

Trade and Inequality: From Theory to Estimation*

Elhanan Helpman
Harvard University
and CIFAR

Oleg Itskhoki
Princeton University
and NBER

Marc-Andreas Muendler
UC San Diego
and NBER

Stephen Redding
Princeton University
and NBER

First version: November 2011

This version: December 12, 2011

PRELIMINARY AND INCOMPLETE

Abstract

While neoclassical theory emphasizes the impact of trade on wage inequality *between* occupations and industries, more recent theories of firm heterogeneity point to the impact of trade on wage dispersion *within* occupations and industries. Using linked employer-employee data for Brazil, we show that much of the increase in wage inequality between 1986 and 1998 has occurred within sector-occupations; the increase in the within component of wage inequality is driven by wage dispersion across firms; and the change in wage dispersion between firms is related to trade participation. We then use an extension of the theoretical model from Helpman, Itskhoki, and Redding (2010a) to construct an econometric model of the effect of trade on inequality, which we estimate with Brazilian data. We show that the estimated model fits the data well, both in terms of some key moments as well as in terms of the overall distributions of wages and employment. International trade is important for this fit. In particular, we show that by shutting down the trade channel the estimated model is significantly less successful in matching the data. Finally, we quantify the contribution of the firm-based channel through which trade affects wage inequality.

Key words: Wage Inequality, International Trade

JEL classification: F12, F16, E24

*We thank the National Science Foundation for financial support. We are very grateful to Eduardo Morales, Lorenzo Casaburi, Adam Guren, Jesse Schreger, Itzik Fadlon and Sam Bazzi for excellent research assistance. We thank Gene Grossman, Ulrich Müller, Andriy Norets, Esteban Rossi-Hansberg, Andres Santos, Chris Sims, John Van Reenen, Jon Vogel, Yoto Yotov and seminar participants at U Toronto, the Phila Fed Trade Workshop and JHU-SAIS for helpful comments and suggestions. The usual disclaimer applies.

1 Introduction

The field of international trade has undergone a transformation in the last decade, as attention has shifted to heterogeneous firms as drivers of foreign trade. Until recently research on the labor market effects of international trade has been heavily influenced by the Heckscher-Ohlin and Specific Factors models, which provide predictions about relative wages across skill groups, occupations and sectors. Guided by these predictions, empirical studies have concluded that the contribution of international trade to growing wage inequality is modest at best (see for example the survey by Goldberg and Pavcnik 2003). But a number of features of the data appear to be at odds with this conclusion, including increased wage inequality in both developed and developing countries, growing residual wage dispersion among workers with similar observed characteristics, and increased wage dispersion across plants and firms *within* industries.

This paper argues that these apparently discordant empirical findings are in fact consistent with a trade-based explanation for growing wage inequality, but one rooted in recent models of firm heterogeneity rather than neoclassical trade theories. For this purpose we extend the theoretical model from Helpman, Itskhoki, and Redding (2010a) and use it to construct an econometric model that we then estimate using linked employee-employer data for Brazil. The estimated model is subsequently used to provide empirical evidence on the extent to which the firm-level mechanism drives the effect of trade on wage inequality.

To motivate our structural model, we first report reduced-form evidence on wage inequality in Brazil. Our analysis reveals a number of features of the changes in Brazilian wage inequality following increased trade openness from the mid-1980s. First, wage inequality increased initially, largely *within sectors and occupations* rather than between sectors and occupations. Second, the increase in wage inequality within sectors and occupations was driven mainly by increased wage inequality *between* rather than within firms. Third, both of these findings are robust to controlling for observed worker characteristics, suggesting that the increased wage inequality between firms within sector-occupations is *within-group* wage inequality. These features of the data motivate our theoretical model's focus on wage inequality across workers with similar observed characteristics, as well as the emphasis on the between-firm component of wage inequality.

Our objective is to quantify the overall contribution of firm-based variation in wages to wage inequality. We identify the firm component of wages by including a firm-occupation-year fixed effect in a regression of log worker wages on controls for observed worker characteristics. This firm-occupation-year fixed effect includes both wage premia for workers with identical characteristics and unobserved differences in workforce composition across firms. Our analysis focuses on this wage component because recent theories of firm heterogeneity emphasize both sources of wage differences across firms. We estimate the firm wage component separately for each sector-occupation-year, because our theoretical model implies that differences in wages across firms can change over time and these changes can be more important in some sectors and occupations than others.

In the data, the firm component of wages is systematically related to export participation. While exporters are on average larger and pay higher wages than nonexporters, there is substantial overlap in

the employment and wage distributions of these two groups of firms, i.e., some nonexporting firms are larger and pay higher wages than some exporting firms. The changes in wage dispersion between firms within sectors and occupations during our sample period are related to changes in export participation.

To account for these features of the data, we develop a structural model of firm heterogeneity and export participation by extending the theoretical model of Helpman, Itskhoki, and Redding (2010a). The extension considers two additional sources of heterogeneity across firms besides productivity heterogeneity: the cost of screening workers and the size of the fixed cost of exporting. The former source of heterogeneity allows for variation in wages across firms after controlling for their employment size and export status, while the latter allows some small low-wage firms to profitably export and some larger high-wage firms to serve only the domestic market. Nevertheless, in this model exporters are on average larger and pay higher wages than nonexporters. Using the Brazilian data on firm wages, employment, and export status, we estimate the parameters of the model using maximum likelihood. We show that the parameterized model provides a good fit to the data, and we use model-based counterfactuals to show that trade openness is quantitatively important in accounting for the observed wage inequality during our sample period.

Our paper is related to a number of strands of the existing literature. As mentioned above, several empirical studies have suggested that the Heckscher-Ohlin and Specific Factors models—as conventionally interpreted—provide at best an incomplete explanation for observed wage inequality. First, changes in the relative returns to observed measures of skills (e.g., education and experience) and changes in industry wage premia typically account for a relatively small share of change in overall wage inequality, leaving a substantial role for within-group wage inequality.¹ Second, the Stolper-Samuelson theorem predicts a rise in the relative skilled wage in skill-abundant countries and a fall in the relative skilled wage in unskilled-abundant countries in response to trade liberalization. Yet wage inequality evidently rises following trade liberalization in both developed and developing countries (e.g., Goldberg and Pavcnik 2007).² Third, much of the change in the relative demand for skilled and unskilled workers in developed countries has occurred within sectors and occupations rather than across sectors and occupations (e.g., Katz and Murphy 1992 and Berman, Bound, and Griliches 1994). Fourth, while wage dispersion between plants and firms is an empirically-important source of wage inequality (e.g., Davis and Haltiwanger 1991, Faggio, Salvanes, and Van Reenen 2010, Oi and Idson 1999, and Van Reenen 1996), neoclassical trade theory is not able to elucidate it. However, these findings can be explained with a model of firm heterogeneity, as we show in this paper.

Models of firm heterogeneity suggest two sets of reasons for wage variance across firms. One line of research assumes competitive labor markets, so that all workers with the same characteristics are paid the same wage, but wages vary across firms as a result of differences in workforce composition (see for example Bustos 2011, Monte 2011, Verhoogen 2008, and Yeaple 2005). Another line of research

¹For developed country evidence, see Autor, Katz, and Kearney (2008), Juhn, Murphy, and Pierce (1993), and Lemieux (2006). For developing country evidence, see Attanasio, Goldberg, and Pavcnik (2004), Ferreira, Leite, and Wai-Poi (2010), Goldberg and Pavcnik (2005), Gonzaga, Menezes-Filho, and Terra (2006), and Menezes-Filho, Muendler, and Ramey (2008).

²To rationalize rising wage inequality in both developed and developing countries, the Stolper-Samuelson Theorem can be re-interpreted as applying at a more disaggregated level within industries, as for example in Feenstra and Hanson (1996) and Treffer and Zhu (2005).

introduces labor market frictions, so that workers with the same characteristics can be paid different wages by different firms. For example, search and matching frictions where parties bargain over the surplus from production, can induce wages to vary across firms (see for example Davidson, Matusz, and Shevchenko 2008, Davidson, Heyman, Matusz, Sjöholm, and Zhu 2011, Coşar, Guner, and Tybout 2011, Helpman, Itskhoki, and Redding 2010a, Helpman, Itskhoki, and Redding 2010b and Helpman, Itskhoki, and Redding 2011).³ Efficiency or fair wages are another potential source of labor market imperfections, where the wage that induces worker effort, or is perceived to be fair, varies with revenue across firms (see for example Amiti and Davis 2011, Davis and Harrigan 2011, and Egger and Kreickemeier 2009).⁴

Following Bernard and Jensen (1995, 1997), empirical research using plant and firm data has provided evidence of substantial differences in wages and employment between exporters and nonexporters. More recent research has used linked employer-employee datasets to examine the extent to which the exporter wage premium is the result of differences in workforce composition versus wage premia for workers with identical characteristics, including Schank, Schnabel, and Wagner (2007), Munch and Skaksen (2008), Fías, Kaplan, and Verhoogen (2009), Davidson, Heyman, Matusz, Sjöholm, and Zhu (2011), Krishna, Poole, and Senses (2011), and Baumgarten (2011). Just as the theoretical literature mentioned in the paragraph above highlights two sources of wage differences across firms, wage premia and workforce composition, these empirical studies typically find that both contribute towards the exporter wage premium, with their relative contributions differing between studies.

In contrast to this empirical literature, which is focused on estimating the exporter wage premia, our objective is to develop a theory-based methodology for estimating a structural model of international trade with heterogeneous firms in which employment and wages are related to export status, and to show how this model can be used to quantify the contribution of the firm-specific component of wages to wage inequality.⁵ Using a structural model, we estimate the extent of heterogeneity in productivity and fixed export costs across firms, and isolate their impact through employment and wages on wage inequality. While much of the existing empirical literature using linked employee-employer datasets estimates a time-invariant wage fixed effect for each firm, a key feature of our approach is that the firm component of wages changes over time and can differ across occupations. Through focusing on the overall firm wage component, including both wage premia and unobserved differences in workforce composition, we avoid the need to make strong assumptions, such as conditional random matching, about the allocation of workers across firms.⁶

The remainder of the paper is structured as follows. In Section 2, we introduce our data and provide some background on wage inequality and trade openness in Brazil. In Section 3, we report reduced-form evidence on the sources of changes in wage inequality in Brazil. Motivated by these findings, Section 4

³Search and matching frictions may also influence income inequality through unemployment, as in Davidson and Matusz (2010), Felbermayr, Prat, and Schmerer (2011), and Helpman and Itskhoki (2010).

⁴In models of both perfectly competitive and imperfectly competitive labor markets, trade in intermediate inputs and offshoring provide other channels through which trade can affect wage inequality, as in Feenstra and Hanson (1999), Grossman and Rossi-Hansberg (2008), and Ebenstein, Harrison, McMillan, and Phillips (2009).

⁵Our econometric model can also account for other sources of wage inequality, such as differences in worker observables.

⁶While the assumption of conditional random matching is typically invoked in the empirical literature using linked employee-employer data, as in Abowd, Kramarz, and Margolis (1999), Abowd, Creedy, and Kramarz (2002), and Woodcock (2008), it is often violated in models of firm heterogeneity and trade.

Table 1: Occupation Employment Shares and Relative Mean Log Wages, 1990

CBO	Occupation	Employment share (percent)	Relative mean log wage
1	Professional and Managerial	7.8	1.08
2	Skilled White Collar	11.1	0.40
3	Unskilled White Collar	8.4	0.13
4	Skilled Blue Collar	57.4	-0.15
5	Unskilled Blue Collar	15.2	-0.35

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Employment share is the share of employment in each occupation in total employment in the formal manufacturing sector. Relative mean log wage is the mean log wage in each occupation minus the overall mean log wage in the formal manufacturing sector.

sets up and estimates a structural heterogeneous-firm model of trade and inequality using the Brazilian data. Section 5 concludes.

2 Data and Background

The main dataset used in our empirical analysis is a linked employee-employer dataset for Brazil from 1986-1998.⁷ The source for these administrative data is the *Relação Anual de Informações Sociais* (RAIS) database of the Brazilian Ministry of Labor, which requires by law that all formally-registered firms report information each year on each worker employed by the firm. The data contain a unique identifier for each worker, which remains with the worker throughout his or her work history, as well as the tax identifier of the worker's employer. We focus on manufacturing industries in the formal sector for which the theories of firm heterogeneity in differentiated product markets discussed below are arguably more relevant.⁸ As discussed further in the data appendix, our sample includes more than 20 million workers and more than 250,000 firms over the period 1986-1998 as a whole.

Each worker is classified in each year by their occupation. In our baseline empirical analysis, we use five standard occupational categories: (1) Professional and Managerial, (2) Skilled White Collar, (3) Unskilled White Collar, (4) Skilled Blue Collar, (5) Unskilled Blue Collar. The employment shares of each occupation and the mean log wage in each occupation relative to the overall mean log wage are reported in Table 1. Skilled Blue Collar workers account for almost 60 percent of employment, while Professional and Managerial workers account for the smallest share of employment. In robustness checks, we also make use of the more disaggregated *Classificação Brasileira de Ocupações (CBO)* definition of occupations, which breaks down manufacturing into around 350 occupations, as listed in the appendix.

Each firm is classified in each year by its main industry according to a classification compiled by the

⁷For further discussion of the data sources and definitions, see the data appendix.

⁸Goldberg and Pavcnik (2003) estimate that the informal sector accounts for around 16 percent of Brazil's manufacturing labor force during our sample period.

Table 2: Industry Employment Shares and Relative Mean Log Wages, 1990

IBGE	Industry	Employment share (percent)	Relative mean log wage
2	Non-metallic mineral products	5.5	-0.12
3	Metallic products	9.8	0.27
4	Machinery, equipment and instruments	6.6	0.38
5	Electrical and telecommunications equipment	6.0	0.37
6	Transport equipment	6.3	0.61
7	Wood products and furniture	6.5	-0.48
8	Paper, publishing and printing	5.4	0.14
9	Rubber, tobacco, leather and fur	7.0	-0.04
10	Chemical and pharmaceutical products	9.9	0.40
11	Apparel and textiles	15.7	-0.32
12	Footwear	4.4	-0.44
13	Food, beverages and alcohol	16.9	-0.30

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Industries as defined in the IBGE classification. Employment share is the share of employment in each industry in total employment in the formal manufacturing sector. Relative mean log wage is the mean log wage in each industry minus the overall mean log wage in the formal manufacturing sector.

Instituto Brasileiro de Geografia e Estatística (IBGE), which disaggregates manufacturing into twelve sectors.⁹ Sectoral employment shares and the mean log wage in each sector relative to the overall mean log wage are reported in Table 2. Apparel and textiles, and Food, beverages and alcohol are the largest sectors (each about 16 percent of employment) and have relatively low wages (along with Wood products, and Footwear). Two other large sectors are Metallic products, and Chemicals and pharmaceuticals, which have relatively high wages (along with Transport equipment). Most other sectors are of roughly the same size and each account for about 6 percent of employment. The employment shares of sectors are relatively constant over our sample time, with the exception of Food, beverages and alcohol (which increases from around 16 to 23 percent) and Electrical and telecommunications equipment (which decreases from roughly 6 to 4 percent). From 1994 onwards, firms are classified according to the more finely-detailed *National Classification of Economic Activities (CNAE)*, which breaks down manufacturing into over 250 industries, as listed in the appendix. In robustness checks, we use this more detailed classification when it is available.

