

Trade, Labor Market Concentration, and Wages

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Abstract

Growing evidence suggests that trade liberalization has large negative effects on wages in labor markets more exposed to import competition. Why? I study one potential mechanism: increased firm labor market power. I develop an imperfectly competitive model of labor markets whereby the effect of trade on a market's average wage markdown can be quantified by two sufficient statistics: the effect of trade on labor market concentration, and the gap between workers' cross-market vs. within-market cross-firm inverse elasticities of substitution. I then use employer-employee linked data and Brazil's 1990s trade liberalization to estimate these key sufficient statistics. I highlight three findings. First, firms had substantial market power before liberalization: workers took home only 50 cents of every marginal dollar they generated. Second, trade increased labor market concentration, an effect driven by employment reallocation to higher-paying exporting firms. Third, this increased concentration raised firm labor market power, and the consequent reduction in wages offset all wage gains from the reallocation to higher-paying firms. However, the magnitude of this market power effect was small, accounting for only 2% of the overall negative effect of trade on wages. The overall effect was instead driven by within-firm reductions in the marginal revenue product of labor.

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1 Introduction

A growing body of evidence suggests that trade significantly reduces wages in labor markets more exposed to import competition, relative to less exposed markets. These patterns have been documented in various contexts, including India (Topalova, 2010), Brazil (Kovak, 2013), and the U.S. (Autor, Dorn and Hanson, 2013). What accounts for them?

This paper analyses one potential mechanism: trade-induced increases in firm labor market power. A robust prediction of trade models with firm heterogeneity (e.g., Melitz (2003)) is that trade liberalization tends to reallocate employment towards larger, more productive firms. This predicted employment reallocation increases labor market concentration. On the one hand, reallocation towards larger, more productive firms can raise the average marginal product of labor, increasing wages. On the other hand, if labor markets are not perfectly competitive, reallocation towards larger firms can increase firm labor market power, reducing wages. On net, the impact of trade-induced increases in concentration on wages is ambiguous, and depends on the magnitude of each channel. This paper quantifies both.

I start by outlining a model that provides the link between labor market concentration and wages. In my model, there is a large number of markets, firms compete for workers à la Cournot, and workers have nested CES preferences over jobs, as in Berger, Herkenhoff and Mongey (2021). In this environment, worker movements in response to shocks are governed by two elasticities: the cross-market elasticity of substitution, and the within-market cross-firm elasticity of substitution. Along with a firm's payroll share in its local labor market, these key elasticities of substitution determine the elasticity of residual labor supply faced by the firm, which then determines the firm's wage markdown. A firm's wage markdown is the ratio of its workers' marginal revenue product of labor to their wage, and it is the standard measure of firm labor market power I adopt in this paper.

To understand how workers' key elasticities of substitution interact with a firm's relative size to determine its wage markdown, consider the following example. When a firm lowers its wage, it loses workers on two margins: (i) to other firms in the same local market, as lowering its wage makes those firms more attractive; and (ii) to other markets, as lowering its wage reduces its local market's average wage, making other markets more attractive. In the extreme case where the firm is a monopsonist in its local labor market, then only effect (ii) is active, and the cross-market elasticity determines the firm's wage markdown. In the other extreme case where the firm is atomistic, then only effect (i) is active, and the within-market cross-firm elasticity determines the markdown. More generally, the markdown set by a firm depends on the magnitude of the two key elasticities of substitution and on its market share.

The first theoretical result of this paper concerns what the firm-level expression for the markdown implies for the market-level average markdown. The latter is the key link between firm labor market power and market-level average wages, whose large reductions in response to trade liberalization, previously documented in the literature, I seek to understand. Taking a weighted average of firms' wage markdowns across all firms in a market, I show that the market-level average markdown is determined by the two key elasticities of substitution, along with the market's payroll Herfindahl, defined as the sum of its firms' squared payroll market shares. The dependency of the market-level average wage markdown on the key elasticities and on the market's level of concentration is similarly intuitive: small elasticities mean weak movements in response to shocks, increasing local firms' power; whereas high concentration means few within-market options for cross-firm movement, also increasing local firms' power.

A direct implication of my model's expression for the wage markdown is that its response to trade can be quantified by just two sufficient statistics: the effect of trade on local labor market concentration, and the *gap* between workers' cross-market vs. the within-market cross-firm elasticities of substitution.¹ If trade has no effect on labor market concentration—the only endogenous component of the wage markdown—it has no effect on firm labor market power. If there is no gap between the two key elasticities of substitution, then workers move far away as easily as they move close by, such that to attract workers firms compete in a unified national labor market. In the latter, wage setting is independent of size, and therefore labor market concentration is irrelevant for market power. Such a unified national market is my model's limiting case of monopsonistic competition, where wage markdowns are constant.² Overall, the larger is the effect of trade on concentration and the larger is the gap between the key elasticities, the larger is the effect of trade on firm labor market power.

