decomposition of the formal log wage variance following Eq. (B.1). Each graph has a definition regarding the groups of workers who entered the formal labor market as a consequence of the change in the informal labor market. Prob=P%, for $P \in \{20, 30, 50, 100\}$ means that P percent of new entries are due to the informality rate decline.

Table B.1. 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. (2.4). $log(wage)$ 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 1. "Control For Informality" refers to the decomposition controlling for the effects of informality. The last columns show the correlation between the components in each specification.

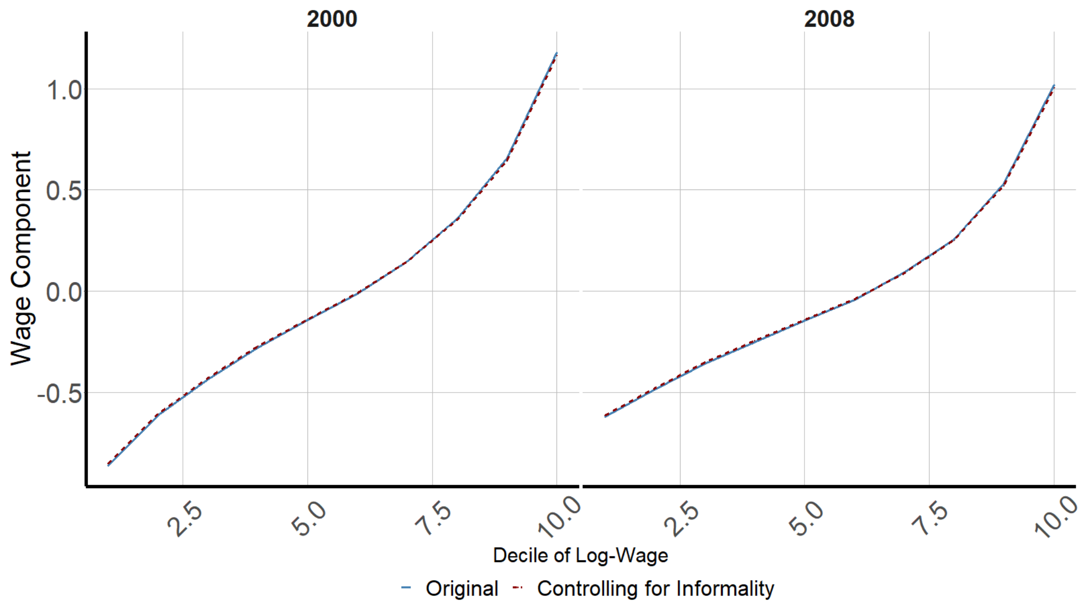


Figure B.4. Estimates of the Occupation-Firm Wage Component by Deciles of the Log Wage Distribution. The figures display the average estimated values of ψ_{of} in the original model based on Eq. (2.4) and controlling by the influence of the fall in the informality rate. The horizontal axis presents the deciles of the log wage distribution in each year.

Appendix C Exposure Measures and First Stage Results

As it is often discussed in the literature, 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.

To obtain consistent estimates of the parameters of interest, we use an identification strategy based on Costa et al. (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 that are specific to Chinese changes 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 except Brazil. In the first stage, we run the following auxiliary regressions:

$$\frac{\widetilde{M}_{ijt} - \widetilde{M}_{ij,2000}}{\widetilde{M}_{ij,2000}} = \alpha_s + \theta_{jt,China} + \varepsilon_{ijt} \tag{C.1}$$

$$\frac{\widetilde{E}_{ijt} - \widetilde{E}_{ij,2000}}{\widetilde{E}_{ij,2000}} = \beta_s + \phi_{jt,China} + \mu_{ijt} \tag{C.2}$$

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 average demand change for imports in each industry j between year t and 2000. Similarly, $\phi_{jt,China}$ represents China's average 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:

$$IPW^*_{jt} = \frac{M_{j2000} \times \hat{\phi}_{jt,China}}{L_{j,2000}} \tag{C.3}$$

$$EPW^*_{jt} = \frac{E_{j2000} \times \hat{\theta}_{jt,China}}{L_{j,2000}} \tag{C.4}$$

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 $\hat{\theta}_{jt,China}$ captures the demand shock from China in each industry j, which is used to construct the instrumental variable for the export exposure to Brazilian industries. $\hat{\phi}_{jt,China}$ captures the Chinese supply shock in each industry j, which we use to construct the instrumental variable for the import exposure in Brazil. To construct instruments for the indirect exposure, we simply substitute the measures in eq. (C.3) and eq. (C.4) into the formulas in eq. (2.3).

The first stage results at the industry level are presented on C.1. Table C.2 presents the descriptive statistics of our measures.

Table C.1. 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. (3.2). 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.

Table C.2. Descriptive Statistics of Trade Shocks

Shock		Percentile					Std. Dev.	Mean			
		10	25	50	75	90		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.

Appendix D Firm Selection in the Reduced-Form Estimates

As discussed in the text, since we only use active firms in our firm-level specifications, we need to control selection. We follow Amiti and Cameron (2012) and estimate and apply the selection procedure as proposed in Heckman (1979). For that, 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 (log) cost of opening a firm is multiplied by the average time to open those firms in the same circumstances. This measure captures the costs associated with opening a firm in Brazil and it is heterogeneous across Brazilian states and the 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. Values from Firjan, The Federation of Manufacturing Industries of Rio de Janeiro (FIRJAN (2010)) for 2010 and are time-invariant.

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. 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. 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).

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 D.1 in the Appendix. The Inverse-Mills ratio (up to third-order polynomial), as suggested in Heckman (1979).

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

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

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 2. 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. (D.1). Our preferred one is a Probit model. The results are reported in Table D.1.

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 control 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 2. 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 D.1. 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 D.1. 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 operated 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 highly educated workers, and formality rate. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix E Model

E.1 Demand

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 $s \in S$

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

$v_s > 0 \; \forall s$ is the normalized share of sector s in the total expenditure, so that $\sum_{s \in S}^{S} v_s = 1$. 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

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

where ϵ determines the elasticity between domestic and imported goods $1/(1-\epsilon) > 1$, also known as Armington elasticity.[4] β controls the elasticity of substitution between varieties equal to $1/(1-\beta) > 1$.[5] The comprehensive price index for domestic varieties is given by:

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

[4] Feenstra et al. (2018) provides a good summary of the use of Armington's elasticity and its estimation challenges.

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

where $p(j)$ is the price of variety j. We define the price index for imported varieties (P_s^*) analogously. From 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

$$P_s^* = \frac{1}{A_d}\tau_m P_s, \tag{E.1}$$

so that there is no arbitrage between domestic and imported varieties. $1/A_d$ is a term that represents relative supply shocks between 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, decreasing $1/A_d$. Thus, we can solve the total domestic expenditure in varieties in sector s:

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

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:

$$E_s = \upsilon_s E,$$

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

$$p(j) = \left(1 + A_d^{1/(1-\epsilon)} \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)} (\upsilon_s E)^{1-\beta} P_s^{\beta} q(j)^{-(1-\beta)}. \tag{E.2}$$

We can obtain a firm's revenue by multiplying prices and quantities for a domestic variety j:

$$r(j) = p(j)q(j) = \left(1 + A_d^{1/(1-\epsilon)} \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)} (\upsilon_s E)^{1-\beta} P_s^{\beta} q(j)^{\beta}.$$

or

$$r(j) = \bar{A}_s \left(1 + A_d \tau_m^{-\epsilon/(1-\epsilon)}\right)^{-(1-\beta)} q(j)^{\beta}, \tag{E.3}$$

where $\bar{A}_s = (v_s E)^{1-\beta} P_s^{\beta}$, and, with some abuse of notation, we can write $A_d \equiv A_d^{1/(1-\epsilon)}$, since later in this work we will be only interested in the non-tariff shifts to imports.

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_d, so that an 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, makes imported goods more expensive relative to domestic goods, leading to a higher demand for the outputs of domestic firms. A reduction in tariffs increases the competition with imported goods, decreasing the domestic firm's revenues.

E.2 Firm Production

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 returns 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. For simplicity, we assume that this elasticity of substitution between foreign and domestic inputs for firms is the same as the elasticity of substitution between foreign and domestic products for consumers.

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. (E.1). The solution leads to

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

which we simplify to

$$I \;=\; \bar{B}_s \left(1 + A_m \tau_m^{-\epsilon/(1-\epsilon)}\right)^{1/\epsilon}. \tag{E.4}$$

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_d. 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. (E.4) makes it bigger than 1. We also incorporate the constant term $B_d^{1/\epsilon} I_d$ into A, 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

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

That yields the revenue for an exporter

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

Together, the conditions for importer/non-importer or exporter/non-exporter firm lead to the revenue:

$$R = \left[1 + \iota_x \left(\Upsilon_x - 1\right)\right]^{1-\beta} \left[1 + \iota_m \left(\Upsilon_m - 1\right)\right]^{\beta/\epsilon} \left[1 + A_d \tau_m^{-\epsilon/(1-\epsilon)}\right]^{-(1-\beta)} \bar{A}_s \bar{B}_s Y^\beta, \tag{E.5}$$

with

$$\Upsilon_x = 1 + A_x \tau_x^{\frac{-\beta}{1-\beta}} \;>\; 1 \quad \text{and} \quad \Upsilon_m = 1 + A_m \tau_m^{\frac{-\epsilon}{1-\epsilon}} \;>\; 1.$$

In this equation, with some notation abuse, we simplify $A_x = \left(\frac{A_x}{A_d}\right)^{\frac{1}{1-\beta}}$, since later in the counterfactual exercises, we do not need to identify all the structural constant terms separately, but only export, import, and demand shifters.