RAIS also reports information on worker educational attainment, which we group into the following four categories: (i) Less than High School, (ii) High School, (iii) Some College, (iv) College Degree. Over our sample period, the employment shares of the two highest educational categories are relatively constant over time, while the share of workers with (without) high-school education rises (declines) by around 10 percentage points. In addition to these data on educational attainment, RAIS also reports demographic information for each worker, including age and sex, as well as labor market experience.

⁹These twelve sectors correspond roughly to two-digit International Standard Industrial Classification (ISIC) industries.

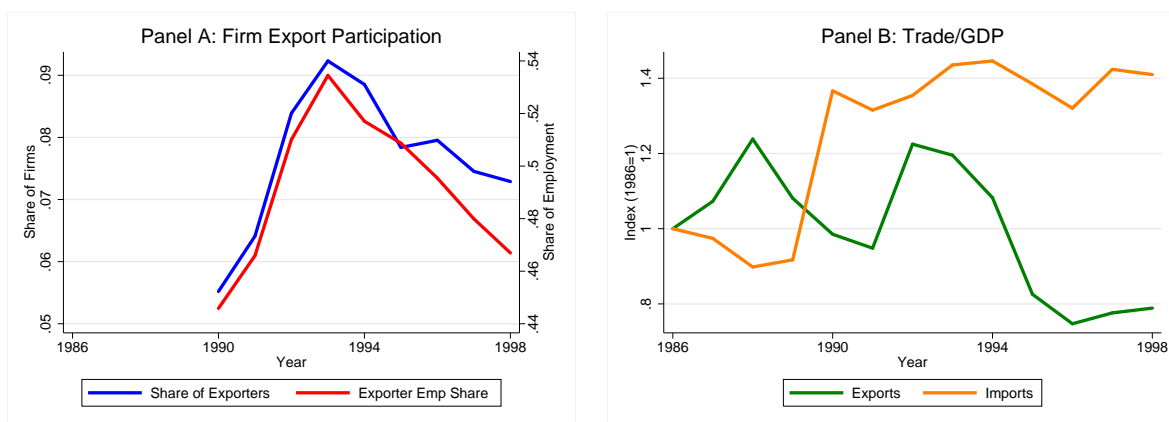


Figure 1: Brazil's Trade Openness

Sources: RAIS manufacturing firms linked to SECEX 1986-98, Brazilian national accounts.

We combine the linked employer-employee data from RAIS with trade transactions data from *Secretaria de Comércio Exterior* (SECEX) that are available for 1990-98. These trade transactions data report for each export shipment the tax identifier of the firm, the product exported, the destination country served and the volume and value of the export transaction. We merge the trade transactions and linked employer-employee data using the tax identifier of the firm and classify firms as exporters and non-exporters in each year.

As shown in Panel A of Figure 1, our sample period is characterized by substantial changes in export participation. Following Brazil's opening to trade in the late 1980s and early 1990s, the share of firms that export (left axis) nearly doubles between 1990 and 1993, and their employment share (right axis) increases by around 10 percentage points.¹⁰ In contrast, following Brazil's real exchange rate appreciation of the mid-1990s, both the share of firms that export and the employment share of exporters decline substantially. In Panel B of Figure 1, we show the evolution of trade openness over a longer time period using the ratio of aggregate trade to GDP from the International Monetary Fund's International Financial Statistics.¹¹ Export openness increases in the mid-1980s and then declines, before increasing again in the early 1990s and declining from 1993 onwards. In contrast, the increase in import openness occurs later (from 1989 onwards), and import and export openness diverge from the mid-1990s onwards. While export openness declines in the aftermath of the real exchange rate appreciation, import openness remains relatively constant.

In Figure 2, we display the mean and variance of the log annual wage (measured in U.S. dollars). Both the level and dispersion of wages increase in the mid-1980s and then decline, before again increasing in the first half of the 1990s and declining thereafter. Over our sample period as a whole, both wage inequality (Figure 2) and export participation (Figure 1) exhibit an inverted U-shaped pattern of rises and

¹⁰For a discussion of trade liberalization in Brazil, see for example Kume, Piani, and Souza (2003).

¹¹Domestic revenue data are not available for the formal manufacturing sector, which precludes constructing measures of the ratio of exports to output for the formal manufacturing sector over our sample period. The ratios of exports and imports to the total wage bill in formal manufacturing display the same qualitative patterns as the measures of export openness for the economy as a whole in Panel B of Figure 1.

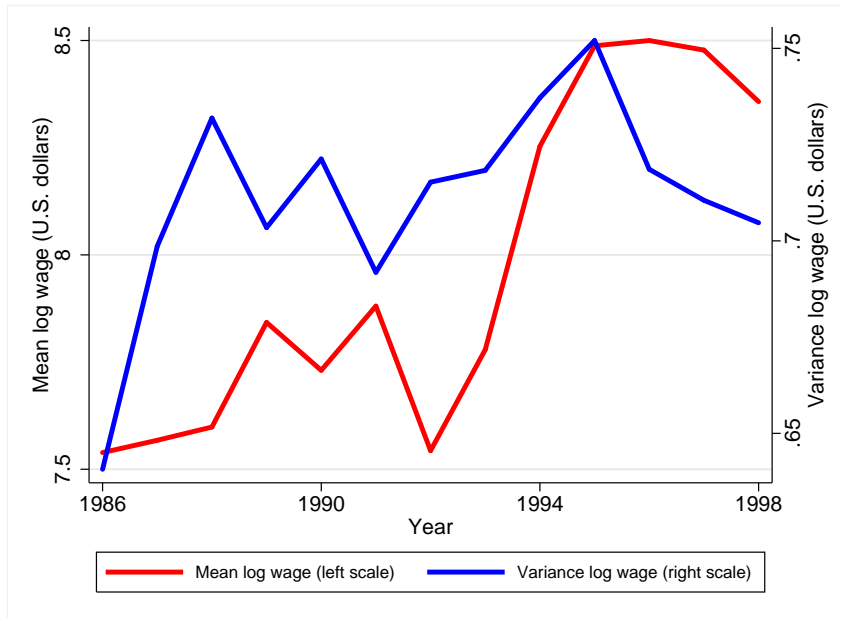


Figure 2: Mean and Variance of Log Wages

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

declines. These similar time-series patterns are suggestive of a relationship between wage inequality and export participation, although there are of course other potential explanations. In the remaining sections of the paper, we present econometric evidence on the determinants of Brazilian wage inequality, and examine the extent to which this evidence is consistent with the mechanisms embodied in theories of international trade.

3 Reduced-form Evidence

In this section, we use a nonstructural approach that imposes relatively few restrictions on the data to provide evidence on the determinants of wage inequality. We use a sequence of variance decompositions to quantify the importance of different components to the level and growth of Brazilian wage inequality. In Section 3.1, we begin by decomposing overall wage inequality into within and between components, using sector, occupation and sector-occupation cells. In Section 3.2, we further decompose wage inequality within sector-occupations into wage dispersion between and within firms. In Section 3.3, we examine the relationship between firm wages, employment and export status.

3.1 Within Versus Between Sectors and Occupations

3.1.1 Variance Decomposition

In each year, overall wage inequality (T) can be decomposed into a within component (W) and a between component (B) as follows:

$$T = W + B \quad (1)$$

for

$$T = \frac{1}{N_t} \sum_{i=1}^{N_t} (w_{it} - \bar{w}_t)^2, \quad W = \frac{1}{N_t} \sum_{\ell \in K} \sum_{i=1}^{N_{\ell t}} (w_{it} - \bar{w}_{\ell t})^2, \quad B = \frac{1}{N_t} \sum_{\ell \in K} N_{\ell t} (\bar{w}_{\ell t} - \bar{w}_t)^2,$$

where workers are indexed by i and time by t ; ℓ denotes sector, occupation or sector-occupation cells; N_t is the number of workers; w_{it} is the log wage; and a bar above a variable denotes a mean. We undertake this decomposition using the log wage (w_{it}), since this ensures that the results of the decomposition are not sensitive to the choice of units for wages, and facilitates the inclusion of controls for observable worker characteristics below.

Taking differences relative to a base year, the proportional growth in overall wage inequality can be expressed as the following weighted average of the proportional growth of the within and between components of wage inequality

$$\Delta T = \Delta W + \Delta B \quad \text{or} \quad \frac{\Delta T}{T} = \frac{W}{T} \frac{\Delta W}{W} + \frac{B}{T} \frac{\Delta B}{B}, \quad (2)$$

where the weights are the initial shares of the within and between components in overall wage inequality.

Figure 3 displays overall wage inequality and its within components from equation (1) using sectors, occupations and sector-occupations. All three within components account for a substantial proportion of overall wage inequality and track its dynamics over time quite closely. To further illustrate this, Figure 4 displays changes in wage inequality over time and its components using sectors (Panel A), occupations (Panel B) and sector-occupations (Panel C). For each variable, we subtract the 1986 value of the variable to generate an index that takes the value zero in 1986, which allows us to quantify the contribution of within and between components to the overall inequality *change* after 1986. Whether we use sectors, occupations or sector-occupations, we find that the within component of wage inequality closely mirrors the time-series evolution of overall wage inequality and accounts for most of its growth over our sample period. For each within component, we observe the same inverted U-shaped pattern as for overall wage inequality.

In Panel A of Table 3, we report the contribution of each within component to the level (in 1990 using (1)) and growth (from 1986-1995 using (2)) of overall wage inequality. From 1986-1995, the variance of log wages increased by 17.4 percent.¹² Almost none of this increase is accounted for by rising wage inequality between occupations (first row, second column). While inequality between sectors in-

¹²While we focus on the variance of log wages as our baseline measure of wage inequality, we find that the 90-10, 90-50 and 50-10 percentile differences for log wages display the same pattern.

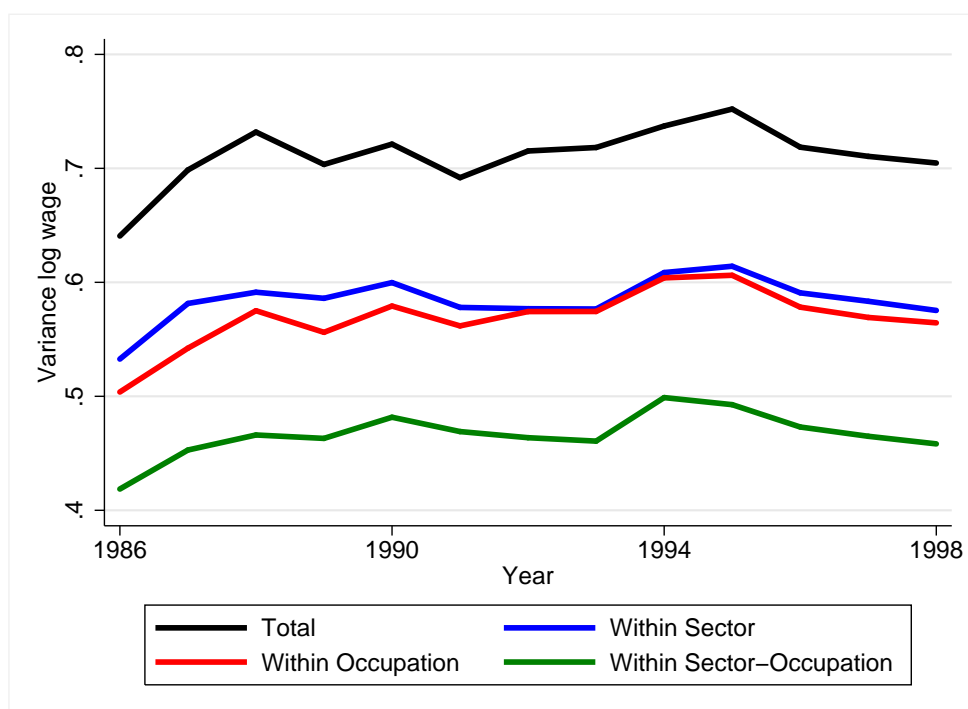


Figure 3: Total and Within Log Wage Inequality

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

creased substantially over this period (by more than 20 percent), the between-sector component accounts for only around 17 percent of the level of wage inequality in the base year, which ensures a modest contribution of the between-sector component to the growth of wage inequality (second row, second column).¹³ Finally, using sector-occupation cells, the between and within components of wage inequality increase by a similar amount over this period, but since the within component accounts for around two thirds of the level of wage inequality in the base year, it also accounts for around two thirds of the growth of wage inequality (third row, second column).¹⁴ We summarize these findings as follows:

Fact 1 *The within sector-occupation component of wage inequality accounts for over two thirds of both the level and growth of wage inequality in Brazil between 1986 and 1995.*

While our baseline results use the IBGE classification of twelve manufacturing sectors and five occupations, the importance of the within component is robust to the use of alternative definitions of sectors and occupations. In Panel A of Table 3, we report results using detailed occupation cells based on more

¹³Given our large number of observations on individual workers, all the changes in variance shown in Table 3 are statistically significant at conventional critical values. More generally, the equality of the wage distributions in 1986 and 1995 is rejected at conventional critical values using a nonparametric Kolmogorov-Smirnov test.

