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Trade and Inequality: From Theory to Estimation

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While neoclassical theory emphasizes the impact of trade on wage inequality *between* occupations and sectors, more recent theories of firm heterogeneity point to the impact of trade on wage dispersion *within* occupations and sectors. Using linked employer–employee data for Brazil, we show that much of overall wage inequality arises within sector–occupations and for workers with similar observable characteristics; this within component is driven by wage dispersion between firms; and wage dispersion between firms is related to firm employment size and trade participation. We then extend the heterogenous-firm model of trade and inequality from Helpman *et al*. (2010) and estimate it with Brazilian data. We show that the estimated model provides a close approximation to the observed distribution of wages and employment. We use the estimated model to undertake counterfactuals, in which we find sizable effects of trade on wage inequality.

Key words: Wage Inequality, International Trade

JEL Codes: F12, F16, E24

1. INTRODUCTION

The field of international trade has undergone a transformation in the last decade, with attention shifting to heterogeneous firms as drivers of foreign trade. Until recently, however, research on the labour 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. In contrast to the predictions of those theories, empirical studies find 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* sectors. In part due to this disconnect, previous studies have concluded that the contribution of trade to growing wage inequality is modest at best.

This article argues that these apparently discordant empirical findings are in fact consistent with a trade-based explanation for wage inequality, but one rooted in recent models of firm heterogeneity rather than neoclassical trade theories. For this purpose, we develop a theoretical model that is consistent with the observed cross-sectional patterns of wages, employment and export status across firms. We develop a methodology for estimating this model and illustrate with Brazilian data how the estimated model can be used to quantify the contribution of trade to wage inequality through the mechanism of firm selection into international trade.

To motivate our theoretical model, we first provide evidence on a number of stylized facts about wage inequality, using Brazilian data from 1986–95.[1] We combine approaches from different parts of the trade and labour literature to provide an integrated view of the sources of wage inequality in the data. First, we document that much of overall wage inequality occurs *within sectors and occupations* rather than between sectors and occupations. Secondly, a large share of this wage inequality within sectors and occupations is driven by wage inequality *between* rather than within firms. Thirdly, both of these findings are robust to controlling for observed worker characteristics, suggesting that this within sector–occupation and between-firm component of inequality is *residual* wage inequality. These features of the data motivate the focus of our theoretical model on wage inequality within sectors, between firms, and for workers in the same occupations and with similar observed characteristics.

We measure the between-firm component of wage inequality by including a firm-occupation-year fixed effect in a Mincer regression of log worker wages on controls for observed worker characteristics. This *firm wage component* includes both wage premia for workers with identical characteristics and returns to unobserved differences in workforce composition across firms. We focus on this overall wage component, because our model features imperfect assortative matching of workers across firms, and hence incorporates both these sources of wage differences across firms. We find a strong relationship between this firm wage component and trade participation: exporters are on average larger and pay higher wages than non-exporters. While these exporter premia are robust features of the data, the exporter and non-exporter employment and wage distributions overlap, so that some non-exporters are larger and pay higher wages than some exporters.

To account for these features of the data, we extend the theoretical framework of Helpman *et al*. (2010), which features heterogeneity in firm productivity, to also incorporate heterogeneity in firm human resource practices (the cost of screening workers) and the size of fixed exporting costs. Heterogeneity in firm productivity drives differences in firm employment size and export status. Heterogeneous firm human resource practices allow for variation in wages across firms after controlling for their employment size and export status, while idiosyncratic exporting costs allow some small low-wage firms to profitably export and some large high-wage firms to serve only the domestic market. We use the structure of the theoretical model to derive a reduced-form econometric model of firm employment, wages and export status. This econometric model explains positive exporter premia for employment and wages and predicts imperfect correlations between firm employment, wages and export status. It also highlights that the exporter wage premium depends on both the *selection* into exporting of more productive firms that pay higher wages and the increase in firm wages because of the greater *market access* of exporters.

We estimate our econometric model using three different identification approaches. Our baseline estimates use the full structure of the model to estimate its parameters using maximum likelihood (ML). Since any model is an approximation to the data, we also consider two alternative identification approaches that rely less strongly on the model's functional form and distributional assumptions. First, we estimate the model using the Generalized Method of Moments (GMM)

1. Similar patterns hold in a number of other countries, including the U.S., as we discuss further below.

under weaker identifying assumptions, which results in an underidentified system of moments of the data. The moments are selected to capture both the salient features of the data and the key mechanisms in the model. We use this underidentified system of moments to provide upper and lower bounds to the counterfactual impact of trade on wage inequality. We show that these bounds define a tight interval for the counterfactual effects of trade on wage inequality, which nests our ML counterfactuals. Secondly, we consider a semi-parametric selection model following Powell (1994) that further relaxes our functional form and distributional assumptions, and uses exclusion restrictions for variables that affect the probability of exporting, but do not affect employment or wages conditional on exporting. Here again we identify effects that are quantitatively consistent with the other two approaches.

We show that the estimated model provides a good fit to the empirical joint distribution of employment and wages across firms conditional on export status. We find that trade participation is important for the model's fit, which deteriorates substantially when we shut down the market access effects of exporting. We further show that the estimated parameters provide sufficient statistics for the impact of trade on wage inequality, so that the estimated reduced form of the model can be used to undertake counterfactuals for the wage inequality impact of changes in fixed and variable trade costs.

Across all three identification approaches, we find similar and sizable effects of trade on wage inequality through the mechanism of firm selection into export markets. In our baseline specification, opening the closed economy to trade leads to around a 10% increase in the standard deviation of log worker wages. Starting from the model's estimates for our baseline year of 1994, the observed Brazilian tariff reductions from 1986 to 1995 are predicted to increase the share of workers employed by exporting firms by around 10 percentage points, as in the data, and to increase wage inequality by around 2%. In comparison, the standard deviation of log worker wages increased in Brazil by around 8% between 1986 and 1995. Extending our baseline model to incorporate multiple export destinations magnifies the impact of trade on wage inequality, with opening the closed economy to trade raising wage inequality by around 20%.

Our article is related to a number of strands of research, including the labour market effects of trade, heterogeneous firms, the estimation of search models of the labour market, and the estimation of firm and worker wage components. We briefly discuss here the trade and labour literature, and provide a more detailed discussion of the broader related labour literature in the Supplementary Materials. Models of firm heterogeneity and trade suggest two sets of reasons for wage variation across firms. One line of research assumes competitive labour markets and assortative matching of heterogeneous workers and firms, with wages varying across firms as a result of differences in workforce composition (see, e.g. Yeaple, 2005; Verhoogen, 2008; Bustos, 2011; Burstein and Vogel, 2012; Monte, 2011; Sampson, 2014). Another line of research introduces labour market frictions so that workers with the same characteristics can be paid different wages by different firms. For example, efficiency or fair wages can result in wage variation across firms when the wage that induces worker effort, or is perceived to be fair, varies with the revenue of the firm (see, e.g. Egger and Kreickemeier, 2009; Davis and Harrigan, 2011; Amiti and Davis, 2012). Furthermore, search and matching frictions and the resulting bargaining over the surplus from production can induce wages to vary across firms (see, *e.g.* Davidson *et al*., 2008; Helpman *et al*., 2010). Methodologically, our work connects most closely with the wider literature quantifying models of international trade, heterogenous firms and labour markets, including Eaton *et al*. (2013), Egger *et al*. (2013) and Coşar *et al*. (2016).[2]

2. The related literature estimating models of trade and labour markets without firm heterogeneity includes Kambourov (2009), Artuc *et al*. (2010), Coşar (2013), and Dix-Carneiro (2014).

Related empirical research using plant and firm data finds substantial differences in wages and employment between exporters and non-exporters following Bernard and Jensen (1995; 1997). More recent research using linked employer–employee datasets has sought to determine the sources of the exporter wage premium, including Schank *et al*. (2007), Munch and Skaksen (2008), Frías *et al*. (2009), Davidson *et al*. (2014), Krishna *et al*. (2014), and Baumgarten (2013). This literature typically makes the assumption that the matching of workers to firms is random after controlling for time-varying worker observables, firm fixed effects, worker fixed effects and in some cases match fixed effects. These empirical studies typically find that the exporter wage premium is composed of both unobserved differences in workforce composition and wage premia for workers with identical characteristics, with the relative importance of these two forces varying across studies.

The literature estimating search models of the labour market includes Burdett and Mortensen (1998), Postel-Vinay and Robin (2002), Cahuc *et al*. (2006), and Postel-Vinay and Thuron (2010). Our main contribution relative to this previous research is to embed a model of heterogeneous firms and search frictions in a rich product market structure following Melitz (2003) that can be used to analyse the effects of international trade on the distributions of wages and employment across firms. A key feature of this product market structure is that each firm faces a downward-sloping demand function in the domestic and export markets that pins down equilibrium firm size and the allocation of sales between the domestic and export markets. While much of the existing search-theoretic literature models jobs rather than firms, a small number of papers do introduce firm effects (see, e.g. Postel-Vinay and Robin, 2002). However, this literature typically assumes perfect competition and constant returns to scale, so that firm size is determined by search frictions in the labour market rather than by the product market. Incorporating a richer model of the product market is central to the international trade issues addressed in our article.

The remainder of the article is structured as follows. In Section 2, we introduce our data and some background information. In Section 3, we present the stylized facts about wage inequality in Brazil. Motivated by these findings, Section 4 develops a heterogeneous-firm model of trade and inequality, uses the structure of the model to derive a reduced-form econometric model, and discusses the alternative identifying assumptions used in the estimation. In Section 5, we estimate the model and conduct counterfactuals. Specifically, Section 5.1 discusses the estimation using ML and the fit of the estimated model. Section 5.2 uses the estimated model to evaluate the counterfactual effects of trade on wage inequality. Then, Section 5.3 relaxes our identifying assumptions and uses a GMM system to provide upper and lower bounds to the impact of trade on wage inequality. Section 5.4 reports the results from an alternative semi-parametric specification. Finally, Section 6 considers an extension of the model to multiple export destinations, and Section 7 concludes. Some derivations and additional results are presented in the Appendix at the end of the article, while separate Supplementary Material contains detailed derivations, further discussion of the data sources and definitions, extensions and generalizations of the model, and additional results.

2. DATA AND BACKGROUND

Our main dataset is a linked employer–employee dataset for Brazil from 1986–98, which we briefly describe here and discuss in further detail in the Supplementary Material. The source for these administrative data is the *Relação Anual de Informações Sociais* (RAIS) database of the Brazilian Ministry of Labor. By law, all formally registered firms are required to report information each year on each worker employed by the firm, as recorded in RAIS. 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 the manufacturing sector, because we expect the mechanisms of both heterogeneous firm and traditional trade models to be relevant for this sector. On the one hand, manufacturing goods are tradable, there is substantial heterogeneity across firms within sectors, and only some firms export, as in heterogeneous firm theories. On the other hand, there are substantial differences in factor intensity across sectors within manufacturing (e.g. Textiles versus Steel), as in traditional trade theories. Therefore, there is the potential for the mechanisms in both sets of theories to be at work in the data. Manufacturing is also an important sector in Brazil, accounting for over 20% of total employment (formal and informal) and around 70% of total merchandise exports. Our data cover all manufacturing firms and workers in the formal sector, which Goldberg and Pavcnik (2003) estimates accounts for around 84% of manufacturing employment.[3]

Our annual earnings measure is a worker's mean monthly wage, averaging the worker's wage payments over the course of a worker's employment spell during a calendar year.[4] For every worker with employment during a calendar year, we keep the worker's last recorded job spell and, if there are multiple spells spanning into the final month of the year, the highest-paid job spell (randomly dropping ties). Therefore, our definition of firm employment is the count of employees whose employment spell at the firm is their final (highest-paid) job of the year. As a check on the quality of the Brazilian matched employer–employee data, Menezes-Filho *et al*. (2008) show that these data exhibit many of the same properties as the matched employer–employee data for France and the U.S. We also show below that we find similar patterns of wage inequality for Brazil as for other countries including the U.S. As an additional check, the Supplementary Material shows that we find similar wage inequality results using Brazilian household survey data for formal and informal sector workers. As a further robustness test, the Supplementary Material also re-estimates our econometric model using Colombia firm-level data and demonstrates a similar pattern of results.

We undertake our analysis at the firm rather than the plant level, because recent theories of firm heterogeneity and trade are concerned with firms, and wage and exporting decisions are arguably firm based. For our baseline sample, we focus on firms with five or more employees, because we analyse wage variation within and across firms, and the behaviour of firms with a handful of employees may be heavily influenced by idiosyncratic factors. But we find a similar pattern of results using the universe of firms. Our baseline sample includes 20.4 million workers and 270 thousand firms from 1986–98.

Each worker is classified in each year by her or his occupation. In our baseline empirical analysis, we use five standard occupational categories that are closely related to skill groups, described in the Appendix Table A1. Each firm is classified in each year by its main sector according to a classification compiled by the *Instituto Brasileiro de Geografia e Estatistica* (IBGE), which disaggregates manufacturing into twelve sectors that roughly correspond to two-digit International Standard Industrial Classification (ISIC) sectors, as reported in Table A2.[5] Since neoclassical trade theory emphasizes differences across occupations and sectors (e.g. in

3. We find similar results if we expand the sample to include agriculture and mining, as shown in the Supplementary Material.

4. Wages are reported as multiples of the minimum wage, which implies that inflation that raises the wages of all workers by the same proportion leaves this measure of relative wages unchanged. Empirically, we find a smooth left tail of the wage distribution in manufacturing, which suggests that the minimum wage is not strongly binding in manufacturing during our sample period. RAIS does not report hours, overtime, investment or physical capital.

5. In robustness tests, we further break down manufacturing employment into 350 occupations (according to the *Classificação Brasileira de Ocupações*, CBO) and over 250 industries (according to the *National Classification of Economic Activities*, CNAE), with the latter classification only available for a part of our sample period (from 1994 onwards).

factor intensity), we would expect these differences to be relevant across such distinct categories as managers versus unskilled blue-collar workers and textiles versus steel. Indeed, there exists substantial variation in average wages across both occupations and sectors, as can be seen from Tables A1 and A2. Skilled white-collar workers are paid on average 68% and 116% above skilled and unskilled blue-collar workers respectively. Machinery and equipment sectors pay an average wage premium of around 62% compared with the typical manufacturing wage, while furniture and footwear sectors pay on average less than two-thirds of the typical manufacturing wage.

RAIS also reports information on worker educational attainment. In our baseline specification, we distinguish the following four categories: Less than High School, High School, Some College, and College Degree, consistent with the labour economics literature (e.g. Autor *et al*., 1998; Katz and Autor, 1999). We also report the results of a robustness test using nine more disaggregated educational categories. In addition to these data on educational attainment, RAIS also reports information on age and gender for each worker. Finally, we construct a measure of a worker's tenure with a firm based on the number of months for which the worker has been employed by the firm.

We combine the linked employer–employee data from RAIS with trade transactions data from *Secretaria de Comércio Exterior* (SECEX) that are available from 1986–98. These trade transactions data report for each export customs shipment the tax identifier of the firm, the product exported and the destination country served. We merge the trade transactions and linked employer–employee data using the tax identifier of the firm. As shown in Table A2, exporters account for a much larger share of employment than the number of firms: the fraction of exporters ranges from 4.1% to 25.4% across sectors, while the exporter share of employment ranges from 34.6% to 75.3%. Since exporters account for a disproportionate share of employment, differences in wages between exporters and non-exporters can have substantial effects on the distribution of wages across *workers*.

Our sample period includes changes in both trade and labour market policies in Brazil. Tariffs are lowered in 1988 and further reduced between 1990 and 1993, whereas non-tariff barriers are dropped by presidential decree in March 1990. Following this trade liberalization, the share of exporting firms nearly doubles between 1990 and 1993, and their employment share increases by around 10 percentage points.[6] In contrast, following Brazil's real exchange rate appreciation of 1995, both the share of firms that export and the employment share of exporters decline by around the same magnitude. In 1988, there was also a reform of the labour market. Finally, the late 1980s and early 1990s witnessed some industrial policy initiatives, which were mostly applied on an industry-wide basis.[7]

3. STYLIZED FACTS

In this section, we combine different approaches from the trade and labour literatures to develop a set of stylized facts on wage inequality in Brazil.[8] We present a sequence of variance

6. For an in-depth discussion of trade liberalization in Brazil, see, for example, Kume *et al*. (2003). The changes in the exporter employment share discussed above are reflected in a similar pattern of aggregate manufacturing exports, as shown in the Supplementary Material.

7. The main elements of the 1988 labour market reform were a reduction of the maximum working hours per week from 48 to 44, an increase in the minimum overtime premium from 20 to 50%, and a reduction in the maximum number of hours in a continuous shift from 8 to 6 hours, among other institutional changes. As regards the industrial policy initiatives, some tax exemptions differentially benefited small firms while foreign-exchange restrictions and special import regimes tended to favour select large-scale firms until 1990.

8. See the Supplementary Material for a detailed comparison of our results for Brazil with those for a number of other countries, where similar patterns also hold.

TABLE 1
Within Sector–occupation and Residual Wage Inequality

A. Contribution of the within component	Level 1994, %	Change 1986–95, %
Within occupation	82	92
Within sector	83	73
Within sector–occupation	68	66
Within detailed-occupation	61	60
Within sector–detailed-occupation	56	54
Within detailed-sector–detailed-occupation	47	—
B. Contribution of the residual component		
Residual wage inequality	59	49
— within sector–occupation	89	90

Notes: Panel A reports the contribution of the within component to total log wage inequality (in levels and in changes), at the respective levels of disaggregation (twelve sectors, five occupations, or sixty sector–occupations cells in the baseline case, and 350 detailed occupation and 250 detailed industries in the extension). The unreported between component is 100% minus the reported within component. The first row of Panel B decomposes the level and change of overall log wage inequality into the contributions of worker observables (unreported) and residual (within-group) wage inequality using a standard Mincer regression. The unreported contribution of worker observables equals 100% minus the reported contribution of residual wage inequality. The second row of Panel B reports the within sector–occupation component of residual wage inequality. Appendix A.2 provides the formal details behind these decompositions.

decompositions that quantify the relative importance of alternative possible sources of wage inequality. In each year, we decompose the overall inequality in log wages into within and between components, as formally stated in Appendix A.2. We undertake this decomposition for sectors and occupations, and then assess the respective contributions of worker observables and firm effects. The use of the log wage ensures that this decomposition is not sensitive to the choice of units for wages and facilitates the inclusion of controls for observable worker characteristics. We report results for the level of wage inequality for 1994, because this year is after trade liberalization and before the major appreciation of the Real. We report results for the growth of wage inequality for 1986–95, a period corresponding to a rapid growth in wage inequality in Brazilian manufacturing. We find a similar pattern of results for different years, as we report in the Supplementary Material.

3.1. *Within versus between sectors and occupations*

In Panel A of Table 1, we report the contribution of the within component (at different levels of disaggregation) to the level and growth of overall wage inequality. As reported in the first three rows, inequality within occupations, sectors and sector–occupation cells accounts, respectively, for 82%, 83%, and 68% of the overall level of wage inequality. Similarly, the majority of the growth in the variance of log wages of around 17.4% (or, equivalently, an 8.3% increase in the standard deviation) is explained by wage inequality within occupations, sectors and sector–occupations.

These baseline decompositions use the twelve manufacturing sectors and five occupations detailed in Tables A1–A2 in the Appendix. While the contribution of the within component inevitably falls as one considers more and more disaggregated categories, we show that its importance is robust to the use of alternative more detailed definitions of sectors and occupations. Specifically, rows four through six of Panel A of Table 1 report further results using 350 occupations and 250 industries, amounting at the finest to around 40,000 sector–occupation cells. In summary, the within sector–occupation component robustly accounts for a major part of overall inequality, in levels as well as in changes.[9]

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

3.2. *Worker observables and residual wage inequality*

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 a standard Mincer regression for log worker wages:

$$w_{it} = z_{it}' \vartheta_t + \nu_{it}, \tag{3.1}$$

where w_{it} is the log wage of worker i, z_{it} is a vector of observable worker characteristics, ϑ_t is a vector of returns to worker observables, and ν_{it} is a residual. We estimate this Mincer regression for each year separately, allowing the coefficients on worker observables to change over time to capture changes in the rate of return to these characteristics. We control for worker observables nonparametrically by including indicator variables for the following categories: education (four categories in the baseline specification), age (5-year bins), quintiles of experience (tenure) at the firm, and gender.