In these equations, (ι_x, ι_m) are the indicators of whether firms export or import, respectively. $\Upsilon_x^{1-\beta}$ and $\Upsilon_m^{\beta/\epsilon}$ are the firm revenue premium from exporting and importing, respectively. They are decreasing in the bilateral trade cost parameter (τ_x, τ_m) and increasing in the foreign demand shifters (A_x, A_m). The firm's revenue is decreasing on shifters of demand for external goods (A_d), reflecting the effect of importing competition.

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.

E.3 Labor Market

Each firm hires a measure H of workers. Following Helpman et al. (2010), each worker has an ability level, a, which firms do not directly observe and have an incentive to screen. With heterogeneous screening costs added to the model, à la Helpman et al. (2017), the production technology is

$$Y = e^{\theta} H^{\gamma} \bar{a}, \quad 0 < \gamma < 1, \tag{E.6}$$

where $\bar{a}$ represents the average ability of the hired workers, γ is the elasticity of employed workers. Following Helpman et al. (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 et al. (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:

$$W = \frac{\beta\gamma}{1+\beta\gamma}\frac{R}{H}. \tag{E.7}$$

E.4 Firm's Problem

Timing i) firms independently draw a cost of operating in each sector of the economy $C_{\pi,s}$, and choose the sector to operate based on the expected profit; ii) Once in a sector, firms draw their idiosyncratic components $(\theta, \eta, \varepsilon_x, \varepsilon_m)$; iii) pay for fixed costs of searching, screening, exporting, and importing; iv) choose the amount of intermediate inputs, workers, production; and v) finally engages in multilateral bargaining with its H workers over wages.

Firms solve the following problem (we omit firm and sector subscripts for simplification):

$$\Pi(\theta,\eta,\varepsilon) = \max_{N, a_c, \iota_x, \iota_m \in \{0,1\}} \left\{ \frac{1}{1+\beta\gamma} R\left(N, a_c, \iota; \theta\right) - bN - e^{-\eta}\frac{C}{\delta}\left(a_c\right)^{\delta} - \iota_x e^{\varepsilon_x} C_x - \iota_m e^{\varepsilon_m} C_m \right\}, \tag{E.8}$$

where the revenue $R\left(N, a_c, \iota; \theta\right)$ is defined by eq. (E.5), eq. (E.6), and the functions that determine the workers hired and their expected ability. The solution to the firm's profit maximization problem yields the following equations:

$$R = \kappa_r \left[1 + \iota_x\left(\Upsilon_x - 1\right)\right]^{\frac{1-\beta}{\Gamma}} \left[1 + \iota_m\left(\Upsilon_m - 1\right)\right]^{\frac{\beta}{\epsilon\Gamma}} \left[1 + A_d \tau_m^{-\epsilon/1-\epsilon}\right]^{-\frac{1-\beta}{\Gamma}} \left(e^{\theta}\right)^{\frac{\beta}{\Gamma}} \left(e^{\eta}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}}, \tag{E.9}$$

$$H = \kappa_h \left[1 + \iota_x\left(\Upsilon_x - 1\right)\right]^{\frac{(1-\beta)(1-k/\delta)}{\Gamma}} \left[1 + \iota_m\left(\Upsilon_m - 1\right)\right]^{\frac{\beta(1-k/\delta)}{\epsilon\Gamma}} \left[1 + A_d \tau_m^{-\epsilon/1-\epsilon}\right]^{\frac{-(1-\beta)(1-k/\delta)}{\Gamma}} \left(e^{\theta}\right)^{\frac{\beta(1-k/\delta)}{\Gamma}} \left(e^{\eta}\right)^{-\frac{k-\beta}{\delta\Gamma}} \tag{E.10}$$

$$W = \kappa_w \left[1 + \iota_x\left(\Upsilon_x - 1\right)\right]^{\frac{k(1-\beta)}{\delta\Gamma}} \left[1 + \iota_m\left(\Upsilon_m - 1\right)\right]^{\frac{k\beta}{\epsilon\delta\Gamma}} \left[1 + A_d \tau_m^{-\epsilon/1-\epsilon}\right]^{-\frac{k(1-\beta)}{\delta\Gamma}} \left(e^{\theta}\right)^{\frac{\beta k}{\delta\Gamma}} \left(e^{\eta}\right)^{\frac{k(1-\beta\gamma)}{\delta\Gamma}}, \tag{E.11}$$

Eq. (E.9) to eq. (E.11) are sufficient to determine a firm's profits. Thus, we also find sufficient conditions for firms to export or import is given by

$$\kappa_\pi \left(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1 \right) \left(e^\theta \right)^{\frac{\beta}{T}} (e^\eta)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} \geq C_x e^{\varepsilon_x} \tag{E.12}$$

and

$$\kappa_\pi \left(\Upsilon_m^{\frac{\beta}{\epsilon\Gamma}} - 1 \right) \left(e^\theta \right)^{\frac{\beta}{T}} (e^\eta)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} \geq C_m e^{\varepsilon_m}. \tag{E.13}$$

Eq. (E.9) to eq. (E.13) 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. (E.9), eq. (E.10) and eq. (E.11) 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. (E.12) establishes a sufficient condition for the firm to become an exporter, whereas eq. (E.13) presents a sufficient condition for the firm to become an importer.

Eq. (E.10) and eq. (E.11) 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.[6] As a consequence, it also characterizes the positive correlation between firm size and wage.[7] 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. (E.12) and eq. (E.13) 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 employ more workers, as determined in eq. (E.10) and eq. (E.11). This is consistent with our reduced-form findings and other papers in the literature. HIMR calls the mechanism derived from eq. (E.12) and eq. (E.13) as *selection effect* and the premia implied in eq. (E.10) and eq. (E.11) as *market access*. Amiti and Davis (2012) calls the combination of such effects as *import globalization* and *export globalization*.

[6] Notice that higher screening efficiency means that firms are better at obtaining information about the *unobserved ability* of a worker. Screening efficiency should not affect occupational or educational composition changes because these are *observable* by firms.

[7] 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.

Appendix F Econometric Framework

F.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

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

because u and v are not correlated as assumed in eq. (4.13).

We have

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

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

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

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 is expressed in eq. (4.17). Using the distributions for $(z_x, z_m | u, v)$, u, and v, we can transform the distribution for the likelihood functions in eq. (4.14).

Constraints eq. (4.15) and eq. (4.16) are straight from the model, as shown by HIMR (see Lemma S.1 in the online appendix).

We estimate eq. (4.18) 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. (4.12) and eq. (4.13). Firstly, the assumptions that unconditional variance of z_x and z_m equal one, which are derived from eq. (E.12) and eq. (E.13). 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[8]

$$\zeta \;\leq\; \frac{\mu_{w,xs}}{\mu_{h,xs}}\,,\ \frac{\mu_{w,ms}}{\mu_{h,ms}} \;\leq\; \frac{\sigma_v^2}{(1+\zeta)\sigma_u^2}, \tag{F.3}$$

and

$$\mu_{w,xs}, \mu_{h,xs}, \mu_{w,ms}, \mu_{h,ms} \;>\; 0 \tag{F.4}$$

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

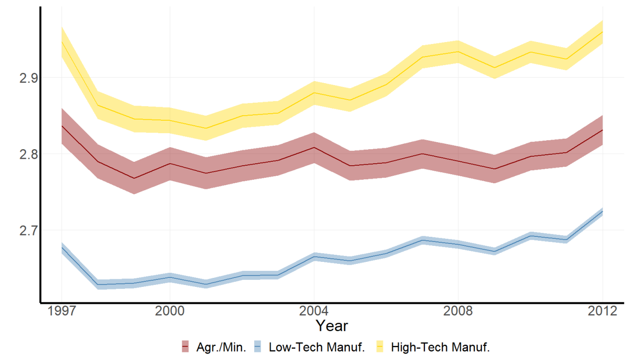
$$(1-\rho_{ux}^2-\rho_{vx}^2)(1-\rho_{um}^2-\rho_{vm}^2)-(\rho_{xm}-\rho_{ux}\rho_{um}-\rho_{um}\rho_{vm})^2 \;>\; 0 \tag{F.5}$$

Therefore, the ML estimator maximizes eq. (4.18) subject to constraints eq. (F.3), eq. (F.4), and eq. (F.5).[9] HIMR argue that those constraints are essential to identify separately the parameters of 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.

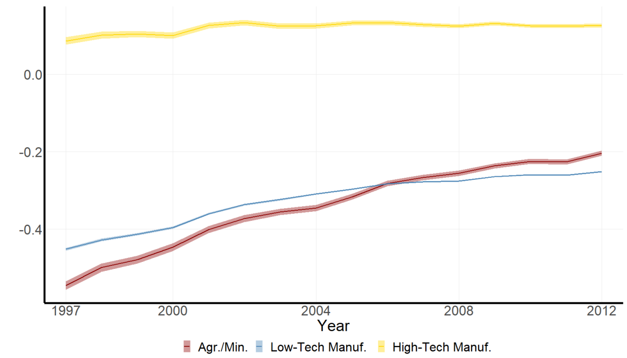
[8] We omit the formal derivation of those terms but can provide them upon request. Nonetheless, they do not fundamentally differ from Helpman et al. (2010), Helpman et al. (2017) and their respective online appendices.

[9] An additional constraint is $\rho_{xm} > 0$, which accounts for the abstraction in the implied by the sufficient conditions imposed in eq. (E.12) and eq. (E.13), 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.