With clear guidance on the key sufficient statistics needed to quantify the effect of trade on firm labor market power, I next proceed to estimate them using employer-employee linked data and Brazil's 1990s trade liberalization. In 1990, Brazil announced an import tariff reduction reform, to be completed by 1994, whereby import tariffs on all sectors would be reduced from a pre-reform average of 33% to a post-reform average of 13%. As sectors differed in their pre-reform levels of protection—a consequence of industrial policies set decades earlier during the military dictatorship—the reform generated substantial cross-sector variation in import tariff changes. This cross-sector variation in 1990-1994 changes

¹Specifically, the gap between the *inverses* of the key elasticities of substitution.

²The other limiting case is perfect competition, when both inverse elasticities are zero.

in import tariffs is the granular policy-induced variation I exploit to estimate my model’s sufficient statistics.

The first step towards quantifying the effect of trade on firm labor market power is to estimate its effect on labor market concentration. I define a local labor market as a microregion \times occupational group cell,³ motivated by evidence from workers’ job-to-job transition matrices,⁴ and proceed to design an empirical strategy for the effect of trade on these markets’ payroll Herfindahl indices. My identification strategy leverages local labor markets’ differential exposure to import tariff reductions depending on each market’s pre-liberalization sectoral composition, similar to the approach in Dix-Carneiro and Kovak (2017). I estimate a difference-in-differences regression of the change in a local market’s payroll Herfindahl on its “import competition exposure,” a shift-share treatment intensity measure whose “shift” is the set of tariff reductions experienced by each firm in the local labor market, and whose “share” is the firm’s contribution to the market’s baseline year payroll Herfindahl. This particular functional form is guided by the model outlined above, though I also consider alternative measures as robustness checks.

I find that a 10 percent increase in import competition exposure increased local labor markets’ payroll Herfindahl by 0.02 points relative to less affected markets, with no evidence of pre-trends. This effect is a 7% increase relative to a pre-liberalization 0.28 payroll Herfindahl average, and is robust to alternative measures of import competition exposure and labor market concentration, defining labor markets solely as microregions, and to alternative clustering.⁵ To understand the nature of the employment reallocation that led to increased concentration, I test the cross-firm reallocation hypothesis discussed earlier, that workers were reallocated towards a particular type of large, more productive firms: exporters. In the case of Brazil’s unilateral import tariff reductions, theory predicts that exporters would be less negatively affected because a positive share of their revenues does not compete with products affected by Brazil’s import tariffs, coming from foreign consumers instead.

Indeed, I find that import competition primarily reduced employment of non-exporting tradable sector firms, but had no detectable effect on total employment of either exporters or

³The most common boundaries used the literature are defined by region \times occupation, region \times sector, or simply region. See footnote 22.

⁴Conditional on switching jobs, Brazilian workers are more likely to stay within microregions and occupations than within sectors. Felix and Wang (2021) explore this further to answer what constitutes a labor market, finding strong evidence that occupation boundaries are a prominent component of workers’ outside options in Brazil.

⁵I also show in placebo regressions that my shift-share treatment intensity measure does not overreject the null, an important check following the recent literature on shift-share instruments (e.g., Adao, Kolesár and Morales (2019)).

non-tradable sector firms. This differential incidence resulted in a within-market compositional reallocation of employment, increasing labor market concentration as exporters—who already were on average 20 times larger and paid 3 times more than other firms—captured a larger share of total employment. I also test and confirm that export status is the key driver of the employment reallocation as opposed to simply firm size.

The next step towards quantifying the effect of trade on firm labor market power is to estimate my model’s two key elasticities of substitution. My model provides the regression specifications, and my setting the quasi-exogenous variation. First, to identify the within-market cross-firm inverse elasticity of substitution, I estimate a regression of the change in a firm’s log wage premium⁶ in its local labor market on the change in the firm’s log employment in the market, plus a market fixed effect. The key identification threat is that changes in employment could be correlated with changes in workers’ taste for the firm-market pair (i.e., the error term per my model). I therefore instrument the change in firm log employment with a labor demand shock, the change in import tariffs on the firm’s sector. The within-market cross-firm elasticity is thus identified by cross-sector tariff changes within each labor market (i.e., microregion \times occupational group cell).

Second, having estimated the within-market cross-firm elasticity of substitution, I compute the wage and employment indices needed to estimate the cross-market elasticity of substitution.⁷ According to my model, the latter can be estimated using a regression of the change in a market’s log wage premium index on the change in its log employment index. The coefficient on the market’s log employment index is the gap between the cross-market and the within-market cross-firm inverse elasticities of substitution, whose key threat to identification is once again correlation with changes in workers’ taste for that particular market (i.e., the error term per my model). I address this by instrumenting the change in the market’s log employment index with the market’s previously-defined change in import competition exposure.