¹⁴For example, the quantitative decomposition of inequality (2) into between and within sector-occupations components over this period is as follows:

$$\begin{aligned} \Delta T/T &= W/T \cdot \Delta W/W + B/T \cdot \Delta B/B \\ 17.4\% &= 0.67 \cdot 17.7\% + 0.33 \cdot 16.8\%. \end{aligned}$$

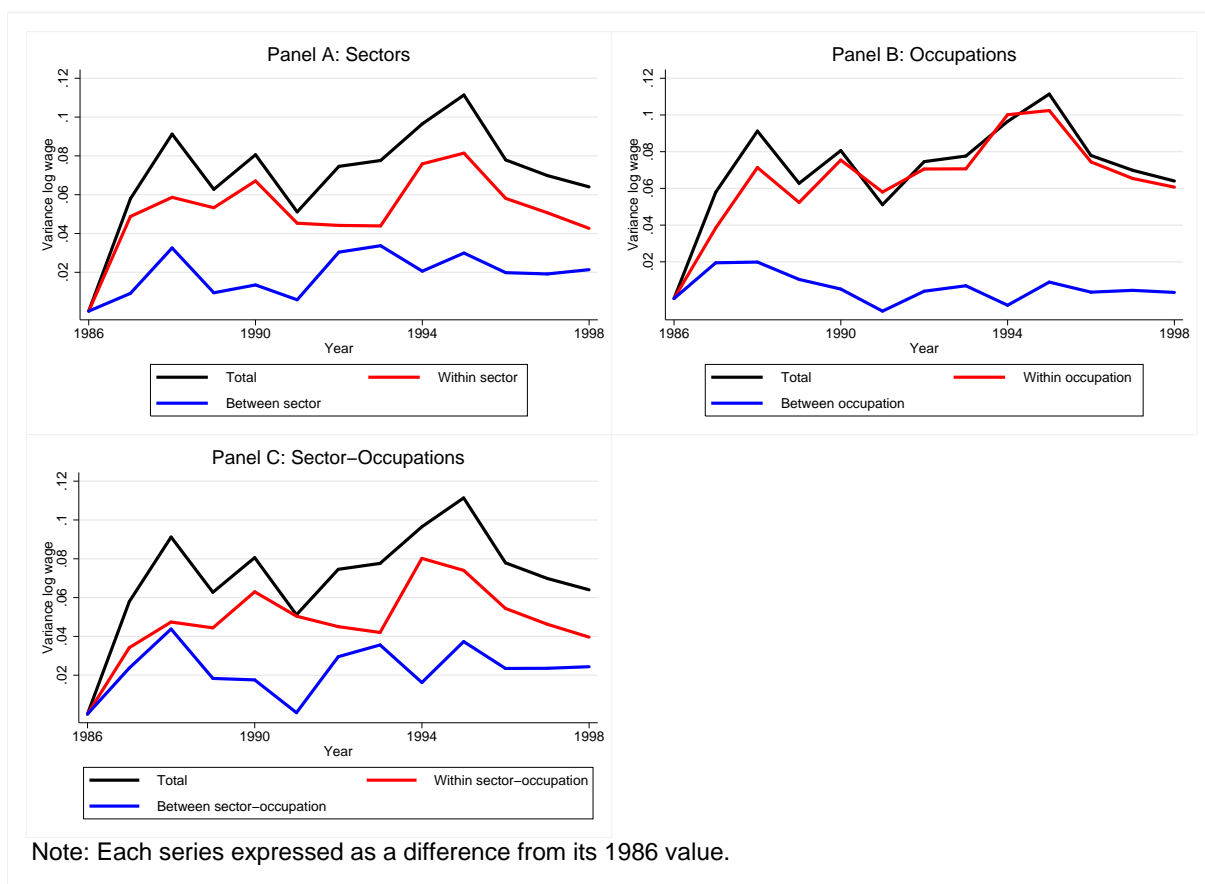


Figure 4: Changes in Log Wage Inequality and its Components

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Each series expressed as difference from its 1986 value.

than 300 occupations in the CBO classification (fourth row) and using sector-detailed-occupation cells defined using IBGE sectors and CBO occupations (fifth row). As a further robustness check, Panel B of Table 3 reports results using the more finely-detailed CNAE sector classification, which is available from 1994 onwards and breaks down manufacturing into more than 250 disaggregated industries. Since this classification is available for a more limited time period, we show results for the level (1994) and growth (between 1994 and 1998) of overall wage inequality. To provide a point of comparison, the first row of Panel B reports results for this later period using our twelve IBGE sectors and five occupations (compare with row three of Panel A for the earlier time period). In the second row of Panel B, we report results using detailed-sector-detailed-occupation cells based on more than 300 CNAE sectors and more than 250 CBO occupations. While some occupations do not exist in some sectors, there are still around 40,000 sector-occupation cells in this specification, yet we continue to find that the within component accounts for around 50 percent of the level and all the growth of wage inequality.¹⁵

¹⁵In fact, the between and the within components of inequality move in the opposite direction in this period, with the movement in the within component dominating the movement in the between component.

Table 3: Contribution of the Within Component to Log Wage Inequality

	Level (percent)	Change (percent)
A. Main Period	1990	1986–95
Within occupation	80	92
Within sector	83	73
Within sector-occupation	67	67
Within detailed-occupation	58	60
Within sector–detailed-occupation	52	54
B. Late Period	1994	1994–98
Within sector-occupation	68	125
Within detailed-sector–detailed-occupation	47	140

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Decomposition of the level and growth of wage inequality. 12 sectors are 5 occupations as in Tables 1 and 2. Detailed occupations are based on the CBO classification, which disaggregates manufacturing into 348 occupations. Detailed sectors are based on the CNAE classification, which disaggregates manufacturing into 283 sectors. Firms are only classified according to the CNAE sector classification from 1994 onwards. Each cell in the table reports the contribution of the within component of total log wage inequality. In the first column, the contribution of the within component (W) to total wage inequality (T) is calculated as $100 \cdot W/T$ from equation (1). In the second column, the contribution of the within component to the growth in total wage inequality is calculated according to (2) as $100 \cdot (W/T)(\Delta W/W)/(\Delta T/T) = 100 \cdot \Delta W/\Delta T$, where Δ denotes a forward difference operator. The unreported between component is 100 percent minus the reported within component. Since the between component can be negative, the within component can be greater than 100 percent.

Our results are consistent with prior findings in the labor economics literature. Davis and Haltiwanger (1991) show that between-plant wage dispersion within sectors accounts for a substantial amount of the level and growth of wage inequality in U.S. manufacturing from 1975-86.¹⁶ Katz and Murphy (1992) find that shifts in demand within industry-occupation cells are more important than those across industry-occupation cells in explaining changes in U.S. relative wages for different types of workers from 1963-87. Our findings show the importance of wage inequality within sectors, occupations and sector-occupations in accounting for the growth in wage inequality following Brazil's opening to trade in the late 1980s and early 1990s.

Neoclassical theories of international trade emphasize wage inequality between different types of workers (Heckscher-Ohlin model) or industries (Specific Factors model). Our findings suggest that this concentration on the between component abstracts from an important potential channel through which trade can affect wage inequality. Of course, our results do not rule out the possibility that Heckscher-Ohlin and Specific-Factors forces play a role in the wage distribution. As shown in Feenstra and Hanson (1996) and Treffer and Zhu (2005), the Stolper-Samuelson Theorem can be re-interpreted as applying at a more disaggregated level within sectors and occupations. But these neoclassical theories emphasize *dissimilarities* across sectors and occupations, and if their mechanisms are the dominant influences

¹⁶See Faggio, Salvanes, and Van Reenen (2010) for U.K. evidence on between-firm wage dispersion and Krueger and Summers (1988) for U.S. evidence on between-industry wage dispersion.

on the growth of wage inequality, we would expect to observe a substantial between-component for grossly-different occupations and sectors (e.g., Managers versus Unskilled Blue-collar workers and Textiles versus Chemicals and pharmaceuticals). Yet the within component dominates the growth in wage inequality in the final column of Table 3, and this dominance remains even when we consider around 40,000 disaggregated sector-occupations. Therefore, while the forces highlighted by the Heckscher-Ohlin and Specific-Factors models are active, there appear to be other mechanisms that are at least as important for explaining the data.¹⁷

3.1.2 Controlling for Worker Observables

We now examine whether the contribution of the within-sector-occupation component of wage inequality is robust to controlling for observed worker characteristics. To control for worker observables, we estimate the following OLS Mincer regression for log worker wages:

$$w_{it} = X_{it}\vartheta_t + \nu_{it}, \quad (3)$$

where we denote workers by i and time by t ; X_{it} is a matrix of observable worker characteristics; and ν_{it} is a stochastic error.

We control for worker observables nonparametrically by including indicator variables for the following categories: education (high school, some college, and college degree, where less than high school is the excluded category), age (10-14, 15-17, 18-24, 25-29, 30-39, 40-49, 50-64, 65+), experience quintiles, and sex. We estimate the Mincer regression for every year separately, allowing the coefficients on worker observables (ϑ_t) to change over time to capture changes in the rate of return to these characteristics.

The empirical specification (3) serves as a conditioning exercise, in which we decompose the variation in log wages into the component correlated with worker observables and the orthogonal component, where OLS approximates the conditional expectation function between the left- and right-hand side variables even if the true relationship between them is nonlinear. Since the residuals ($\hat{\nu}_{it}$) are orthogonal to worker observables ($X_{it}\hat{\vartheta}_t$), they provide an empirical measure of *within-group* or *residual* wage inequality. Using this orthogonality property, overall wage inequality can be decomposed into the contributions of worker observables ($\text{Var}(X_{it}\hat{\vartheta}_t)$) and within-group inequality ($\text{Var}(\hat{\nu}_{it})$):

$$\text{Var}(w_{it}) = \text{Var}\left(X_{it}\hat{\vartheta}_t\right) + \text{Var}(\hat{\nu}_{it}), \quad (4)$$

where a hat denotes an estimate. The resulting measure of within-group wage inequality ($\text{Var}(\hat{\nu}_{it})$) can further be decomposed into its within and between components (W and B) using sector, occupation or sector-occupation cells, as in (1) and (2) above.

In Panel A of Table 4, we report the results of the variance decomposition (4). We find that worker observables ($\text{Var}(X_{it}\hat{\vartheta}_t)$) and within-group ($\text{Var}(\hat{\nu}_{it})$) components make roughly equal contributions

¹⁷This is also consistent with the findings of Burstein and Vogel (2003) who extend the Heckscher-Ohlin model with skill-biased firm-level technology and firm productivity heterogeneity to quantify the contributions of Heckscher-Ohlin and firm-heterogeneity forces to rising skill premia.

Table 4: Worker Observables and Residual Log Wage Inequality

	Level (percent)	Change (percent)
A. Overall Wage Inequality: Main Period	1990	1986-95
Observables inequality	43	52
Residual wage inequality	57	48
B. Residual Wage Inequality: Main Period	1990	1986-95
Within sector-occupation	88	91
C. Residual Wage Inequality: Late Period	1994	1994-98
Within sector-occupation	89	103
Within detailed-sector–detailed-occupation	83	110

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Decomposition of the level and growth of the overall log wage inequality into the contribution of worker observables and residual (within-group) wage inequality, according to (4) based on a Mincer regression of log wages on observed worker characteristics (3). 12 sectors are 5 occupations as in Tables 1 and 2. 348 detailed occupations and 283 detailed sectors (data 1994 onwards) as described in the note to Table 3. The cells in Panel B report the within sector-occupation component of residual wage inequality, applying decompositions (1) and (2) to residuals from Mincer regression (3).

towards both the level (1990) and growth (1986-1995) of overall wage inequality. In Panels B and C of Table 4, we decompose the level and growth of within-group wage inequality ($\mathbb{V}\text{ar}(\hat{\nu}_{it})$) into its within and between sector-occupation components using (1) and (2). We find that the within sector-occupation component dominates whether we use our baseline definitions of sector-occupations (Panel B) or our more finely-detailed definitions featuring around 40,000 sector-occupations (Panel C). Indeed, we find that the within sector-occupation component is more important for within-group wage inequality (Table 4) than for overall wage inequality (Table 3), which is consistent with the fact that much of the variation in worker observables is between sector-occupation cells.

Figures 5 and 6 show results for changes in wage inequality over time. Figure 5 uses (4) to decompose changes in overall wage inequality into the contributions of changes in worker observables ($\mathbb{V}\text{ar}(X_{it}\hat{\nu}_t)$) and within-group inequality ($\mathbb{V}\text{ar}(\hat{\nu}_{it})$) relative to the base year of 1986. While both components of overall wage inequality initially increase from 1986 onwards, overall wage inequality inherits its inverted U-shaped pattern from within-group wage inequality, which rises until 1994 and declines thereafter. Figure 6 uses (1) and (2) to decompose changes in within-group wage inequality ($\mathbb{V}\text{ar}(\hat{\nu}_{it})$) into its within and between components, again relative to the base year of 1986. We show results for sectors (Panel A), occupations (Panel B), and sector-occupations (Panel C). In each case, the time-series evolution of within-group wage inequality is entirely dominated by the evolution of the within component, while the between component remains relatively stable over time.

One possible source of wage variation within sector-occupations for workers with the same observed characteristics is variation in wages across regions. To show that our findings for wage inequality within sector-occupations are not driven by regional effects, we re-estimate the Mincer equation (3) and repeat our within-between decomposition using only data for Sao Paulo, which is the Brazilian state that ac-

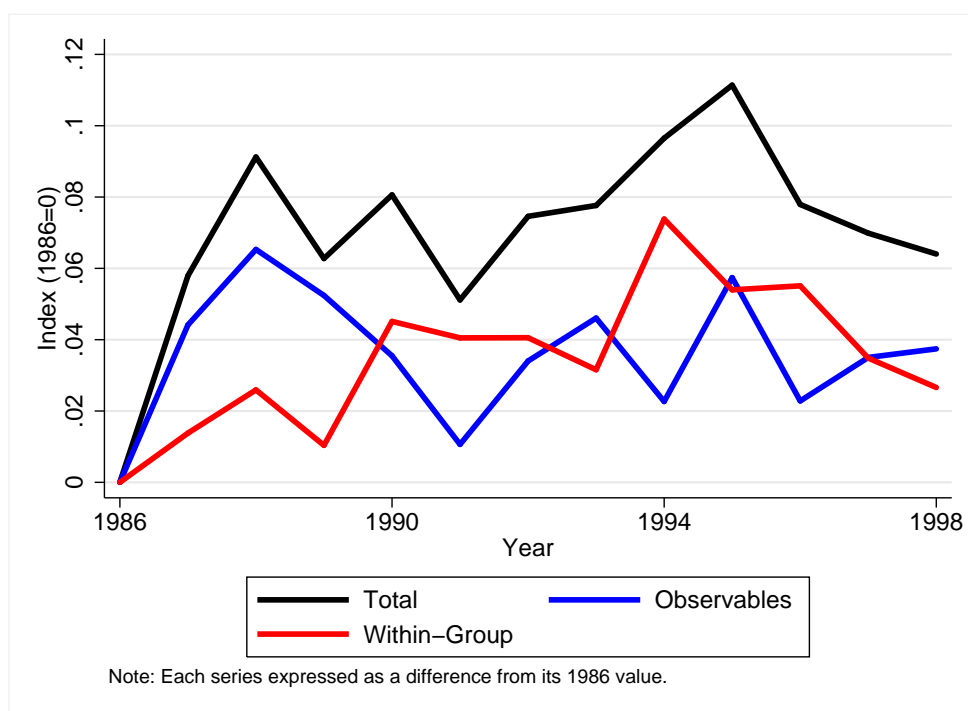


Figure 5: Changes in Observable and Residual Log Wage Inequality

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Each series expressed as difference from its 1986 value.

counts for the largest share of manufacturing employment.¹⁸ We find a similar pattern of results for Sao Paulo state, with wage inequality within sector-occupations accounting for 91 percent of the level of Brazilian wage inequality and 71 percent of its growth from 1986-1995. As a further robustness check, we also re-estimated the Mincer equation (3) including a full set of interactions between industry and Brazilian state fixed effects. Again wage inequality within sector-occupations dominates, accounting for 95 percent of the level of residual wage inequality in 1990 and 92 percent of its growth from 1986-1995. Therefore our findings of substantial wage inequality within sector-occupations for workers with the same observed characteristics do not appear to be driven by regional differences in wages across Brazilian States.

Our estimates of the role played by worker observables are in line with the existing empirical literature, which finds that observed worker characteristics typically account for around one third of the cross-section variation in worker wages, as discussed in Mortensen (2003). Our finding that worker observables contribute towards the rise in overall wage inequality following Brazilian trade liberalization is corroborated by other studies that have found an increase in the estimated returns to schooling during our sample period, such as Attanasio, Goldberg, and Pavcnik (2004) and Menezes-Filho, Muendler, and Ramey (2008).¹⁹ Our finding that within-group wage inequality shapes the time-series evolution of over-

¹⁸For empirical evidence of wage variation across Brazilian states, see for example Fally, Paillacar, and Terra (2010) and Kovak (2011).