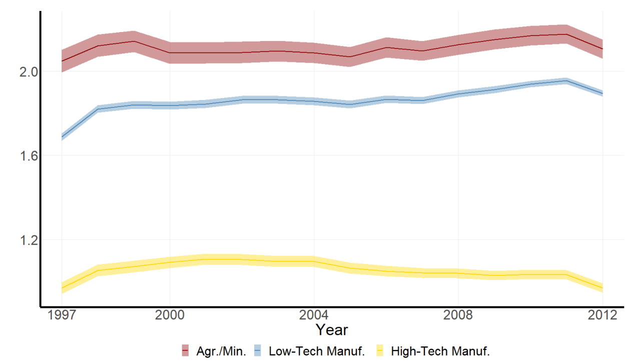
Appendix G Estimated Structural Parameters and Model Fit



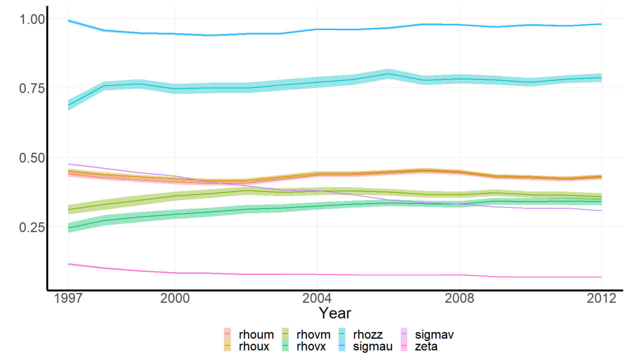
(A) α_h



(B) α_w

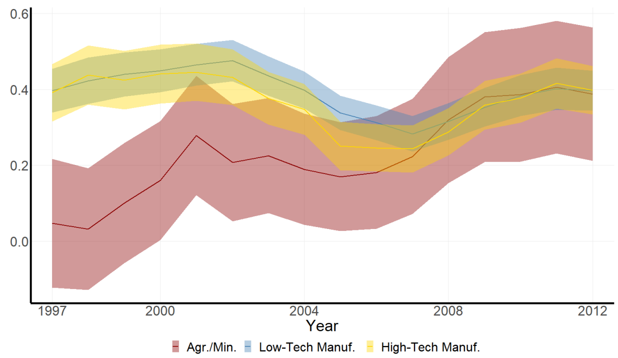


(C) c_x

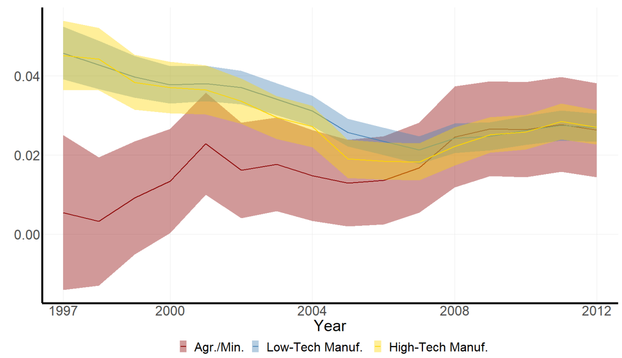


(D) Σ

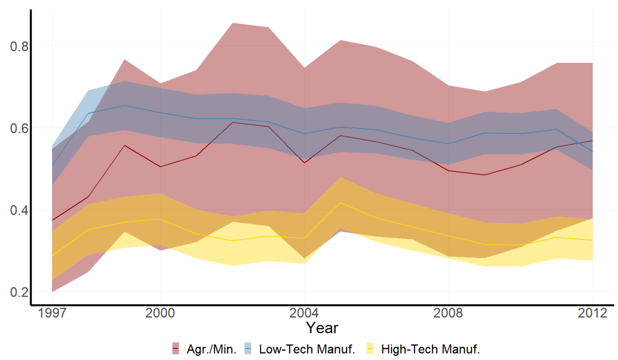
Figure G.1. Model Estimates: Aggregate Estimates and Confidence Interval by Sector and Year. The figures display the point estimates and confidence intervals for the aggregate parameters in the structural model in Eq. (4.12). Shaded areas represent 95% confidence intervals for the parameters.



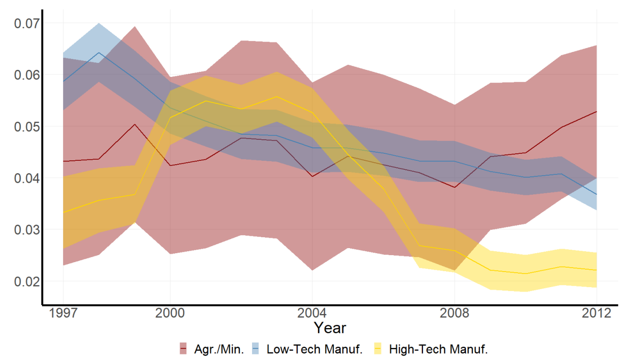
(A) μ_{hx}



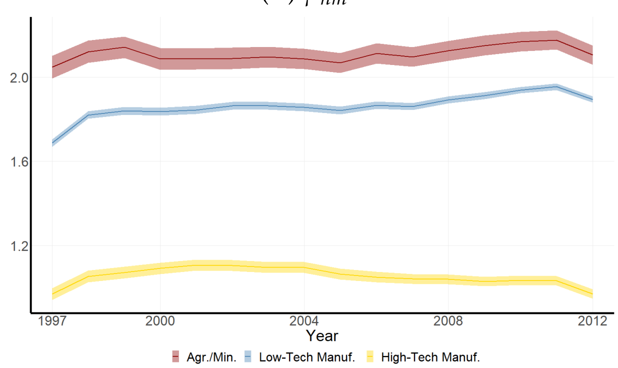
(B) μ_{wx}



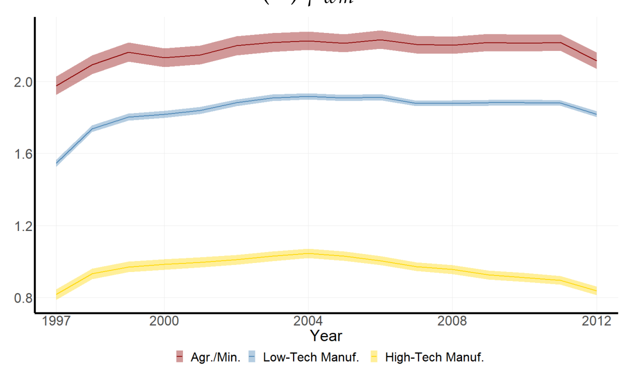
(C) μ_{hm}



(D) μ_{wm}



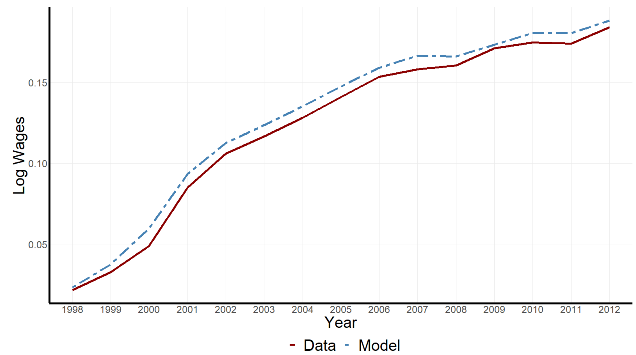
(E) c_x



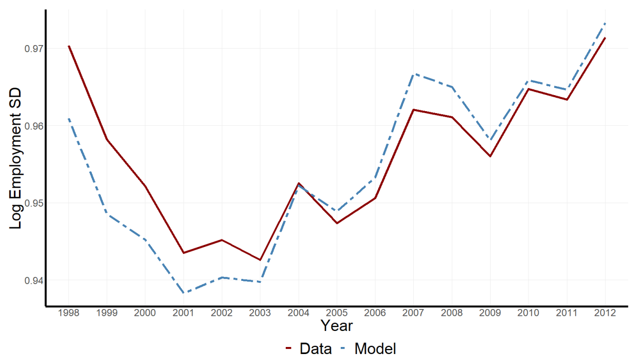
(F) c_m

Figure G.2. 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. (4.12). Shaded areas represent 95% confidence intervals for the parameters.

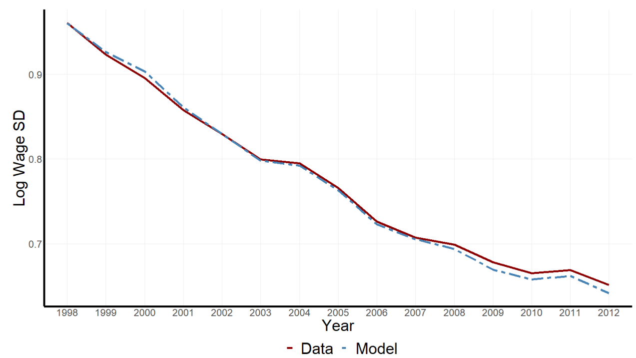
(A) Average h



(B) Average w



(C) Standard Deviation h

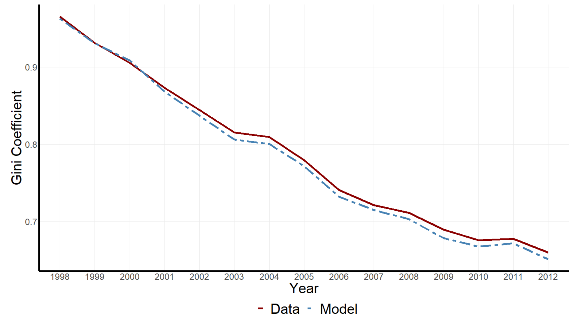


(D) Standard Deviation w

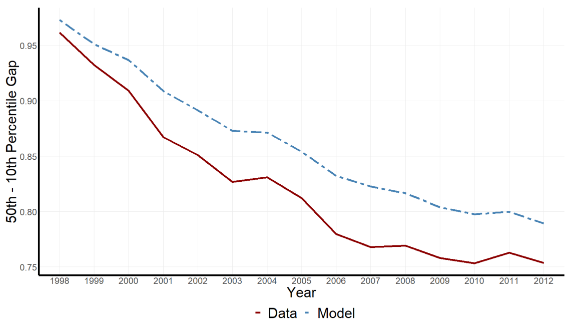
(E) Correlation h and w

Figure G.3. 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.