With these specifications, I estimate a within-market cross-firm inverse elasticity of substitution of 0.985, and a cross-market inverse elasticity of substitution of 1.257. In other words, in 1990s Brazil, a firm that increased its wage by 0.985 percent attracted one percent more workers from within its local labor market, whereas a market whose wage level

⁶A firm’s wage premium in its local labor market measures its wage after controlling for worker characteristics. It is the theory-consistent empirical measure for wages in my model because I assume workers are equally productive. I estimate these premia as firm-market pair fixed effects in a regression of worker log wages on flexible controls for education, age, and gender, plus the fixed effects.

⁷These indices can be interpreted as amenity-adjusted wages and employment at the market level.

increased by 1.257 percent attracted one percent more workers from other markets. Both point estimates are robust to alternative wage measures, alternative tariff shocks, and to relevant alternative samples. These elasticities—along with the pre-liberalization level of labor market concentration—imply that prior to liberalization, Brazilian workers took home 50 cents for every dollar of marginal revenue product of labor. This suggests that Brazil’s formal sector features more firm labor market power than other essentially formal sector settings (e.g., 65 cents on the dollar for US manufacturing by Hershbein, Macaluso and Yeh (2019)).⁸

Importantly, I reject my model’s limiting case of monopsonistic competition whereby these two inverse elasticities are the same ($p\text{-value} < 0.02$). I estimate their gap at 0.272, which, combined with my estimates of the effect of trade on labor market concentration, implies that a 10% increase in import competition exposure reduced markets’ average wage premia by 0.29% via a small but statistically significant increase in wage markdowns. This wage reduction was large enough to completely offset a 0.27% increase in wage premia driven by cross-firm reallocations towards exporters, but small relative to the overall effect of trade on wages, a point to which I turn next.

Overall, the 0.29% wage loss from increased firm labor market power accounted for only 2% of the overall 13.8% negative effect of trade on average wages. The overall effect was instead driven by within-firm reductions in the marginal revenue product of labor, and is consistent with import competition primarily reducing prices in goods markets. Thus, I find that while there existed substantial labor market power in 1990s Brazil, and trade further increased this market power, nevertheless greater firm labor market power does not explain the bulk of the wage declines we see in response to trade.

This paper contributes to growing literatures on the regional incidence of trade and firm labor market power. First, this is the first paper to provide a comprehensive study of the relationship between trade, labor market concentration, and wages. I provide clear guidance on the parameters needed to estimate the effect of trade on firm labor market power, and I quantify the two offsetting effects of a trade-induced increase in labor market concentration: the negative effect via market power, and the positive effect via reallocation towards higher-paying firms.

⁸See Section 6 for additional estimates from the literature. Appendix D.1 provides an extensive discussion of the external validity of my estimates to incorporating the informal sector. Evidence suggests market power is more prevalent under informality. It is also under informality that near-slavery working conditions (arguably the most extreme form of firm labor market power) persist, a topic whose relationship to trade I explore in Felix (2021b).

Second, the availability of within-market cross-firm tariff shocks allows me to improve upon the methodology introduced by Berger, Herkenhoff and Mongey (2021) to estimate labor supply elasticities under Cournot competition. This variation allows me to use a “bottom up” estimation approach that adapts Costinot, Donaldson and Smith (2016)’s estimation of nested CES demand to a labor supply context. I estimate the bottom nest (i.e., within markets) elasticity using within-market cross-firm variation in tariff shocks, and then estimate the top nest (i.e., cross markets) elasticity using cross-market variation in tariff shocks. This is in contrast to Berger, Herkenhoff and Mongey (2021)’s “top down” approach, which uses cross-market shocks only (i.e., variation in tax rates across states) to back out both elasticities from shock heterogeneity by firm size, a method that requires bias-correction via simulation of firm behavior and indirect inference.

Finally, my data and setting allow me to contribute more broadly to our understanding of labor market concentration and firm labor market power. First, most estimates of the levels of either labor market concentration or firm labor market power are limited to either *developed* countries or to *subsets* of what are essentially formal sector firms.⁹ My estimates are based on the *universe* of formal sector employment in a *developing* country setting, and they suggest market power is indeed more prevalent in this context. Third, nearly all estimates in the literature are based on plant-level data, whose wages include the compositional effects of worker demographics and/or within-plant occupational distribution. My estimates are not confounded by either factor, because my data are disaggregated at the worker level. Finally, the transition matrices I compute to inform my definition of labor market boundaries are the first job-to-job transition matrices documented for a developing country, adding to a growing literature on worker network mobility (e.g., Schubert, Stansbury and Taska (2019); Nimczik (2017); Schmutte (2014)).¹⁰

The rest of the paper proceeds as follows. Section 2 presents my model that links labor market concentration to wages, from which I derive the expression for estimating the effect of trade on firm labor market power. Section 3 presents my data and setting. Section 4 presents my empirical strategy and estimates of the effect of trade on labor market concentration. Section 5 presents my empirical strategy to estimate my model’s key elasticities, whose estimates are presented in Section 6. Section 7 combines my estimates from Sections 4 and 6 to estimate implications for average wages. Section 8 concludes.

⁹See Section 6.3 for a review.