The empirical specification (3.1) serves as a conditioning exercise, which allows us to decompose the overall variance of log wages into the contribution of worker observables and the orthogonal residual component, referred to as *residual* wage inequality. We further decompose residual wage inequality into its within and between components using sector, occupation and sector–occupation cells. Panel B of Table 1 reports the results of this variance decomposition. We find that the worker observables and residual components make roughly equal contributions towards both the level and growth of overall wage inequality.[10] Furthermore, the dominant part (around 90%) of the residual wage inequality arises within sector–occupations, in line with the fact that much of the variation in worker observables is between sector–occupation cells.

Note that residual wage inequality is measured relative to the worker characteristics included in the regression (3.1). In principle, there can be other unmeasured worker characteristics that matter for wages and that are observed by the firm but are uncorrelated with the worker characteristics available in our data. To the extent that this is the case, the contribution of worker characteristics could be larger than estimated here. On the other hand, the wage regression (3.1) projects all variation in wages that is correlated with the included worker characteristics on worker observables. Therefore, if the firm component of wages is correlated with these worker characteristics, some of its contribution to wage variation can be attributed to worker observables, overstating their role, as we further discuss in the next subsection. Keeping these caveats in mind, we state:

9. As the detailed industry classification is only available from 1994 onwards, we therefore only report the variance decomposition in levels in the last specification in Panel A of Table 1. For a later time period (1994–98), for which the more finely detailed industry classification is available, the within component dominates the between component and accounts for the majority of the change in the overall wage inequality (namely, 141% of the overall change, as the within and between components move in offsetting directions during this time period).

10. The results are quantitatively similar when we control for nine more disaggregated education categories. In both cases, we find an increase over time in the estimated returns to education and experience (tenure), consistent with Attanasio *et al*. (2004) and Menezes-Filho *et al*. (2008). See the Supplementary Material for details.

Fact 2. *Residual wage inequality is at least as important as worker observables in explaining the overall level and growth of wage inequality in Brazil from 1986–95. Most of the level and growth of residual wage inequality is within sector–occupation.*

One potential concern is that regional differences in wages could drive wage inequality within sector–occupations for workers with similar observed characteristics (see Fally *et al.*, 2010; Kovak, 2013, for evidence on wage variation across Brazilian states). In the Supplementary Material, we document the robustness of our findings to controlling for region by reporting results using sector–occupation-region cells instead of sector–occupation cells, where we define regions in terms of either twenty-seven states or 136 meso regions. The within component in this case still plays a central role in shaping both the level and growth of wage inequality.

Another potential concern is that our findings for wage inequality could be influenced by changes in workforce composition. Residual wage inequality is typically higher for older workers, more experienced workers and workers with greater education. Therefore changes in the composition of the workforce according to age, experience and education can influence the magnitude of residual wage inequality and its contribution to overall wage inequality. To address this concern, we follow Lemieux (2006) by constructing a counterfactual measure of residual wage inequality, in which workforce composition across cells is held constant at its beginning of the sample values. Using this approach, we find the same quantitative patterns of residual wage inequality (see the Supplementary Material). Therefore, our findings for residual wage inequality are not driven by changes in observable workforce composition.

3.3. *Between versus within-firm wage inequality*

We now decompose wage inequality within sectors and occupations into the contributions of within-firm and between-firm components. To do so, we estimate the Mincer log wage regression (3.1) for each sector–occupation including *firm effects*:

$$w_{it} = z_{it}' \vartheta_{\ell t} + \psi_{j\ell t} + \nu_{it}, \tag{3.2}$$

where i again indexes workers, ℓ indexes sector–occupation cells, and j indexes firms (classified into one of the sectors), and $\psi_{j\ell t}$ denote firm-occupation-year dummies measuring the average log wage paid by firm j to workers with the same observables within an occupation.[11] We allow the coefficients $\vartheta_{\ell t}$ on observed worker characteristics z_{it} to differ across sector–occupations ℓ and time t to capture variation in their rate of return. We also consider a restricted version of equation (3.2) excluding the controls for worker observables, in which case $z_{it}' \vartheta_{\ell t}$ consists solely of the regression constant. We distinguish between our estimates of $\psi_{j\ell t}$ with and without the controls for worker observables by using the terms conditional and unconditional firm wage components, respectively, $\psi_{j\ell t}^{C}$ and $\psi_{j\ell t}^{U}$.

Using the estimates from equation (3.2), we decompose wage inequality within each sector–occupation year into the contributions of worker observables, firm effects, the covariance between

11. We normalize the firm-occupation-year effects $\psi_{j\ell t}$ to sum to zero for each sector–occupation-year, which allows to separately identify the regression constant that is absorbed into the worker observables component. In Table 2, we treat the estimated firm effects $\hat{\psi}_{j\ell t}$ as data, consistent with the model of Section 4, in which each firm's choices determine $\psi_{j\ell t}$ without uncertainty. Alternatively, without this theoretical assumption, the $\hat{\psi}_{j\ell t}$ should be interpreted as estimates. As we show in the Supplementary Material, the required adjustment for the sampling error is small given the average size of the firm in the data of about seventy employees.

TABLE 2
Between versus Within Firm Wage Inequality

	Unconditional firm wage component		Conditional firm wage component	
	Level 1994	Change 1986–1995	Level 1994	Change 1986–1995
Between-firm component	55	115	39	86
Within-firm component	45	−15	37	−11
Worker observables			13	2
Covariance term			11	24

Notes: All entries are in percentage. The table reports the results of the decomposition in equation (3.3) of the level and change of wage inequality within sector–occupations (employment-weighted average of the results for each sector–occupation). The decomposition in the first two columns corresponds to the unconditional firm wage component that does not control for worker observables. The decomposition in the last two columns corresponds to the conditional firm wage component that controls for worker observables. Figures may not sum exactly to 100% due to rounding.

worker observables and firm effects, and the within-firm component (residual), according to:

$$\text{var}(w_{it}) = \text{var}\left(z_{it}'\hat{\vartheta}_{\ell t}\right) + \text{var}\left(\hat{\psi}^{C}_{j\ell t}\right) + 2\text{cov}\left(z_{it}'\hat{\vartheta}_{\ell t}, \hat{\psi}^{C}_{j\ell t}\right) + \text{var}\left(\hat{\nu}_{it}\right), \tag{3.3}$$

where the residual term is orthogonal to the other terms by construction. In the restricted version of equation (3.2) excluding the controls for worker observables, the decomposition (3.3) includes only the between-firm and within-firm components. We summarize the aggregate results from these decompositions as the employment-weighted average of the results for each sector–occupation-year cell. These aggregate results capture the average importance of the between-firm and within-firm components in accounting for wage variation within sector–occupations.

In the first two columns of Table 2, we report the results for the unconditional firm wage component, $\hat{\psi}^{U}_{j\ell t}$. We find that between and within-firm wage inequality make roughly equal contributions to the level of wage inequality within sector–occupations. In contrast, the growth of wage inequality within sector–occupations is almost entirely explained by wage inequality between firms. In the final two columns of Table 2, we summarize the results for the conditional firm wage component, $\hat{\psi}^{C}_{j\ell t}$. We find that the between-firm and within-firm (residual) components account for roughly equal amounts of the level of wage inequality within sector–occupations (39% and 37%, respectively). Of the other two components, worker observables account for 13% and the covariance between worker observables and the firm component of wages accounts for the remaining 11%. In contrast, changes in between-firm wage dispersion account for most (86%) of the growth in wage inequality within sector–occupations. The next largest contribution (24%) comes from an increased correlation between worker observables and the firm wage component, consistent with increased assortative matching on worker observables. Changes in residual within-firm wage dispersion make a small negative contribution, while the contribution of worker observables is negligible.[12]

12. Note that these results are not affected by average differences in wages between occupations within firms, because the firm-occupation year effects are normalized to be mean zero for each sector–occupation year. We find similar results using firm-year rather than firm-occupation-year effects. For example, in this case the estimates corresponding to the third column of Table 2 are 29%, 37%, 21% and 13%, respectively, while the contribution of the between-firm component over time still accounts for 76% of the growth in wage inequality within sectors from 1986 to 1995.

Fact 3. *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 largely accounted for by between-firm wage dispersion.*

A few remarks are in order. First, in the Supplementary Material, we report the results of the decomposition in equation (3.3) for each occupation, sector, and for different types of firms (exporters and non-exporters). For each occupation and sector and for both exporters and non-exporters, we find a substantial between-firm component (see, Supplementary Material Tables H5–H8). Therefore, our findings are not driven by an individual sector, occupation or type of firm, but are rather robust features of the data.[13]

Secondly, the contribution of worker observables in Table 2 is smaller than in Panel B of Table 1 both because we now control for firm-occupation-year effects, and also because we now focus on wage inequality within sector–occupations. Empirically, these two differences contribute roughly equally to the reduction in the role of worker observables.

Thirdly, since location is a fixed characteristic of the firm, the Mincer regression (3.2) cannot be augmented with region fixed effects. However, we can evaluate what fraction of the between-firm wage variation happens within and across regions in Brazil. Specifically, we decompose the variation in the firm-occupation-year effects $\psi_{j\ell t}$ into variation within and between 136 meso regions (assigning multi-plant firms to the region with the firm's mode employment). Although this specification is conservative in that it attributes the variation across firms located in different regions to geographical differences (region-year fixed effects), the majority of the between-firm wage inequality occurs within 136 meso regions, both in levels and in changes.[14]

We use the estimated conditional firm-occupation-year effects, $\hat{\psi}^{C}_{j\ell t}$, as our baseline measure of the firm component of wages in our econometric model below. They capture both firm wage premia for workers with identical characteristics and unobserved differences in workforce composition across firms (including average match effects). Our model features imperfect assortative matching of workers across firms, and hence incorporates both these sources of wage differences across firms. We allow the firm wage component to change over time, because theories of heterogeneous firms and trade such as Helpman *et al*. (2010) emphasize that firm wages vary with firm revenue (e.g. as firms enter and exit export markets).[15] Similarly, we allow the firm wage component to differ across occupations because these theories imply that the sensitivity of firm wages to firm revenue can differ across occupations.

13. This result holds whether we use raw wages or whether we control for worker observables using the Mincer wage regression. The main difference across occupations is that worker observables and the covariance between the firm wage component and worker observables are more important for professional and managerial workers and skilled white-collar workers than for the other occupations.

14. More precisely, the within-region share of the between-firm wage component is around 60% in levels in 1994 and more than 50% in changes between 1986 and 1995, for both conditional and unconditional firm wage components.

15. As a robustness test, Subsection H.15 of the Supplementary Material considers an alternative specification of the Mincer regression (3.2) including time-invariant firm fixed effects, time-invariant worker fixed effects, and time-varying observable worker characteristics. Following Abowd *et al*. (2002), we estimate this specification under the identifying assumptions of no complementarities between worker abilities and conditional random switching of workers between firms. Our theoretical model features complementarities in worker abilities and imperfect assortative matching of workers across firms. Therefore our theoretical model implies that these assumptions are invalid and the firm and worker fixed effects are not separately identified. Nonetheless, we estimate this specification as a robustness test to show that we continue to find that the between-firm component accounts for a substantial proportion of overall wage inequality (around one-third over the sample period as a whole) even after controlling for time-invariant worker fixed effects, which is consistent with the results in both Card *et al*. (2013) and Lopes de Melo (2013).

TABLE 3
Size and Exporter Wage Premia

	Unconditional firm wage component, $\hat{\psi}_{jt}^{U}$	Conditional firm wage component, $\hat{\psi}_{jt}^{C}$
Firm employment size	0.122***	0.104***
	(0.010)	(0.009)
Firm export status	0.262***	0.168***
	(0.042)	(0.024)
Sector fixed effects	Yes	Yes
Within R-squared	0.165	0.130
Observations	91,411	91,411

Notes: Parameter estimates from the cross-section specification (3.4) for 1994; *** denotes statistical significance at the 1% level; standard errors are heteroscedasticity robust.

3.4. *Size and exporter wage premia*

We now examine the relationship between the firm wage component and firm employment and export status, building on the empirical trade literature following Bernard and Jensen (1995, 1997). We first construct a measure of firm wages in each year by aggregating our firm-occupation-year wage components from the previous subsection to the firm-year level using employment weights. We next regress these firm wage components on firm employment and export status for each year:

$$\psi_{jt} = \lambda_{\ell t}^{o} + \lambda_t^s h_{jt} + \lambda_t^x \iota_{jt} + \nu_{jt}, \tag{3.4}$$

where we again index firms by j; ℓ now denotes sectors; h_{jt} is log firm employment; $\iota_{jt} \in \{0,1\}$ is a dummy for whether a firm exports and ν_{jt} is the residual. Coefficients $\lambda_{\ell t}^{o}$ are sector-time fixed effects, λ_t^s is the employment size wage premium and λ_t^x is the exporter wage premium, where we allow both of these premia to vary over time.

In Table 3, we report the results for 1994 for both measures of the firm wage component. Consistent with a large empirical literature in labour economics and international trade, we find positive and statistically significant premia for employment size and export status (see, e.g. the survey by Oi and Idson, 1999). As a check on the quality of the Brazilian wage data, our estimate of the employer-size wage premium using data on raw wages for Brazilian manufacturing of 0.12 compares to a value of 0.14 reported for U.S. manufacturing in Bayard and Troske (1999). Similarly, using raw firm wages, we estimate an exporter premium of 0.26 in Table 7 (after controlling for firm size), which compares to the value of 0.29 reported for U.S. manufacturing in Table 8 of Bernard *et al*. (2007). Using the firm wage component controlling for worker observables ($\hat{\psi}_{jt}^{C}$), we find a size premium of 0.10 and an exporter premium of 0.17.[16] In this reduced-form specification, the exporter wage premium does not have a causal interpretation, because it captures both the non-random selection of high-wage firms into exporting (beyond that captured by firm size) and the impact of exporting on the wage paid by a given firm. In contrast, our structural model below separates out these two components of the exporter wage premium by modelling a firm's endogenous decision to export.

Although the employment size and exporter wage premia are statistically significant in both specifications, the correlation between firm wages, employment and export status is imperfect. After netting out the sector fixed effects, the within R-squared is around 0.15. This pattern of results

16. Augmenting regression (3.4) with firm employment growth has little effect on either the estimated size and exporter wage premia or on the regression fit. In the previous version of the article (Helpman *et al*., 2012), we show that exporter wage premia are also observed in a panel data specification including firm fixed effects.

suggests that there is a systematic component of firm wages (related to firm size and export status) and an idiosyncratic component. While the R-squared of the reduced-form regressions in Table 3 suggests that the idiosyncratic component is large relative to the systematic component, this does not rule out changes in the systematic component having economically meaningful effects on wage inequality. Indeed, changes in the systematic component shift the entire wage distribution and hence can have a substantial effect on overall wage dispersion. Section 5 quantifies the effect of trade on inequality using an estimated model that captures both the systematic and idiosyncratic components of firm wages and hence reproduces the cross-section relationship between firm wages, employment and export status in these regressions.

Fact 4. *Larger firms on average pay higher wages. Controlling for size, exporters on average pay higher wages than non-exporters. Nonetheless, controlling for size and export status, the remaining variation in wages across firms is substantial.*

Taken together, the findings of this section have established a number of key stylized facts about the cross-section distribution of wages, employment and export status. We find that within sector–occupation inequality accounts for much of overall wage inequality. Most of this within sector–occupation dispersion is residual wage inequality. Furthermore, between-firm variation in wages accounts for a substantial proportion of this wage inequality within sector–occupations. Finally, we find that wage variation across firms exhibits robust employment size and exporter wage premia.

4. STRUCTURAL MODEL

In this section, we develop an extension of the Helpman *et al*. (2010, HIR henceforth) model, which accounts for the above stylized facts, and highlights firm selection into export markets as a new mechanism for trade to affect wage inequality.[17] Each of these stylized facts are long-run features of the cross-sectional distribution of wages, employment and export status. Therefore, we develop a static model to explain these steady-state patterns. We use this model to undertake counterfactuals in which we compare the steady-state distributions of wages, employment and export status before and after trade liberalization. By abstracting from dynamics, our model highlights the new mechanism of firm selection into export markets in a particularly transparent way. Furthermore, we show in the Supplementary Material that the same mechanism can be embedded in a dynamic setting, and that the steady-state of this dynamic model yields similar cross-sectional relationships between firm employment, wages and export status to those in the static model.[18] In what follows we first describe and generalize the HIR model; we then develop a method for estimating this extended model; and lastly we apply the model to the Brazilian data

17. We focus our econometric analysis on firm exporting rather than firm importing. While the mechanism linking trade and wage inequality in our theoretical model is driven by firm export-market participation as in Melitz (2003), the model can also be extended to capture firm selection into importing as in Amiti and Davis (2012). To the extent that firm importing increases productivity and raises revenue per worker, it results in a similar *importer* wage premium, and our methodology could be applied to this other dimension of firm selection. In practice, firm exporting and importing are strongly positively correlated in the cross section, and hence in our estimation we capture most of the overall effect of firm trade participation.

18. While our static model results in a log-linear reduced form, the cross-sectional relationships in the steady-state of the dynamic model are non-linear. Nonetheless, these relationships in the dynamic model feature the same pattern of correlations between wages, employment and export status as in the static model (see the Supplementary Material). Also see Itskhoki and Helpman (2014) for a complete characterization of transition dynamics in a related but simpler model without worker heterogeneity.

and use the estimated model to conduct counterfactuals to quantify the effects of globalization on wage inequality.

4.1. *Theoretical framework*

We begin by briefly describing the theoretical framework of HIR, emphasizing the modifications we make in order to take the model to the data. The economy consists of many sectors, some or all of which manufacture differentiated products. The model's predictions for wages and employment across firms within each differentiated sector hold regardless of general equilibrium effects. Therefore we focus on variation across firms and workers within one such differentiated sector.

Within the sector there are a large number of monopolistically competitive 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):

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

where d denotes the domestic market and x the export market. The demand shifter A_m is a measure of product market competition, increasing in the sectoral expenditure and decreasing in the sectoral price index. Since every firm is small relative to the sector, the firm takes this demand shifter as given. The parameter $\beta \in (0,1)$ controls the elasticity of substitution between varieties equal to $1/(1-\beta) > 1$.

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 sector. In addition, there are iceberg 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 its 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, and a *market access* variable (Υ_x):

$$R = [1 + \iota(\Upsilon_x - 1)]^{1-\beta} A_d Y^{\beta}, \qquad \text{where} \quad \Upsilon_x = 1 + \tau^{\frac{-\beta}{1-\beta}} \left(\frac{A_x}{A_d}\right)^{\frac{1}{1-\beta}}, \tag{4.5}$$

and ι is an indicator variable, equal to one when the firm exports and equal to zero otherwise. The revenue of a non-exporter is $R = A_d Y^{\beta}$, while the revenue of an exporter is $R = \Upsilon_x^{1-\beta} A_d Y^{\beta}$. The firm revenue premium from exporting $\left(\Upsilon_x^{1-\beta}\right)$ is decreasing in the variable trade cost parameter (τ) and increasing in the foreign demand shifter relative to the domestic demand shifter (A_x/A_d). To summarize, firms face a decreasing demand schedule, but have the option of shifting out their demand (and hence revenues) by serving an additional market at a fixed cost.

Our second modelling ingredient is a production technology featuring complementarity between firm productivity and worker ability, following the ideas of Rosen (1982). In particular, we assume that firm output (Y) depends on firm productivity (θ), the measure of workers hired by the firm (H), and the average ability of these workers ($\bar{a}$):

$$Y = e^{\theta} H^{\gamma} \bar{a}, \qquad 0 < \gamma < 1. \tag{4.6}$$

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 a managerial time constraint (e.g. a manager with a fixed amount of time who needs to allocate some time to every worker). As we show below, with this production technology, more productive firms choose in equilibrium both larger employments and workforces of greater average ability.

Workers have representative preferences and are endowed with one unit of labour that is supplied inelastically with zero disutility. Workers choose a sector in which to search for employment. Within each sector, search frictions take the same form as in the Diamond–Mortensen–Pissarides model. A firm bears a search cost bN in order to randomly match with N workers. The hiring cost b is endogenously determined by the tightness of the labour market and is taken as given by each firm in the sector. In our econometric model, labour market tightness, and the levels of the product market demand shifters, are absorbed in the constants of the estimation equations. For this reason, we do not elaborate these details below, and the interested reader can find them in HIR.