¹⁹From the estimated coefficients on worker observables in the Mincer log wage equation (3) in each year, we find an increase

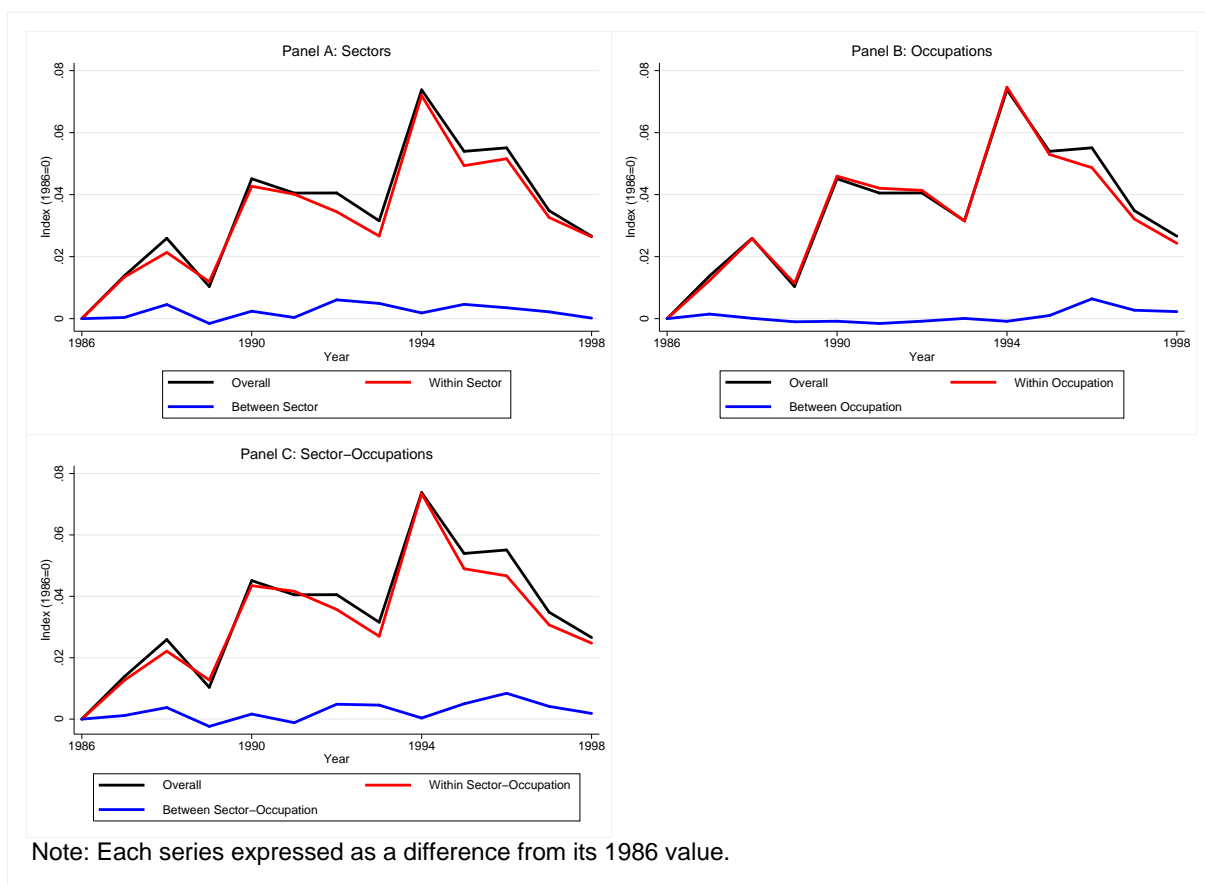


Figure 6: Changes in Residual Log Wage Inequality and its Components

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Each series expressed as difference from its 1986 value.

all wage inequality is consistent with the results of recent studies using U.S. data, as in Autor, Katz, and Kearney (2008), Juhn, Murphy, and Pierce (1993), and Lemieux (2006). The continued dominance of the within-sector-occupation component after controlling for worker observables suggests that a substantial component of wage inequality within sector-occupations is within-group wage inequality.

3.2 Between- Versus Within-Firm Wage Inequality

3.2.1 Variance Decomposition

Having established the importance of wage inequality within sector-occupations, we now further decompose this source of wage inequality into within-firm and between-firm components using directly analogous decompositions to (1) and (2).

In Panel A of Table 5, we report the results from these decompositions as the employment-weighted average of the results for each sector-occupation. While between-firm and within-firm wage inequality in the rate of return to both education and experience over time, as reported in the appendix.

Table 5: Decomposition of Log Wage Inequality *within* Sector-Occupations

	Level (percent)	Change (percent)
A. Unconditional	1990	1986-1995
Between-firm wage inequality	55	115
Within-firm wage inequality	45	-15
B. Controlling for Worker Observables	1990	1986-1995
Worker observables	17	2
Covariance observables and firm effects	11	24
Between-firm wage inequality	38	86
Within-firm wage inequality	34	-11

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Decomposition of the level and growth of wage inequality within sector-occupation (employment-weighted average of the results for each sector-occupation). 12 sectors are 5 occupations as in Tables 1 and 2. The decomposition is done according to (1) and (2) for within-sector-occupation component of inequality (W) reported in Table 3. The decomposition controlling for worker observables in Panel B is done according to (6) and is based on estimating separate Mincer regressions (5) for each sector-occupation-year of log wages on firm-occupation-year fixed effects and worker observables. See the text of the paper for further discussion. Figures may not sum exactly to 100 percent due to rounding.

make roughly equal contributions to the level of wage inequality within sector-occupations (first column), we find that changes in wage inequality within sector-occupations are largely driven by wage inequality between firms (second column). While for brevity Table 5 focuses on the years 1990 and 1986-1995 and uses our baseline specification of sectors and occupations, we find similar results using other years and definitions of sectors and occupations. And while for brevity we concentrate on aggregate results, this same pattern is pervasive across sectors and occupations. We summarize these findings as follows:

Fact 2 *Between-firm and within-firm dispersion make roughly equal contributions to the level of wage inequality within sector-occupations, but the growth of wage inequality within sector-occupations is overwhelmingly accounted for by between-firm wage dispersion.*

3.2.2 Controlling for Worker Observables

To show that the role of between-firm wage dispersion within sectors and occupations is robust to controlling for observed worker characteristics, we estimate the following fixed effects Mincer regression for log worker wages separately for every sector-occupation-year:

$$w_{it} = X_{it}\vartheta_{\ell t} + \varpi_{j\ell t} + v_{i\ell t}, \quad (5)$$

where i indexes workers, j denotes firms, ℓ corresponds to sector-occupations, and t is time; X_{it} is the same matrix of observable worker characteristics discussed above; $\varpi_{j\ell t}$ is a firm-occupation-year

fixed effect; and v_{it} is a stochastic error.²⁰ For each sector-occupation-year cell, we normalize the firm-occupation-year fixed effects ($\varpi_{j\ell t}$) so that their sum is equal to zero, and we absorb the regression constant into $X_{it}\vartheta_{\ell t}$.

Specification (5) allows the coefficients on worker observables ($\vartheta_{\ell t}$) to vary across sector-occupation-years, which captures variation in the rate of return to these characteristics across sectors, occupations and time. We use the estimated firm-occupation-year fixed effects ($\hat{\varpi}_{j\ell t}$) as our measure of the firm component of wages after controlling for worker observables. Since we estimate this specification separately for each sector-occupation-year, the firm component of wages is allowed to vary across sectors, occupations and years. Note that the firm-occupation-year fixed effects ($\hat{\varpi}_{j\ell t}$) can be correlated with worker observables, as will be the case, for example, if there is assortative matching on worker observables across firms. Therefore these estimated fixed effects ($\hat{\varpi}_{j\ell t}$) capture both wage premia for workers with identical characteristics and unobserved differences in workforce composition across firms. The theoretical literature on heterogeneous firms and labor markets considers both these sources of wage differences across firms, and our objective is to quantify the overall contribution of the firm component to wage inequality.²¹

Since the regression residuals (\hat{v}_{it}) are by construction orthogonal to observed worker characteristics ($X_{it}\hat{\vartheta}_{\ell t}$) and the estimated firm-occupation-year fixed effects ($\hat{\varpi}_{j\ell t}$), wage inequality within each sector-occupation-year can be decomposed as follows:

$$\text{Var}(w_{it}) = \text{Var}\left(X_{it}\hat{\vartheta}_{\ell t}\right) + 2\text{Cov}\left(X_{it}\hat{\vartheta}_{\ell t}, \hat{\varpi}_{j\ell t}\right) + \text{Var}\left(\hat{\varpi}_{j\ell t}\right) + \text{Var}\left(\hat{v}_{it}\right). \quad (6)$$

The Mincer regression (5) together with (6) allows us to decompose overall wage inequality within every sector-occupation-year into the contributions of: worker observables ($\text{Var}(X_{it}\hat{\vartheta}_{\ell t})$); the covariance of worker observables and the firm component of wages ($\text{Cov}(X_{it}\hat{\vartheta}_{\ell t}, \hat{\varpi}_{j\ell t})$); between-firm wage dispersion ($\text{Var}(\hat{\varpi}_{j\ell t})$); and within-firm wage dispersion ($\text{Var}(\hat{v}_{it})$).

In Panel B of Table 5, we report the results of this decomposition as the employment-weighted average of the results for each sector-occupation. Again we find that between and within-firm wage dispersion make roughly equal contributions to the level of wage inequality within sector-occupations (first column). These two components each account for 35-40 percent of the variance in wages within sector-occupations, while worker observables account for around one sixth, and the covariance between worker observables and the firm component of wages accounts for the remaining one tenth. In contrast, changes in between-firm wage dispersion account for the lion's share (more than eighty percent) of the growth in the variance of wages within sector-occupations (second column). The next largest contribution (around one quarter) comes from an increased covariance between worker observables and the firm component of wages, which is consistent with increased assortative matching on worker observables across firms. Changes in within-firm wage dispersion make a negative contribution of around one sixth

²⁰Note that firms are assigned to a single main sector and we estimate the Mincer regression (5) separately for each sector-occupation-year, so that the fixed effects (ϖ_{jkt}) vary by firm-occupation-year.

²¹Through focusing on the combined effect of wage premia and unobserved differences in workforce composition, we avoid the need to make assumptions such as time-invariant firm wage effects and a conditional random allocation of workers across firms, which typically do not hold in theories of heterogeneous firms and labor markets.

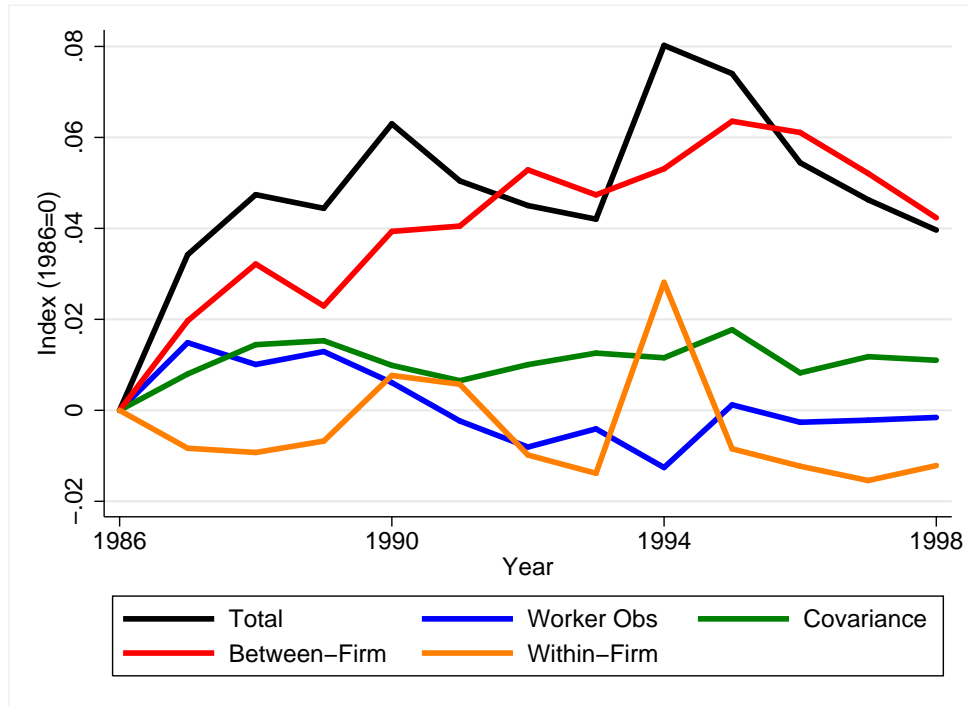


Figure 7: Changes in Log Wage Inequality *within* Sector-Occupations and its Components

Source: RAIS 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Each series expressed as difference from its 1986 value.

to one tenth. Notably, changes in the variance of worker observables account for a negligible share of the growth of wage inequality within sector-occupations, which implies that the substantial contribution of this component to the growth of overall wage inequality in (4) is driven by changes in the variance of worker observables between sector-occupations.

Figure 7 displays the change in wage inequality within sector-occupations and its components in (6) relative to the base year of 1986. Between-firm wage dispersion dominates the evolution of wage inequality within sector-occupations and drives the inverted U-shaped pattern in wage inequality within sector-occupations (which in turn drives the inverted U-shaped pattern in overall wage inequality).

3.3 Between-Firm Wage Inequality

Having established the importance of variation in wages *between* firms *within* sector-occupations for overall wage inequality, we now examine the relationship between firm wages, employment and export status by estimating the following firm-level OLS regression for each sector-occupation-year:

$$Z_{j\ell t} = a_{\ell t} + \alpha_{\ell t} h_{j\ell t} + \rho_{\ell t} b_{j\ell t} + \xi_{j\ell t},$$

where we again index firms by j , sector-occupations by ℓ , and time by t ; the dependent variable ($Z_{j\ell t}$) is either the firm average log worker wage ($\bar{w}_{j\ell t}$) or the firm-occupation-year wage component ($\hat{\omega}_{j\ell t}$); $h_{j\ell t}$

is log firm-occupation-year employment; $\iota_{j\ell t}$ is a $\{0, 1\}$ dummy variable for whether a firm exports; $\xi_{j\ell t}$ is a stochastic error; $\varkappa_{\ell t}$ is a parameter to be estimated that captures the employer-size wage premium; and $\varrho_{\ell t}$ is a parameter to be estimated that captures the exporter wage premium.