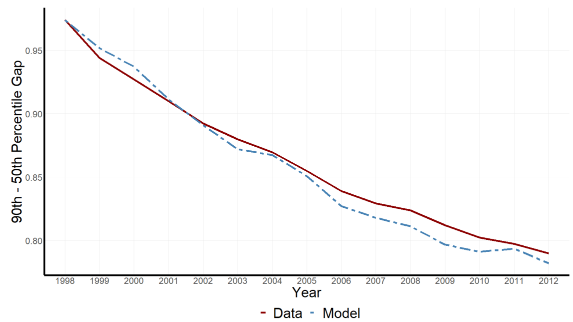
(A) Variance



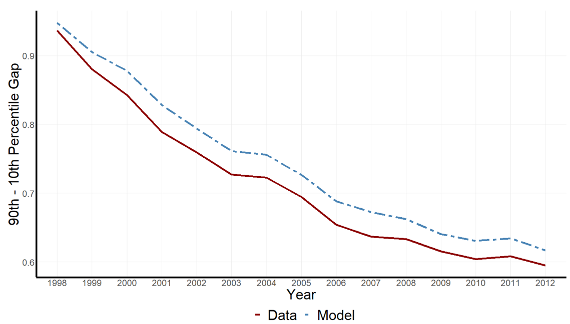
(B) Gini Coefficient



(C) 50-10 Ratio



(D) 90-50 Ratio



(E) 90-10 Ratio

Figure G.4. 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 G.1. 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 H Counterfactuals

H.1 Constructing the Counterfactuals

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_d. Import penetration decreases the demand from a firm output favoring import products. Thus, it represents an increase in A_d. 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 a decrease in A_d.

We can write α_{ws} and α_{hs} as

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

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 normalize countries before the shock so that the initial level of A_d is equal to one. We also assume that changes due to the China shock only impact A_d.

Given the changes in α_{ws} and α_{hs} and that replicate the findings in the reduced-form analysis, we may obtain A_d. 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

$$\exp(\Delta\alpha_{ws}) = \frac{\left(1+A_d\tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)k}{\delta\Gamma}}}{\left(1+\tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)k}{\delta\Gamma}}}$$

$$\exp(\Delta\alpha_{hs}) = \frac{\left(1+A_d\tau_m^{\frac{-\epsilon}{1-\epsilon}}\right)^{-\frac{(1-\beta)(1-k/\delta)}{\Gamma}}}{\left(1+\tau_m^{-\frac{\epsilon}{1-\epsilon}}\right)^{\frac{-(1-\beta)(1-k/\delta)}{\Gamma}}},$$

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. From the expressions above, we can obtain A_d.

Throughout our counterfactual exercises of the impact of a tariff change, we keep constant the term A_d, 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}.

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

$$Y_{xs}^{\frac{1-\beta}{\Gamma}} = \exp[\mu_{hx,s} + \mu_{wx,s}],$$

and

$$Y_{ms}^{\frac{\beta}{\epsilon\Gamma}} = \exp[\mu_{hm,s} + \mu_{wm,s}],$$

where s indexes sector and Y_{js} is defined as in the text for each sector. Using the definitions of Y_{xs} and Y_{ms}, we can obtain A_x and A_m as

$$A_x = \left[\exp(\mu_{hx} + \mu_{wx})^{-\frac{\Gamma}{1-\beta}} - 1\right]\tau_x^{\frac{\beta}{1-\beta}}$$

and

$$A_m = \left[\exp(\mu_{hm} + \mu_{wm})^{-\frac{\epsilon\Gamma}{\beta}} - 1\right] \tau_m^{\frac{\epsilon}{1-\epsilon}}.$$

Following HIMR, given Y_{xs} and Y_{ms} and the changes in $\alpha_{\pi s}$, we pin down the value for the entry cost into j market as

$$c_{xs} = \frac{1}{\sigma_{xs}}(-\alpha_{\pi s} + \log(C_x s) - \log[Y_{xs}^{\frac{1-\beta}{\Gamma}} - 1]),$$

and

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

Unlike a reduction in tariffs, which can be modeled with a change in τ_m, the China shock may have an impact beyond a simple change in A_d, A_m, and A_x, but also in the trade cost components C_x and C_m. For simplicity, we assume that the changes in $log(C_x)$ and $log(C_m)$ are proportional to the change in $\alpha_{\pi s}$, so that

$$\Delta c_{xs} = \frac{1}{\sigma_{xs}}((\delta_{xs} - 1)\Delta\alpha_{\pi s} - \Delta \log[Y_{xs}^{\frac{1-\beta}{\Gamma}} - 1]), \tag{H.1}$$

and

$$\Delta c_{ms} = \frac{1}{\sigma_{ms}}((\delta_{ms} - 1)\Delta\alpha_{\pi s} - \Delta \log[Y_{ms}^{\frac{\beta}{\epsilon\Gamma}} - 1]), \tag{H.2}$$

where δ_{xs} and δ_{ms} are constants that can be calibrated by making the changes in the probabilities of a firm becoming an exporter or an importer. For that, we use the impact of export and import exposure found in the reduced-form results.

Note that for the share of exporter or importer firms to increase as a consequence of the China shock, both Δc_{xs} and Δc_{ms} must be negative. In terms of eq. (H.1) and eq. (H.2), it means that the selection effects arising from increases on Y_{xs} and Y_{ms} and decrease coming from C_{xs} and C_{ms} that influence firms to export and import must be stronger than the import competition effects that result in a decline in $\alpha_{\pi s}$. The terms $(\delta_{xs} - 1)$ and $(\delta_{ms} - 1)$ will guarantee that these conditions hold.

Eq. (H.1) and eq. (H.2) only establish a relationship between firm selection into exports and imports through the trade impact on $\alpha_{\pi s}$. Downstream export exposure shocks increase A_d, which leads to an increase in $\alpha_{\pi s}$ and thus a higher probability of firms becoming both, exporters and importers. Analogously, downstream import exposure shocks decrease A_d, leading to a decline in $\alpha_{\pi s}$ and thus reducing the probability of firms becoming both, exporters and importers. Thus, there is a correlation between import shocks and selection into exports and export shocks and selection into imports.

Finally, after calibrating the values for A_d, A_m, A_x, δ_{xs}, and δ_{ms} 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_d, A_m, A_x, δ_{xs}, and δ_{ms} and change only the import tariffs τ_m to counterfactual levels. This exercise allows us to understand what would have happened if there had been another round of trade opening in the Brazilian economy, together with the China shock.

H.1.1 Modeling Trade Costs Correlation

Note that the correlation coefficient ρ_{xm} between the shock terms z_x and z_m presented in equation eq. (F.2) is given by

$$\rho_{xm} \;=\; E\left[\left(\frac{1}{\sigma_x}(u+v-\varepsilon_x)\right)\left(\frac{1}{\sigma_m}(u+v-\varepsilon_m)\right)|u,v\right], \tag{H.3}$$

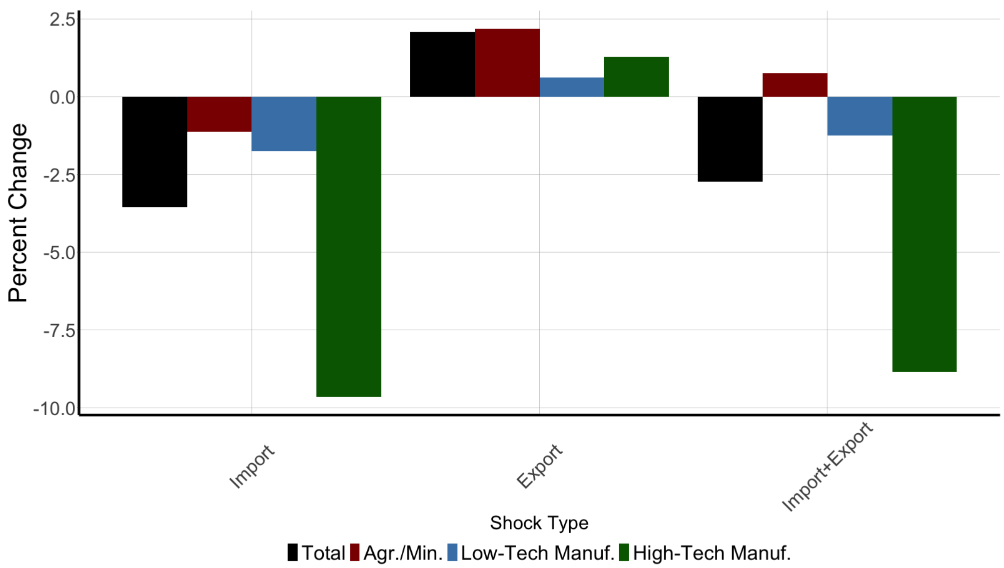
and depends on the correlation between ε_x and ε_m. As shown in the results, high (around 0.75) and relatively constant between 1997 and 2012. As a consequence of such correlation, even under import- or export-only shocks, there will be changes in the selection incentives into the import or export markets.