Workers are heterogenous in their ability a, which is drawn from a Pareto distribution $G(a) = 1-a^{-k}$ for $a \geq 1$ and $k > 1$.[19] We assume that both firms and workers are *ex ante* equally unaware of the realizations for ability and only know the underlying distribution. Although a firm cannot observe the individual abilities of its N matches, 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 each worker. Screening costs increase with the ability threshold and equal $e^{-\eta} C \cdot (a_c)^{\delta}/\delta$, where η is firm specific while δ and C are common to all firms. We assume $\delta > k$, which ensures a positive equilibrium size-wage premium, as found empirically in the previous section. The incentive to screen workers results from the complementarity of firm productivity and worker abilities in the production function (4.6), and we show that the more productive firms choose to be more selective in the labour market. Therefore, higher-ability workers are more likely to end up employed by more productive firms, and the model features imperfect (noisy) assortative matching on unobservables in the labour market.

The timing of decisions is as follows. Each firm in a given sector learns its idiosyncratic draw $(\theta, \eta, \varepsilon)$, corresponding to productivity, human resource management (screening costs), and fixed export costs, respectively. Given this triplet, the firm chooses whether to serve only the domestic market or to also export.[20] Each firm pays the search costs and matches with its chosen number of workers. After matching, each firm chooses its screening threshold and hires the workers with abilities above this threshold. Therefore, a firm that has searched for N workers and has chosen the ability cutoff a_c hires

$$H = N\left[1-G(a_c)\right] = N a_c^{-k} \tag{4.7}$$

workers whose expected ability is

$$\bar{a} = \mathbb{E}\left\{a | a \geq a_c\right\} = \frac{k}{k-1} a_c, \tag{4.8}$$

by the properties of the Pareto distribution. Neither the firm nor its hired workers have information on the abilities of individual workers beyond the fact that they are above the cutoff a_c. Our modelling approach captures in a stylized way both the systematic variation in average workforce

19. We additionally impose $\gamma k < 1$ to ensure that firms choose to screen their workers in equilibrium, as we discuss below.

20. All firms serve the domestic market since we assume no associated fixed costs. In our empirical implementation, we condition on firm entry into production and analyse a firm's decision to serve the export market and its choices of employment and wages. Therefore we do not model the firm's entry decision here. Similarly, we do not explicitly characterize workers' decisions to search for employment in a given sector, and refer the reader to HIR.

ability across firms of different productivities and the substantial role of luck in the labour market outcomes for individual workers, as well as the significant residual (ex post) uncertainty about idiosyncratic worker ability.

After the firm has paid all the fixed costs for search, screening and exporting, it engages in multilateral bargaining with its H workers over wages, as in Stole and Zwiebel (1996). HIR show that the outcome of this bargaining game is the following common wage for all workers within the firm:

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

In words, the wage bill is a fixed fraction of firm revenue. Workers who have not been matched with firms, or whose abilities have fallen below their firm's threshold, become unemployed and are not observed in our data.

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:

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

where the revenue function $R(N,a_c,\iota)$ is defined by equations (4.5)–(4.8). The solution to this profit maximization yields (see (S16) in the Supplementary Material to HIR, and the Supplementary Material to this article):

$$R = \kappa_r \left[1+\iota(\Upsilon_x - 1)\right]^{\frac{1-\beta}{\Gamma}} \left(e^{\theta}\right)^{\frac{\beta}{\Gamma}} \left(e^{\eta}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}}, \tag{4.9}$$

$$H = \kappa_h \left[1+\iota(\Upsilon_x - 1)\right]^{\frac{(1-\beta)(1-k/\delta)}{\Gamma}} \left(e^{\theta}\right)^{\frac{\beta(1-k/\delta)}{\Gamma}} \left(e^{\eta}\right)^{-\frac{k-\beta}{\delta\Gamma}}, \tag{4.10}$$

$$W = \kappa_w \left[1+\iota(\Upsilon_x - 1)\right]^{\frac{k(1-\beta)}{\delta\Gamma}} \left(e^{\theta}\right)^{\frac{\beta k}{\delta\Gamma}} \left(e^{\eta}\right)^{\frac{k(1-\beta\gamma)}{\delta\Gamma}}, \tag{4.11}$$

and a firm chooses to export in addition to serving the domestic market (i.e. $\iota = 1$) if and only if:

$$\kappa_\pi \left(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1\right)\left(e^{\theta}\right)^{\frac{\beta}{\Gamma}} \left(e^{\eta}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} \geq F_x e^{\varepsilon}, \tag{4.12}$$

where $\Gamma \equiv 1-\beta\gamma-\beta(1-\gamma k)/\delta > 0$ is a derived parameter and the κ_s (for $s = r,h,w,\pi$) are combinations of aggregate variables and parameters that are common to all firms in the sector. Equations (4.9)–(4.11) describe firm revenues, employment and wages as functions of firm productivity and screening efficiency draws (θ,η) and firm export status $\iota \in \{0,1\}$. Equation (4.12), in turn, describes the firm's export status as a function of the full set of firm's idiosyncratic draws $(\theta,\eta,\varepsilon)$, and the market access variable Υ_x exogenous to the firms. This condition states that the additional profits from exporting must exceed the fixed exporting cost, and derives from the fact that in our model operational profits are a constant fraction of revenues, given by equation (4.9).

As summarized in equations (4.10)–(4.12), our theoretical model predicts that firms with higher productivity θ hire more workers, are more likely to export, and pay higher wages.[21]

21. In this model with Stole–Zwiebel bargaining, equilibrium wages are equalized with the firm's outside option to replace a worker, since the outside option for all workers is unemployment. Firms that are more selective in the labour market have workforces that are more costly to replace and hence end up paying higher wages, which in equilibrium reflect the greater average workforce ability for these firms. Due to complementarity in production, more productive firms choose to be both larger and more selective, and hence pay higher wages. Through this mechanism, exporters are larger and pay higher wages than non-exporters.

Firms with higher screening efficiency η are both more selective in the labour market and more profitable, and hence pay higher wages and are more likely to export. However, the effect of screening cost draws on firm employment is more subtle because of two opposing forces. Lower screening costs raise a firm's profitability and result in a larger scale of operation (i.e. increase the number of matches N), but also increase a firm's selectivity in the labour market (reduce the ratio of hires H/N). The net effect of lower screening costs is to reduce employment.[22]

This model features two additional sources of firm heterogeneity that do not exist in HIR: heterogeneity in fixed export costs (ε) and heterogeneity in human resource management (screening efficiency η). Without heterogeneous export-market entry costs, a firm's revenue and wage bill would perfectly predict its export status. This prediction is inconsistent with the data, in which there is considerable overlap in the wage and employment distributions between non-exporters and exporters. Some small low-wage firms export in the data, but nonetheless, exporters are on average larger and pay higher wages. Without heterogeneity in screening costs, employment and wages are perfectly correlated across firms, and in particular this results in a zero exporter wage premium conditional on firm employment. Both of these implications are strongly rejected by the data, as was shown in Section 3.4.[23] Incorporating these two additional sources of heterogeneity enables the model to match the empirical cross-sectional distribution of firm employment, wages and export status.[24]

The model features a two-way relationship between exporting and firm characteristics. On the one hand, there is a *selection effect*, whereby firms with high productivity simultaneously have large employment and high wages and are more likely to find it profitable to export. On the other hand, there is a *market access* effect, whereby exporting feeds back into higher firm employment and wages. Access to the foreign market requires a larger scale of production, which is complementary with greater selectivity in the labour market. Hence, exporters have workforces of greater average ability and pay higher wages, even after controlling for their productivity. In the theoretical literature following Melitz (2003), these two effects are typically not separated because firm productivity perfectly predicts export status. Our framework emphasizes the distinction between these two effects, in particular in the way they shape the inequality response to a trade liberalization. We explore these two forces in greater detail in the estimation of our econometric model below.

4.2. *Econometric model*

We now use the structure of the model to derive a reduced-form econometric model for employment, wages and export status. Taking logarithms in equations (4.10)–(4.12), we obtain

22. Although the model also yields predictions for total firm revenue (R) in equation (4.9), data on domestic revenue are not available in the Brazilian linked employer–employee data. Such domestic revenue data are only available from a separate survey for a stratified random sample of firms. We use qualitative information about the correlation between domestic revenue and export status for this stratified random sample of firms in our GMM bounds analysis in Section 5.3.

23. The Supplementary Material further discusses the special case of the model with only two shocks (to productivity and fixed costs), and shows that the third source of heterogeneity (e.g. a shock to revenues and wages conditional on employment that corresponds to the screening cost shock in our model) is quantitatively important in practice.

24. Other candidate shocks to revenues and wages conditional on employment (potential alternatives to the screening cost shock) include variation in bargaining power, monitoring costs, or wage fairness constraints across firms. However, these shocks imply a counterfactual negative correlation between wages and export status conditional on employment. Indeed, high wages with these shocks signal a disadvantage to the firm resulting in a lower profitability (e.g. due to low bargaining power), and thus a lower probability of exporting.

the following log linear selection model:

$$\begin{cases} h &= \alpha_h + \mu_h \iota + u, \\ w &= \alpha_w + \mu_w \iota + \zeta u + v, \\ \iota &= \mathbb{I}\{z \geq f\}, \end{cases} \tag{4.13}$$

where $\mathbb{I}\{\cdot\}$ denotes an indicator function. We now in turn describe the vector of firm observables $x \equiv (h, w, \iota)$, the vector of reduced-form idiosyncratic firm shocks (u, v, z), and the vector of reduced-form model parameters Θ. The firm observables include the natural logarithms of employment and wages (h and w, respectively, where we use the conditional firm wage component ψ_{jt}^C as our measure of wages), as well as the firm export status ($\iota \in \{0, 1\}$).

The reduced-form shocks (u, v, z) are linear transformations of the underlying structural shocks $(\theta, \eta, \varepsilon)$ defined from the structural equations (4.10)–(4.12).[25] We additionally impose a *joint normality assumption* for the structural shocks, which implies also joint normality for the reduced-form shocks:

$$(u, v, z) \sim \mathcal{N}(\mathbf{0}, \Sigma), \qquad \text{with} \qquad \Sigma = \begin{pmatrix} \sigma_u^2 & 0 & \rho_u \sigma_u \\ 0 & \sigma_v^2 & \rho_v \sigma_v \\ \rho_u \sigma_u & \rho_v \sigma_v & 1 \end{pmatrix}, \tag{4.14}$$

where Σ is the covariance matrix and (ρ_u, ρ_v) denote the correlations between the (u, v) and z shocks, respectively. Note that the mean-zero normalization for all shocks, the unit-variance normalization for the export-participation shock z and the orthogonality normalization for the shocks to employment and wages (u, v) are all without loss of generality in this log-normal model.

Finally, our reduced-form model has ten coefficients, $\Theta \equiv \{\alpha_h, \alpha_w, \zeta, \sigma_u, \sigma_v, \rho_u, \rho_v, \mu_h, \mu_w, f\}$. These coefficients Θ are reduced-form functions of the parameters of our theoretical model and variables such as trade costs and relative market demand. Therefore we expect the coefficients of the reduced-form model to change over time with these variables. Appendix A.3 and the Supplementary Material provide explicit expressions for the reduced-form coefficients as functions of the parameters and variables of the structural model. In particular, we show that the intercepts α_h and α_w absorb equilibrium variables, such as labour market tightness and product market competition, that are common across all firms.[26]

Not all primitive structural parameters of the model can be recovered from the values of the reduced-form coefficents Θ. Nonetheless, as we show in Section 5.2, the reduced-form coefficients form *sufficient statistics* for undertaking trade and inequality counterfactuals in the model, which is the goal of our analysis. In particular, the coefficients (μ_h, μ_w) capture the *market access* effects of trade on employment and wages, while the correlations (ρ_u, ρ_v) capture the *selection effects* of

25. Specifically, the reduced-form and structural shocks are related as follows:

$$u \equiv \frac{\beta(1-k/\delta)}{\Gamma}\theta - \frac{k-\beta}{\delta\Gamma}\eta \qquad \text{and} \qquad \omega \equiv \frac{\beta k}{\delta\Gamma}\theta + \frac{k(1-\beta\gamma)}{\delta\Gamma}\eta = \zeta u + v.$$

We define v as the projection residual of ω onto u, $v \equiv \omega - \mathbb{E}\{\omega|u\} = \omega - \zeta u$, where ζ is the projection coefficient such that $\text{corr}(u, v) = 0$. Finally, we denote the composite shock in the export selection equation (4.12) with:

$$z \propto \frac{\beta}{\Gamma}\theta + \frac{\beta(1-\gamma k)}{\delta\Gamma}\eta - \varepsilon = (1+\zeta)u + v - \varepsilon,$$

and scale it to have a unit variance, $\text{var}(z) = 1$. See Appendix A.3 for further details.

26. The coefficients $(\zeta, \sigma_u, \sigma_v)$ capture the covariance structure of the shocks to employment and wages, and depend on both the covariance matrix of the structural shocks (θ, η) and other structural parameters of the model.

high employment and wage firms into exporting. These two sets of coefficients play the central role in shaping the response of wage inequality to trade liberalization in the model.

We end our description with the explicit expressions for the three reduced-form coefficients that directly depend on the variable and fixed costs of trade—the two market access variables:

$$\mu_h = \frac{\delta - k}{\delta} \log \Upsilon_x^{\frac{1-\beta}{\Gamma}} \qquad \text{and} \qquad \mu_w = \frac{k}{\delta - k} \mu_h, \tag{4.15}$$

and the export threshold:

$$f = \frac{1}{\sigma}\Big[-\alpha_\pi + \log F_x - \log\Big(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1\Big)\Big], \tag{4.16}$$

where α_π and σ are composite parameters defined in Appendix A.3.

A reduction in the fixed costs of trade F_x affects directly only the reduced-form parameter f, and through it the extensive margin decision of firms to export ι. This extensive margin decision in turn feeds back into the employment and wages of firms through the market access variables μ_h and μ_w. Note that the parameter restrictions of the model ($\Upsilon_x > 1$, $\delta > k$, and $\Gamma > 0$) imply positive market access variables: $\mu_h, \mu_w > 0$. A reduction in the variable trade cost τ leads to an increase in Υ_x (defined in equation (4.5)), and thus to an increase in both market access premia μ_h and μ_w and a reduction in the export threshold f, by making the foreign market more profitable for exporters. Similarly, a reduction in export demand relative to domestic demand A_x/A_d (e.g. because of an exchange rate appreciation) decreases firm export revenues through Υ_x, and hence reduces μ_h and μ_w and raises f.

Finally, we note that our reduced-form model (4.13) may not be exclusive to the structural model described in Section 4.1, but apply more broadly (exactly or as an approximation) to a class of models with selection into the export market and firm wages that in equilibrium increase with firm revenues or profits. Such models include fair wage models, as in Egger and Kreickemeier (2012), and models with competitive assortative matching, as in Sampson (2014). In the Supplementary Material, we provide a further formal analysis of a class of models that are isomorphic in terms of their predictions for wages, employment and export status if no restrictions are imposed on the three sources of stochastic shocks to wages, employment and export status.[27] However, some theoretical models within this class generate a positive correlation between wages and export status conditional on employment, while others generate a negative correlation (see footnote 24 above).

4.3. *Identification*

Our econometric model defined by equations (4.13)–(4.14) takes a form similar to a Tobit Type 5 model in Amemiya (1985) or a regression model with endogenous switching in Maddala (1983), and admits a simple likelihood function. A unit of observation in the model is a firm j, and each observation is a triplet of firm log employment, log wages and binary export status, $x_j = (h_j, w_j, \iota_j)$.

27. This class of models is defined by the following assumptions: (1) revenues and employment are power functions of export status and two stochastic shocks, (2) profits and wage bills are constant shares of revenues, (3) fixed exporting costs are subject to a third stochastic shock, (4) the three stochastic shocks are joint normally distributed. We show that all models within this class imply the same reduced-form econometric model, the same likelihood function, the same GMM moment conditions, and the same counterfactual predictions for the effects of changes in trade openness on wage inequality.

In the Supplementary Material, we show that the likelihood function of the data is $\mathcal{L}\big(\Theta|\{x_j\}\big) \equiv \prod_j \mathbb{P}_\Theta\{x_j\}$ with:

$$\mathbb{P}_\Theta\{x_j\} = \frac{1}{\sigma_u}\phi\big(\hat{u}_j\big)\frac{1}{\sigma_v}\phi\big(\hat{v}_j\big)\left[\Phi\left(\frac{f-\rho_u\hat{u}_j-\rho_v\hat{v}_j}{\sqrt{1-\rho_u^2-\rho_v^2}}\right)\right]^{1-\iota_j}\left[1-\Phi\left(\frac{f-\rho_u\hat{u}_j-\rho_v\hat{v}_j}{\sqrt{1-\rho_u^2-\rho_v^2}}\right)\right]^{\iota_j}, \tag{4.17}$$

where $\hat{u}_j \equiv \big(h_j-\alpha_h-\mu_h\iota_j\big)/\sigma_u$ and $\hat{v}_j \equiv \big[(w_j-\alpha_w-\mu_w\iota_j)-\zeta\sigma_u\hat{u}_j\big]/\sigma_v$, and the functions $\phi(\cdot)$ and $\Phi(\cdot)$ are, respectively, the density and cumulative distribution functions of a standard normal. This simple expression for the density of the data x_j is intuitive: the first two terms reflect the likelihood of the continuous distribution of shocks which result in the observed employment and wages, while the last two terms are a standard Probit likelihood for binary export status given the employment and wages of the firm. In addition to the likelihood function, the model admits analytical expressions for a rich set of moments of the data, which can be used in a GMM estimation.

As in the class of selection models following Heckman (1979), the main challenge in estimating the model is to separately identify the premia (μ_h and μ_w) and the selection forces (ρ_u and ρ_v). Without further assumptions, the model identifies these parameters exclusively from the adopted functional forms: the structure of the theoretical model and log normality. Since any model is an approximation to the data, we impose additional identifying assumptions so as not to rely on functional form alone. As any identifying assumption can be disputed, we report the results of three different (yet mutually consistent) identification strategies, and show that they yield similar quantitative conclusions.

Our benchmark ML estimation strategy in Section 5.1 relies on a structural identifying assumption, which restricts to zero the correlation between the structural shocks θ and η, as is a common practice in the structural econometrics literature following Koopmans (1949), Fisher (1966), and Wolpin (2013). This structural covariance restriction ($\text{corr}(\theta,\eta)=0$) implies the following reduced-form inequality constraint for the market access premia μ_w/μ_h (see Appendix A.3):[28]

$$\zeta \le \mu_w/\mu_h \le \zeta + \frac{\sigma_v^2}{(1+\zeta)\sigma_u^2}. \tag{4.18}$$

This condition helps to separately identify the market access and selection forces by placing bounds on the relative market access effects (μ_h/μ_w). We maximize the likelihood function (4.17) subject to the constraint (4.18), where for most years the lower bound of this constraint holds with equality. We show that this approach identifies the parameters of the model and in particular the relative importance of market access effects (μ_h,μ_w) and selection effects (ρ_u,ρ_v).[29] In our

28. The interpretation of these inequalities is as follows. In the model without the screening shocks ($\eta\equiv 0$), employment and wages are perfectly correlated, which implies $\zeta=\mu_w/\mu_h$. When the screening shocks are introduced, this becomes an inequality as in equation (4.18), because ζ controls the covariance between employment and wages within the groups of non-exporters and exporters, and this covariance becomes weaker with the importance of screening shocks. At the same time, the difference between μ_w/μ_h and ζ is bounded above by the relative dispersion of the screening and productivity shocks, which explains the upper bound in equation (4.18).

29. In the Supplementary Material, we report the results of a Monte Carlo exercise, in which we show that our ML estimation correctly recovers the true values of the model's parameters when the data are generated according to the model. We also report closed-form expressions for the score of the likelihood function, which show the mapping from moments in the data to the model's parameters. Finally, we report the results of an alternative overidentified GMM estimator that uses first and second moments of wages and employment conditional on export status. In this case, the

estimation, we do not impose the model parameter restrictions $\mu_h, \mu_w > 0$, and verify later that they are indeed satisfied.

Although the estimated model provides a good approximation to the observed distribution of wages and employment, we find that it is less successful at matching some higher-order conditional moments (as shown in Section 5.1). Therefore, since ML estimation can be sensitive to such misspecification, Section 5.3 reports the results of a different identification approach based on a GMM bounds analysis, in which we relax the structural covariance restriction $\text{corr}(\theta, \eta) = 0$, and hence dispense with the resulting reduced-form parameter constraint (4.18). We further restrict attention to the conditional first and unconditional second moments that are well approximated by the model. The resulting GMM system is under-identified and hence provides set rather than point identification of the model's parameters. Given the identified set of parameters, we conduct inequality counterfactuals for each parameter vector in the set, and show that this provides tight upper and lower bounds on the counterfactual effects of trade on wage inequality, which in particular nest the counterfactual effect from our ML estimation.