Since the estimated residuals ($\hat{\xi}_{j\ell t}$) are by construction orthogonal to firm size ($h_{j\ell t}$) and export status ($\iota_{j\ell t}$), between-firm wage dispersion within each sector-occupation-year can be decomposed into the contributions of the dispersion of firm size, the dispersion of firm export status, the covariance between these two variables, and the variance of the residuals:

$$\text{Var}(\hat{\omega}_{j\ell t}) = \hat{\varkappa}_{j\ell t}^2 \text{Var}(h_{j\ell t}) + \hat{\varrho}_{\ell t}^2 \text{Var}(\iota_{j\ell t}) + 2 \text{Cov}(\varkappa_{\ell t} h_{j\ell t}, \varrho_{\ell t} \iota_{j\ell t}) + \text{Var}(\hat{\xi}_{j\ell t}).$$

Taking differences relative to a base year, the growth in between-firm wage dispersion within each sector-occupation can be similarly decomposed into the contributions of the change in each of these components: firm size ($\Delta[\hat{\varkappa}_{j\ell t}^2 \text{Var}(h_{j\ell t})]$), firm export status ($\Delta[\hat{\varrho}_{\ell t}^2 \text{Var}(\iota_{j\ell t})]$), the covariance between these variables ($2 \Delta \text{Cov}(\varkappa_{\ell t} h_{j\ell t}, \varrho_{\ell t} \iota_{j\ell t})$) and the residual ($\Delta \text{Var}(\hat{\xi}_{j\ell t})$).²²

Consistent with a large empirical literature in labor economics (e.g. Oi and Idson 1999) and international trade (e.g. Bernard and Jensen 1995, 1997), we find positive and statistically significant premia for employment size and export status. Both premia are of around the same magnitude as in existing empirical studies: using the firm-occupation-year wage component ($\hat{\omega}_{j\ell t}$), the employment-weighted average estimates across sectors and occupations are $\varkappa_{j\ell t} = 0.07$ and $\varrho_{\ell t} = 0.28$ respectively.

In Table 6, we report the results of the above decompositions as the employment-weighted average of the sector-occupation values. The first column decomposes the level of between-firm wage dispersion in 1990, while the second column decomposes changes in between-firm wage dispersion from 1986-1995. In Panel A, the dependent variable is the mean log worker wage of the firm ($\bar{w}_{j\ell t}$) for each sector-occupation-year, while in Panel B the dependent variable is the estimated sector-occupation-year firm fixed effect ($\hat{\omega}_{j\ell t}$). Comparing the two panels, we find similar results using the two different wage measures. For the level of between-firm wage dispersion, firm employment makes a contribution of around 7 percent, with firm export status and the covariance between firm employment and export status each being responsible for around 2-3 percent. By far the largest contribution of close to 90 percent comes from the residual. For the growth of between-firm wage dispersion, firm export status accounts for at least one third (66 percent in Panel A and 33 percent in Panel B), with a further positive contribution coming from an increased covariance between firm employment and export status (24 percent in Panel A and 16 percent in Panel B). In contrast, the dispersion of firm employment declines during our sample period, as reflected in the negative contributions of -41 and -36 percent in Panels A and B, respectively.²³ The residual accounts for the remaining 51 percent in Panel A and 88 percent in Panel B of the growth in between-firm wage dispersion.

Fact 3 *Larger firms pay higher wages than smaller firms and exporters pay higher wages than nonex-*

²²While we can further decompose some of these components into a change in premium and a change in dispersion, we refrain from doing so in the interest of brevity.

²³These negative contributions reflect a decline in the dispersion of firm employment ($\text{Var}(h_{j\ell t})$) rather than a decline in the size-wage premium ($\hat{\varkappa}_{j\ell t}$).

Table 6: Decomposition of *Within*-sector-occupation *Between*-firm Log Wage Inequality

	Level (percent)	Change (percent)
A. Unconditional	1990	1986-1995
Firm Employment	7	-41
Firm Export Status	3	66
Covariance Employment-Export Status	3	24
Residual	88	51
B. Controlling for Worker Observables	1990	1986-1995
Firm Employment	7	-36
Firm Export Status	2	33
Covariance Employment-Export Status	2	16
Residual	89	88

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Decomposition of the level and growth of between-firm wage inequality within sector-occupations (employment-weighted average of the results for each sector-occupation). 12 sectors are 5 occupations as in Tables 1 and 2. Between-firm wage dispersion in Panel A is measured using the mean of the log worker wage for each firm. Between-firm wage dispersion in Panel B is measured using the firm-occupation-year fixed effects from Panel B of Table 5, which are estimated separately for each sector-occupation-year and control for worker observables according to (5). See the text of the paper for further discussion.

porters. Export status explains between one third and one half as much of the level of between-firm wage dispersion as employment does. A growing dispersion in export status contributes significantly to the growth of between-firm wage dispersion, whereas the dispersion of firm employment declines over time.

4 Structural Estimation

Guided by the empirical findings in the previous section, we now develop an extension of Helpman, Itskhoki, and Redding (2010a, HIR henceforth). In the HIR model, wages vary between firms within sector-occupations, a firm's employment and wages are related to each other, and this relation is impacted by trade participation. In what follows we present an extension of the HIR model, we develop a method for structurally estimating this enhanced model, and then we apply it to the Brazilian data.

4.1 Theoretical Framework

The economy consists of many sectors, some or all of which manufacture differentiated products. We are interested in variations across firms and workers within a differentiated product sector. Therefore we focus the exposition on one such industry.

Within the sector there is a continuum of firms, each supplying a distinct horizontally-differentiated variety. Demand functions for varieties emanate from constant elasticity of substitution (CES) preferences. As a result, a firm's revenue in market m (domestic or foreign) can be expressed in terms of its

output supplied to this market (Y_m) and a demand shifter (A_m):

$$R_m = A_m Y_m^\beta, \quad m \in \{d, x\},$$

where d denotes the domestic market and x the export market. The demand shifter A_m depends on aggregate sectoral expenditure and the sectoral price index in market m . Since every firm is of measure zero, the firm takes this demand shifter as given. The parameter $\beta \in (0, 1)$ controls the elasticity of substitution between varieties.

In order to export, a firm has to incur a fixed cost $e^\varepsilon F_x$, where ε is firm-specific and F_x is common to all firms in the industry. In addition, there are iceberg-type variable trade costs: $\tau > 1$ units of a variety have to be exported for one unit to arrive in the foreign market.

An exporting firm allocates output between the domestic and export market to maximize revenue. As a result, the firm's revenue ($R = R_d + R_x$) can be expressed as a function of its output ($Y = Y_d + Y_x$), the demand shifter in the domestic market (A_d), and a market access variable (Υ_x):

$$R = [1 + \iota(\Upsilon_x - 1)]^{1-\beta} A_d Y^\beta, \quad (7)$$

where

$$\Upsilon_x = 1 + \tau^{\frac{-\beta}{1-\beta}} \left(\frac{A_x}{A_d} \right)^{\frac{1}{1-\beta}}$$

and ι is an indicator variable, equal to one when the firm exports and to zero otherwise. The revenue of a nonexporter is $R = A_d Y^\beta$, while the revenue of an exporter is $R = \Upsilon_x^{1-\beta} A_d Y^\beta$. The revenue is larger the lower the variable trade cost parameter is and the larger the foreign demand shifter is relative to the domestic demand shifter.

We assume that firm output (Y) depends on a firm productivity (θ), the measure of workers it has hired (H), and the average ability of these workers (\bar{a}):

$$Y = e^\theta H^\gamma \bar{a}, \quad 0 < \gamma < 1. \quad (8)$$

HIR show that this production function can be derived from human capital complementarities (e.g., production takes place in teams and the productivity of a worker depends on the average productivity of her team), or from a model of managerial time constraint (e.g., a manager with a fixed amount of time needs to allocate some time to every worker). Importantly, technology (8) exhibits complementarity between the firm's productivity and average worker ability.

Firms and workers are matched in a labor market that exhibits search and matching frictions of the Diamond-Mortensen-Pissarides type. A firm bears a search cost bN in order to randomly match with N workers. The hiring cost b is endogenously determined by tightness of the labor market, yet it is taken as given by every firm in the industry.²⁴

Upon matching with a firm, a worker draws a match-specific ability (a) from a Pareto distribution

²⁴In our econometric model, labor market tightness is absorbed in the constants of the estimation equations. For this reason we do not elaborate these details below. The interested reader can find them in Helpman, Itskhoki, and Redding (2010a).

$G_a(a) = 1 - (a_{\min}/a)^k$ for $a \geq a_{\min} > 0$ and $k > 1$. This distribution is identical and independent across workers. Although a firm cannot observe the match-specific abilities of its N workers, it can invest resources in screening in order to obtain a signal of these abilities. By choosing an ability threshold a_c , a firm can identify workers with abilities below a_c , but it cannot identify the precise ability of every worker. Screening costs increase with the ability threshold and equal $e^{-\eta}Ca_c^\delta/\delta$, where η is firm specific while δ and C are common to all firms. The incentive to screen workers results from the complementarity of worker abilities in the production function (8). We also assume $\delta > k$, which ensures a positive size-wage premium (i.e., the empirically-observed positive relationship between firm wages and employment).

The timing of decisions is as follows. Firms and workers enter the industry. Every firm draws a triplet $\{\theta, \eta, \varepsilon\}$, which represents its idiosyncratic components of productivity in production, screening costs, and fixed export costs. Given this triplet, the firm chooses whether to serve only the domestic market or also export (every firm in the industry serves the domestic market). Firms that stay in the industry post vacancies. Based on these vacancies, firms are matched with workers. After the matching, every firm chooses its screening threshold and hires the workers with match-specific abilities above this threshold. Therefore, a firm that has been matched with N workers and has chosen the ability cutoff a_c hires

$$H = N \left(\frac{a_{\min}}{a_c} \right)^k$$

workers whose average ability is

$$\bar{a} \equiv \mathbb{E}[a|a \geq a_c] = \frac{ka_c}{k-1}, \quad (9)$$

where \mathbb{E} is the expectations operator. After the firm has paid all fixed costs (production, exporting, matching and screening), it engages in multilateral bargaining with its H workers over wages, as in Stole and Zwiebel (1996). HIR show that the outcome of this bargaining game is a wage rate

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

That is, the wage bill (WH) is a fixed fraction of the revenue (R). Workers who have not been matched with firms, or whose match-specific abilities have fallen below their firm's threshold, become unemployed.

Anticipating this bargaining outcome, a firm maximizes its profits by choosing the number of workers to match with (N), the screening threshold (a_c), and whether to export:

$$\Pi = \max_{N, a_c, \iota \in \{0,1\}} \left\{ \frac{1}{1 + \beta\gamma} R(N, a_c, \iota) - bN - \frac{Ce^{-\eta}}{\delta} a_c^\delta - \iota F_x e^\varepsilon \right\},$$

where the revenue function $R(N, a_c, \iota)$ is derived from (7)–(9). HIR show that the solution to this

problem yields²⁵

$$R = \kappa_r [1 + \iota (\Upsilon_x - 1)]^{\frac{1-\beta}{\Gamma}} (e^\theta)^{\frac{\beta}{\Gamma}} (e^\eta)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}},$$

$$H = \kappa_h [1 + \iota (\Upsilon_x - 1)]^{\frac{(1-\beta)(1-k/\delta)}{\Gamma}} (e^\theta)^{\frac{\beta(1-k/\delta)}{\Gamma}} (e^\eta)^{\frac{\beta(1-\gamma k)(1-k/\delta)}{\delta\Gamma} - \frac{k}{\delta}}, \quad (10)$$

$$W = \kappa_w [1 + \iota (\Upsilon_x - 1)]^{\frac{k(1-\beta)}{\delta\Gamma}} (e^\theta)^{\frac{\beta k}{\delta\Gamma}} (e^\eta)^{\frac{k}{\delta} \left(1 + \frac{\beta(1-\gamma k)}{\delta\Gamma}\right)}, \quad (11)$$

where $\Gamma \equiv 1 - \beta\gamma - \beta(1 - \gamma k)/\delta > 0$ is a derived parameter and the κ_i 's ($i = r, h, w$) are combinations of variables and parameters that are common to all firms in the industry. Given these solutions, a firm chooses to serve only the domestic market when the additional profits from exporting are negative, or

$$\kappa_\pi \left(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1 \right) (e^\theta)^{\frac{\beta}{\Gamma}} (e^\eta)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} < F_x e^\varepsilon, \quad (12)$$

where κ_π is constant across firms. When this inequality is reversed, the firm serves both the domestic market and the export market. A firm is more likely to export the higher are its production and screening productivity draws, θ and η , and the lower is its fixed export cost productivity draw ε . When condition (12) holds, $\iota = 0$; otherwise $\iota = 1$.

Equations (10)–(12) describe firm employment, wages, and export participation. This model features two sources of firm heterogeneity that do not exist in HIR: heterogeneity in screening and in fixed export costs. Without heterogeneous screening costs, employment and wages are perfectly correlated across firms, inconsistent with the data. And without heterogeneous export-market entry costs, a firm's revenue and wage bill perfectly predict its export status, which is also inconsistent with the data. Our extensions have the potential to generate the correlations observed in the Brazilian data, which we expect to also hold for other data sets.

Our theoretical model predicts that firms with higher productivity in production (higher θ) hire more workers (for $\delta > k$), pay higher wages, and are more likely to export. However, while firms with higher productivity in screening (higher η) also pay higher wages and are more likely to export, they may hire more or fewer workers. The reason for this ambiguity stems from two opposing incentives on hiring. On the one hand, lower screening costs raise overall profitability, thereby raising the incentive to expand and hire more workers. On the other hand, lower screening costs make selectivity in hiring more attractive, thereby lowering employment. On net, lower screening costs may increase or reduce employment.

Lower fixed export costs make exporting more profitable for more firms. In the model, exporting raises a firm's employment and wages compared to nonexporters with similar productivity levels in production and screening. An exporter employs more workers because it has access to a larger market, and having access to a larger market makes a larger output more profitable. The higher wage results from the exporter being larger than a nonexporter, as a result of which the exporter screens workers more selectively and ends up with a better labor force (a higher average match-specific ability \bar{a}). A higher average ability raises in turn the cost of losing a worker, which improves the workers' stance in the

²⁵See eq. (S16) in the online supplement to HIR at http://www.econometricsociety.org/ecta/Supmat/8640_extensions.pdf.

wage bargaining. Consequently, exporters pay higher wages. This export wage premium is important for matching the model to the data.

The heterogeneity of fixed exporting costs implies that the productivity draws in production and screening only imperfectly determine a firm's export status. As a result, some small and low-wage firms find it profitable to export while some large and high-wage firms prefer to serve only the domestic market. Yet on average, exporters are larger and pay higher wages than nonexporters, as observed in the data.