¹⁰Aggregate statistics on job transitions have however been reported for Costa Rica (e.g., Alfaro Urena, Manelici and Vasquez (2021) for 2006-2008) and Brazil (e.g., Fogel and Modenesi (2021) for 2009-2012), and are consistent with the degree of permanence within markets I document.

2 Concentration and wages: An empirical model

In this section I introduce an empirical model of Brazilian labor markets that provides the relationship between labor market concentration and wages. As in Berger, Herkenhoff and Mongey (2021), labor supply is nested CES, firms compete for workers à la Cournot, and there is a large number of labor markets.^{11,12} Combined, these assumptions imply that the impact of trade on firm labor market power can be quantified by two key sufficient statistics only: the effect of trade on labor market concentration, and workers' cross-market vs. within-market cross-firm inverse elasticities of substitution. In the following sections I then estimate these sufficient statistics leveraging employer-employee linked data and Brazil's 1990s trade liberalization.

2.1 Labor supply: Discrete choice

I follow a similar setup as in Berger, Herkenhoff and Mongey (2021)'s micro-foundation of a nested CES labor supply system, which I extend to incorporate worker taste shifters for specific markets and for firm-market pairs. These taste shifters give structural interpretation to the regression residuals in the empirical specifications I use to estimate the model's key elasticities of substitution.

The economy consists of a continuum of homogenous workers j , a large but finite number of local labor markets m , and a finite number of firms z within each local labor market. Each worker chooses to which firm-market pair zm they provide l_{zm}^j units of labor subject to making reservation earnings $y^j \sim F(y)$, solving the following discrete choice problem to minimize the disutility of work V_{zm} :

$$\begin{aligned} \min_{zm} V_{zm}^j &= \ln l_{zm}^j + \ln \xi_m + \ln \xi_{zm} - \xi_{zm}^j \\ \text{s.t. } l_{zm}^j w_{zm} &\geq y^j \end{aligned}$$

where $\xi_{zm} > 0$ and $\xi_m > 0$ are firm-market- and market-specific taste shifters common to all

¹¹But unlike Berger, Herkenhoff and Mongey (2021), I remain agnostic about firms' production functions and goods market structure because my empirical model focuses on measurement (of firm labor market power and its response to trade) as opposed to general equilibrium counterfactuals, for which further assumptions are needed.

¹²This setup applies to a labor supply context the product demand setup from Atkeson and Burstein (2008), and parallels a standard approach in the IO literature: make assumptions about good demand and goods market structure allows in order to recover price markups. Similarly, I make assumptions about labor supply and labor market structure to recover wage markdowns.

workers, w_{zm} is the wage paid by firm z in local labor market m to identical workers, and ξ_{zm}^j is an idiosyncratic worker taste shifter with a General Extreme Value (GEV) distribution:¹³

$$G(\{\xi_{zm}^j\}) = \exp \left[- \sum_m \left(\sum_{z \in \Theta_m} e^{-(1+\eta)\xi_{zm}^j} \right)^{\frac{1+\theta}{1+\eta}} \right] \quad (1)$$

where Θ_m is the set of firms operating in market m .

The parameters $\theta > 0$ and $\eta > 0$ correspond to workers' cross-market and within-market cross-firm elasticities of substitution,¹⁴ whose nesting structure is shown in Figure 1 from the point of view of worker j 's decision. These are the two key elasticities of substitution whose estimates drive this paper's empirical findings.

Since ξ_{zm}^j follows a GEV distribution, the probability that worker j chooses firm z in market m can be written as a function of wages, taste-shifters, and the elasticities of substitution.¹⁵ Aggregating these probabilities to the firm-market level gives the model's equation for residual labor supplied to firm z in market m :

$$l_{zm} = L \left(\frac{w_{zm}}{W_m} \right)^\eta \left(\frac{W_m}{W} \right)^\theta (\xi_{zm}^{1+\eta} \xi_m^{1+\theta})^{-1} \quad (2)$$

where W_m , W , and L are CES wage and labor supply indices (i.e., "amenity-adjusted" wages and employment indices), whose expressions can be found in Appendix C.1.

Equation 2 encapsulates the following intuition. The residual labor supplied to firm z in market m is increasing in how attractive its wage w_{zm} is relative to market m 's wage level W_m , as well as in how attractive market m 's wage level is relative to all other markets. It is also decreasing in the disamenity taste shifters ξ_{zm} and ξ_m , and larger if there is overall more (amenity-adjusted) labor L supplied to all markets.

Finally, inverting equation 2 gives the model's equation for the wage w_{zm} firm z must

¹³The specific functional form shown in equation 1 corresponds to the Gumbel distribution, a member of the GEV family. However, by the results in McFadden (1978), similar equations to those in this section can be derived for any member of the GEV family.

¹⁴Berger, Herkenhoff and Mongey (2021) show that the nested discrete choice setup can be mapped into a representative worker problem where the representative worker has nested CES preferences over firms and markets, with θ wage elasticity of substitution across markets, and η wage elasticity of substitution within markets across firms.