There exists a plausible relationship between trade costs C_x and C_m that are not modeled explicitly in Eq. (H.1) and eq. (H.2). To account for that, we also calibrate and simulate the model, assuming more explicitly that the correlation between the trade costs directly affects the selection choices. For that, we introduce the correlation by multiplying eq. (H.1) and eq. (H.2) by the conditional variance-covariance matrix between ε_{xs} and ε_{ms} given in eq. (F.2)

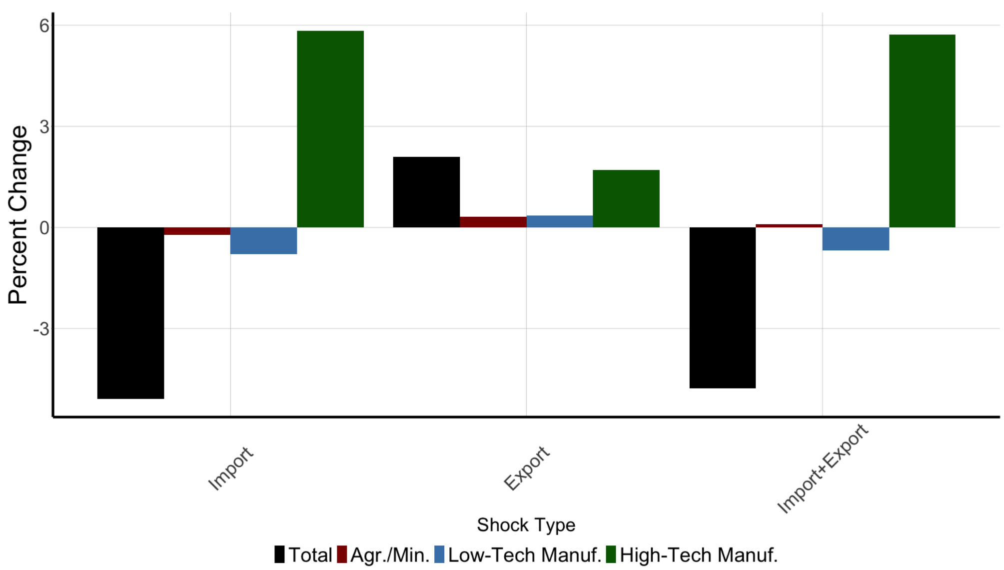
$$\begin{bmatrix}\Delta c_{xs}\\ \Delta c_{ms}\end{bmatrix} = \bar{\Sigma}_{xm} \times \begin{bmatrix}\frac{1}{\sigma_{xs}}((\delta_{xs}-1)\Delta\alpha_{\pi s} \;-\; \Delta\log[\mathrm{Y}_{xs}^{\frac{1-\beta}{\Gamma}}-1])\\ \frac{1}{\sigma_{ms}}((\delta_{ms}-1)\Delta\alpha_{\pi s} \;-\; \Delta\log[\mathrm{Y}_{ms}^{\frac{\beta}{\epsilon\Gamma}}-1])\end{bmatrix}, \tag{H.4}$$

where $\bar{\Sigma}_{xm}$ is that condition variance-covariance matrix between ε_{xs} and ε_{ms} as shown in eq. (F.2). In the main text, we report the results without this assumption. Here we report Figures H.1 to H.4

which are equivalent to Figures 4 to 7 from the main text, but when incorporating the formal correlation between trade costs from Eq. (H.4). Overall, the results remain very similar to the ones presented in the main text. The main difference is that the magnitudes of the counterfactual effects are slightly stronger following higher levels of trade openness. This is due to the fact that because of the positive correlation between selection into exporter and importer status, more firms will select into exporter status following trade openness.

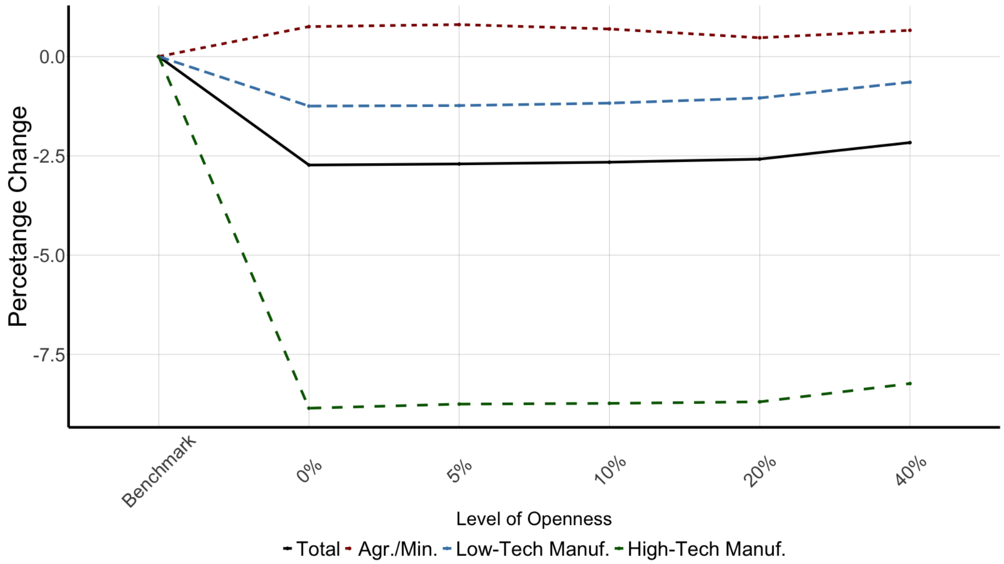


(A) Average Wages

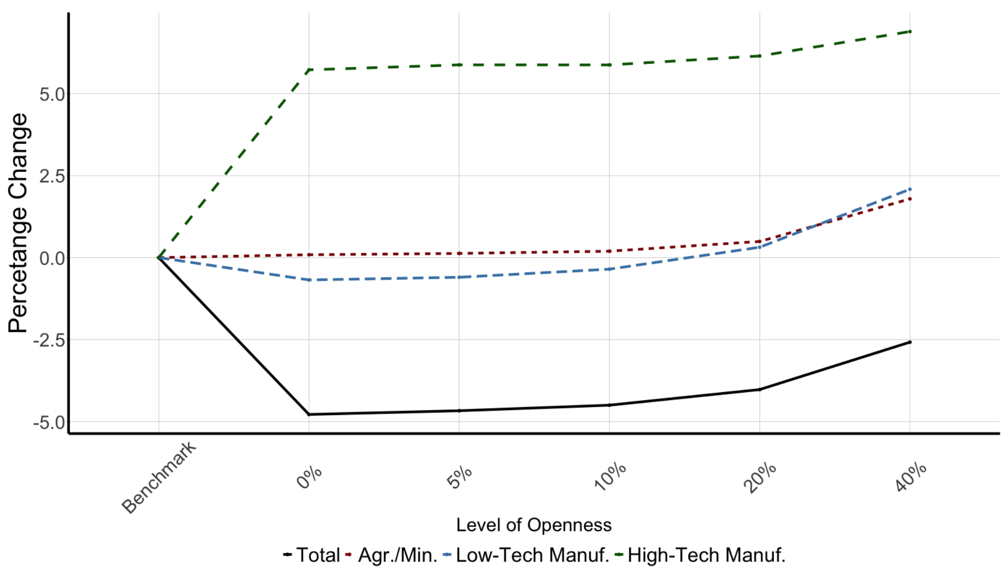


(B) Wage Variance

Figure H.1. Impact of the China Shock on Average Wages and Wage Variance Panel (A) displays the changes in average wage and Panel (B) the wage variance across sectors and for the whole economy 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.