Our third identification strategy in Section 5.4 further relaxes the functional form and joint log normality assumptions by adopting a semi-parametric selection model following Powell (1994). We again do not impose the structural covariance restriction. Instead we identify the market access premia (μ_h, μ_w) using exclusion restrictions for variables that affect fixed exporting costs (and hence export selection) but do not affect wages and employment conditional on export status. Using this quite different identification strategy, we find similar market access premia for employment and wages and counterfactual effects of trade on wage inequality as for our benchmark ML estimation under our structural identifying assumption (4.18).

5. MODEL ESTIMATION AND COUNTERFACTUALS

5.1. *MLE and model fit*

We now report the results of our benchmark ML estimation. We first discuss the coefficient estimates and the model fit. Next, in Section 5.2, we use the estimated model to undertake counterfactuals that quantify the impact of trade on wage inequality through export market participation. Consistent with our focus on residual wage inequality, we use the firm wage component (ψ_{jt}^C) from the Mincer regression (3.2), which aggregates the firm-occupation wage components to the firm-level using employment weights. As for the stylized facts reported above, we pick 1994 as the baseline year for our estimation, and the Supplementary Material shows how the results carry over to the other years.[30]

As pointed out earlier, the key coefficients of interest for the effects of trade on wage inequality in the model are the market access coefficients (μ_h, μ_w), the selection correlation coefficients (ρ_u, ρ_v), and the export threshold (f). In Table 4, we report the estimated values of these coefficients and their standard errors for our baseline year. As shown in the first column in the table, we indeed find positive market access premia ($\mu_h, \mu_w > 0$), even though we did not impose this restriction on the estimation. Therefore entry into exporting raises the employment and wages of a given firm. We also find positive selection effects ($\rho_u, \rho_v > 0$), so that high-employment and high-wage firms are more likely to select into exporting. The export threshold f captures the fraction of

mapping between the moments in the data to the model parameters is particularly transparent, as the GMM system has a recursive structure, in which we can sequentially solve for the model parameters using the moments in the data.

30. The Supplementary Material also reports a robustness test in which we estimate our model using the Colombian data from Clerides *et al*. (1998) and find a similar pattern of results. Therefore, our results are not special to the context of Brazil, but rather capture the more general role of export participation in influencing firm wage and employment distributions.

TABLE 4
Coefficient Estimates

	Coefficient	Std Error
μ_h	1.992	0.017
μ_w	0.197	0.006
ρ_u	0.023	0.003
ρ_v	0.199	0.006
f	1.341	0.004

Notes: ML estimates and robust (sandwich-form) asymptotic standard errors (see the Supplementary Material) for 1994. Number of observations (firms): 91,411.

exporters, which is equal to $1-\Phi(f)$ in the model. As reported in the second column of the table, all coefficients are precisely estimated given the large size of the sample.

In the Appendix Figure A1, we display the evolution of the estimated coefficients of the reduced-form model for each year of our sample. Recall from equation (4.15), that the estimated market access premia μ_h and μ_w that determine the effect of trade on wage inequality depend both on variable trade costs τ and the relative demand shifter in the export market A_x/A_d. Therefore we expect these market access premia to change over time, because our sample period includes both trade liberalization and real exchange rate appreciation which affects relative demand for Brazilian goods. Indeed, we observe such variation over time in the estimated market access coefficients, yet they remain of around the same magnitude throughout our sample period: μ_h varies between 1.86 and 2.38 and μ_w varies between 0.13 and 0.27.[31]

We next examine the model's fit. In Table 5, we report moments in the data and in an artificial dataset simulated using the estimated model. We focus on the first and second moments of the firm employment and wage distributions, both unconditional and conditional on firm export status. These moments provide a good characterization of the overall joint distribution of firm employment, wages and export status.[32] Table 5 shows that the model matches all first moments, both conditional and unconditional, as well as the unconditional second moments. The fit of the model is worse for the conditional second moments, in particular for the standard deviations of firm employment and wages among exporters. Indeed, the model does not allow for significant variation in the standard deviations of wages and employment across exporters and non-exporters, while the data exhibit such variation. Given that the model does not fit the second conditional moments perfectly, in Sections 5.3–5.4, we explore alternative identification strategies that rely less strongly on the specific functional forms and distributional assumptions than our benchmark ML estimation.

As a summary measure of the model's fit, we compute the square root of the GMM objective function based on the eleven conditional first and second moments for exporters and non-exporters reported in Table 5.[33] Our baseline ML estimates imply a value for the GMM objective function

31. The estimated export premia first increase and then start to fall after 1990, which in the context of our theoretical model is explained by a reduction in export market demand (e.g., due to demand shocks or exchange rate appreciation). This fall in the export premium for employment after 1990 is compatible with the results of Menezes-Filho and Muendler (2011), which finds that exporters do not absorb the labour displaced by reductions in tariffs on imports. While our estimation exploits *cross-section* variation in wages, employment and export status across firms, that estimation uses *time-series* changes in tariffs. Therefore the two sets of results use quite different moments in the data.

32. As a result, we find that an overidentified GMM estimator using eleven conditional first and second moments reported in Table 5, recovers parameter estimates close to our ML estimates, as discussed further in the Supplementary Material.

33. Specifically, the objective function is the sum of the squared moment conditions of the overidentified GMM estimator (based on the moments reported in Table 5, see footnote 32), scaled by the empirical standard deviations of the

TABLE 5
Firm Moments

	All firms		Non-exporters		Exporters	
	Data	Model	Data	Model	Data	Model
Mean h	2.96	2.96	2.78	2.78	4.82	4.82
Mean w	−0.33	−0.33	−0.37	−0.37	−0.01	0.00
Std deviation h	1.20	1.20	1.00	1.05	1.46	1.05
Std deviation w	0.43	0.43	0.43	0.42	0.38	0.42
Correlation h & w	0.33	0.33	0.24	0.25	0.32	0.24
Fraction of exporters	9.0%	9.0%				

Notes: Moments in the data and in the ML-estimated model, for 1994; h is log firm employment and w is log firm wage, where the conditional firm wage component, ψ_{jt}^{C}, from equation (3.2) is used as firm wage data in estimation.

TABLE 6
Moments of Worker Wage Dispersion

Moment	Data	Model	Moment	Data	Model
Std deviation	0.42	0.46	90/10-ratio	2.95	3.24
— non-exporters	0.42	0.42	— 50/10-ratio	1.81	1.80
— exporters	0.35	0.42	— 90/50-ratio	1.63	1.80
Gini coefficient	0.22	0.25			

Notes: Each worker is assigned the wage of the firm, i.e. the conditional firm wage component from equation (3.2), to construct the distribution of wages across workers. 90/10 ratio is the ratio of the wages in the 90th percentile and the 10th percentile in the wage distribution (and similar for 90/50 and 50/10).

of 0.038, which implies a cumulative discrepancy between the moments in the model and in the data equal to 3.8% of the sample standard deviation of the moments. In comparison, the fit of the model deteriorates substantially if we shut down the effects of trade on employment and wage distributions. Specifically, when we reestimate the model imposing the restrictions that $\mu_h = 0$ and $\mu_w = 0$ (without further imposing equation (4.18)), the resulting value of the GMM objective function is 0.149, an order of magnitude larger. Therefore, the data viewed through the prism of our econometric model suggests that trade participation is an important determinant of employment and wage variation across firms.

We next examine the model's ability to fit the moments of the wage distribution across workers. Consistent with the model, we calculate the worker-level moments by assigning the firm wage (firm wage component from equation (3.2)) to each worker employed by the firm. Table 6 shows the model's fit for moments capturing worker wage dispersion—the standard deviation of log wages, Gini coefficient and percentile ratios. The model overpredicts wage dispersion in the upper tail and among exporters, while matching it closely in the lower tail and among non-exporters. Although these moments are complex non-linear transformations of the firm employment and wage distributions that are not targeted directly in the estimation, we find that the model matches these moments relatively closely. Furthermore, the quality of the fit is similar across the different measures of wage inequality. We thus proceed with the remainder of the analysis by using the standard deviation of log worker wages as our main inequality measure, but the results are similar for the other measures of wage inequality.

moments, as discussed in Section D3 of the Supplementary Material. Since we use an overidentified set of moments, the GMM objective is separated from zero, and its proximity to zero is a measure of the model's fit.

TABLE 7
Employment and Exporter Wage Premia

	Data	Model
Employment premium	0.10	0.10
Exporter premium	0.16	0.16
R-squared	0.11	0.11

Notes: Coefficients and *R*-squared from the regression of firm log wages (firm wage component from equation (3.2)) on firm log employment and export status. To ensure the comparability of the results in the data and model, these regressions exclude industry fixed effects, which explains the small difference in estimates from Table 3.

In the Appendix Figure A2, we additionally examine the ability of the model to fit the entire distributions of observed employment and wages, both across firms and across workers. We find that the model is overall successful in fitting these distributions, and in particular captures both the wide overlap in the employment and wage distributions across exporters and non-exporters, as well as the noticeable rightward shift in the employment and wage distributions of exporters relative to non-exporters.

Finally, we examine the model's ability to fit the cross-sectional relationship between firm wages, employment and export status in the reduced-form regressions of Table 3 in Section 3.4. These multivariate regressions depend on the full joint distribution of wages, employment and export status, and hence contain additional information relative to the moments reported in Table 5. In Table 7, we compare the coefficients and *R*-squared in this regression estimated in the data and in the simulated dataset from the estimated model. The model matches the employment-size and exporter premia as well as the overall fit of the regressions. In both the model and data, larger firms pay higher wages (with an elasticity of 10%) and exporters pay higher wages conditional on their employment size (by 16%). In both cases, wages vary considerably conditional on firm size and export status, with these variables explaining only around 11% of the variation in wages. This cross-sectional relationship between wages, firm size and export status is at the core of the trade-and-inequality mechanism that we emphasize in this article, and hence, the ability of the model to replicate this empirical relationship is an important specification check.

5.2. *MLE counterfactuals*

We now use the estimated model to undertake counterfactuals to quantify the impact of trade on wage inequality. We consider in turn the effects of a reduction in fixed and variable trade costs. Recall from equations (4.15)–(4.16) that the fixed exporting cost F_x affects directly the reduced-form coefficient f only, while the variable iceberg trade cost τ also affects the employment and wage export premia μ_h and μ_w. In our counterfactuals, we hold all other parameters constant at their estimated values in the baseline year, and vary only these three reduced-form coefficients to trace out the effects of changes in trade costs on wage inequality. In particular, holding constant the estimated distribution of the idiosyncratic firm shocks (4.14), we generate counterfactual firm wages, employment and export status from our estimated model in equation (4.13) for different values of the reduced-form parameters (μ_h, μ_w, f), which correspond to the counterfactual values of variable and fixed trade costs. The focus of these counterfactuals is on the changes in the standard deviation of log worker wages as our measure of inequality.

An advantage of our empirical approach is that the reduced-form coefficients $(f,\ \mu_h,\ \mu_w)$ are sufficient statistics for the impact of trade on wage inequality, which justifies the internal consistency of our counterfactuals even in the absence of a fully spelled-out general equilibrium environment. Indeed, changes in domestic product and labour market competition, which may be triggered by a reduction in trade costs, are captured in the intercepts α_h and α_w, which are common to all firms. Starting from equation (4.13), it is straightforward to show that changes in these intercepts do not affect wage inequality measures.[34] Further, changes in the relative export market demand A_x/A_d affect the market access premia μ_h and μ_w, as can be seen from equations (4.15) and (4.5). In our fixed cost counterfactuals, we consider a special case in which μ_h and μ_w are held constant, which implicitly holds constant the relative export market demand A_x/A_d, as for example is the case with symmetric countries when $\Upsilon_x = 1+\tau^{-\beta/(1-\beta)}$. In our variable trade cost counterfactuals, we allow changes in τ to affect μ_h, μ_w and f both directly and indirectly through changes in relative export market demand A_x/A_d.

For each counterfactual value of trade costs, we show wage inequality against the aggregate share of workers employed by exporting firms. This measure of trade openness plays an important role in our model, because it determines the fraction of workers that receive the wage premium paid by exporting firms.[35] For ease of interpretation, we display wage inequality in each counterfactual as a percentage increase over the autarky level of wage inequality. The autarky counterfactual corresponds to infinite trade costs, $F_x = \infty$ or $\tau = \infty$, which implies $\iota \equiv 0$ for all firms (note that this is also equivalent to setting $\mu_h = \mu_w = 0$). Hence, the autarky firm employment and wages are simulated from the model (4.13) under the estimated parameters of the joint distribution of firm shocks in equation (4.14), but with the counterfactual parameter value $f = \infty$, implying $\iota \equiv 0$. We generate counterfactual employment and wages for finite values of trade costs following a similar procedure. We start with the fixed exporting costs, which we gradually vary from high values ($F_x = \infty$) when no firms export to low values ($F_x = 0$) when all firms export. Note from equation (4.16) that this translates into variation in the reduced-form export threshold $f \in (-\infty, +\infty)$, and we hold all other parameters of the reduced-form model (4.13)–(4.14) constant. Figure 1 displays the results of this counterfactual with a dashed black line, and the blue circle corresponds to our estimated model in the baseline year.

There are two main observations that come out of the fixed exporting cost counterfactual in Figure 1. First, the figure emphasizes a hump-shape relationship between wage inequality and trade openness. Intuitively, wage inequality is strictly higher when some but not all firms export, because in this case some but not all firms pay the exporter wage premium to their workers. This hump-shape pattern is a key theoretical result in the HIR model, in which it is obtained under substantially more stylized assumptions (in particular, the stylized model does not match the observed overlap in the employment and wage distributions between exporters and non-exporters in the data). Therefore, we now confirm that this theoretical conclusion also holds in a substantially richer quantitative model capable of capturing the salient features of the observed employment and wage distributions.

The second observation is that, quantitatively, the wage inequality predicted by the model for 1994 (corresponding to the blue circle in Figure 1) is 7.6% above the counterfactual level of inequality in autarky. Interestingly, this corresponds roughly to the peak of inequality with respect to different values of fixed exporting costs. Therefore, starting from the level of fixed exporting costs corresponding to the estimates for 1994, further reductions in these fixed costs do not lead to additional increases in inequality. This is because at this level of trade openness almost half

34. See HIR for a complete general equilibrium analysis of this model, which emphasizes this point. Note, however, that counterfactual welfare analysis, in contrast to inequality analysis, requires a fully specified general equilibrium setup.

35. Although different, this exercise is similar in spirit to the *sufficient statistic* analysis in ACR (Arkolakis *et al.*, 2012), where the impact of trade is conditioned on observable variables (the domestic trade share in that paper) rather than on unobserved trade costs.

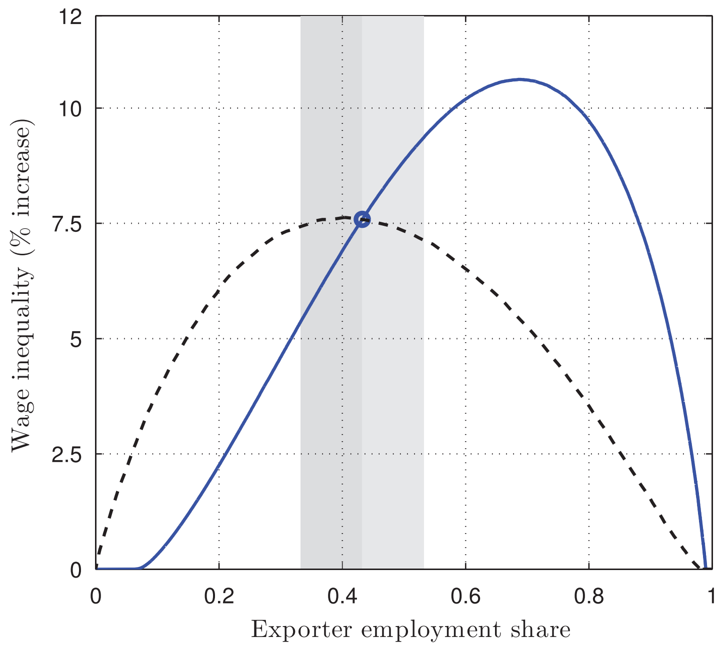

FIGURE 1

Counterfactual wage inequality. The figure plots counterfactual standard deviation of log worker wages as a percentage increase over its counterfactual autarky level (equal to 0.43) against the employment share of exporting firms. The dashed black line corresponds to the counterfactual in which we vary the fixed cost of trade F_x; the solid blue line to the counterfactual with the variable trade cost τ; the blue circle corresponds to the benchmark model parameter estimates (for 1994); the shaded areas mark 10 percentage point increase and decrease in the exporter employment share relative to the 1994 benchmark. Counterfactuals are obtained from the model (4.13)–(4.14), with parameters held constant at their 1994 (benchmark year) estimated values, with the exception of (μ_h, μ_w, f), which are varied according to equations (4.15)–(4.16) consistent with changes in the fixed and variable trade costs, respectively.

of the Brazilian manufacturing labour force is employed by exporting firms, and hence further increases in trade participation make the distribution of wages only more equal.

This is not the case, however, for the variable trade cost counterfactual also shown in Figure 1 with a solid blue line. In the model, the direct effect of the variable trade cost τ on equilibrium employment and wages is mediated by the market access premium Υ_x defined in equation (4.5), which affects both the extensive and intensive margins of trade. Indeed, as can be seen from equations (4.15)–(4.16), Υ_x affects both the fraction of exporting firms (through the reduced-form cutoff f), as well as the employment and wage choices of the exporters (through the reduced-form premia μ_h and μ_w). As we reduce variable trade costs τ from high to low values, Υ_x rises from low to high values, and the exporter employment share increases from zero to one. This variable trade cost counterfactual allows for possible general equilibrium effects of variable trade costs on Υ_x through relative market demand A_x/A_d when countries are asymmetric.[36] Any further general equilibrium effects affect only the intercepts α_h and α_w of the model (4.13), and therefore have no

36. More precisely, in our model, $\Upsilon_x^{(1-\beta)/\Gamma}$ is a sufficient statistic for both the employment share of exporters and wage inequality, but we do not need to take a stand on the particular values of the structural parameters $\beta \in (0,1)$ and $\Gamma > 0$. Note from equations (4.15)–(4.16) that $\mu_h + \mu_w = \log \Upsilon_x^{(1-\beta)/\Gamma}$, and therefore by varying $\log \Upsilon_x^{(1-\beta)/\Gamma}$ we can

impact on the inequality counterfactual. As with the fixed cost counterfactual, we hold constant all other reduced-form coefficients of the model at their estimated values in the baseline year, including the distributional parameters of the idiosyncratic shocks in equation (4.14).

As can be seen from Figure 1, the variation in variable trade costs also results in a hump-shape relationship between trade openness and wage inequality. However, the peak of this relationship occurs for a higher exporter employment share of around 70%, and corresponds to an increase in inequality of 10.7% above autarky. The reason for this difference from the fixed exporting cost counterfactual is that reductions in variable trade costs not only lead to additional entry of firms into exporting, but also increase the employment and wage premia of inframarginal exporters.

The shaded area in Figure 1 corresponds to counterfactuals in which the exporter employment share changes by 10 percentage points below and above its value in the baseline year (indicated with the blue circle). Higher variable trade costs that reduce the exporter employment share by 10 percentage points decrease wage inequality by 2.1 percentage points (from 7.6% to 5.3% above the autarky level), while lower variable trade costs that raise the exporter employment share by 10 percentage points increase wage inequality by 1.7 percentage points (to 9.4% above the autarky level).

We close by putting these quantitative magnitudes into an empirical perspective. First, we provide a back-of-the-envelope calculation of the magnitude of the symmetric changes in variable trade costs τ in the model required for a 10 percentage points movement in the exporter employment share. This calculation requires a calibration of the structural parameters β and Γ and the initial level of the variable trade costs τ, which are not identified in the estimation. We provide the details of this calibration in A.5. Within the model, the symmetric reduction in trade costs (or tariffs) required for an increase in the exporter employment share of 10 percentage points relative to the baseline value in 1994 is 43 percentage points. This is of the same order of magnitude as the Brazilian tariff reduction during our sample period. As reported in Kume *et al.* (2003), average tariffs in Brazil fell from 59.5 to 11.7% between 1986 and 1995, a reduction of almost 48 percentage points, although this liberalization was mainly unilateral (with some reciprocal reductions in tariffs within MERCOSUR). To increase the exporter employment share by another 10 percentage points would require a further symmetric reduction in tariff or non-tariff trade costs in the model of around 45 percentage points. While these calculations are admittedly back-of-the-envelope, they confirm the quantitative relevance of our new mechanism for trade to affect wage inequality through export market selection.