We have derived theoretical relationships between a firm's employment, wages, and export status from a model of search and matching in the labor market, match-specific worker abilities, and costly screening of employees. The structural shocks $\{\theta, \varepsilon, \eta\}$ play a key role in matching this model to the data, and our theoretical framework imposes restrictions on the values of some of the parameters that we will estimate. After developing the econometric model in the next section, we report the estimation results for the Brazilian data in the following section.²⁶

4.2 Econometric model

Our econometric model consists of two equations, for employment and wages, and an inequality for export status. Taking logarithms of (10)–(12), we obtain:

$$\begin{cases} h &= \alpha_h + \mu_h \iota + \frac{\beta(1-k/\delta)}{\Gamma} \theta + \left(1 - \frac{k}{\delta}\right) \left[\frac{\beta(1-\gamma k)}{\delta \Gamma} - \frac{k/\delta}{1-k/\delta} \right] \eta, \\ w &= \alpha_w + \mu_w \iota + \frac{\beta k}{\delta \Gamma} \theta + \frac{k}{\delta} \left(1 + \frac{\beta(1-\gamma k)}{\delta \Gamma}\right) \eta, \\ \iota &= \mathbb{I}\{\tilde{u} \geq \tilde{f}\}, \end{cases},$$

where h and w are the natural logarithms of employment (H) and wages (W), respectively, and

$$\begin{aligned} \alpha_i &= \log \kappa_i, \quad i = h, w, \\ \mu_h &= \left(1 - \frac{k}{\delta}\right) \log \Upsilon_x^{(1-\beta)/\Gamma}, \\ \mu_w &= \frac{k}{\delta} \log \Upsilon_x^{(1-\beta)/\Gamma}, \\ \tilde{f} &= \log \kappa_\pi + \log F_x - \log \left[\Upsilon_x^{(1-\beta)/\Gamma} - 1 \right], \\ \tilde{u} &= \frac{\beta}{\Gamma} \theta + \frac{\beta(1-\gamma k)}{\delta \Gamma} \eta - \varepsilon, \end{aligned}$$

and $\mathbb{I}\{\cdot\}$ is an indicator function that equals one when the condition in the brackets is satisfied and zero otherwise. We show in the appendix how this system can be transformed into:

$$\begin{cases} h &= \alpha_h + \mu_h \iota + v, \\ w &= \alpha_w + \mu_w \iota + \zeta v + z, \\ \iota &= \mathbb{I}\{u \geq f\}, \end{cases} \quad \begin{pmatrix} v \\ z \\ u \end{pmatrix} \sim \mathcal{N} \left[\mathbf{0}, \begin{pmatrix} \sigma_v^2 & 0 & \rho_v \sigma_v \\ 0 & \sigma_z^2 & \rho_z \sigma_z \\ \rho_v \sigma_v & \rho_z \sigma_z & 1 \end{pmatrix} \right], \quad (13)$$

²⁶Variation in wages across firms within an industry—which our model delivers and which is an important feature of the data—can also be derived from other theoretical models, including models of search and matching (e.g., Davidson, Matusz, and Shevchenko 2008 and Coşar, Guner, and Tybout 2011), fair wages (e.g., Amiti and Davis 2011 and Egger and Kreickemeier 2009), and efficiency wages (e.g., Davis and Harrigan 2011). We discuss alternative interpretations of our econometric model in the next section.

where

$$\begin{aligned} v &= \frac{\beta(1-k/\delta)}{\Gamma} \theta + \left(1 - \frac{k}{\delta}\right) \left[\frac{\beta(1-\gamma k)}{\delta \Gamma} - \frac{k/\delta}{1-k/\delta} \right] \eta, \\ z &= \frac{k/\delta}{1-k/\delta} (\eta - \mathbb{E}[\eta | v]), \\ \zeta &= \frac{k/\delta}{1-k/\delta} (1 + \mathbb{E}[\eta | v]), \end{aligned}$$

and u and f are transforms of \tilde{u} and \tilde{f} , respectively.²⁷ In order to estimate this model, we assume that the idiosyncratic shocks $\{\theta, \eta, \varepsilon\}$ are independently normally distributed with zero means, and we normalize the variance of u to equal 1. Although these distributional assumptions are not needed for estimation, we adopt them in order to facilitate the interpretation of results.

The theoretical model implies certain parameter restrictions. First, in the special case where shocks to the screening technology do not affect employment, the following parameter restriction must hold:

$$\frac{\beta(1-\gamma k)}{\delta \Gamma} = \frac{k/\delta}{1-k/\delta},$$

which implies that v is perfectly correlated with θ and z is perfectly correlated with η . In other words, in this case variation in v faithfully reflects variation in production productivity while variation in z faithfully reflects variation in screening costs. This parameter restriction is satisfied if and only if

$$\mu_w = \zeta \mu_h, \quad (14)$$

or if and only if $\mathbb{E}[\eta|v] = 0$. When this restriction is not satisfied, v is a nondegenerate linear combination of θ and η , while z is a residual from the projection of $[(k/\delta)/(1-k/\delta)]\eta$ on v . Moreover, in all cases u is a linear combination of all three shocks $\{\theta, \eta, \varepsilon\}$, with positive weights on the first two and a negative weight on the third. As a result, v and z are orthogonal, while u is positively correlated with both of them. Together with $\Upsilon_x > 1$, this implies the following nonnegativity constraints on the parameters of the econometric model (13):

$$\mu_h, \mu_w, \rho_v, \rho_z \geq 0. \quad (15)$$

In words, both exporter size and wage premia are nonnegative and there is positive selection into exporting for large and high-wage firms. It follows that a positive correlation between export status, firm size, and wages results from causality running in both directions: low fixed export costs cause firms to export as well as to be large and pay high wages, while high productivity shocks cause firms to be large, pay high-wages, and export.

Finally, the theoretical model (10)–(12) imposes one additional restriction on the parameters of (13) (see the appendix for details):

$$\frac{\rho_v}{\rho_z} = (1 + \zeta) \frac{\sigma_v}{\sigma_z}. \quad (16)$$

This restriction emanates in the model from wage bills, revenues, and operating profits (gross of fixed costs) being perfectly correlated in the cross-section. As a result, the joint correlation structure between

²⁷Note that $\mathbb{E}[\eta|v] = \hat{b}v$, where \hat{b} is the regression coefficient of η on v . Also note that $\mu_h + \mu_w = \log \Upsilon_x^{(1-\beta)/\Gamma}$, which allows us to remove terms in this variable from our empirical estimates of f , and hence isolate the fixed cost of exporting up to a constant.

employment, wages, and export status has to satisfy (16).

Our econometric model (13) takes a form similar to a Tobit Type 5 model in ? or a switching regression model with endogenous switching in ?. This model admits a closed-form likelihood function, which we now derive. Since we have data on employment, wages, and export status, we observe for every firm j the vector (h_j, w_j, ι_j) . The aim is to estimate the ten parameters of (13): $\alpha_h, \alpha_w, \zeta, \sigma_v, \sigma_z, \rho_v, \rho_z, \mu_h, \mu_w$ and f . We show in the appendix that the likelihood function of this system is

$$\begin{aligned}\mathcal{L} &= \prod_j P\{h_j, w_j, \iota_j\} = \prod_{j, \iota_j=0} P\{h_j, w_j, \iota_j = 0\} \prod_{j, \iota_j=1} P\{h_j, w_j, \iota_j = 1\}, \\ P\{h_j, w_j, \iota_j = 0\} &= \frac{1}{\sigma_v} \phi(\hat{v}_j) \frac{1}{\sigma_z} \phi(\hat{z}_j) \Phi\left(\frac{f - \rho_v \hat{v}_j - \rho_z \hat{z}_j}{\sqrt{1 - \rho_v^2 - \rho_z^2}}\right), \\ P\{h_j, w_j, \iota_j = 1\} &= \frac{1}{\sigma_v} \phi(\hat{v}_j) \frac{1}{\sigma_z} \phi(\hat{z}_j) \left[1 - \Phi\left(\frac{f - \rho_v \hat{v}_j - \rho_z \hat{z}_j}{\sqrt{1 - \rho_v^2 - \rho_z^2}}\right)\right],\end{aligned}$$

where

$$\hat{v}_j = \frac{h_j - \alpha_h - \mu_h \iota_j}{\sigma_v} \quad \text{and} \quad \hat{z}_j = \frac{(w_j - \alpha_w - \mu_w \iota_j) - \zeta(h_j - \alpha_h - \mu_h \iota_j)}{\sigma_z},$$

$\Phi(\cdot)$ is the standard normal cumulative distribution function and $\phi(\cdot)$ is the corresponding standard normal density.

We identify the model's parameters through functional form and distributional assumptions, including the theoretical restrictions (15)–(16). As a check on our functional form assumptions, we show that the resulting estimates provide a good approximation to the data. In the next section we report estimates for every year in our sample, allowing the estimated parameters to change over time. We estimate the model separately for every year to allow the estimated parameters to change over time, because the export threshold (f) and the export premia (μ_h and μ_w) depend on trade costs—fixed (F_x) and variable (τ)—and on the foreign relative to the domestic demand (A_x/A_d), which vary over time. We report results for both the unconstrained model and the model that satisfies the theoretical restrictions (15)–(16).²⁸

As we mentioned before, there exist other models of search and matching in the labor market, including fair wages and efficiency wages, which can generate a firm wage-size premium and export size and wage premia. Moreover, it may be possible to derive from these models an econometric specification similar to (13). To obtain the desirable correlations between shocks to employment and wages on the one hand and shocks to export participation on the other, is not simple, however. For example, if in our theoretical model we were to replace the shock to screening with a shock to the bargaining power of a firm relative to its workers, the resulting correlations would not be consistent with the data. In other words, not every model that predicts variation of wages, size and export status across firms in an industry is capable of explaining the data. While we do not know whether there exist other models that lead to

²⁸The model yields closed-form expressions for the means, variances and covariances of export status, wages and employment. We show in the appendix how to use this information to estimate the model with the Generalized Method of Moments (GMM). The GMM results provide an additional check on the model's functional form assumptions. While the GMM and ML estimates are similar, GMM is less efficient. For this reason, we focus on the ML results in the main text.

Table 7: Maximum Likelihood Estimates, 1994

	Specification	$\log \mathcal{L}$	percent loss in $\log \mathcal{L}$	LR
(i)	Unconstrained	-45,170.2	—	—
(ii)	Structural model	-45,239.5	0.15	138.4
(iii)	No trade effects ($\mu_h = \mu_w = \rho_v = \rho_z = 0$)	-57,774.1	27.90	25,207.8

Source: Maximum likelihood estimates using RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Unconstrained model (i) maximizes the likelihood function imposing no constraints on the parameters. Structural specification (ii) imposes inequality constraint (15) which turns out to be not binding and equality constraint (16) implied by the structural model. No-trade-effects specification (iii) sets both selection correlations (ρ_v and ρ_z) and exporter premia (μ_h and μ_w) to zero implying no link between trade participation and firm employment and wage distributions; that is, the firm employment and wage distribution in this case are independent from the distribution of export status.

an econometric specification similar to (13), we conjecture that models of this type exist, and, moreover, (13) may be a good approximation to some models even if it does not represent an exact specification. A theoretical underpinning of the econometric model is desirable, however, because it helps to identify parameters of interest.

4.3 Estimation results

We estimate the econometric model (13) with data on firm export status, employment, and wages. Since the theory deals with firm-specific wages of workers with similar ex-ante characteristics, we use the fixed effects $\hat{\omega}_{j\ell v}$ from the Mincer regressions (5) in Section 3.2 for wages. These fixed effects for firm-occupation-year cells are conditioned on worker observables, and therefore represent wage variation across firm-occupation-year cells for workers with similar characteristics. Since the selection equation is defined at the firm level, we aggregate the firm-occupation-year fixed effects across occupations for every firm-year cells, using occupation employment as weights. For employment and export status we use the actual data.²⁹

Table 7 reports statistics for three specifications of the econometric model: (i) unconstrained; (ii) our structural model (constraints (15) and (16)); and (iii) a model in which exports do not impact employment and wages (constraints $\mu_h = \mu_w = \rho_v = \rho_z = 0$). For every specification the table reports the log of the likelihood function, and for the two constrained specifications it also reports the percentage decline in the log likelihood value that results from the constraints, as well as the likelihood ratio test statistic (LR) that assesses the validity of the constraints (the latter equals twice the difference between the log likelihood of the unconstrained and constrained models). Using an asymptotic χ^2 test for LR , our large sample of about 100,000 firms rejects every conceivable constraint on the parameters of the econometric

²⁹The present draft of the paper reports only results for the case of firm fixed effects. We also intend to estimate the model with actual wages, inclusive of returns to observed worker characteristics.

model. Because a constraint that is statistically rejected can have little impact on a model’s fit, we focus instead on how well the model fits the data.

From a comparison of the log likelihoods, specification (iii) yields a fit that is substantially worse than the unconstrained specification (i) or the constrained specification (ii). We therefore conclude that selection into exporting is important for explaining variation in employment and wages, or that foreign trade substantially impacts the wages and employment level of firms. Second, imposing the constraints of the theoretical model reduces the log likelihood value by only a little, 0.15 percent, although the likelihood ratio test statistic, equal to 138.4, rejects these constraints at conventional confidence levels. Moreover, as we report in the appendix, unconstrained estimates do not yield positive export premia, but once we impose (16) the resulting estimates also satisfy (15).³⁰ Therefore, based on the similar model fit of specifications (i) and (ii) and the theoretically more meaningful parameter estimates in specification (ii), we focus on the latter as our preferred specification.

The data strongly suggest that trade is an important determinant of employment and wage distributions across firms; omitting export participation substantially worsens the model’s fit. Furthermore, the unconstrained model—which allows arbitrary exporter premia and correlations of employment and wages with selection into exporting—generates a relatively flat likelihood function around the maximands in the parameter space $(\mu_h, \mu_w, \rho_v, \rho_z)$. The theoretical restrictions help us discipline the parameter choice, which underscores an important role for a structural approach such as ours. Below we focus on comparing the unconstrained specification (i) with the constrained specification (ii) that admits the theoretical restrictions.

Fit of the model. Figure 8 presents *ML* estimates of all the parameters of the constrained model (ii) (ten in total) for the years 1990-98, for which we have data on export status.³¹ These estimates exhibit substantial employment and wage export premia μ_h and μ_w . In addition, they show positive but very small correlations ρ_v and ρ_z , which means that there is weak selection into exporting. The dispersion of v falls over time, and this is driven by the decreasing dispersion of employment across firms. More surprisingly, the size-wage parameter ζ decreases over time, in contrast to the size-wage premium in the data. As we show in Table 9, however, this does not hamper the model’s ability to trace the size-wage premium in the data. The dispersion of z follows a humped shape over time, paralleling the dispersion of wages across firms. Finally, the export cost parameter f follows a U shape, which tracks the inverted U shape of the share of exporters over time (see Figure 1).

Next consider the model’s fit in the cross section. The first column in Tables 8 and 9 reports cross-section moments in the data, the second column reports predicted moments of the unconstrained model,

³⁰We have also estimated the model with other constraints. For example, when we add (14) to the theoretical restrictions (15)–(16) the fit worsens substantially, from which we conclude that shocks to screening costs should be allowed to impact employment (recall that (14) imposes the restriction that shocks to screening costs do not affect employment, in which case $t = \theta$ and $z = \eta$). Moreover, imposing the constraints $\mu_h = \mu_w = 0$ (i.e., no export premia in employment and wage) leads to a large deterioration in the model’s fit, which implies that export premia are important for explaining the data.

³¹We are currently working on deriving standard errors for the constrained specification; the standard errors for the unconstrained specification are very small (the confidence intervals are very tight), and we expect the standard errors for the constrained specification to be small as well. In addition, we have recently obtained exporting data for the years 1986-89 and we plan to extend the estimates to these earlier years.