¹⁵See Appendix C for detailed derivations of all results in this section.

pay in market m to obtain l_{zm} units of labor:

$$w_{zm} = W \left(\frac{l_{zm}}{L_m} \right)^{\frac{1}{\eta}} \left(\frac{L_m}{L} \right)^{\frac{1}{\theta}} \xi_{zm}^{1+\frac{1}{\eta}} \xi_m^{1+\frac{1}{\theta}} \quad (3)$$

where L_m is market m 's amenity-adjusted employment index, whose expression can also be found in Appendix C.

Equation 3 encapsulates a similar intuition as equation 2, its counterpart. The wage w_{zm} needed to attract l_{zm} units of labor is increasing in the disamenity taste shifters ξ_{zm} and ξ_m —indicating workers must be compensated to move to a firm or market they dislike—, as well as in the country-level wage index W . Sometimes referred to as the firm's wage equation, equation 3 is the firm's inverse residual labor supply, and it is the key equation underlying my empirical strategy to estimate $\frac{1}{\eta}$ and $\frac{1}{\theta}$, which I present in Section 5.

2.2 Labor demand: Cournot competition

Labor markets are imperfectly competitive. Firms compete à la Cournot, choosing their labor demand in each market to maximize their profits while taking as given the labor demand of other firms. Firm profits are given by

$$\Pi_z = R_z(\{l_{zm}, l_{-zm}\}, X) - \sum_m w_{zm}(\{l_{zm}, l_{-zm}\}) l_{zm} \quad (4)$$

where R_z is the firm's revenue function—capturing both technology and goods market structure, which I remain agnostic about—and w_{zm} is the wage that firm z would need to pay to obtain l_{zm} units of labor in local labor market m . The expression $\{l_{zm}, l_{-zm}\}$ in curly braces denotes that, from firm z 's perspective, both R_z and w_{zm} depend on the full profile of labor demanded by all firms in all markets,¹⁶ while X represents any exogenous shock to firm z 's revenues.

Firm z 's first-order condition for profit maximization equates marginal revenue to marginal

¹⁶Note that l_{-zm} denotes the units of labor employed by all other firms (other than z) or in all other markets (other than m). This includes: a) workers employed by z in markets other than m ; b) workers employed by competitors in m ; and c) workers employed by competitors in markets other than m . The wage w_{zm} is a function of all of these components, as shown in Equation 3 (they enter either L_m or L or both). Similarly, R_z is a function of all of these components because they either directly affect firm z 's production function (e.g., depending on how firm z combines labor across different markets to produce output), or directly affect firm z 's revenues via output equilibrium prices (e.g., because labor employed by competitors affects how much they produce, which affects goods market structure).

cost, giving the firm's profit-maximizing wage setting formula:

$$w_{zm} \times \underbrace{(1 + \varepsilon_{zm}^{-1})}_{\mu_{zm}} = \frac{\partial R_z}{\partial l_{zm}} \quad (5)$$

where $\varepsilon_{zm}^{-1} \equiv \frac{\partial \ln w_{zm}}{\partial \ln l_{zm}}$ is the inverse elasticity of residual labor supply faced by firm z in market m —on which I elaborate below—, and $\partial R_z / \partial l_{zm}$ is the marginal revenue product of labor.

The term μ_{zm} in equation 5 is firm z 's wage markdown in market m . This is a number, ranging from one to infinity, that equals the ratio of a firm's marginal revenue product to the wage. Therefore, the wage take-home share—the share of workers' marginal revenue product paid in wages—is simply the markdown inverse, $\mu_{zm}^{-1} = (1 + \varepsilon_{zm}^{-1})^{-1}$, a number between zero and one. The question is: does the assumption of nested CES labor supply from Section 2.1 imply anything about ε_{zm}^{-1} ?

It does. When worker preferences are nested CES as in Section 2.1, it is a standard result that differentiating equation 3 with respect to l_{zm} gives the following expression for ε_{zm}^{-1} that is solely a function of firm z 's payroll share in market m and workers' key elasticities of substitution:

$$\varepsilon_{zm}^{-1} = \frac{1}{\theta} s_{zm} + \frac{1}{\eta} (1 - s_{zm}) \quad (6)$$

where

$$s_{zm} \equiv \frac{w_{zm} l_{zm}}{\sum_j w_{jm} l_{jm}} = \frac{\partial \ln L_m}{\partial \ln l_{zm}} \quad (7)$$

is firm z 's payroll share in market m . This means that the markdown of firm z in market m can be written as

$$\mu_{zm} = 1 + \varepsilon_{zm}^{-1} = 1 + \frac{1}{\theta} s_{zm} + \frac{1}{\eta} (1 - s_{zm}) \quad (8)$$

Equation 7 is the key standard result that makes equation 6 hold. It states that a firm's marginal effect on its market's amenity-adjusted employment index L_m when hiring a marginal worker equals its payroll share.