Secondly, we undertake a simple accounting exercise to evaluate the contribution of trade to the evolution of income inequality over the years in our sample. We solve for the implied values of variable trade costs τ, and hence the export threshold and market access premia (f, μ_h, μ_w), that exactly match the evolution of the exporter employment share over 1986–1998, while holding all other parameters constant at their estimated values for 1994. After the trade and labour market reforms of the late 1980s, the employment share of exporters in Brazilian manufacturing increased by 9 percentage points from the trough of 1990 to the peak of 1993 (when it reached 53%), and then gradually fell by 7 percentage points by 1998 with the steep Real appreciation after 1995. Adjusting variable trade costs τ to match these movements in the exporter employment share, the model predicts a rise in inequality from 1990 to 1994 of about 2% followed by a decline of about 1.5% thereafter. Comparing these counterfactual predictions to the data, they account for about two-fifths of the inequality increase between 1990 and 1994 and about a quarter of the inequality reduction thereafter. Over the period from 1986 to 1995 as a whole, the standard deviation of log

fully trace out the model-consistent variation in the reduced-form parameters (μ_h, μ_w, f), since the ratio μ_w/μ_h is pinned down by the structural model parameters and hence is invariant to trade costs. See A.5 for further details.

wages in Brazil increased by around 8%, and hence the model can explain about a quarter of this overall increase, as discussed further at the end of Appendix A.7.

5.3. *GMM bounds on inequality*

As shown in Subsection 5.1, our model closely approximates the observed employment and wage distributions and is successful in matching the conditional first moments and unconditional second moments of wages and employment (see Table 5 and Figure A2). However, our model is necessarily an abstraction, and it is less successful in matching the second moments of wages and employment conditional on export status. In particular, the model predicts little variation in the variance of employment and wages between exporters and non-exporters, and yet we find significant differences in these moments in the data.

Our ML estimates could be sensitive to this departure between the model and data, because they exploit all information in the data, including the conditional second moments. To address this concern, we now adopt an alternative estimation strategy that does *not* impose the structural covariance restriction (and hence dispenses with the resulting reduced-form parameter constraint (4.18)). This approach focuses on the first moments and second unconditional moments for which the model provides a good approximation to the data. In particular, we consider an underidentified GMM estimator that uses the following baseline set of eight moments from Table 5: the fraction of exporters, the means of firm log employment and wages conditional on export status, and the unconditional second moments of firm log employment and wages (including their covariance). We augment these baseline moments with the coefficients (and R^2) from the regression of log firm wages on log employment and export status reported in Table 7, as these are key empirical features of the data that relate to the export market selection mechanism in the model. Formally, this regression, which parallels specification (3.4) in Section 3, can be written as:

$$\mathbb{E}\{w|h,\iota\}=\lambda^o+\lambda^s h+\lambda^x \iota. \tag{5.19}$$

We prove in Appendix A.6 that the additional information contained in the estimates from this regression, relative to the baseline moments, is fully summarized in the *size premium* coefficient λ^s.[37] Hence, this contributes an additional moment to our GMM system: indeed, λ^s contains information about the conditional (on export status) covariance between firm employment and wages, while our baseline moments contain only unconditional second moments.

The resulting GMM system is *underidentified*, as it contains only 9 moments for the 10 parameters of our reduced-form model (4.13)–(4.14). Therefore, we can identify only a parameter set, rather than a point estimate, as in the work of Imbens and Manski (2004) and Chernozhukov *et al*. (2007). We further constrain the set of parameters by the structural model requirement that $\mu_h,\mu_w>0$, which however turns out not to bind for the identified set, as we show below.[38] Finally, we bring in an additional piece of information from data on domestic revenues for a stratified random sample of Brazilian manufacturing firms, in order to further tighten the identified set. Specifically, we use the qualitative feature of the data that the domestic sales of exporting firms are on average larger than the domestic sales of non-exporters.[39] This implies

37. The logic of the proof is that, given λ^s and the baseline moments, one can reconstruct the other two coefficients λ^o and λ^x, as well as the R^2, in this regression. Note that $\lambda^s\equiv\mathrm{cov}\big(h-\mathbb{E}\{h|\iota\},w-\mathbb{E}\{w|\iota\}\big)/\mathrm{var}\big(h-\mathbb{E}\{h|\iota\}\big)$.

38. Naturally, we also impose the definitional restrictions on the parameter space that $|\rho_u|,|\rho_v|<1$ and $\sigma_u,\sigma_v>0$.

39. From summary statistics for this stratified random sample of Brazilian manufacturing firms in 1994, the domestic sales of exporting firms are 185 log points above those of non-exporting firms (or, equivalently, 5 times larger). A similar pattern is observed for other years and in datasets for other countries (see, e.g. Eaton *et al*., 2011).

the following restriction on the covariance structure of the idiosyncratic shocks of the model (see Appendix A.6):

$$(1+\zeta)\rho_u\sigma_u + \rho_v\sigma_v > 0, \tag{5.20}$$

where from equation (4.14) the left-hand side of this inequality equals $\operatorname{cov}\big((1+\zeta)u+v,z\big)$. Intuitively, the domestic revenues of firms increase with their combined productivity draw $(1+\zeta)u+v$, while their export status is determined by the reduced-form variable z. Therefore, inequality (5.20) must be satisfied in order to match the observed positive correlation between domestic sales and export status.

To summarize, our identification relies on 9 moment equalities and three inequalities on reduced-form parameters, including equation (5.20). As we show below, the identified set in our case is a unidimensional curve (with finite end points) in the ten-dimensional parameter space. In what follows, we first characterize the identified parameter set. We next provide bounds for the effects of trade on wage inequality by undertaking the fixed exporting cost and variable trade cost counterfactuals of Section 5.2 along the full length of the identified set. This allows us to trace out the range of possible effects of trade on inequality, disciplined by the moments of the data.

The system of moments has a recursive structure that makes the identification of the reduced-form coefficients particularly transparent. We spell out the details in Appendix A.6, and here we discuss only the moments that are central for the identification of market access versus selection forces, which are at the core of our theoretical mechanism. The two moments that discipline the possible combinations of (μ_h,ρ_u) and (μ_w,ρ_v), given other parameters, are the unconditional employment and wage premia of exporters:

$$\bar{h}_1 - \bar{h}_0 = \mu_h + \rho_u\sigma_u(\lambda_1-\lambda_0), \tag{5.21}$$

$$\bar{w}_1 - \bar{w}_0 = \mu_w + \rho_\omega\sigma_\omega(\lambda_1-\lambda_0), \tag{5.22}$$

where $\bar{h}_1$ ($\bar{h}_0$) and $\bar{w}_1$ ($\bar{w}_0$) are the average log employment and wages of exporters (non-exporters), respectively, and $(\lambda_1-\lambda_0)>0$ is the difference in the inverse Mills ratios evaluated at the exporting cutoff.[40] For convenience, we express the wage moment in equation (5.22) as a function of the second moments of $\omega \equiv \zeta u + v$, a composite shock in the wage equation (4.13).[41] The moment conditions (5.21)–(5.22) constrain the set of values for the parameters of the model to be consistent with the average employment and wage differentials between exporters and non-exporters. Specifically, given the values of σ_u and σ_ω (which are closely related to the standard deviations of log employment and wages in the data), conditions (5.21)–(5.22) define two downward sloping loci for (μ_w,ρ_u) and (μ_h,ρ_ω), respectively. Indeed, a higher average employment of exporters relative to non-exporters can be explained either by a stronger selection into exporting ($\rho_u>0$) or a higher market access premium ($\mu_h>0$), and similar for wages.

The additional source of identification comes from the unconditional covariance of log employment and wages σ_{hw} and the regression coefficient λ^s of firm log wages on log employment in equation (5.19), which is related to the covariance of log employment and wages conditional

40. Specifically, $\lambda_1 \equiv \phi(f)/[1-\Phi(f)]$ and $\lambda_0 \equiv \phi(f)/\Phi(f)$, where $\phi(\cdot)$ and $\Phi(\cdot)$ are, respectively, the density and the cumulative distribution function of a standard normal random variable, and $1-\Phi(f)=\mathbb{P}\{z\ge f\}$ equals the fraction of exporting firms. Since exporting is relatively infrequent, the fraction of non-exporters $\Phi(f)\approx 0.9$, and hence $\lambda_1>\lambda_0$.

41. Note the symmetry between ω and u, a corresponding shock in the employment equation (see footnote 25). Further note the direct relationship between the moments of the shocks ω and v: $\sigma_\omega^2=\zeta^2\sigma_u^2+\sigma_v^2$ and $\rho_\omega\sigma_\omega=\zeta\rho_u\sigma_u+\rho_v\sigma_v$. This allows us to restate the parameter inequality (5.20) as $\rho_u\sigma_u+\rho_\omega\sigma_\omega>0$, as well as to recover (ρ_v,σ_v) from the values of $(\rho_\omega,\sigma_\omega)$, given the other parameters of the model.

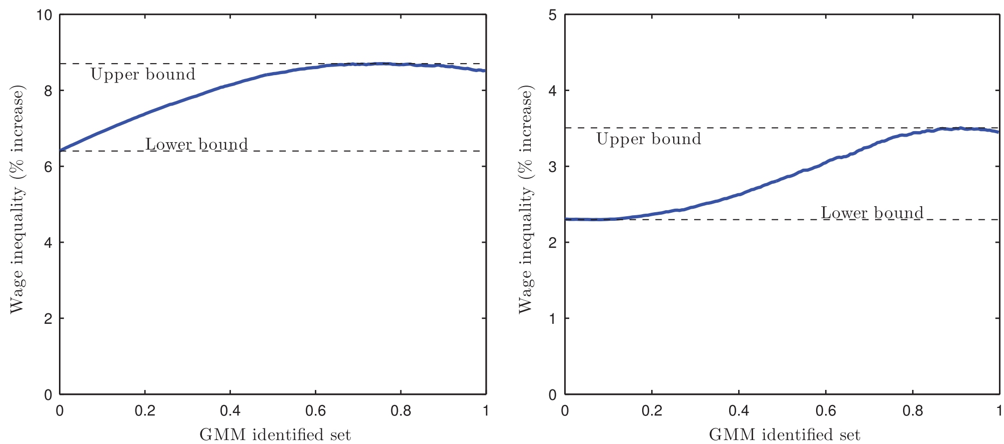

FIGURE 2

GMM bounds for the effects of trade on inequality. Autarky and variable trade cost counterfactual. The figure plots two inequality counterfactuals (solid blue lines) for every element of the GMM identified set, which we parameterize on $[0,1]$ on the x-axis and rank by the corresponding values of μ_h (see Appendix A.6). Both panels report the change in the standard deviation of log worker wages relative to a counterfactual economy with higher trade costs; in the left panel the counterfactual trade costs are infinite resulting in autarky, while in the right panel the counterfactual increase in the variable trade costs is such that the exporter employment share falls by 10 percentage points.

on firm export status. We show in Appendix A.6 that these two moments offer another restriction on the empirically relevant values of our parameters $(\mu_w, \mu_h, \rho_u, \rho_\omega)$. This leaves us with a unidimensional interval in the parameter space, *the identified set*, which we plot in Figure A3 in the Appendix using the moments from the Brazilian data for the baseline year 1994. In particular, we verify that along the whole identified set, the values of the exporter premia parameters μ_h and μ_w are positive, even though we did not impose these restrictions when constructing the set.[42] The values of the selection correlations ρ_u and ρ_ω are also positive, while the value of ρ_v is close to zero.

We now turn to characterizing the GMM bounds for the counterfactual impact of trade on wage inequality. Recall that each element of the identified set is a parameter vector that allows our reduced-form model (4.13)–(4.14) to (exactly) match the selected set of moments that we described above. For each element of the identified set we undertake two counterfactual calculations, as in Section 5.2, and plot the results in Figure 2. The first exercise, in the left panel of the figure, is the autarky counterfactual, evaluating the change in wage inequality relative to the counterfactual autarky equilibrium. In the second counterfactual, we increase variable trade costs to reduce the exporter employment share by 10 percentage points, and display in the right panel the corresponding counterfactual change in wage inequality. In both cases, we report the percentage increase in the standard deviation of log worker wages relative to the counterfactual equilibrium with higher trade costs. Each point on the horizontal axis of Figure 2 corresponds to a parameter vector in the identified set, which for concreteness we ranked by the corresponding value of μ_h. For reference, the figure also plots the lower and upper bounds for the GMM counterfactuals.

As shown in Figure 2, we obtain tight bounds for the counterfactual effects of trade on wage inequality. For the autarky counterfactual, the inequality bounds are $[6.4\%, 8.8\%]$, which includes

42. Specifically, the values of μ_h in the identified set span the interval $[0.122, 2.046]$ and the values of μ_w span $[0.178, 0.354]$.

our ML estimate of 7.6% from Section 5.2. For the increase in variable trade costs that reduces the exporter employment share by 10 percentage points, the bounds for the change in wage inequality are [2.3%, 3.5%], slightly above our ML estimate of 2.2%. Therefore, although the GMM identified set allows for a wide range of variation in the parameters (μ_h, μ_w, ρ_u), as can be seen in Figure A3 in the Appendix, this variation is coordinated to ensure the fit of the moment conditions. This in turn, results in quantitatively similar counterfactual predictions for the impact of trade on wage inequality across the GMM identified set of parameters. Furthermore, despite the differences in identification strategy and estimates of individual parameters, the GMM identified set yields similar counterfactual predictions for the wage inequality effects of trade as our baseline ML estimates.

5.4. *Semi-parametric estimation*

As an additional robustness check, we now consider a different identification strategy based on the semi-parametric selection model of Powell (1994), which like the GMM bounds exercise does *not* impose the structural covariance restriction, and additionally relaxes the functional form assumptions shaping the selection effects in the employment and wage equations. Our model predicts that the probability a firm exports can be estimated from the following probit model:

$$\mathbb{P}\{\iota = 1\} = 1 - \Phi(m'\xi), \tag{5.23}$$

where ξ is a vector of parameters and m is a vector of *excluded* variables that affect the fixed exporting cost F_x, and hence the reduced-form export threshold f and the probability of exporting, but have no direct effect on employment and wages conditional on export status.

In our semi-parametric specification, we include a third-order polynomial in the fitted values for the probability of exporting from the probit model (5.23) in the wage and employment equations ($g_h(\hat{\iota})$ and $g_w(\hat{\iota})$, respectively) to control semi-parametrically for the selection correction terms:

$$\begin{aligned} h &= \alpha_h + \mu_h \iota + g_h(\hat{\iota}) + u, \\ w &= \alpha_w + \mu_w \iota + g_w(\hat{\iota}) + \omega, \end{aligned} \tag{5.24}$$

where we again use the firm log wage component as our measure of firm log wages ($w = \psi^C$).

We consider two sources of excluded variables (m) that exploit quite different sources of variation in the data. First, we follow Helpman *et al*. (2008) and construct an empirical proxy for a firm's fixed costs of exporting using the World Bank ranking of countries in terms of the number of procedures for starting a business (World Bank, 2014). For each firm, we compute its average ease of starting a business in export markets based on the export destinations that it serves, weighting each export destination by its total imports from the whole world. The idea behind this excluded variable is that countries with worse environments for starting a business (higher ranks) have higher fixed exporting costs. Therefore firms that export to these countries have higher fixed exporting costs. Our identifying assumption is that conditional on export status the average ease of starting a business in export markets does not directly affect firm employment and wages, which requires that the average ease of starting a business in export markets affects fixed rather than variable trade costs.

Secondly, we consider the fraction of the firm's workforce that is foreign. The idea behind this excluded variable is that a larger share of foreign workers reduces the fixed cost of exporting, because foreign workers are likely to be better informed about foreign markets than domestic workers. Our Mincer regression (3.2), from which we obtain the firm wage component (ψ^C), controls for differences in observable characteristics across workers, including education, tenure with the firm, age and gender. After controlling for these observable characteristics, we assume that foreign and domestic workers are perfect substitutes for variable production costs, but that the share of foreign workers reduces fixed exporting costs. Hence our identifying assumption is that conditional on export status there is no direct effect of the share of foreign workers on firm employment and wages.

Although we control for observable worker characteristics in the Mincer regression, a remaining concern could be that exporters and non-exporters select foreign workers with different unobservables, which could directly affect both firm wages and employment. As a first approach to addressing this concern, we consider the share of foreign workers in total employment within a firm's meso-region-CNAE-industry pair as an excluded variable, which provides a measure of the local labour market supply of workers who are likely to be better informed about foreign markets. To more fully address this concern, we next consider the share of foreign workers in mass layoffs within a firm's meso-region-CNAE-industry pair as an excluded variable, where mass layoffs are defined as workers displaced from another firm at plants that lose one third of their employment during a calendar year. Following Jacobson *et al*. (1993), the idea behind this excluded variable is that mass layoffs from other firms provide a measure of the local labour market supply of foreign workers that is plausibly not under the firm's control.

Table 8 reports the semi-parametric estimation results. Column (1) reports the results using the ease of starting a business. Columns (2), (3), and (4) report the results using the share of foreign workers for the firm, meso-region-CNAE-industry and mass layoffs in the meso-region-CNAE-industry, respectively. Column (5) reports results using both the ease of starting a business and mass layoffs in the meso-region-CNAE-industry. Panel A reports the first-stage (selection equation) estimates for export status. Panels B and C report the second-stage (outcome equation) estimates for employment and wages, respectively. Standard errors are clustered by meso-region-CNAE-industry to address the fact that in Columns (3)–(5) the foreign worker excluded variable is measured at the meso-region-CNAE-industry level and hence at a more aggregated level than the firm (Moulton, 1990).

In Columns (1)–(3) of Panel A, we find that the ease of starting a business, the firm foreign worker and meso-region-CNAE-industry foreign worker excluded variables have power for predicting export status. All three excluded variables have first-stage F-statistics in excess of 10. In Column (4) of Panel A, the mass layoff meso-region-CNAE-industry foreign worker has less power for predicting export status, which reflects the relatively small number of mass layoffs within meso-region-CNAE-industry pairs. However, when we use both this variable and the ease of starting a business in Column (5) of Panel A, we again find a first-stage F-statistic in excess of 10.

In Panels B and C, we find that the third-order polynomial in the fitted values for the probability of exporting that controls for the non-random selection of firms into exporting is statistically significant at conventional critical values for both employment and wages in all specifications (as shown by the p-values for the second-stage F-statistics). Across the five columns of the table, we find a similar pattern of market access premia of around 2 for employment and 0.35 for wages. This similarity of the estimation results using excluded variables that exploit entirely different sources of variation in the data provides support for our identifying assumptions. To generate such similar market access premia across all five specifications, we require either that both sets of exclusion restrictions are valid, or that both exclusion restrictions are invalid and there is an improbable pattern of correlation between the excluded variables and the errors in the outcome equations (for further discussion, in a different context, see Duranton and Turner, 2012).