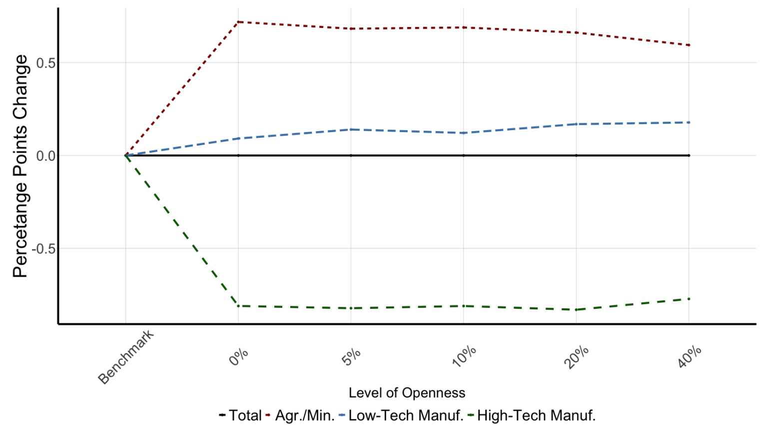


(A) Average Wage

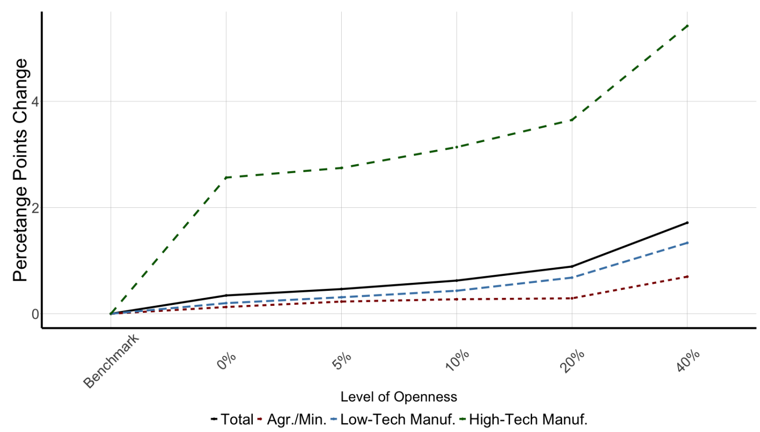


(B) Wage Variance

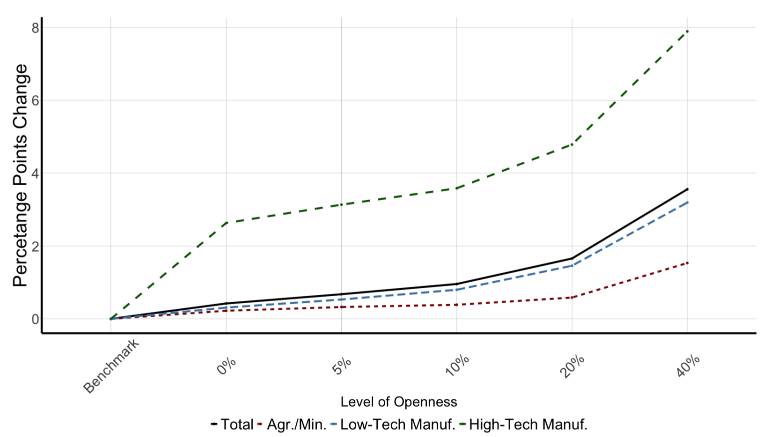
Figure H.2. **Impact of Trade Exposure and Openness on Wages.** The figures compare the average wages (Panel A) and wage variance (Panel B) for different exposures to trade shocks and levels of openness. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "0%" are the model predictions under Import+Export exposure and no change in tariffs; the remaining terms refer to predictions that combine both Import+Export exposure and assumptions on tariff reduction: 5%, 10%, 20%, and 40%.



(A) Share of Workers per Sector



(B) Share of Workers in Exporter Firms



(C) Share of Workers in Importer Firms

Figure H.3. Impact of Trade Exposure and Openness on the Share of Workers in Exporter and Importer Firms. The figures compare the changes in the share of workers in exporter firms (Panel A) and importer firms (Panel B) firms for different exposure to trade shocks and levels of openness. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "0%" are the model predictions under Import+Export exposure and no change in tariffs; the remaining terms refer to predictions that combine both Import+Export exposure and assumptions on tariff reduction: 5%, 10%, 20%, and 40%.

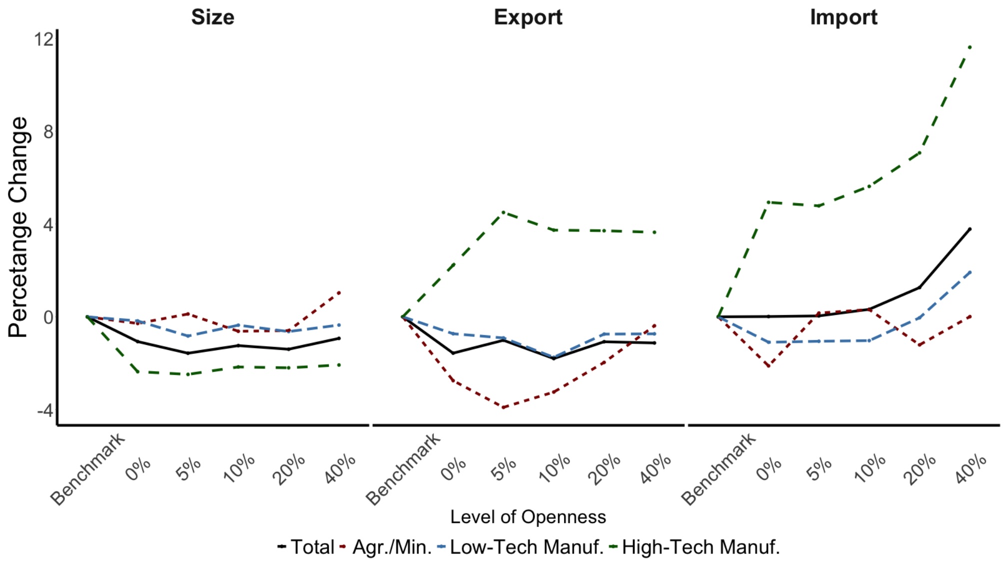


Figure H.4. Impact of Trade Exposure and Openness on Size, Export and Import Premia. The figures compare the change on size, export, and import premia. The horizontal axis displays levels of openness: "Benchmark" are the model predictions in 2000 (normalized to 1); "0%" are the model predictions under Import+Export exposure and no change in tariffs; the remaining terms refer to predictions that combine both Import+Export exposure and assumptions on tariff reduction: 5%, 10%, 20%, and 40%.

H.2 Substitution between Domestic and Imported Products

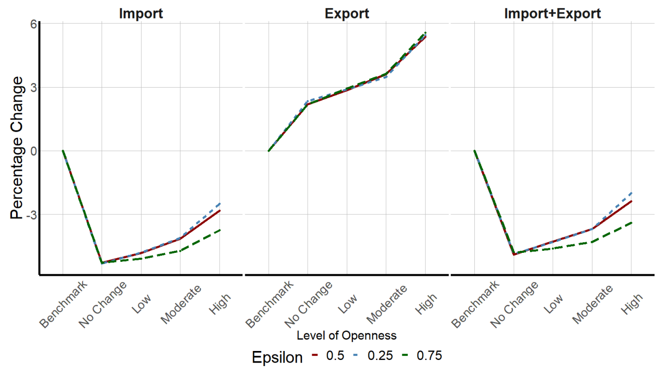
In the text, we follow Feenstra et al. (2018) and that the elasticity of substitution between domestic and imported varieties (also known as Armington's or macro elasticity) is at most equal to the elasticity of substitution between domestic varieties (also known as micro elasticity). Moreover, Feenstra et al. (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 4), 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).

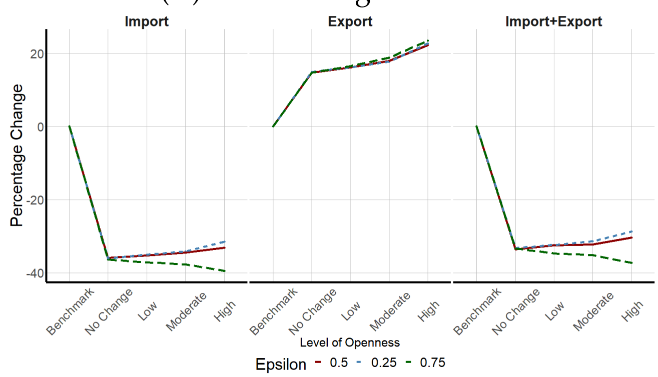
Because different assumptions over the macro elasticity reflect mainly on the import competition effect of trade shocks, we must expect that different values for this parameter will mainly reflect the variance across sectors and the null effect within the sector. In our model, import competition has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

Figure H.5 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.

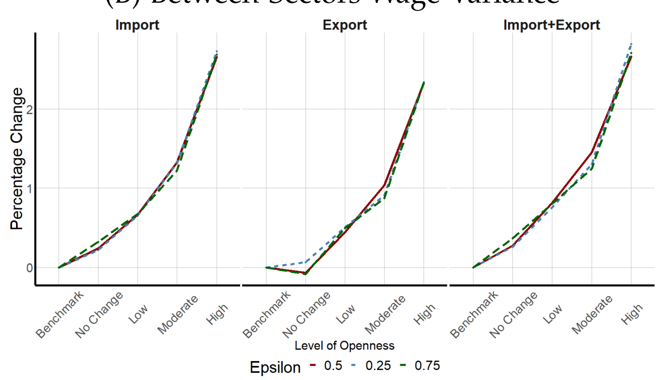
There are slight differences for each assumption on values for ϵ, mainly in the between-sector wage variance and virtually none in the within-sector wage variance. It is important to highlight the negative effect of import competition with Chinese products on wage variance. As in the main text, we documented 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 H.5. Changes Overall, Between-Sector, and Within-Sector for Assumptions on Macro Elasticity. The figures compare the percentage changes in the overall wage variance (Panel A), the between-sectors (Panel B), and within-sectors (Panel C) 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 to the values of parameter ϵ: 0.5 (our benchmark in the text), 0.25, and 0.75.