A nice feature of Equation 8 is that, while it results from the assumption that firms compete for workers à la Cournot, it encompasses as limiting cases both monopsonistic and perfect competition. When $\frac{1}{\eta} = \frac{1}{\theta}$, workers substitute across labor markets as strongly as

they substitute across firms within markets, such that firms compete in a unified national labor market. This is the monopsonistic competition limiting case, where μ_{zm} is constant, and firm labor market power is therefore independent of firm size. If in addition $\frac{1}{\eta} = \frac{1}{\theta} = 0$, workers move instantaneously across firms anywhere in response to shocks. This is the perfect competition limiting case, and it implies that $\mu_{zm} = 1$: the full marginal revenue product of labor is paid in wages.¹⁷

2.3 Labor market concentration and the average wage markdown

Aggregating the right-hand side of equation 8 across all firms in a local labor market, using payroll shares as weights, gives the key relationship between the degree of firm labor market power in the labor market and its concentration level:

Proposition 1. *When labor supply is nested CES, and firms compete for workers à la Cournot, as in the labor market environment described in Sections 2.1-2.2, the average wage markdown at labor market m is given by:*

$$\mu_m \equiv \frac{\bar{r}_m}{\bar{w}_m} = 1 + \varepsilon_m^{-1} = 1 + \frac{1}{\theta} HHI_m + \frac{1}{\eta} (1 - HHI_m) \quad (9)$$

where \bar{r}_m and \bar{w}_m are market m 's (employment-weighted) average marginal revenue product of labor and average wage, respectively, ε_m^{-1} is the (payroll-weighted) average inverse elasticity of firm-specific residual labor supply across firms in market m , and $HHI_m = \sum_{z \in \Theta_m} s_{zm}^2$ is the market's payroll Herfindahl.

Proof. See Appendix C.2.3. □

In other words, a market's average wage markdown is directly proportional to its level of concentration, and more specifically to the weighted average of workers' key inverse elasticities of substitution, whose weights are given by concentration. Because it is generally assumed (although not imposed later during estimation) that workers substitute more easily across firms within markets than across markets (i.e., $\frac{1}{\theta} \geq \frac{1}{\eta}$), equation 9 implies that the

¹⁷Trade's large negative effects on local wages might also be rationalized under perfect competition so long as workers cannot easily move across markets, a mechanism Dix-Carneiro and Kovak (2017) explores. Instead, my paper considers the possibility suggested by Manning (2003) that imperfect worker mobility is itself an outcome of an environment where firms can exploit workers' heterogeneous preferences over markets and firms to mark wages down when maximizing profits. And whether the resulting equilibrium leads to market outcomes that are essentially equivalent to either perfect or monopsonistic competition depends on workers' key elasticities of labor supply.

higher the level of concentration in a market, the larger is its average wage markdown. In addition, the larger are the *inverse* elasticities of substitution, the weaker are worker movement in response to wage shocks, and thus the larger is the wage markdown.¹⁸

This paper’s key theoretical result, used later in Section 7 to quantify the causal effect of trade liberalization on local labor markets’ average wage markdown, is a direct implication of Proposition 1:

Corollary 1. *In the labor market environment described in Proposition 1, the effect of an exogenous shock X on market m ’s average wage markdown μ_m at time t is given by:*

$$\gamma_t \equiv \frac{d\mu_{mt}}{dX} = \left(\frac{1}{\theta} - \frac{1}{\eta} \right) \beta_t \quad (10)$$

where $\beta_t \equiv \frac{dHHI_{mt}}{dX}$ is the effect of the exogenous shock on market m ’s payroll Herfindahl at time t , $\frac{1}{\theta}$ is workers’ cross-market inverse elasticity of substitution, and $\frac{1}{\eta}$ is workers’ within-market cross-firm inverse elasticity of substitution.

Proof. Differentiate equation 9 with respect to X . See Appendix C.2.5 for details. □

To see the intuition behind Corollary 1, suppose that the exogenous shock X is trade liberalization, whose policy-induced shock variation I introduce later in Section 4. Then, two things must hold in order for trade liberalization to increase market m ’s average wage markdown, and thereby reduce wages in market m via firm labor market power.

First, trade must increase labor market concentration (i.e., $\beta_t > 0$). The reason is simple: labor market concentration is the only endogenous component of a market’s average wage markdown. The other two components are simply labor supply parameters, which by assumption do not change. Intuitively, the source of market power in the labor market environment described in Section 2 is worker preference heterogeneity for markets and firms.

¹⁸Note that Proposition 1 refers to the average *wage markdown* at a *local labor market*, as opposed to the *country-level labor share*, a common statistic of interest in the labor and macro literatures. The wage markdown concerns wage-setting only (which occurs at the margin), whereas the labor share concerns payments to and revenues generated by *all* workers (including infra-marginal), for which additional assumptions are needed on firms’ production functions and on goods’ market structure. However, depending on these assumptions, a country’s average markdown—the weighted average of market-level markdowns—is closely related to its aggregate labor share. Such is the case when, for example, firms share the same Cobb-Douglas production function, and goods and capital markets are perfectly competitive, as in Berger, Herkenhoff and Mongey (2021). Specifically, in Appendix C.2.4 I show that the country-level wage take-home share derived from equation 9 is mathematically equivalent to a sub-component of the country-level labor share derived by Berger, Herkenhoff and Mongey (2021). As I have not imposed restrictions on firm z ’s revenue function R_z , I also show in Appendix C.2.6 that Proposition 1 still holds under these additional assumptions.