Although this semi-parametric specification uses a different identification strategy, which does not impose restrictions on the parameters or the functional forms of the selection effects, we find a similar pattern of results as in our earlier specifications. The semi-parametric estimate with both

TABLE 8
Semi-parametric Coefficient Estimates

	Business	Foreign Workers			Both Excluded
	Procedures (1)	Firm (2)	Meso (3)	Layoff (4)	Variables (5)
Panel A: Selection					
Business procedures	−0.139***	—	—	—	−0.139***
	(0.025)				(0.025)
Foreign worker	—	0.070***	0.129***	0.022**	0.019*
		(0.008)	(0.034)	(0.010)	(0.010)
First-stage F-statistic	30.60	85.96	14.56	4.36	37.36
[p-value]	[0.000]	[0.000]	[0.000]	[0.037]	[0.000]
Panel B: Employment					
Employment premium (μ_h)	2.004***	1.997***	2.032***	2.039***	2.012***
	(0.031)	(0.034)	(0.034)	(0.033)	(0.032)
Second-stage F-statistic	16.57	83.40	2.69	2.18	14.37
[p-value]	[0.000]	[0.000]	[0.045]	[0.088]	[0.000]
Panel C: Wages					
Wage premium (μ_w)	0.361***	0.343***	0.312***	0.356***	0.361***
	(0.016)	(0.015)	(0.012)	(0.016)	(0.017)
Second-stage F-statistic	4.07	59.70	171.67	2.30	4.00
[p-value]	[0.007]	[0.000]	[0.000]	[0.075]	[0.007]

Notes: Number of observations: 91,409 (firms); year: 1994. Probit selection equation estimated using ML. Employment and wage equations estimated using Ordinary Least Squares (OLS) and including a third-order polynomial in the fitted values from the selection equation as a control function to capture the non-random selection of firms into export status (Powell, 1994). Business Procedures is a weighted average of the World Bank ranking of countries by the number of procedures to start a business, where the weights are countries' total imports for those export markets served by a firm. Firm foreign worker is the share of a firm's workers that are foreign (non-native and non-naturalized Brazilian). Meso foreign worker is the share of workers within a firm's meso-region-CNAE-industry pair that are foreign. Layoff foreign worker is the share of workers from mass layoffs in a firm's meso-region-CNAE-industry pair that are foreign. Mass layoffs are defined based on reductions of firm employment of one-third or more during a calendar year following Jacobson *et al*. (1993). All excluded variables normalized by their standard deviations. Column (5) uses both the business procedures and foreign mass layoff excluded variables. Standard errors in parentheses and p-values in square parentheses are clustered by CNAE-industry-meso-region pair. First-stage F-statistic tests for the significance of the excluded variables. Second-stage F-statistic tests for the significance of the control function. * denotes statistical significance at the 10 percent level; ** denotes statistical significance at the 5 percent level; *** denotes statistical significance at the 1 percent level.

excluded variables for μ_h is 2.01, similar to our ML estimate of 1.99, while the semi-parametric estimate for μ_w is 0.36, above the ML estimate of 0.20 (recall Table 4 in Section 5.1). The estimated pair (μ_h, μ_w) lies inside the GMM identified set of Section 5.3, as shown in Figure A3 in the Appendix. In particular, along the identified set, $\mu_h = 2.01$ corresponds to μ_w of 0.36, as well as to positive (but small) selection correlations ρ_u and ρ_v. Therefore, our semi-parametric estimates for market access premia, as well as the implied selection correlations, are consistent with the GMM bounds of Section 5.3. The implied wage inequality counterfactual, given our semi-parametric estimates of the market access premia, is an 8.5% inequality increase in the observed open-economy equilibrium relative to the counterfactual autarky equilibrium, as compared to the 7.6% counterfactual increase using our structural ML estimates and the [6.4%, 8.8%] estimated GMM bounds.[43] Hence the semi-parametric specification also generates similar counterfactual predictions for the impact of trade on wage inequality.

43. As a robustness check, we re-estimated our preferred semi-parametric specification (Column (5)) under the assumption of normality, replacing the third-order polynomial in the employment and wage equations with the inverse

To summarize, we view the results of this subsection as providing further support for our baseline estimates obtained under the functional form assumptions of our structural model, as well as to the quantitative credibility of our counterfactual exercises using these baseline estimates. All of our three estimation procedures, which take quite different approaches to identification, yield consistent quantitative estimates of the impact of trade on wage inequality.

6. MULTIPLE EXPORT DESTINATIONS

In Sections 4–5, we have quantified the impact of trade on wage inequality in the benchmark model of firm heterogeneity following Melitz (2003), which takes a stylized view of firm exporting as a zero-one decision. In the data, however, exporters differ a great deal, from smaller firms serving only the neighbouring Argentine market to large multinationals supplying many destinations around the world, including some remote markets. This section offers an extension of our analysis, which provides a refinement to the modelling of the firm exporting decision.[44]

Specifically, we allow for multiple export destinations, where access to each additional export market gives a boost to firm revenues, yet involves an additional fixed cost. The least successful firms serve only the domestic market; firms of intermediate capabilities export to larger markets with lower fixed access costs; and the most capable firms can profitably supply all markets, including remote small export markets. Exporting to more markets raises firm employment and wages (through the model's market access forces), while firms that export to more destinations are also on average more productive due to selection forces. The forces are, thus, similar to our single-destination baseline model, yet now the exporting decision involves multiple extensive margins, which has the potential to magnify the impact of trade on wage inequality.

To keep the analysis tractable, we incorporate multiple export destinations by splitting exporters into three mutually exclusive bins based on the number of destinations served. The bins of firms are denoted with $\ell \in \{0,1,2,3\}$, where $\ell = 0$ corresponds to non-exporters, while the other three bins correspond to three categories of exporters based on the number of export markets they serve. We report results for two different definitions of bins for export destinations. In specification A, we distinguish between firms exporting to only one destination, 2–5 destinations, and 6 and more destinations. In specification B, we consider firms exporting to 5 or fewer countries, 6–24 countries, and 25 and more countries. Though stylized, this provides a simple and tractable specification for generalizing the analysis to multiple export destinations.

Formally, we consider a domestic market with demand shifter A_d and three ranked export destinations with demand shifters $A_{x,\ell}$, $\ell = 1,2,3$. The variable trade costs τ are assumed to be the same to all destinations, but this is without loss of generality since the destination-specific component of variable trade costs is absorbed into the market shifter $A_{x,\ell}$. This results in the following generalization to the market access variable (see the derivation in Appendix A.7):

$$\Upsilon_x = 1 + \tau^{-\frac{\beta}{1-\beta}} \sum_{\ell=1,2,3} \iota_\ell \left(\frac{A_{x,\ell}}{A_d} \right)^{\frac{1}{1-\beta}}, \tag{6.25}$$

Mills ratios. In this specification, we find a similar pattern of results, with a smaller employment premium ($\mu_h = 1.180$ with standard error 0.154) and a larger wage premium ($\mu_w = 0.624$ with standard error 0.233). This change in the point estimates and increase in standard errors is consistent with our earlier findings that the assumption of normality does not provide a perfect fit for the data (in particular, for the second conditional moments), which is the reason why this section relaxes the model's distributional assumptions. Despite these differences, we find similar counterfactual effects of opening the closed economy to trade on wage inequality of 6.9%, as the higher estimated wage premium is offset by a lower employment premium.

44. In the Supplementary Material, we report the results of additional robustness tests and extensions, including sector and region heterogeneity, alternative wage measures, and estimating the model using Colombian firm data.

where ι_ℓ is an indicator variable for whether the firm serves the destination market ℓ. Given this new Υ_x, the revenues of the firms are still given by the expression in equation (4.5), $R = \Upsilon_x^{1-\beta} A_d Y^\beta$, and hence the solutions for firm employment and wages are still given by equations (4.10)–(4.11).

We denote the common component of the fixed access cost to the destination market ℓ by $F_{x,\ell}$, while the firm-idiosyncratic fixed cost component is still ε and is assumed to be common across all export destinations. Therefore, each firm faces a menu of fixed costs $e^\varepsilon F_{x,\ell}$ for $\ell = 1,2,3$, and thus its exporting decision is characterized by (see the derivation in Appendix A.7):

$$\iota_\ell = \mathbb{I}\left\{\kappa_\pi \left[\Upsilon_{x,\ell}^{\frac{1-\beta}{\Gamma}} - \Upsilon_{x,\ell-1}^{\frac{1-\beta}{\Gamma}}\right]\left(e^\theta\right)^{\frac{\beta}{\Gamma}}\left(e^\eta\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} \geq e^\varepsilon F_{x,\ell}\right\}, \qquad \ell = 1,2,3, \tag{6.26}$$

where we use $\Upsilon_{x,\ell}$ to denote the value of Υ_x when the firm exports to all destinations up to ℓ, but not to $\ell+1$ and above. Note that $\Upsilon_{x,0} = 1$, which corresponds to non-exporting firms. The selection equation (6.26) generalizes condition (4.12) in the single-destination model.[45]

Given this structure, and the same distributional assumption on the structural shocks as in Section 4, we derive the reduced form for this multi-destination model, which generalizes our econometric model in equations (4.13)–(4.14). We further follow the same steps as in the case of the single-destination model to estimate the multi-destination model using ML. Finally, we use these estimates to conduct the same trade counterfactuals, as in Section 5.2. The details of all these steps are spelled out in Appendix A.7, and here for brevity we report only the results of the counterfactuals.

We start with an autarky counterfactual in which we keep constant the estimated parameters of the model, but make all firms non-exporters by setting $\iota_\ell = 0$ for all ℓ and all firms. We then compare the standard deviation of log worker wage in the estimated model with that in the corresponding counterfactual autarky equilibrium. In the two specifications of the multi-destination model, wage inequality is, respectively, 13.8% and 15.7% above the counterfactual autarky level (shown by the blue and red circles in Figure 3, respectively). This contrasts with the 7.6% inequality increase relative to autarky predicted by our single-destination model. This amplification of the effects of trade on wage inequality is intuitive, as the multi-destination model allows for multiple extensive margins, each of which contributes to wage inequality. Indeed, as we show in Tables A3 and A4 in the Appendix, in the estimated model the smaller exporters in bin $\ell = 1$ pay an exporter wage premium of around 15% (in specification B), while the few largest exporters in bin $\ell = 3$ pay a wage premium of around 50% (in specification B).

Next, we undertake a variable trade cost counterfactual, as in Figure 1 of Section 5.2. In this counterfactual we vary iceberg trade costs τ to all destinations, which translates into changes in the market access variables $\Upsilon_{x,\ell}$ according to equation (6.25), and corresponding changes in the export status of the firms according to equation (6.26). Using the model, we trace out the effects of these changes (holding the other model parameters constant at their estimated values) on the distributions of employment and wages across firms. Figure 3 plots the counterfactual standard deviation of log worker wages (relative to autarky) against the fraction of workers employed by all exporting firms. This figure presents the results for both specifications of the multi-destination model and reproduces the same counterfactual in the single-destination model from Figure 1 for comparison. The circles in the figure identify the points corresponding to the model estimates for 1994, and hence reflect the autarky counterfactuals just discussed.

45. We rank our three export destinations ℓ by $\left[\Upsilon_{x,\ell}^{\frac{1-\beta}{\Gamma}} - \Upsilon_{x,\ell-1}^{\frac{1-\beta}{\Gamma}}\right]/F_{x,\ell}$ in a decreasing order, so that no firm chooses to serve destination $\ell+1$ without serving destination ℓ (for $\ell = 1,2$), which is satisfied in the data because the bins ℓ are defined by the number of export markets served. As in the single-destination model, all firms serve the domestic market.

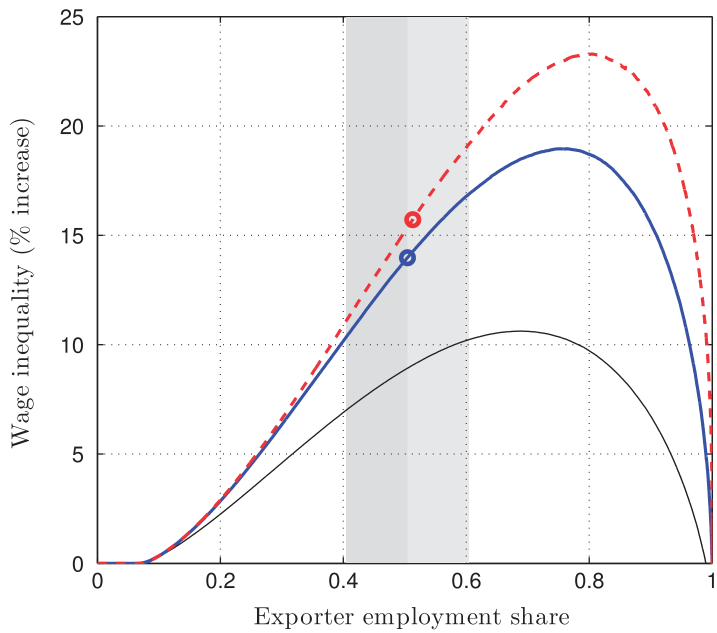

FIGURE 3

Trade counterfactual in multi-destination model. The figure plots the counterfactual standard deviation of log worker wages as a percentage increase over its counterfactual autarky level (equal to 0.43) against the employment share of exporting firms in the multi-destination model as we vary the variable trade cost τ. The solid blue line corresponds to multi-destination specification A (as described in the text), the dashed red line to specification B, while the thin black line reproduces the single-destination counterfactual from Figure 1. The circles identify the corresponding 1994 estimates in the two specifications of the multi-destination model, respectively. The shaded areas identify the 10 percentage point change in the exporter employment share relative to the 1994 estimate for the multi-destination specification A. Also see Table A4 in the Appendix.

Figure 3 clearly illustrates how the opportunity to access multiple destinations amplifies the inequality effects from a reduction in variable trade costs. The peak inequality levels relative to autarky are now 19.0% and 23.3% in the two specifications, respectively, in contrast with a 10.7% peak inequality in the single-destination model.[46] The shaded areas in Figure 3 correspond to a 10 percentage points increase and reduction in the exporter employment share, in parallel with the counterfactuals in Section 5.2. Specifically, a change in variable trade costs, which is associated with a 10 percentage points reduction in the exporter employment share, causes wage inequality to decrease by 3.6% and 4.3% in the two specifications of the multi-destination model, respectively. This is in contrast with a 2.3% change in wage inequality in the single-destination model. Conducting a similar accounting exercise to the one at the end of Subsection 5.2, but using the estimated mutli-destination model, we find that trade can account for almost three-quarters (versus two-fifths in the baseline model) of the inequality increase between 1990 and 1994, when

46. Note that the peak inequality levels in the multi-destination case correspond to a larger exporter employment share of around 80%, in contrast with slightly less than 70% in the single-destination case. This is intuitive because when all exporters already account for 80% of total employment, the most selective group of exporters in bin $\ell=3$ still accounts only for about 15% of total employment.

the exporter employment share rose sharply by almost 10 percentage points. We provide further details about these counterfactuals in Appendix A.7.

To summarize, the multi-destination extension amplifies the predicted counterfactual inequality effects of a trade liberalization: across our counterfactual exercises, the inequality effects in a multi-destination model are about 1.5–2 times larger than in the single-destination model. In particular, a finer partitioning of firms by export status implies greater scope for further increases in wage inequality beyond the levels achieved in Brazil in 1994. As trade costs are reduced further, there is a reallocation of employment not only from exporters to non-exporters, but also towards exporters serving more destination markets that are larger and pay higher wages.

7. CONCLUSION

Using linked employer–employee data for Brazil, we provide evidence on between-firm differences in wages as a mechanism for trade to affect wage inequality in recent theories of heterogeneous firms. We begin by developing a set of stylized facts that provide support for this mechanism. We find that around two-thirds of overall wage inequality occurs within sector–occupations. Most of this within sector–occupation inequality is residual wage inequality. Between-firm wage dispersion accounts for a substantial proportion of this residual wage inequality within sectors and occupations. These between-firm differences in wages are systematically but imperfectly related to trade participation: exporters on average pay higher wages than non-exporters even after controlling for firm size.

Guided by these stylized facts, we extend the heterogeneous-firm model of trade and inequality from Helpman *et al*. (2010) and estimate it using the Brazilian data. This extended model incorporates three dimensions of firm heterogeneity—productivity, human resource management (the cost of screening workers) and fixed exporting costs—each of which is central to matching the data. We use the structure of the theoretical model to derive a reduced-form econometric model for wages, employment and export status that features two channels through which trade affects wage inequality: a market access effect (exporting raises the employment and wages of a given firm) and a selection effect (exporting firms are on average larger and pay higher wages than other firms). We then use three different identification approaches to estimate the model and quantify the implied contribution of trade to wage inequality.

We show that the estimated model approximates well the observed distributions of wages and employment across both firms and workers. Across the three different identification approaches, we find similar and sizable effects of trade on wage inequality, with the opening of the closed economy to trade raising the standard deviation of log worker wages by around 10%. The estimated model implies a non-monotonic relationship between wage inequality and trade openness, where trade liberalization at first raises and later reduces wage inequality, confirming the theoretical prediction of Helpman *et al*. (2010).

Although trade expands the set of opportunities for all firms and workers, only some firms find it profitable to take advantage of these opportunities, which is the mechanism driving trade's effect on wage inequality in our model. We show that enriching the model to introduce a finer partitioning of trading opportunities (e.g. by distinguishing between multiple destination markets) magnifies further the effect of trade on wage inequality.

A. APPENDIX

A.1. *Industries and Occupations*

Tables A1 and A2 introduce our baseline occupations and sectors, discussed in Section 2, and provide some descriptive statistics on the size, average wages, and trade exposure by sector and occupation. As discussed in the main text, we

TABLE A1
Occupation Employment Shares and Relative Mean Log Wages, 1994

CBO	Occupation	Employment share (%)	Relative mean log wage
1	Professional and managerial	7.2	1.12
2	Skilled white collar	10.8	0.38
3	Unskilled white collar	8.8	0.07
4	Skilled blue collar	63.1	−0.14
5	Unskilled blue collar	10.0	−0.39

Notes: The table reports the split of total manufacturing employment into five standard occupational categories. Column (1) reports the share in total formal manufacturing employment. Column (2) reports the log occupation-average wage relative to the overall average wage in manufacturing; for example, skilled white-collar workers are paid a wage premium of 38 log points (46%) above the average overall manufacturing wage, and 77 log points (=0.38−(−0.39), or 116%) above the unskilled blue-collar workers.

TABLE A2
Sectoral Employment Shares and Relative Mean Log Wages

				Exporter share (%)	
IBGE	Sector	Employment share (%)	Relative mean log wage	Firms	Employment
2	Non-metallic minerals	4.6	−0.21	4.7	34.6
3	Metallic products	10.3	0.31	9.9	57.6
4	Mach., equip. and instruments	5.9	0.48	25.4	71.8
5	Electrical & telecomm. equip.	4.3	0.41	19.9	70.9
6	Transport equip.	6.0	0.73	13.6	75.3
7	Wood & furniture	6.9	−0.51	8.0	39.7
8	Paper & printing	5.5	0.20	4.8	37.0
9	Rubber, tobacco, leather, etc.	5.1	−0.05	12.8	56.7
10	Chemical & pharm. products	9.4	0.31	15.6	56.8
11	Apparel & textiles	15.1	−0.34	4.8	42.7
12	Footwear	5.4	−0.44	16.8	72.3
13	Food, beverages & Alcohol	21.3	−0.18	4.1	42.1
	All manufacturing sectors	100	0.00	9.0	51.8

Notes: The table reports the split of total manufacturing employment into twelve IBGE sectors (roughly corresponding to two-digit ISIC sectors). As in Table A1, the first two columns report the share of the sector in total formal manufacturing employment and the log sector-average wage relative to the average overall manufacturing wage. The last two columns report the share of firms that export and the employment share of exporters in the sector.

also report results for more disaggregated definitions of occupations and industries. See the table notes for further details.

A.2. *Wage decompositions in Section 3*

In each year, we decompose overall wage inequality T_t into within and between components:

$$T_t = W_t + B_t, \qquad \text{where}$$

$$T_t = \frac{1}{N_t}\sum_{\ell}\sum_{i\in\ell}(w_{it}-\bar{w}_t)^2, \quad W_t = \frac{1}{N_t}\sum_{\ell}\sum_{i\in\ell}(w_{it}-\bar{w}_{\ell t})^2, \quad B_t = \frac{1}{N_t}\sum_{\ell}N_{\ell t}(\bar{w}_{\ell t}-\bar{w}_t)^2.$$

Here workers are indexed by i and time by t; ℓ denotes sector, occupation or sector–occupation cells depending on the specification; N_t and $N_{\ell t}$ denote the overall number of workers and the number of workers within cell ℓ; w_{it}, $\bar{w}_{\ell t}$ and $\bar{w}_t$ are the log worker wage, the average log wage within cell ℓ and the overall average log wage. Due to the linearity of this decomposition, it also holds in changes:

$$\Delta T_t = \Delta W_t + \Delta B_t.$$

Panel A of Table 1 reports the share of the within component, measured as the ratio W_t/T_t in a given year, as well as the contribution of the within component to the growth of the overall inequality, measured as $\Delta W_t/\Delta T_t$. Panel B of Table 1 alternatively decomposes the total wage inequality $T_t \equiv \text{var}(w_{it})$ into the contribution of the worker observables and the residual component:

$$\text{var}(w_{it}) = \text{var}\big(z_{it}'\hat{\vartheta}_t\big) + \text{var}\big(\hat{\nu}_{it}\big),$$

where $\hat{\vartheta}_t$ are the estimated parameters from the OLS Mincer wage regression (3.1) and $\hat{\nu}_{it}$ are the residuals, orthogonal to worker observables z_{it} by construction. Again, the same decomposition applies in changes as well. Consequently, we report $\text{var}(\hat{\nu}_{it})/\text{var}(w_{it})$ and $\Delta\text{var}(\hat{\nu}_{it})/\Delta\text{var}(w_{it})$ as the contribution of residual wage inequality to total wage inequality, in levels and changes, respectively. The complementary shares are the contributions of worker observables.