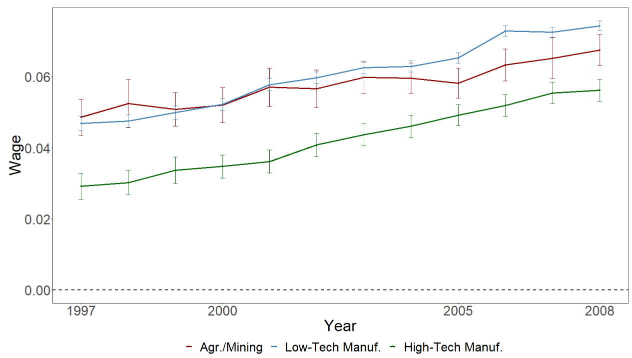
Appendix I Wages and Within-Firm Dispersion

I.1 Empirical Patterns in Within-Firm Dispersion

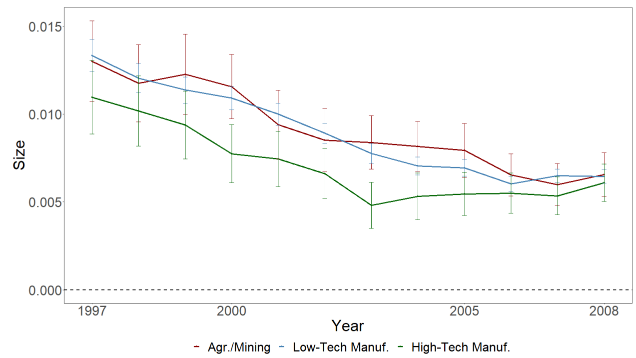
Our main empirical approach uses the wage decomposition in eq. (2.4), from which we derive an observed within-firm-occupation component ($X'_{it}\Lambda_t$), a between firm-occupation (ψ_{oft}) component, and the residual wage ($\varepsilon_{i,t}$). Following the terminology in the literature, we refer 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 wage 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 I.1 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.

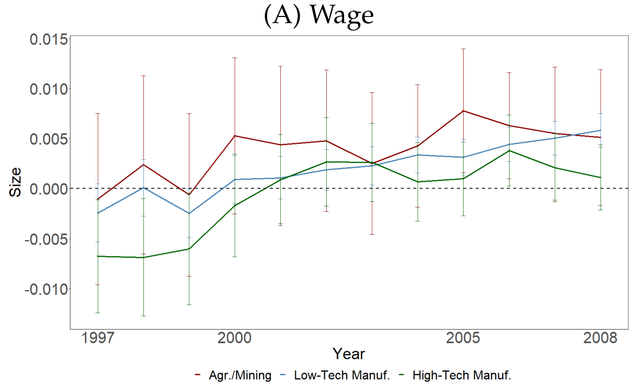
We further assess the relationship between within- and between-firm components in Figure I.2. These graphs display the binned scatter relationship between $var(\varepsilon_{ft})$ on the vertical axis and $\hat{\psi}_{ft}$ on the horizontal axis, separately for 2000 and 2008. Note that there is a strong, 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 I.1, 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.



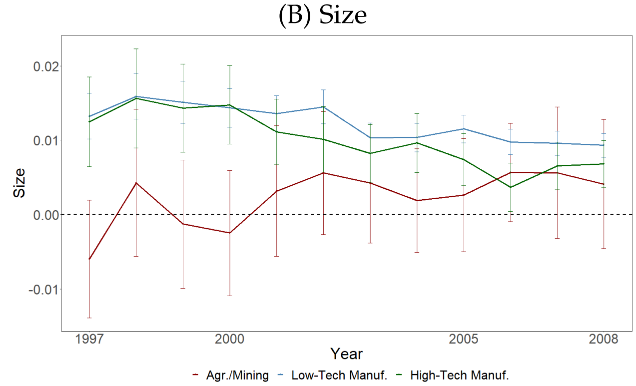
(A) Wage



(B) Size

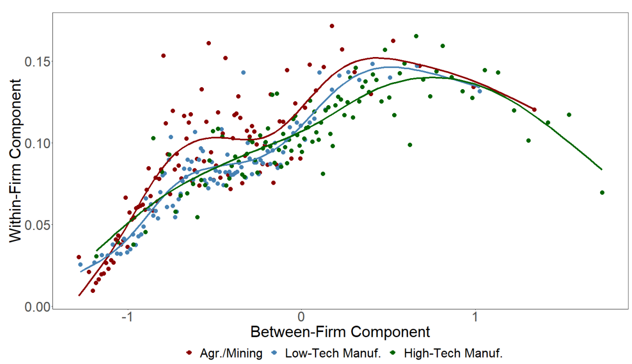


(C) Export

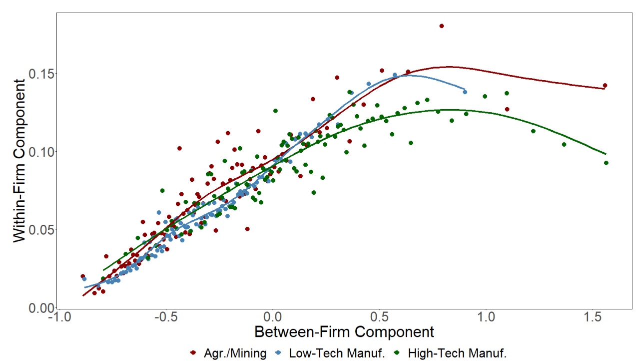


(D) Import

Figure I.1. 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 Panel (A), firm size (log of number of employees) in Panel (B), export indicator in Panel (C), and import indicator in Panel (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.



(A) Within vs. Between 2000



(B) Within vs. Between 2008

Figure I.2. 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.

Within-Firm 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.[10] Some empirical studies, however, have shown that trade liberalization can affect within-firm wage dispersion. Amiti and Cameron (2012), for instance, shows that trade liberalization in Indonesia reduced the wage skill premium within firms that imported intermediate inputs.

To investigate whether the China shock significantly impacted the within-firm-group wage dispersion, we estimate eq. (3.2) using firm-level measures of wage inequality as dependent variables. We define our main measure as the firm-level $var(\varepsilon_{it})$ resulting from Eq. (2.4), 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.[11] We use the estimates of ψ_{oft}, denoted $\hat{\psi}_{oft}$, to separate workers into two mutually exclusive groups.[12] 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).[13]

The results are presented in Table I.1. Each column displays the estimates of Eq. (3.2) for 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

[10] Helpman et al. (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 et al. (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. Pupato (2017) includes within-firm wage inequality due to optimal performance pay contracts, which generates wage dispersion among co-workers.

[11] In Helpman et al. (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.

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

[13] 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.

$\hat{\psi}_{ft}^{High} - \hat{\psi}_{ft}^{Low}$. The sample size differs from the main analysis because it is restricted to the firms for which 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 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.

I.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

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

Table I.1. 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. (3.2). Each column displays a dependent variable derived from decomposition in Eq. (2.4); $\hat{\psi}_{ft}$ 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.

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 et al. (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

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

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.[14]

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 incentivize the worker to reveal 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

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

subject to

[14] 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.

$$w(a_C) \geq 0$$

$$w(\bar{a}) = \bar{W}$$

$$w'(a) > 0$$

$$\int_{a_C}^{\infty} w(a) \frac{g(a)}{1 - G(a_C)} da = \bar{W}.$$

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

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

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. (I.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).

I.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

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

f is a second-order polynomial fit, and η_{ft} is the idiosyncratic component. The reaming terms are identical to eq. (4.12). We simplify the model by assuming that the error term v_ε is independent of the error structure in the model eq. (4.12). 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. (I.2), we estimate the first 4 equations using the same procedure described in Section 4. Separately, we estimate f using the observed variance of ε_f on the left-hand side and the wage component ψ_f on the right-hand side using f as constant and 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 4.

We plot the comparison between the observed data and the simulated data in Figure I.3. 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.

I.4 Implications to Counterfactual Analysis

In this section, we explore the implications to the model estimates after incorporating the within-firm wage variance. Results are presented in Figure I.4. 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 pay 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 I.5 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.

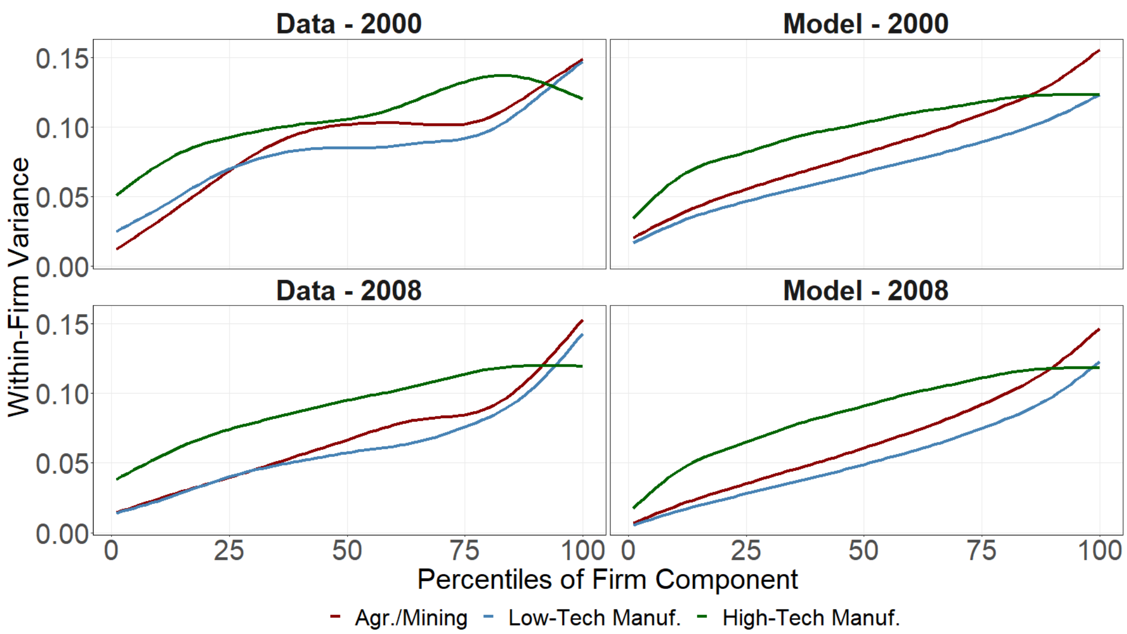


Figure I.3. Within-Firm Variance and Firm-Component. The horizontal axis displays the percentiles of the between-firm component ψ_{ft} (Data) and the simulated ψ_{ft} (Model). The vertical axis displays the average within-firm variance for each percentile of ψ_{ft}.