Firms can “exploit” this preference heterogeneity to mark wages down. The bigger a firm is relative to its competitors, the more it can mark wages down without workers easily leaving because there are fewer employment options nearby, and workers tend to prefer switching locally across firms before switching markets completely. Thus, the degree of market power in a local labor market can only meaningfully change if the relative sizes of its firms meaningfully change. That’s what changes in labor market concentration capture.

Second, there must be a gap between workers’ key inverse elasticities of substitution (i.e., $\frac{1}{\theta} - \frac{1}{\eta} > 0$). If there is no gap, then workers move far away as easily as they move close by in response to shocks, such that to attract workers firms must compete in a unified country-level labor market, where their wage setting ability is independent of size. In this scenario, the effect of trade on labor market concentration would be irrelevant for changes in firm labor market power. Such is the case under my model’s two limiting cases: monopsonistic competition (i.e., no gap to induce *effects* on market power, but because $\frac{1}{\theta} = \frac{1}{\eta} > 0$, there is still some *level* of market power); and perfect competition (i.e., no gap to induce effects, and because $\frac{1}{\theta} = \frac{1}{\eta} = 0$, no level of market power either).

I next describe in Section 3 the rich data and setting I leverage to estimate the key sufficient statistics in equation 10.

3 Data and setting

I use three main data sources for workers, tariffs, and exporting activity, spanning the years surrounding Brazil’s 1990s trade liberalization, supplemented with census data for informality estimates. Appendix B describes these datasets in detail.

3.1 Data: Formal sector, tariffs, exporters, informality

First, rich labor market data come from Brazil’s administrative employer-employee linked database Relações Anuais de Informações Sociais (RAIS), spanning years 1986-2000. RAIS covers the universe of Brazilian formal sector workers. I focus on the sample of private sector workers aged 18 to 65, or roughly 15 million private sector workers per year.

Second, data on tariffs come from UNCTAD TRAINS, which I map to RAIS via the 5-digit economic activity code CNAE95.¹⁹ Third, exporting activity is mapped to RAIS using firms’ unique identifier CNPJ. What I observe in terms of exporting activity is the

¹⁹See Appendix B for details on mapping procedures.

list of exporting firms for years 1990-1994, which were provided by the (extinct as of 2019) Ministry of Development, sector, and Foreign Trade, currently a part of the Ministry of the Economy.

Finally, I use data from the 1991 and 2000 Brazilian census when discussing in Appendix D.1 the external validity of my estimates to incorporating Brazil’s informal sector.

3.2 Setting: Brazil’s 1990s trade liberalization

The key policy-induced variation I leverage throughout my analyses comes from Brazil’s 1990s unilateral import tariff reductions. Dix-Carneiro and Kovak (2017) provide an in-depth discussion of Brazil’s 1990s import tariff reform. Tariffs were reduced from a pre-liberalization average of 33% to a post-reform average of 13%.²⁰ with some sectors experiencing larger reductions than others because they were previously more protected, as shown in Appendix Figure A.10.

These tariff reductions generated plausibly exogenous variation in labor demand shocks across firms and across markets, which I exploit to estimate the key sufficient statistics in equation 10. Kovak (2013) argues that the striking correlation between pre-liberalization tariff levels and reform-induced tariff cuts, as documented in Appendix Figure A.10, is precisely the biggest support for exogeneity of the tariff cuts. In particular, because the pre-liberalization levels of protection were set decades earlier (Kume, Piani and Souza, 2003), it is unlikely that the 1990s tariff cuts were correlated with counterfactual sector performance at the time. Instead, the reductions were motivated by the broader national goal to reduce all tariffs towards a much lower and much more equalized level of protection across all sectors.

The main identification concern posed by using Brazil’s import tariff reductions as exogenous shocks is pre-trends. Despite the plausible exogeneity in tariff cuts, one might be concerned that the decades-long level of protection enjoyed by the sectors experiencing the largest tariff cuts might induce differential trends in sector outcomes. For example, if the most protected sectors were also the least productive ones, one might observe negative pre-trends in either wages or employment, which could confound the negative estimates of the effect of trade on these outcomes. To address this concern, I estimate year-specific regression coefficients for all outcomes of interest to check for pre-trends.

²⁰Simple 1990 averages of nominal tariffs at CNAE95 level. See Appendix B for details.

4 Effect of trade on local labor market concentration

My first step towards quantifying the effect of trade on firm labor market power is to estimate parameter β_t from equation 10. Specifically, I leverage the market-level exogenous labor demand shocks spurred by Brazil’s trade liberalization to estimate β_t as the effect of trade on local labor markets’ payroll Herfindahl indices.