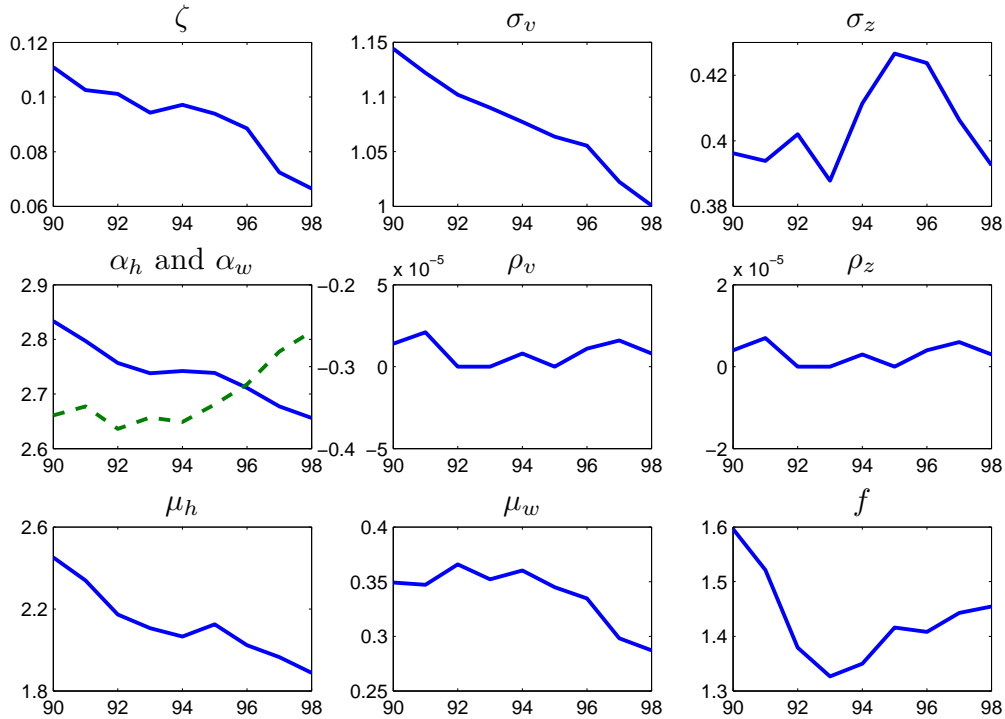


Figure 8: Maximum Likelihood Parameter Estimates Across Years

Source: Maximum likelihood estimates using RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: ML estimates from a structural specification under constraints (15) and (16). Parameters are estimated from the cross-section of employment, wages and export status across firm for each year.

and the third column reports predicted moments of the constrained model, all for 1994. The predicted moments are calculated from simulated data (drawing a triplet $\{v, z, u\}$ for every firm) of the estimated unconstrained and constrained models. Table 8 presents firm-level moments: mean employment, mean wages, the standard deviation of employment, the standard deviation of wages, and the covariance between wages and employment. These moments are presented for the full sample as well as for nonexporters and exporters separately. In addition, the table reports the share of exporters in the sample.³²

Table 9 presents worker-level moments: mean wages (Panel A) and standard deviations of wages (Panel B) for the full sample, as well as for employees of exporters and nonexporters. In Panel C of Table 9, we show four measures of wage inequality (the 90/10 percentile ratio, the 90/50 percentile ratio, the 50/10 percentile ratio, and the Gini coefficient). To compute worker moments in the data, the firm-year fixed effects from the wage equation are weighted by the number of workers employed by each firm in that year.³³ Similar calculations are performed with the simulated data for each one of the two

³²We use in the appendix the moments from Table 8 for GMM estimation.

³³Note that the firm-occupation-year fixed effects are normalized, so that in every year their mean is zero across workers within every sector-occupation cell. For this reason the mean firm-year fixed effect equals zero across all workers.

Table 8: Model Fit for Firm-level Moments, 1994

	Data	Model	
		Unconstrained	Structural
A. Full Sample			
Mean Employment	2.9	2.9	2.9
Mean Wage	-0.34	-0.34	-0.34
Share of Exporters	0.089	0.087	0.088
Standard deviation Employment	1.2	1.2	1.2
Standard deviation Wage	0.44	0.44	0.44
Covariance Employment-Wage	0.17	0.17	0.17
B. Nonexporters			
Mean Employment	2.7	2.7	2.7
Mean Wage	-0.37	-0.37	-0.37
Standard deviation Employment	1.03	1.08	1.08
Standard deviation Wage	0.43	0.43	0.43
Covariance Employment-Wage	0.11	0.12	0.11
C. Exporters			
Mean Employment	4.8	4.8	4.8
Mean Wage	-0.01	-0.01	0.00
Standard deviation Employment	1.47	1.08	1.08
Standard deviation Wage	0.38	0.39	0.42
Covariance Employment-Wage	0.18	0.10	0.11

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Moments for log wages and log employment in the data and in the simulated data generated using ML estimates for 1994 from the unconstrained and structural specifications. The moments are means, standard deviations and covariances across firms. The log wage measure in the data is the firm-occupation fixed effect estimated from (5), aggregated to the firm level using occupation employment weights.

models. In Panel D of Table 9 we report coefficients from regressing firm wages on firm employment and export status, which provide measures of the wage-size and wage-export premia, and we present the employment share of exporters.

Judging by the moments in Tables 8 and 9, the model provides a relatively close fit to the data. Both firm and worker moments generated by the constrained model closely match the moments in the data, and this match is not worse than the moments generated by the unconstrained model. As a rule, the constrained model is more successful in explaining the distribution of firm wages than the distribution of firm employment (see Table 8), with the largest discrepancies occurring for the standard deviation of employment and the covariance of employment and wages across exporters. The model's prediction for the distribution of wages across workers depends on its predictions for both firm wages and employment. Therefore, while we generally find the predictions for worker wages to be close to those in the data, the differences are larger than for firm wages (see Table 9). Of particular interest is the fact that the model fits not only the first and second moments of firm employment and wage distributions, but also nonlinear

Table 9: Model Fit for Worker-level Moments, 1994

	Data	Model	
		Unconstrained	Structural
A. Mean Wage			
Full Sample	0.0	-0.1	-0.1
Exporters	0.16	0.10	0.12
Nonexporters	-0.17	-0.25	-0.26
B. Standard deviation Wage			
Full Sample	0.42	0.45	0.46
Exporters	0.35	0.40	0.42
Nonexporters	0.42	0.42	0.43
C. Wage Inequality			
Gini	0.23	0.24	0.26
90/10	3.0	3.1	3.3
90/50	1.6	1.7	1.8
50/10	1.8	1.8	1.8
D. Wage Premia and Exporter Shares			
Size premium	0.097	0.099	0.097
Exporter premium	0.16	0.16	0.17
Exporter Employment Share	0.52	0.43	0.44

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Moments for log wages and log employment in the data and in the simulated data generated using ML estimates for 1994 from the unconstrained and structural specifications. Moments are calculated across workers; the wage measures are the firm-occupation fixed effects estimated from (5), aggregated to the firm level using occupation employment weights, and weighted by the number of workers employed by the firm. 90/10 denotes the ratio of the 90-th and 10-th percentiles of log worker wage distribution, and similarly for 90/50 and 50/10. Size and exporter premia are coefficients estimates from a regression of log firm wages on log firm employment and a dummy for firm exporting.

transformations of the worker wage distribution such as the 90/10, 90/50 and 50/10 wage percentile ratios, the Gini coefficient, and the exporter wage premia.³⁴

Figures 9–10 provide further evidence of the quality of the cross-sectional fit; they display kernel density estimates of the distributions of employment and wages across firms and workers in the data and the simulations of the constrained model. The comparison is for 1994; results for other years are similar. Figure 9 displays densities for distributions across firms while Figure 10 displays densities for distributions across workers. Here too we see that the fit is particularly good for wages and less so for employment. The left two panels of Figure 9 report results for employment while the right two panels report results for wages. The upper panels report results for all firms while the lower panels report separate estimates for exporters and nonexporters. A striking feature of the data is the substantial overlap between the employment and wage distributions of exporters and nonexporters, although both distributions of employment and wages are more to the right for exporters than for nonexporters. As we

³⁴Moreover, the model generates a Lorenz curve that closely tracks the Lorenz curve in the data.

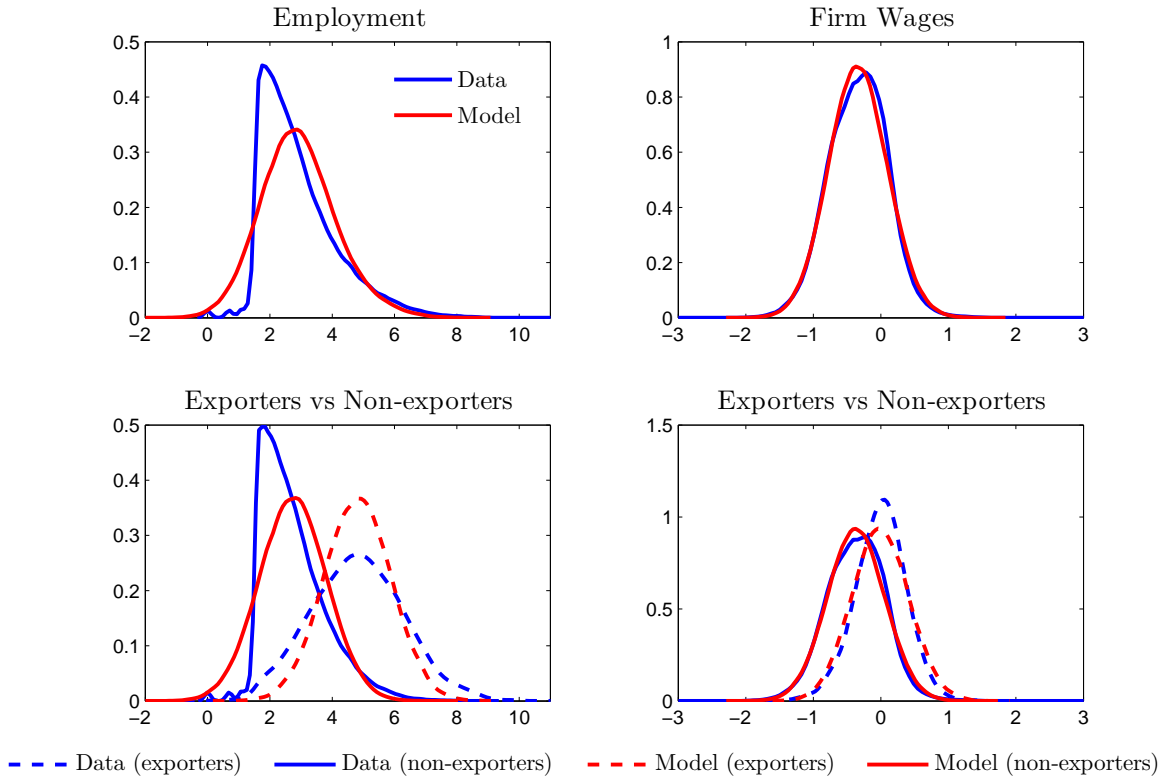


Figure 9: Model Fit for the Distribution of Log Employment and Log Wages across Firms

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Kernel densities for employment and wage distributions across firms in the data and in the simulated data generated from the model with ML estimated parameters with the structural constraints (15) and (16) imposed.

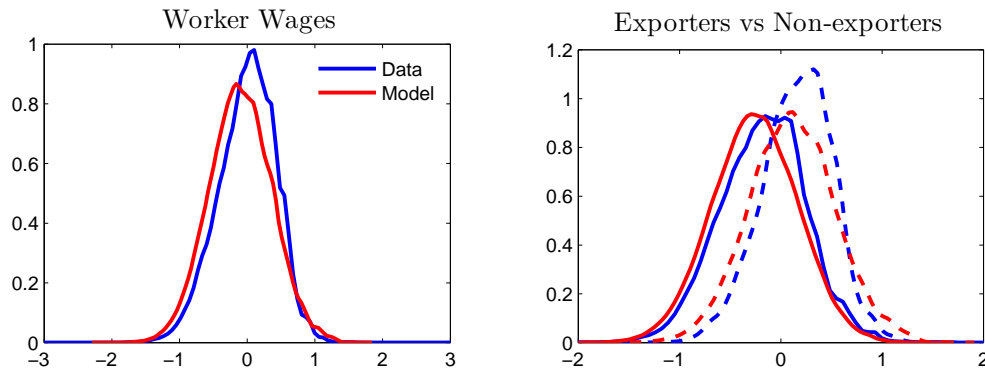


Figure 10: Model Fit for the Distribution of Log Wages across Workers

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Kernel densities for wage distribution across workers, weighted by firm employment, in the data and in the simulated data generated from the model with ML estimated parameters with the structural constraints (15) and (16) imposed.

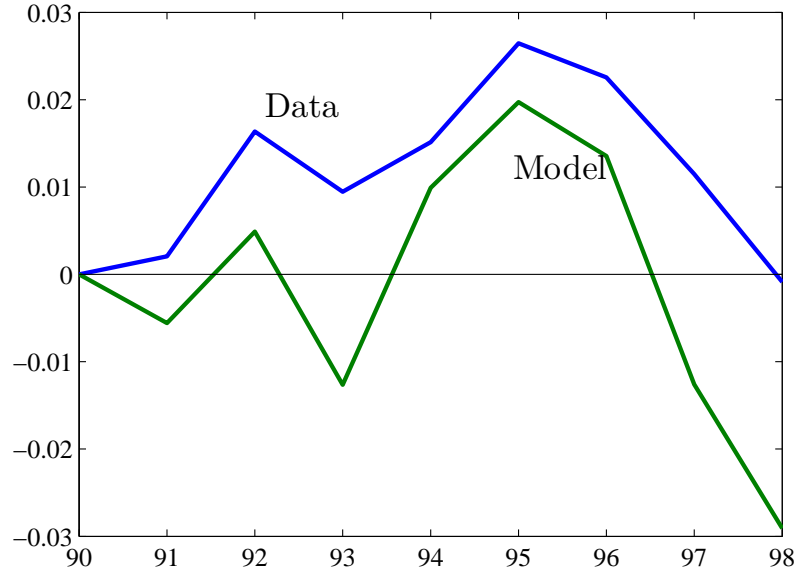


Figure 11: Model Fit for the Change over Time in Log Wage Inequality

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Variance of log wages (firm fixed effect from Mincer regression (5)) in the data and in the simulated data generated with the ML estimates of the parameters under the structural specification subject to constraints (15) and (16). The data from the model is generated separately for each year using the respective parameter estimates.

explained in the theoretical Section 4.1, all three shocks $\{\theta, \eta, \varepsilon\}$ are needed to match this pattern.

Confirming our earlier results for selected moments of these distributions, we see that the model provides a good fit to the data. While the fit of the employment distribution is satisfactory, the structural assumptions of the model do not allow it to match two features of the data. One is the skewness and heavy right tail of the employment distribution among nonexporters, which appears to be closer to Pareto than to log-normal. The second is the higher dispersion of employment among exporters relative to nonexporters, which the model cannot match with a common σ_v among all firms (i.e., a dispersion that is independent of export status). On the other hand, as shown in Figure 10, the model fits well the distribution of wages across all workers, as well as across workers employed by exporting firms and nonexporting firms. However, it slightly underpredicts the variance of wages among the exporters.