A.3. *Some derivations for Section 4*

Taking logs in equations (4.10) and (4.11), we have:

$$h = \alpha_h + \mu_h \iota + u, \qquad u \equiv \frac{\beta(1-k/\delta)}{\Gamma}\theta - \frac{k-\beta}{\delta\Gamma}\eta, \tag{A1}$$

$$w = \alpha_w + \mu_w \iota + \omega, \qquad \omega \equiv \frac{\beta k}{\delta\Gamma}\theta + \frac{k(1-\beta\gamma)}{\delta\Gamma}\eta, \tag{A2}$$

where u and ω denote the combined structural shocks in each equation, $\alpha_s = \log\kappa_s$ for $s = h, w$, and the market access premia equal (reproducing equation (4.15) in the text):

$$\mu_h = (1-k/\delta)\log\Upsilon_x^{\frac{1-\beta}{\Gamma}} \quad \text{and} \quad \mu_w = \frac{k}{\delta}\log\Upsilon_x^{\frac{1-\beta}{\Gamma}}, \quad \text{where} \quad \Upsilon_x = 1 + \tau^{\frac{-\beta}{1-\beta}}\left(\frac{A_x}{A_d}\right)^{\frac{1}{1-\beta}}. \tag{A3}$$

The joint normality of (θ, η) implies the joint normality of (u, ω). Using this property, we project ω onto u, denoting with v the projection residual:

$$\omega = \mathbb{E}\{\omega|u\} + v, \qquad \mathbb{E}\{\omega|u\} = \zeta u, \qquad \zeta = \frac{\text{cov}(\omega, u)}{\text{var}(u)},$$

where ζ is the projection coefficient and the residual v is jointly normal with (u, ω) and orthogonal with u (i.e. $\text{cov}(u, v) = 0$).

The Supplementary Material provides a closed form expression for ζ, which depends on the second moments of the structural shocks (θ, η) and the parameters of the model.

Further, we take logs on both sides of the selection equation (4.12):

$$\log\kappa_\pi + \log\left(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1\right) + \frac{\beta}{\Gamma}\theta + \frac{\beta(1-\gamma k)}{\delta\Gamma}\eta \geq \varepsilon + \log F_x. \tag{A4}$$

Using the definitions of u and ω above, the sum of the two shocks on the left-hand side of this selection equation equals $u + \omega$. Also note from the definition of v that $u + \omega = (1+\zeta)u + v$. Therefore, we can define the overall shock to the selection equation as:

$$z = \frac{1}{\sigma}\big(u + \omega - \varepsilon\big), \qquad \text{where} \qquad \sigma \equiv \sqrt{\text{var}\big(u + \omega - \varepsilon\big)}. \tag{A5}$$

By normalization, the shock z has the following properties:

$$\text{var}(z) = 1, \qquad \text{cov}(z, s) = \rho_s\sigma_s, \qquad \text{where} \qquad s = u, \omega, v,$$

where $\rho_s \equiv \text{corr}(z, s)$ is the correlation between z and some variable s, and $\sigma_s \equiv \sqrt{\text{var}(s)}$ is the standard deviation of s. Derived parameters σ, ρ_s and σ_s can be all expressed as functions of the second moments of $(\theta, \eta, \varepsilon)$ and the parameters of the model (see the Supplementary Material). Here we provide the relationships between the variances and covariances of ω and v, given that $\omega = (1+\zeta)u + v$ and that v and u are orthogonal:

$$\sigma_\omega^2 = (1+\zeta)^2\sigma_u^2 + \sigma_v^2 \qquad \text{and} \qquad \rho_\omega\sigma_\omega = (1+\zeta)\rho_u\sigma_u + \rho_v\sigma_v. \tag{A6}$$

Using the definition of z, we rewrite the selection equation (A4) as:

$$z \geq f \equiv \frac{1}{\sigma}\left[-\alpha_\pi + \log F_x - \log\left(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1\right)\right],$$

which corresponds to equation (4.16) in the text, and where $\alpha_\pi \equiv \log\kappa_\pi$. The intercepts α_h, α_w and α_π capture the general equilibrium environment, including the competition (tightness) in the product and labour markets, as we formally define in the Supplementary Material. This completes the characterization of the reduced-form coefficients of the model, $\Theta = (\alpha_h, \alpha_w, \zeta, \sigma_u, \sigma_v, \rho_u, \rho_v, \mu_h, \mu_w, f)'$.

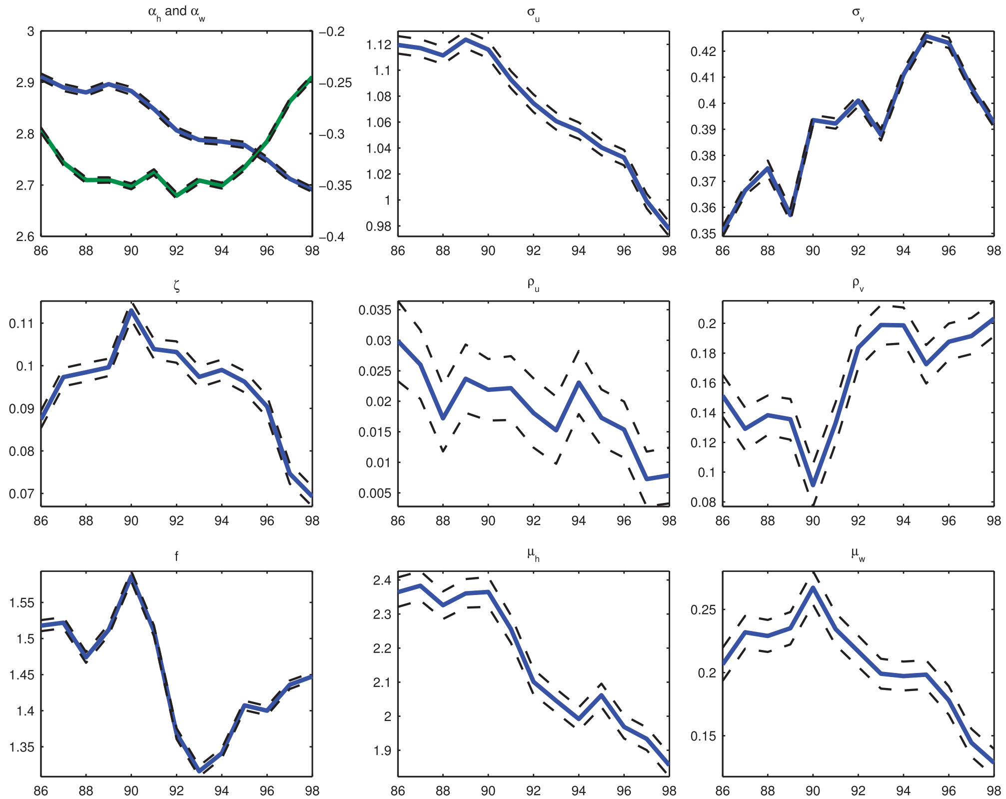

FIGURE A1

Coefficient estimates, 1986–1998. ML estimates of the coefficients of the reduced-form model and two-standard-error bounds (robust (sandwich-form) asymptotic standard errors). The coefficients are estimated using cross-sectional data year-by-year.

Lastly, we show how the orthogonality condition between the structural shocks θ and η implies the parameter restriction in equation (4.18) in the text. First, using the definitions of ζ, u, ω above, and the orthogonality between θ and η, we can express ζ as:

$$\zeta = \frac{\frac{\beta k}{\delta\Gamma}\frac{\beta(1-k/\delta)}{\Gamma}\sigma_\theta^2 - \frac{k(1-\beta\gamma)(k-\beta)}{(\delta\Gamma)^2}\sigma_\eta^2}{\left(\frac{\beta(1-k/\delta)}{\Gamma}\right)^2\sigma_\theta^2 + \left(\frac{k(1-\beta\gamma)}{\delta\Gamma}\right)^2\sigma_\eta^2} = \frac{k}{\delta-k} - \frac{k(1-\beta\gamma)}{\delta\Gamma}\frac{\sigma_\eta^2}{\sigma_u^2} \leq \frac{k}{\delta-k},$$

where the second equality is obtained using straightforward algebraical manipulation. Next, note from equation (A3) that $\mu_w/\mu_h = k/(\delta-k)$. This immediately implies the first inequality in equation (4.18), $\zeta \leq \mu_w/\mu_h$, which holds with equality only in the limiting case of $\sigma_\eta^2 = 0$, i.e. no screening cost shocks. The Supplementary Material further manipulates the expression for ζ to obtain the exact upper bound for μ_w/μ_h in equation (4.18) and express it as a function of the reduced-form coefficients.

A.4. *Additional ML estimation results for Section 5.1*

Figure A1 plots the estimated coefficients of the reduced-form model along with two-standard-error bands. The coefficients are estimated using cross-sectional data year-by-year, and we plot them over time for convenience of presentation. As discussed in Section 5.1, these estimated coefficients are reduced-form functions of the parameters of our theoretical model and variables such as trade costs and relative demand in the export and domestic markets. Therefore, we expect these estimated coefficients of the reduced-form model to change over time with these variables (e.g. if real exchange rate appreciation changes relative demand in the export and domestic markets).

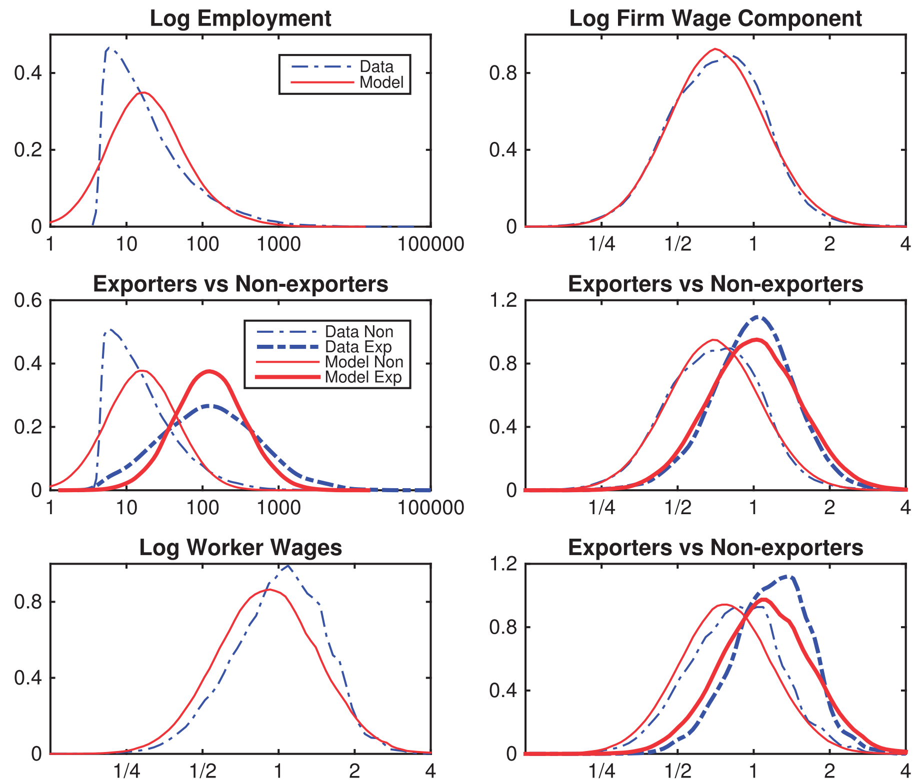

FIGURE A2

Kernel densities for firm and worker employment and wages. The figure shows kernel densities of log firm employment (scale: number of workers) and log firm and worker wages (scale: multiples of sample average log wage) in the data and in the simulated dataset for the estimated model, both for the baseline year 1994. The top two panels display the distributions of employment and wages across firms (first unconditional and then conditional on export status of the firms), and the bottom panel displays the distribution of wages across workers (also unconditional and conditional on the export status of the employer).

Figure A2 examines the ability of the model to fit the entire distribution of observed employment and wages, both across firms and workers. The top panel (row) of the figure displays kernel densities for firm employment (left) and wages (right) across all firms. The middle panel displays these kernel densities for exporters and non-exporters separately. The bottom panel displays kernel densities for the distribution of wages across workers, both for all workers (left) and for workers employed by exporters and non-exporters separately (right). We plot these densities both in the data (solid lines) and in the model (dashed lines). We find that the model is overall successful in fitting these distributions, including the wide overlap and the rightward shift in the distributions for exporters, as we discuss in Section 5.1.[47]

A.5. *Inequality counterfactual of Section 5.2*

In this Appendix, we provide additional details behind the counterfactuals and back-of-the-envelope calculations in Section 5.2. First, recall from equations (4.15)–(4.16) that the reduced-form parameters (μ_h, μ_w, f) depend on $\Upsilon_x^{(1-\beta)/\Gamma}$,

47. One noticeable failure in the fit of the distributions is that the employment distribution in the data is more skewed than the log-normal distribution assumed in the structural model. As a result, the model underpredicts the employment share of the exporters, despite matching exactly the fraction of exporting firms. The multi-destination model addresses this failure and matches the employment share of the exporters.

where from equation (4.5) the structural market access variable is:

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

The other reduced-form parameters of the model relevant for the inequality counterfactuals (i.e. ζ, σ_s, ρ_s for $s = u, v$) do not depend on Υ_x or trade costs. Expressions in equation (4.15) further imply that:

$$\Upsilon_x^{\frac{1-\beta}{\Gamma}} = \exp\{\mu_h + \mu_w\} \qquad \text{and} \qquad \frac{\mu_w}{\mu_h} = \frac{k}{\delta - k}.$$

Therefore, variable trade costs affect Υ_x and through it the reduced-form parameters of the model (μ_h, μ_w, f), yet leaving the ratio of the two reduced-form exporter premia μ_w/μ_h unchanged.

In our benchmark year, 1994, our estimates are $\mu_h = 1.992$ and $\mu_w = 0.197$ (see Table 4), so that $\Upsilon_x^{(1-\beta)/\Gamma} = \exp\{1.992 + 0.197\} = 8.93$. Using the reduced-form model (4.13)–(4.14), we reduce/increase $\Upsilon_x^{(1-\beta)/\Gamma}$ (and correspondingly shift μ_h, μ_w and f) until the exporter employment share reaches 10 percentage points below/above the benchmark level that corresponds to the model estimate for 1994; this results in $\Upsilon_x^{(1-\beta)/\Gamma} = 5.76$ ($\Upsilon_x^{(1-\beta)/\Gamma} = 13.53$, respectively).[48] We simulate the model under these counterfactual parameter values to obtain the counterfactual inequality level (corresponding to the values on the solid blue line at the edges of the shaded areas in Figure 1). The other points on the counterfactual inequality locus (i.e. the solid blue line) in Figure 1 correspond to the same exercise under alternative values of $\Upsilon_x^{(1-\beta)/\Gamma}$, which can be mapped to different values of the variable trade costs τ, as we discuss below.

The variable trade cost counterfactual requires a calibration of one unidentified parameter in addition to the estimates of the reduced-form coefficients Θ. This parameter is the variance σ of the selection shock z, which enters the definition of f in equation (4.16) and is defined in equation (A5). In the benchmark counterfactual, we set σ to satisfy:

$$\sigma^2 = \frac{(1+\zeta)^2 \sigma_u^2 + \sigma_v^2}{\rho_u^2 + \rho_v^2},$$

which is a natural benchmark because $\sigma z = (1+\zeta)u + v - \varepsilon$ and the projection of z onto (u, v) has an $R^2 = \rho_u^2 + \rho_v^2$.[49] In addition, we experiment with a wide range of smaller and larger values of σ and find largely the same outcomes of the counterfactual. This is because in the variable trade cost counterfactual the extensive margin (operating indirectly, through changes in f) plays a smaller role relative to the intensive margin (operating directly, through changes in μ_h and μ_w). See the Supplementary Material for further discussion.

For our back-of-the-envelope calculation on trade costs, we need to calibrate the structural parameters of the model, namely (β, Γ) and τ. We set $\beta = 0.75$, which corresponds to an elasticity of substitution of 4 within sectors, and is a standard value in the literature. Additionally, we set $\gamma = 0.5$ and $k = 4/3$, and infer δ from k and the estimated ratio of $\mu_w/\mu_h = k/(\delta - k)$, obtaining $\delta = 11.1 \cdot k$. Under these circumstances, the derived parameter

$$\Gamma = 1 - \beta\gamma - \frac{\beta}{\delta}(1 - \gamma k) = 0.61.$$

For any $k > 1$ (so that average worker ability is finite) and reasonable values of γ (elasticity of employment $\gamma \geq 0.5$), the last term in Γ is negligible as $\delta > 11.1$, so that we have $\Gamma \approx 1 - \beta\gamma$. We experiment with the empirically relevant $\gamma \in [0.5, 2/3]$ and obtain quantitatively similar conclusions.

Finally, we set the benchmark value of variable trade cost $\tau = 1.6$, a common value used in the literature. We experiment with variable trade costs in the range of $\tau \in (1.3, 1.75)$ and reach similar quantitative conclusions. Given the estimate of $\Upsilon_x^{(1-\beta)/\Gamma}$ in the benchmark year and our calibration for (τ, β, Γ), we can recover the remaining endogenous objects from the value of $\mu_h + \mu_w = \log \Upsilon_x^{(1-\beta)/\Gamma}$ and using the structural expression for Υ_x in equation (4.5):

$$\left(\frac{A_x}{A_d} \right)^{\frac{1}{1-\beta}} = \tau^{\frac{\beta}{1-\beta}} \left[\exp\left\{ \frac{\Gamma}{1-\beta} (\mu_h + \mu_w) \right\} - 1 \right].$$

To convert the changes in $\Upsilon_x^{(1-\beta)/\Gamma}$ that correspond to a 10-percentage points reduction (increase) in the exporter employment share into movements in the variable trade cost τ, we hold the value of $(A_x/A_d)^{1/(1-\beta)}$ constant, which is

48. The exporter employment share is calculated in the simulated model as a ratio of the cumulative employment of exporters (firms with $\iota = 1$ in the counterfactual simulation) to the total employment in the industry (i.e. employment of all firms). The employment in this calculation is taken in levels (i.e., by exponentiating h obtained from the reduced-form model (4.13)). Note that here again the counterfactual value of α_h does not affect the exporter employment share (as it cancels out in the numerator and the denominator), and therefore does not affect our results.

49. Since (z, u, v) are jointly normal and u and v are orthogonal, we have $\mathbb{E}\{z|u, v\} = \rho_u u/\sigma_u + \rho_v v/\sigma_v$ with an $R^2 = \text{var}\big(\mathbb{E}\{z|u, v\}\big)/\text{var}(z) = \rho_u^2 + \rho_v^2$. Therefore, the contribution of u and v to the dispersion of z is $\rho_u^2 + \rho_v^2$, while the dispersion of $(1+\zeta)u + v$ is $(1+\zeta)^2 \sigma_u^2 + \sigma_v^2$, explaining the choice of our benchmark, which corresponds to (u, v) uncorrelated with ε.

an approximation accurate when trading countries (regions) are affected symmetrically by a reduction in trade costs. The resulting variable trade cost is $\tau = 2.29$ ($\tau = 1.14$) for the reduction (increase) in the exporter employment share. Note that

$$\frac{\Delta\tau}{\tau} = \frac{2.29-1.6}{1.6} = 0.431 \qquad \left(\frac{\Delta\tau}{\tau} = \frac{1.14-1.6}{1.6} = 0.288\right),$$

i.e. a 43% increase (29% reduction) in trade costs. We further assume that $\tau = 1.6$ corresponds to a product of technological trade costs d and the residual tariffs t equal to 11.7% observed in Brazil in 1994. Then we can solve for the tariffs t_{-1} that raise τ to 2.29 (corresponding to a 10-percentage point lower exporter employment share):

$$2.29 = d \cdot \frac{t_{-1}}{1.117} \qquad \Rightarrow \qquad t_{-1} = 1.599,$$

i.e. a tariff of 59.9%, close to the tariff rate in Brazil pre trade liberalization.

A.6. *GMM bounds and identified set*

For the GMM analysis, it is convenient to express the reduced-form of the model in terms of (u, ω, z), as in equations (A1)–(A2). The eight first conditional and second unconditional moments of the data (h, w, ι) used for the GMM bounds are (see derivations in the Supplementary Material):

$$\begin{cases} \bar{\iota} &= 1-\Phi, \\ \bar{h} &= \alpha_h + \mu_h \bar{\iota}, \\ \bar{w} &= \alpha_w + \mu_w \bar{\iota}, \\ \bar{h}_1 - \bar{h}_0 &= \mu_h + \rho_u \sigma_u (\lambda_1 - \lambda_0), \\ \bar{w}_1 - \bar{w}_0 &= \mu_w + \rho_\omega \sigma_\omega (\lambda_1 - \lambda_0), \\ \sigma_h^2 &= \sigma_u^2 + \mu_h^2 \Phi(1-\Phi) + 2\mu_h \rho_u \sigma_u \phi, \\ \sigma_w^2 &= \sigma_\omega^2 + \mu_w^2 \Phi(1-\Phi) + 2\mu_w \rho_\omega \sigma_\omega \phi, \\ \sigma_{hw} &= \zeta \sigma_u^2 + \mu_h \mu_w \Phi(1-\Phi) + [\mu_h \rho_\omega \sigma_\omega + \mu_w \rho_u \sigma_u]\phi, \end{cases} \tag{A7}$$

where σ_ω and ρ_ω are defined in equation (A6), $\phi = \phi(f)$ and $\Phi = \Phi(f)$ are the standard normal density and the cumulative distribution function evaluated at f, λ_1 and λ_0 are the Mills ratios evaluated at f and defined in footnote 40.