The results in Panel A Figure I.6 show that the decrease in the wage variance due to the China shock is mainly related to the between-sector component. Panel B of Figure I.6 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

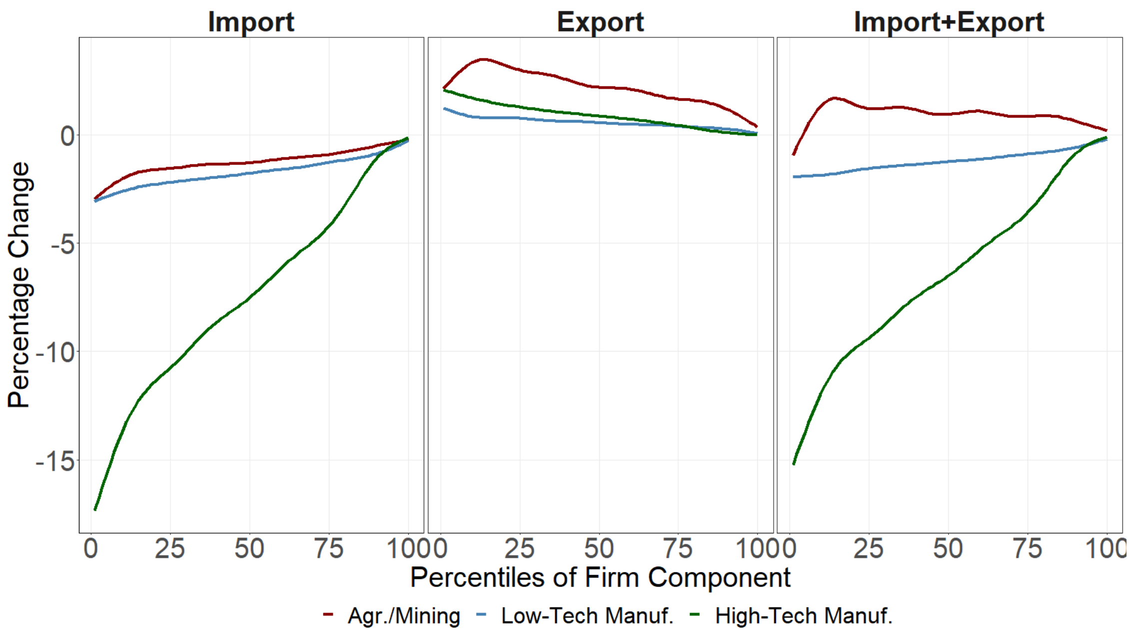


Figure I.4. Impact of the China Shock on the Within-Firm Wage Dispersion. The Figures depict the change in within-firm wage dispersion due to the China shock relative to the model predictions in 2000. The horizontal axis displays the percentiles of the between-firm component ψ_{ft} (Data) and the simulated ψ_{ft} (Model). The vertical axis displays the percentage change of the average variance within each percentile of the ψ_{ft} distribution.

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. (I.2). The increase is primarily due to the import exposure effect, which incentivizes 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 increased 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.

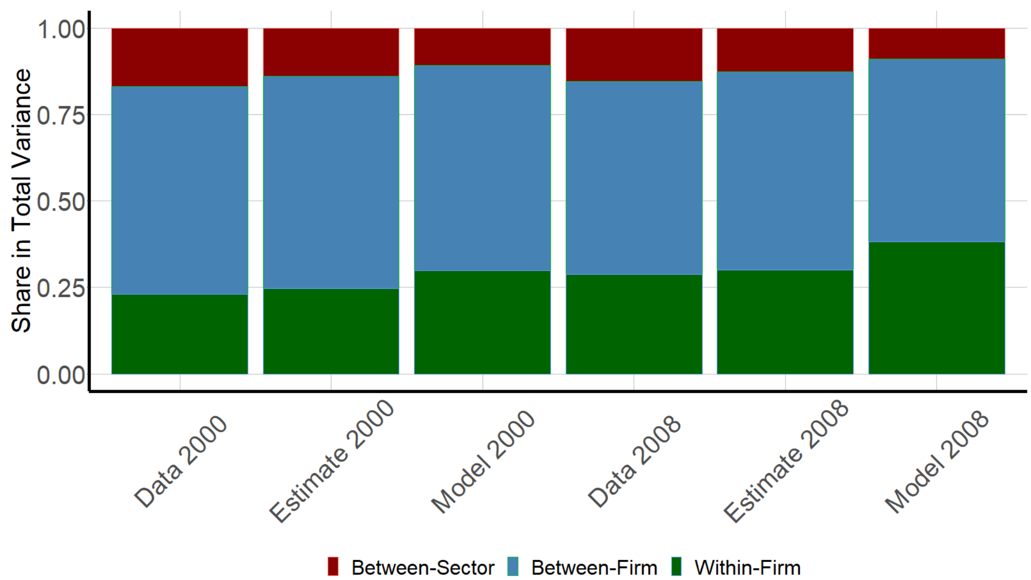
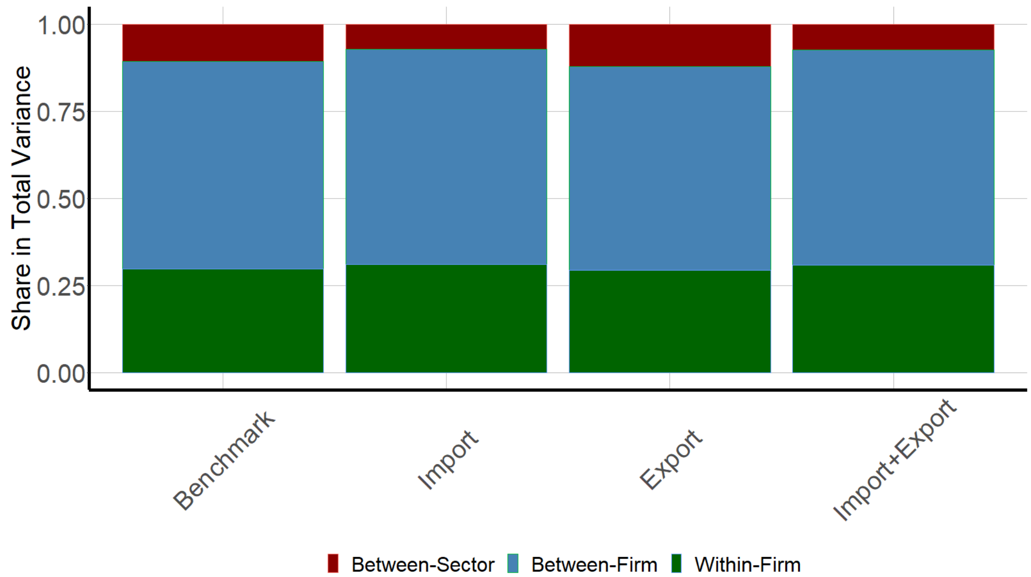
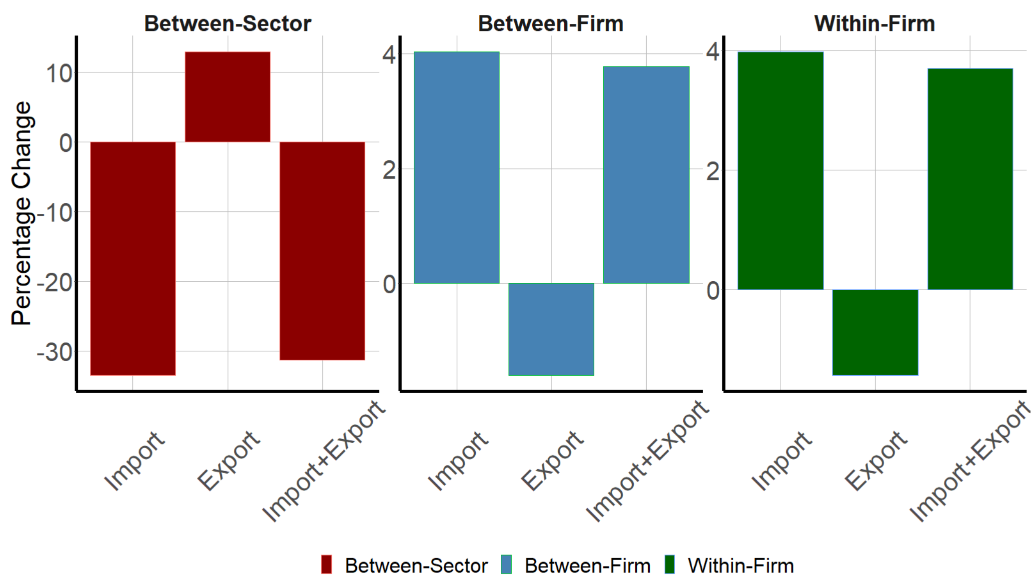


Figure I.5. Comparison of Variance Composition Across Models. The Figure displays the variance composition for the different models. "Data" presents the observed composition in the data, "Estimate" presents the fitted model in the observed data, and "Model" presents the model simulations.



(A) Model vs. Counterfactual



(B) Change in the Variance Component

Figure I.6. Variance Composition with Within-Firm Dispersion. In Panel (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. Panel (B) displays the percentage changes between the components showed in (B) and the benchmark model.

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