Taken together, the results in Tables 8–9 and Figures 9–10 strongly support our econometric model. Despite the model’s sparsity and its reliance on functional forms, we find that it approximates the data reasonably well. The model captures both the higher average employment and wages of exporters relative to nonexporters, and the substantial overlap in the distributions of employment and wages between these two groups of firms.

Counterfactuals. Figure 11 displays the variance of log worker wages from 1990-98, and compares it to the variance of simulated log wages from the annually estimated structural model. Evidently, the

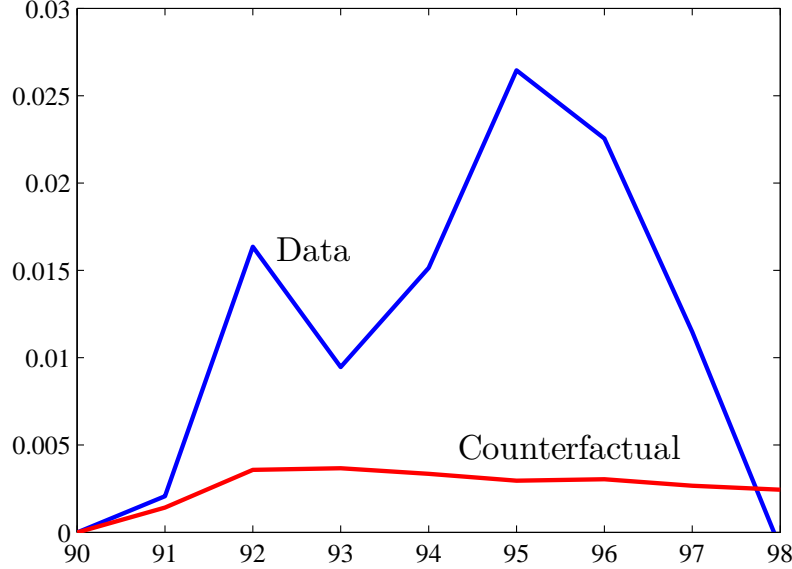


Figure 12: Data and Counterfactual: Contribution of Trade to Log Wage Inequality Dynamics

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Variance of log wages (firm fixed effect from Mincer regression (5)) in the data and the counterfactual evolution of variance of log wages in the simulated data in which all parameters are held fixed at their 1994 estimated levels (in the structural specification (iii)), except for f which varies over time according to its estimated values depicted in Figure 8.

structural model captures the inverted U-shaped pattern in the data; wage inequality rises from 1990 to 1995 and declines thereafter. The model captures about 80 percent of the empirical rise in inequality between 1990 and 1995.

Next, we present in Figure 12 a counterfactual simulation in which the distribution of wages changes over time in response to the estimated changes in the export cutoff f , holding constant all the other parameters of the structural model at their 1994 values. This exercise is consistent with a case in which f changes as a result of changes in the common export fixed cost F_x , while $\mu_h + \mu_w$ and hence market access Υ_x remain constant. For this reason the counterfactual pattern of wage dispersion displayed in Figure 12 does not fully capture trade liberalization, which typically also involves changes in variable trade costs (τ) and changes in the demand shifters in the domestic and export market (A and A^*) that determine Υ_x .³⁵ Nonetheless, changes in the common fixed exporting cost F_x alone affect the fraction of exporting firms and their average wages and employment.³⁶

The figure shows that variation in the common fixed exporting cost parameter alone explains a sizeable fraction of inequality dynamics after 1990. Indeed, this channel explains over 30 percent of the

³⁵In the case of symmetric countries, market access depends on variable trade costs alone: $\Upsilon_x = 1 + \tau^{-\beta/(1-\beta)}$.

³⁶While this exercise identifies one channel of trade's impact on inequality, there are other channels that it disregards. In particular, movements in μ_h and μ_w impact wage inequality. In the data, μ_h exhibits a marked decrease over time while μ_w is stable until 1995 and decreases thereafter. Both of these trends contributed to a decline in wage inequality, in particular after 1995. Furthermore, our model does not allow the variances σ_v and σ_z to depend on export status, which imposes a substantive constraint.

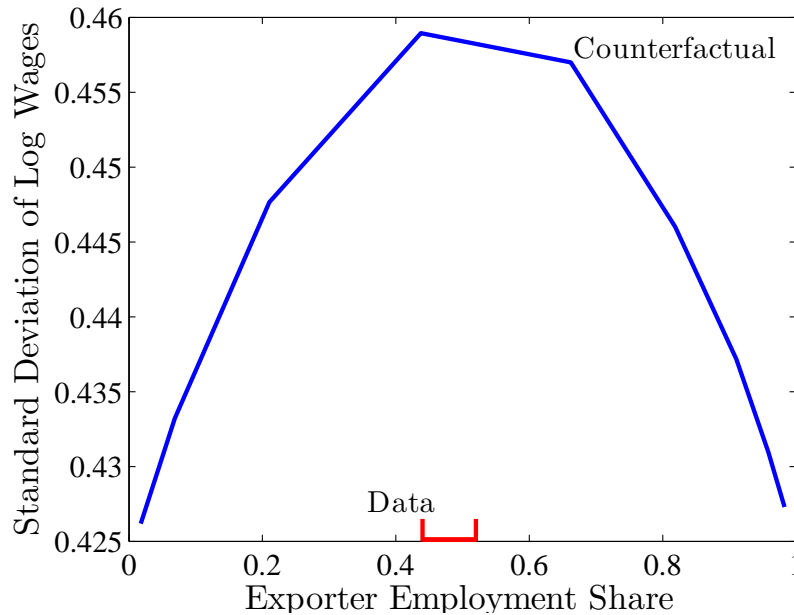


Figure 13: Counterfactual Relationship between Trade Openness and Log Wage Inequality

Source: RAIS and SECEX 1986-98, workers at manufacturing firms with positive wage (last-held top-paid job per year).

Note: Counterfactual variance of log wages in the simulated data in which all parameters are held fixed at their 1994 estimated levels (in the structural specification (iii)), except for f which varies from small to large values corresponding to a high and a low share of employment in exporting firms respectively. Red interval corresponds to variation in the share of employment in exporting firms in the data.

inequality dynamics between 1990 and 1994. However, this channels fails to predict the surge in wage inequality between 1994 and 1995. As a result, it accounts for only 15 percent of the inequality increase between 1990 and 1995.

Figure 13 describes another counterfactual exercise, designed to better understand the forces that shape the relationship between wage inequality and trade. As in Figure 12, the simulations in Figure 13 hold constant the parameters of the structural model at their 1994 values, except for the trade participation cutoff f . Unlike Figure 12, however, in Figure 13, f varies not according to its estimated values but rather from arbitrarily small to arbitrarily large values. By varying f in this range, we vary the fraction of exporting firms and their share in employment between zero and one. Again we hold constant Υ_x and all other parameters. For each value of f , the figure depicts the corresponding relationship between wage inequality and exporters' share of employment. In other words, Figure 13 tracks the evolution of wage inequality as the economy moves from autarky to a trade equilibrium in which all firms export. This relationship has an inverted U shape, as in the theoretical model of Helpman, Itskhoki, and Redding (2010a).

In addition to the simulated patterns of wage inequality, Figure 13 displays the actual range of the employment share of exporters in the data between 1990 and 1998. In the figure, the peak of worker wage inequality predicted by the structural model is attained around the share of exporter employment

that existed in Brazil in 1994. As a result, the small variation in the actual share of exporters in this range inevitably leads to a small variation in worker wage inequality. For this reason one cannot hope to adequately account for the rise in worker wage inequality in the data with changes in the common fixed cost of exporting F_x only, which explains why the counterfactual simulation in Figure 12 explains only a modest share of the inequality increase.³⁷ Note, however, that the difference between the peak of wage inequality and its value in autarky is large, which implies that the structural model has the potential of explaining larger changes in wage inequality through variation in the common fixed cost of exporting F_x .

To summarize, while the trade channel is important for the cross-sectional fit of the structural model and it can explain out-of-sample (e.g., going from autarky to actual levels of trade openness) substantial increases in wage inequality, given the level of Brazil's trade openness in the 1990s the model predicts that further increases in the extensive margin of trade are unlikely to contribute much to growing wage inequality. On the other hand, further increases in the intensive margin of trade (through the employment and wage premia μ_h and μ_w) can significantly raise wage inequality.

5 Conclusion

Recent theories of firm heterogeneity and trade point to variation in wages across firms and the self-selection of firms into export markets as a mechanism for international trade to affect wage inequality. Guided by these theories, we use micro data for Brazil to provide evidence on the empirical relevance of this mechanism for observed wage inequality.

In contrast to neoclassical trade theory, which emphasizes wage inequality between sectors and occupations, we find that most of the increase in wage inequality in Brazil since the mid-1980s occurred within sectors and occupations. Consistent with recent theories of firm heterogeneity and trade, we find that this increase in within-sector-occupation wage inequality largely occurred between firms. Furthermore, this increase in between-firm wage inequality is not simply explained by an increase in the dispersion of firm-size. And these findings become even stronger after controlling for observed worker characteristics, which is in line with the emphasis in heterogeneous-firm theories on residual, or within-group, wage inequality.

Motivated by these findings, we estimate a structural econometric model of firm export status, employment and wages, which is derived from an augmented version of Helpman, Itskhoki, and Redding (2010a) that incorporating heterogeneity in fixed exporting and screening costs. We show that the econometric model is successful in empirically accounting for observed patterns of wage inequality, and we find support for the restrictions on its parameters imposed by the theory.

While the relative unimportance of wage changes between sectors and occupations has often been viewed as evidence against a role for trade in explaining wage inequality, this perspective is based on

³⁷The fraction of exporting firms increased from 5.5 percent in 1990 to a peak of over 9 percent in 1994. However, the new exporters were small relative to the incumbent exporters, which explains the moderate rise in the fraction of workers hired by exporters from 44 percent in 1990 to 52 percent in 1994. As it turns out, the variation in the share of workers hired by exporters in the 1990s is concentrated around the peak of the worker wage inequality curves in Figure 13.

neoclassical trade theory. Using both reduced-form and structural approaches, we find strong evidence in support of the view that trade has a sizable impact on wage inequality.

Appendix

TO BE COMPLETED

A Data Appendix

Our main data source is the linked employer-employee database RAIS (*Relação Anual de Informações Sociais*) for the period 1986 to 2001, a nationwide administrative register of workers formally employed in any sector of Brazil's economy (including the public sector). Brazilian law requires every Brazilian plant to submit annual reports with detailed employment and demographic information on every formally employed worker to the ministry of labor (*Ministério de Trabalho*, MTE). The original intention of the RAIS records is to provide information for a federal wage supplement program (*Abono Salarial*), by which every worker with formal employment during the calendar year receives the equivalent of a monthly minimum wage. A strong incentive for compliance is that workers' benefits depend on RAIS so that workers follow up on their records. The payment of the worker's annual public wage supplement (*Abono Salarial*) is exclusively based on RAIS records. The ministry of labor estimates that currently 97 percent of all formally employed workers in Brazil are covered in RAIS, and that coverage exceeded 90 percent throughout the 1990s. The raw data have 71.1 million workers with 556.3 million job spells at 5.52 million plants in 3.75 million firms between 1986 and 2001.

We restrict our sample to the manufacturing sector and to firms with at least five workers, and we aggregate the monthly worker-plant information to firms and to calendar years. For this purpose, we first restrict the worker sample to all proper worker identifiers (*PIS/PASEP*) with the required 11 digits. For every worker, we then retain her or his last employment per year (which may or may not occur in December).³⁸ If a worker holds more than one simultaneous job at that time, we keep the job with the highest pay (randomly dropping ties). We infer a firm's sector in RAIS as its worker mode sector across the firm's plants. For wage information, we use the RAIS reported average wage that the worker earns over the course of the job spell during the calendar year. RAIS records the average wage in multiples of the current minimum wage, which we transform into the annual equivalent wage in current US-Dollars, multiplying the monthly average wage by twelve and using the end-of-year nominal exchange rate along with the prevailing minimum wage for the currency conversion.

We classify occupations into five categories. Occupation information in RAIS 1986-2001 is reported under the *CBO* system of 1994 (*Classificação Brasileira de Ocupações*), which we convert to the internationally comparable *ISCO-88* categories following Muendler, Poole, Ramey, and Wajenberg (2004). For the conversion, we reset unknown *CBO* codes in RAIS at the four-digit level to the nearest applicable miscellaneous occupation category at the four-digit level. We then group the *ISCO-88* categories into five broad occupations: Professional & Managerial occupations (including professionals, senior officials, and managers), Technical & Supervisory occupations (including technicians and associate professionals),

³⁸In contrast, Menezes-Filho, Muendler, and Ramey (2008) only retain observations of jobs on December 31st of the calendar year.

Other White Collar occupations (including clerks, service workers, shop and market sales workers), Skill Intensive Blue Collar occupations (including plant and machine operators and assemblers, craft and related workers, skilled agricultural and fishery workers), and Other Blue Collar occupations (elementary occupations in *ISCO-88*).

We categorize worker demographics into age, education, and gender groups. The eight age categories are Child (10-14), Youth (15-17), Adolescent (18-24), Nascent Career (25-29), Early Career (30-39), Peak Career (40-49), Late Career (50-64) and Post Retirement (65+). The four education categories are Primary School or less education (up to 8 grades of education including illiteracy), Some High School education (up to 12 grades of education), Some College education (college enrollment without college degree), and College Graduate. There are two gender categories.

Exporter data. We obtain information on the employer's export status from national customs records. The exports records are available to us from SECEX (*Secretaria de Comércio Exterior*) for 1990 through 2001. We set the indicator variable for a firm's export status to one if SECEX records show exports by the firm of any product to any destination in a given year.³⁹ We link the export-status indicator to RAIS at the firm level.

When we combine the SECEX exporter data with the linked employer-employee information from RAIS for 1990-2001 (no firm size restriction), we find that 23,518 manufacturing firms are exporters in at least one sample year (87,050 exporter-year observations). This means that only around 5 percent of formal manufacturing firms are exporters, similar to the around 5 percent exporter share in the U.S. universe of manufacturing firms (Bernard, Jensen, and Schott 2009). Single-employee firms enter the RAIS records, explaining the apparently low share of exporter firms in the total, compared to data for most other developing countries that censor their samples at a minimum employment level. In terms of employment, manufacturing exporters account for roughly half of Brazilian formal employment during the sample period.

Regression sample. For wage regressions, we only keep workers with a non-zero wage and firms in the manufacturing sector (subsector *IBGE* codes 2 through 13), and we remove manufacturing firms with strictly less than five positive-wage workers. For wage regressions, we restrict the sample to the period 1990-1998. The resulting estimation data for the Mincer log wage regressions contain 7.3 million workers (7,298,623) and 96,385 firms over the nine sample years 1990-98 and, for our five occupation groups, 234,353 firm-occupation cells. For the distributions related to firm-wide exports and destination percentiles, we aggregate the firm-occupation data to the firm level, weighting by firm-occupation employment.

³⁹We do not use a minimum exports per sales ratio to define the export indicator because sales information is only available for a small subsample of firms from a manufacturing survey.

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