The Supplementary Material further derives the expressions for the coefficients in the wage regression (5.19) on employment (size premium) and export status (exporter premium):[50]

$$\lambda^s = \frac{\operatorname{cov}\big(w - \mathbb{E}\{w|\iota\}, h - \mathbb{E}\{h|\iota\}\big)}{\operatorname{var}\big(h - \mathbb{E}\{h|\iota\}\big)} = \zeta - \frac{\rho_u \sigma_u \rho_v \sigma_v}{\sigma_u^2 (1-\rho_u^2)}, \tag{A8}$$

$$\lambda^x = \mathbb{E}\{w - \lambda^s h | \iota = 1\} - \mathbb{E}\{w - \lambda^s h | \iota = 0\} = (\mu_w - \lambda^s \mu_h) + (\lambda_1 - \lambda_0)(\rho_\omega \sigma_\omega - \lambda^s \rho_u \sigma_u). \tag{A9}$$

The Supplementary Material also provides closed-form expressions for the intercept λ^o and the R^2 in the regression (5.19). The coefficient λ^s in (A8) is the regression coefficient of firm wages on employment conditional on export status, and it is easy to verify that λ^s provides additional information not contained in the moments in equation (A7). Intuitively, λ^s contains information on the covariance between h and w conditional on export status (i.e., net of the exporter market access premia), while σ_{hw} is the unconditional covariance, which depends on the market access effects, as can be seen from equation (A7). The expression for λ^x in equation (A9) immediately implies that, given λ^s and the conditional first moments of h and w contained in equation (A7), λ^x contains no additional information for identification. The Supplementary Material establishes similar results for the intercept λ^o and the R^2 in the wage regression (5.19), which proves our claim in Section 5.3.

We next establish the parameter restriction in (5.20). In the model, the total revenues of a firm are proportional to the wage bill (see equations (4.9)–(4.11)) and can be written in logs as:

$$r = \alpha_r + (\mu_h + \mu_w)\iota + u + \omega,$$

where $\alpha_r = \log \kappa_r$. For non-exporters (i.e. $\iota = 0$), r corresponds to the revenues from the domestic market ($r^d = r$). The domestic-market revenues for exporters are a fraction $1/\Upsilon_x$ of the total revenues (as we formally show in HIR and in

50. The expression for λ^s as a ratio of conditional covariance and conditional variance is a standard result for multivariate regression. The expression for λ^x is special and relies on the fact that ι is an indicator variable. Indeed, from the definition of the regression in equation (5.19), $\lambda^x = \mathbb{E}\{w - \lambda^s h | h, \iota = 1\} - \mathbb{E}\{w - \lambda^s h | h, \iota = 0\}$. By the definition of λ^s, $(w - \lambda^s h)$ conditional on ι is independent of h. Therefore, h can be dropped from the conditioning in the expression for λ^x, resulting in equation (A9).

the Supplementary Material), so that $r^d = r - \log\Upsilon_x$ for exporters (i.e., $\iota = 1$). Recall that $\log\Upsilon_x = \frac{1-\beta}{\Gamma}(\mu_h + \mu_w)$, and therefore we can write the log domestic revenues of any firm as:

$$r^d = \alpha_r - \left[\frac{\Gamma}{1-\beta} - 1\right](\mu_h + \mu_w)\iota + u + \omega.$$

The definition of Γ and the restrictions on the structural model parameters ($\gamma < 1$ and $\delta > k > 1$) imply $\Gamma > 1-\beta$, therefore the square bracket above is positive, and the domestic revenues for an exporter are smaller than for a non-exporter holding the productivity draw constant. This is a natural result of the decreasing returns to scale (employment) in production (4.6), since exporting increases the scale of production and pushes up the marginal cost of the firm. Nonetheless, the correlation between domestic revenues and export status can be positive in the model, as is the case in the data, due to the selection forces. That is, given

$$\text{cov}(r^d, \iota) = \text{cov}(u+\omega, \iota) - \left[\frac{\Gamma}{1-\beta} - 1\right](\mu_h + \mu_w)\text{var}(\iota) > 0,$$

and as the second term on the right-hand side is negative, we must necessarily have

$$\text{cov}(u+\omega, \iota) = \phi \cdot [\rho_u \sigma_u + \rho_\omega \sigma_\omega] > 0,$$

where the equality above is derived in the Supplementary Material. Intuitively, the sign of the covariance between $(u+\omega)$ and ι is the same as the sign of the covariance between $(u+\omega)$ and z, since $\iota = \mathbb{I}\{z \geq f\}$, and this latter covariance equals $\rho_u \sigma_u + \rho_\omega \sigma_\omega$. Using equation (A6), this implies equation (5.20) in the text.

Lastly, we discuss identification using the GMM system, and the resulting identified set. The system of moments in equations (A7)–(A8) has a recursive structure that makes the identification of the reduced-form coefficients particularly transparent. The fraction of exporters ($\bar{\iota}$) identifies f. The unconditional means of employment and wage ($\bar{h}$ and $\bar{w}$) identify the intercepts α_h and α_w, given the values of μ_h and μ_w. The next block of moments contains the differences in the conditional means and unconditional variance of log employment h and wages w, e.g. $\bar{h}_1 - \bar{h}_0$ and σ_h^2 for employment and similarly for wages. This provides two conditions for three parameters $(\sigma_u, \rho_u, \mu_h)$ and similarly another two conditions for $(\sigma_\omega, \rho_\omega, \mu_h)$. In other words, given μ_h and μ_w, these moment conditions allow us to recover the value of $(\rho_u, \rho_\omega, \sigma_u, \sigma_\omega)$. One can show that, along these moment conditions, larger values of μ_h (μ_w) correspond to smaller values of ρ_u (ρ_ω), while σ_u (σ_ω) varies non-monotonically and over a limited range (as the values of the variances of the shocks are pinned down by the variances of employment and wages). The final two moment conditions are the covariance of employment and wages and the size wage premium λ^s, which together identify ζ given the other parameters of the model and provide an additional joint restriction on $(\mu_h, \mu_w, \rho_u, \rho_\omega)$. This latter point can be seen by combining the expressions for σ_{hw} and λ^s to solve out ζ. Taken altogether, this leaves us with one remaining degree of freedom for the model parameters consistent with the moments in equations (A7)–(A8). This results in a unidimensional identified set in the ten-dimensional parameter space, which we now characterize using the moments from the Brazilian data in 1994.

Since the identified set is unidimensional, we can parametrize it with a single variable. It proves convenient to parametrize it with the value of the exporter employment premium parameter μ_h, as all other elements of the identified set can be represented as functions of μ_h. As we increase μ_h, the value of ρ_u decreases, the value of μ_w increases and the value of ρ_ω decreases.[51] The restriction that $\rho_u \leq 1$ limits the range of variation of μ_h from below (with the minimum value for μ_h of 0.122). The parameter restriction in equation (5.20), $(1+\zeta)\rho_u\sigma_u + \rho_v\sigma_v = \rho_u\sigma_u + \rho_\omega\sigma_\omega > 0$, limits the range of variation of μ_h from above (with the maximum value for μ_h of 2.046). Therefore, along the identified set, $\mu_h \in [0.122, 2.046)$, which corresponds to $\mu_w \in [0.178, 0.354)$. That is, both the exporter wage and employment premia are positive for each element of the identified set, which satisfies the requirement of our structural model (without us imposing it in calculating the identified set). We illustrate the values of key parameters along the identified set in Figure A3, and plot them as functions of μ_h as we vary it over $[0.122, 2.046)$. In other words, each value of μ_h on the horizontal axis corresponds to one element of the identified set, and we plot on the vertical axis the corresponding values of the other parameters (e.g. the solid blue line plots the values of μ_w corresponding to each value of μ_h).

A.7. *Multiple export destinations*

Given the structure of the multi-destination extension described in Section 6, as summarized in equations (6.25) and (6.26), we can generalize the benchmark reduced-form model (4.13) to this case as follows:

$$\begin{cases} h &= \alpha_h + \mu_{h,1}\iota_1 + (\mu_{h,2} - \mu_{h,1})\iota_2 + (\mu_{h,3} - \mu_{h,2})\iota_3 + u, \\ w &= \alpha_w + \mu_{w,1}\iota_1 + (\mu_{w,2} - \mu_{w,1})\iota_2 + (\mu_{w,3} - \mu_{w,2})\iota_3 + \zeta u + v, \\ \iota_\ell &= \mathbb{I}\{f_{\ell-1} \leq z \leq f_\ell\}, \qquad \ell = 1, 2, 3, \end{cases} \tag{A10}$$

51. For the other parameters, ζ increases with μ_h; σ_u and σ_ω are U-shaped; σ_v is hump-shaped; and the selection correlation ρ_v is U-shaped in μ_h and close to zero in magnitude.

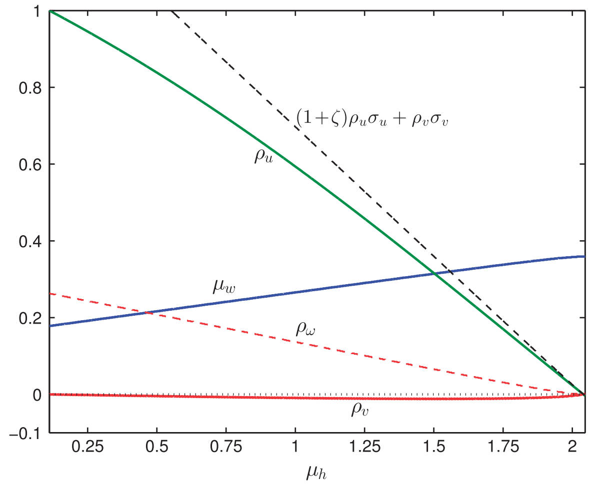

FIGURE A3

GMM identified set. The figure plots the values of parameters (μ_w, ρ_u, ρ_v) against μ_h across the elements of the GMM identified set, which are parametrized by $\mu_h \in [0.122, 2.046)$. Along the identified set, μ_w increases (from 0.178 to 0.354) with μ_h, while ρ_u and ρ_ω decrease with μ_h and μ_w, respectively. At the left end of the identified set $\rho_u = 1$, while at the right end the parameter inequality (5.20), plotted in the figure with a dashed black line, starts to bind.

where (u, v, z) is still the vector of reduced-form idiosyncratic firm shocks distributed according to equation (4.14). The change relative to the single-destination model is that the data now contains five variables $\{h, w, \iota_1, \iota_2, \iota_3\}$, and the market access and fixed cost reduced-form coefficients $\{\mu_{h,\ell}, \mu_{w,\ell}, f_\ell\}_{\ell=1,2,3}$ are now market specific. In particular, these reduced-form coefficients generalize from the single-destination case (4.15)–(4.16) in a straightforward way:

$$\mu_{h,\ell} = \frac{\delta - k}{\delta} \log \Upsilon_{x,\ell}^{\frac{1-\beta}{\Gamma}}, \qquad \mu_{w,\ell} = \frac{k}{\delta - k} \mu_{h,\ell}, \tag{A11}$$

$$f_\ell = \frac{1}{\sigma}\left[-\alpha_\pi + \log F_{x,\ell} - \log\left(\Upsilon_{x,\ell}^{\frac{1-\beta}{\Gamma}} - \Upsilon_{x,\ell-1}^{\frac{1-\beta}{\Gamma}}\right)\right], \tag{A12}$$

for $\ell = 1, 2, 3$, and $f_0 = -\infty$, and where $\Upsilon_{x,\ell} = 1 + \tau^{-\frac{\beta}{1-\beta}} \sum_{j=1}^{\ell} \left(\frac{A_{x,j}}{A_d}\right)^{\frac{1}{1-\beta}}$ for $\ell \geq 1$ and $\Upsilon_{x,0} = 1$.

The likelihood function for the multidestination model (A10) and (4.14) is an immediate generalization of equation (4.17), as we show in the Supplementary Material. We now have a total of 16 parameters to estimate, and the structure of the model imposes the following parameter restrictions (from equation (6.25) and (A11)):

$$\mu_{h,\ell}, \mu_{w,\ell} \geq 0 \quad \text{and} \quad \mu_{w,\ell} = \chi \mu_{h,\ell}, \qquad \ell = 1, 2, 3 \tag{A13}$$

where $\chi \equiv k/(\delta - k) > 0$ is a derived parameter of the structural model. As in the ML estimation of Section 5.1, we impose an identifying orthogonality assumption on the structural shocks (as discussed in Section 4.3). In our multi-destination extension, this identifying assumption results in the following parameter restriction:

$$\zeta \leq \chi \leq \zeta + \frac{\sigma_v^2}{(1+\zeta)\sigma_u^2}, \tag{A14}$$

which parallels (4.18) in the single-destination model. We estimate the multi-destination model by maximizing the likelihood function subject to the inequality restriction (A14) and using the relationship $\mu_{w,\ell} = \chi \mu_{h,\ell}$ from equation (A13). Analogous to the single-destination model, we estimate the multi-destination model without imposing the inequality restriction from equation (A13) that the market access premia are positive, and check whether the estimates in fact satisfy this requirement of the theoretical model. The reduced-form market access premia $(\mu_{w,\ell}, \mu_{h,\ell})$ and export thresholds (f_ℓ) are again sufficient statistics for the impact of trade on wage inequality. Therefore, we can undertake similar counterfactuals for the inequality effects of trade as for the single-destination model in Subsection 5.2.

Tables A3 and A4 summarize the results from our multi-destination extension, using the data for our baseline year of 1994. Table A3 reports the estimated values of the main parameters of interest—the selection correlations and the market

TABLE A3
Multiple Export Destinations: Parameter Estimates

Parameter estimates	ρ_u	ρ_v	$\mu_{h,1}$	$\mu_{h,2}$	$\mu_{h,3}$	$\mu_{w,1}$	$\mu_{w,2}$	$\mu_{w,3}$
Single-destination benchmark	0.023	0.199	1.99	—	—	0.197	—	—
Multi-destination A	0.043	0.203	1.25	2.08	3.48	0.123	0.203	0.340
Multi-destination B	0.040	0.202	1.58	2.89	4.33	0.154	0.283	0.423

Notes: ML estimates for our baseline year of 1994. For example, in Specification B, the smaller exporters in Bin 1 pay a wage premium of $\mu_{w,1}=0.154$ (15.4 log points or equivalently 16.7%), while the more selective Bin 3 of the largest exporters pays an average wage premium of $\mu_{w,3}=0.423$ (42.3 log points or 52.7%).

TABLE A4
Multiple Export Destinations: Counterfactuals

			10 p.p. increase in exp. empl. share	
Counterfactuals	Autarky	Peak	To 1994 level	From 1994 level
Single-destination benchmark	7.6%	10.7%	2.3%	1.8%
Multi-destination A	13.8%	19.0%	3.6%	3.0%
Multi-destination B	15.7%	23.3%	4.3%	3.8%

Notes: Counterfactual changes in the standard deviation of log worker wages (normalized by its counterfactual autarky level); all counterfactuals correspond to a variation in the variable trade costs τ, as described in the text.

access premia—for the two specifications of the multi-destination model. Comparing these results with those for the single-destination model in Subsection 5.1, two observations stand out. First, both multi-destination specifications yield similar positive estimates of the selection correlations, which are also quantitatively consistent with the single-destination estimates. Second, both specifications yield positive estimates of market access parameters for both employment and wages, which monotonically increase with the number of export destinations, consistent with the predictions of the structural model. In other words, there are additional market access effects associated with serving larger numbers of export destinations.

We use the estimated multi-destination model to perform a number of counterfactuals to evaluate the effects of trade on wage inequality, as discussed in Section 6. Here we provide an additional summary of these counterfactuals in Table A4, comparing the results from the two specifications of the multi-destination model with the single-destination benchmark. The first column of Table A4 presents the results of the autarky counterfactual. The next three columns report three more counterfactual exercises in which we change the variable trade cost τ in equation (6.25). We assume that changes in τ result in a proportional shift in all market access premia parameters, according to equations (6.25) and (A11). This implicitly assumes that the relative demand shifters $A_{x,\ell}/A_d$ stay unchanged, which would be the case in a world of symmetric trading regions. We first vary τ to reach the peak level of inequality in each specification of the model, and report the results in the second column of Table A4. The final two counterfactuals parallel those in Section 5.2 and correspond to a change in the variable trade cost τ that results in a 10-percentage point increase in the exporter employment share. We report results both starting from a lower exporter employment share and ending up at the value in our baseline year (Column (3) of Table A4) and starting from the exporter employment share in our baseline year and ending up at a lower value (Column (4) of Table A4). We report in the table the corresponding counterfactual change in wage inequality (in both cases an increase in wage inequality). The shaded areas in Figure 3 correspond to these two counterfactual exercises.

Lastly, Figure A4 reports the accounting exercise for both the baseline and the multi-destination models, as described at the end of Sections 5.2 and 6, respectively. Specifically, we solve for the implied value of symmetric variable trade costs τ, and hence the export threshold and market access premia (f,μ_h,μ_w), that exactly match the evolution of the exporter employment share over 1986–98, while holding all other parameters constant at their estimated values for 1994. In the data, the exporter employment share declines somewhat until 1990, increases by 9 percentage points up to 1993, and after that falls by 6 percentage points to 1998. The model reproduces these movements with mirror-image dynamics in variable trade costs—they increase slightly at first, then sharply decrease, before increasing again. These implied variable trade costs capture all shocks to relative export profitability, and their evolution over time is consistent with the timing of trade liberalization and exchange rate movements in Brazil. As discussed in Section 2 and Kume *et al*. (2003), the main trade liberalization in Brazil occurs from 1988–93, and there is an exchange rate appreciation from 1995 onwards.

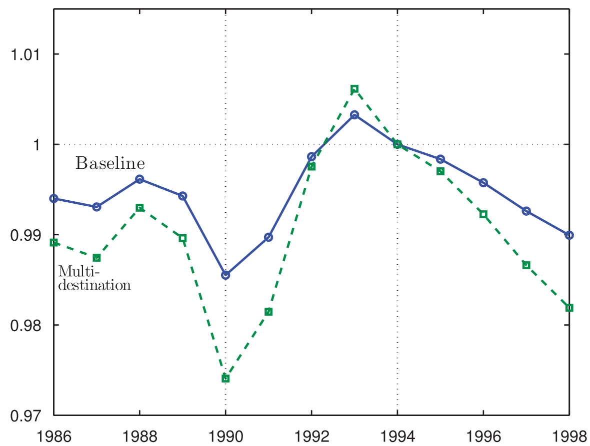

FIGURE A4

Counterfactual inequality evolution. The figure plots the counterfactual evolution of the standard deviation of log worker wages in the model, where variable trade costs τ, and hence (μ_h, μ_w, f), are varied to exactly match the evolution of the exporter employment share in the data, while all other parameters are held constant at their 1994 estimated values. The solid blue line corresponds to the baseline model of Subsections 5.1–5.2, while the dashed green line corresponds to the multi-destination model of Section 6. The level of inequality in 1994 in both models matches the observed inequality in the data, and we normalize it to 1 in the figure for ease of comparison.

This time path for variable trade costs generates the counterfactual predictions for wage inequality shown in Figure A4: there is a slight decrease in inequality before 1990, followed by a sharp increase with a peak in 1993, and then a gradual decrease until 1998. The multi-destination model predicts a 2.5% increase in inequality between 1990 and 1994 and a 2% decrease thereafter, in both cases almost double the size of the movement in the baseline single-destination model. When we compare these results with the actual evolution of inequality in the data, these counterfactual predictions miss the increase in inequality between 1986 and 1990, because at this time the exporter employment share was decreasing, and hence none of that inequality increase in the data can be attributed to trade (conditional on our estimated model). After 1990, the model fairs much better: the multi-destination model can account for 72% of the inequality increase from 1990 to 1994 and for 49% of the reduction in inequality thereafter (for the baseline model, these shares are 40% and 27%, respectively).

Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

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