4.1 Empirical strategy

From Section 4.1 onwards, I define a local labor market as a microregion \times occupational group cell.²¹ My definition is motivated by the striking job-to-job transition patterns presented in Appendix Figures A.3-A.6, and summarized in Appendix Table A.3. Conditional on switching jobs, Brazilian workers tend to stay within microregions and occupational groups much more frequently than within sectors, suggesting geography and occupation feature more prominently into workers’ mobility decisions than sectors do. I therefore define local labor markets as microregion \times occupational group cells, and present robustness to alternative borders for all main effects.²²

My identification strategy for estimating the effect of trade on local labor market concentration follows the shift-share treatment intensity approach adopted by other papers on the regional incidence of trade (e.g., Kovak (2013); Dix-Carneiro and Kovak (2017)). The key idea is that the reduction in import tariffs spurred by Brazil’s 1990s liberalization would have a differential effect across local labor markets depending on these markets’ pre-liberalization sectoral composition. The precise functional form linking sector-level tariff reductions to market-level shocks is guided by the model I outlined in Section 2. Specifically, I define local

²¹Appendix Table A.1 presents summary statistics of these roughly 20,000 local labor markets.

²²There is wide variation in how labor markets are defined in the literature. The most commonly used boundaries are geography \times occupation (e.g., Azar, Marinescu and Steinbaum (2017); Azar et al. (2018); Schubert, Stansbury and Taska (2021)), geography \times sector boundaries (e.g., Alfaro Urena, Manelici and Vasquez (2021); Berger, Herkenhoff and Mongey (2021)), and geography only (e.g., Topalova (2010); Dix-Carneiro and Kovak (2017); Hoang (2021); Kovak (2013); Autor, Dorn and Hanson (2013)). Felix and Wang (2021) conduct a theory-driven empirical analysis of what constitutes a labor market boundary, finding strong evidence that occupations are particularly important for workers’ outside options in Brazil, while Fogel and Modenesi (2021) develop a data-driven method to identify such boundaries.

labor market m 's Import Competition Exposure (ICE) shock as

$$\Delta ICE_m \equiv - \sum_{z \in \Theta_m^T} \kappa_{zm} \ln \left(\frac{1 + \tau_{z,1994}}{1 + \tau_{z,1990}} \right) \quad (11)$$

$$\kappa_{zm} \equiv \frac{s_{zm,1991}^2}{\sum_{j \in \Theta_m^T} s_{jm,1991}^2}, \quad s_{zm,1991} \equiv \frac{w_{zm,1991} l_{zm,1991}}{\sum_j (w_{jm,1991} l_{jm,1991})}$$

where Θ_m^T is the set of all tradable sector firms in market m in the baseline year of 1991,²³ $s_{zm,1991}$ is the 1991 payroll share of each of these firms as a fraction of all firms operating in the market, and $\tau_{z,t}$ is the import tariff faced by firm z 's output sector in year t .

In other words, ΔICE_m is a weighted average of the firm-level shocks experienced by tradable sector firms, where the weight κ_{zm} of each firm z is its contribution to the tradable sector's component of market m 's pre-liberalization payroll Herfindahl, $HHI_{m,1991}^T \equiv \sum_{j \in \Theta_m^T} s_{jm,1991}^2$. The functional form for κ is guided by equation 7, according to which the effect of a firm hiring a marginal worker on its market's labor supply index is precisely the firm's payroll share. This suggests that firm-level labor demand shocks should be aggregated to the market level in proportion to firms' baseline payroll shares. Finally, to further align a firm's weight with its contribution to the market's payroll Herfindahl, I construct κ_{zm} by placing firm z 's squared baseline payroll share in the numerator, and dividing through by the tradable sector's component of market m 's baseline Herfindahl. I then present robustness checks to alternative definitions of ΔICE and to alternative measures of tariff shocks.²⁴

Appendix Figure A.1 displays the variation in ΔICE_m across geography for two example occupations, while Appendix Table A.1 provides the mean and key percentiles of the distribution of ΔICE_m across local labor markets. The mean change in import competition exposure was 12%, ranging from a 10th percentile of no exposure change (i.e., a local market made primarily of non-tradable sector firms) to a 90th percentile of 23% increase.

Having defined the import competition exposure shock, I proceed to estimate its effect on local labor market outcomes using a difference-in-differences strategy. Specifically, I estimate the cumulative effect (as of year k) of import competition on a local labor market's outcome

²³Because year-end wages and employment for 1990 might also reflect the impact of removal of non-tariff barriers in 1990, I follow Dix-Carneiro and Kovak (2017) in choosing 1991 as the base year for all analyses.

²⁴While my measure of import competition exposure serves as a shift-share shock for identification the effect of trade on labor market outcomes, I note that it does not have an independent structural interpretation as in the measure derived by Kovak (2013) under assumptions on labor mobility, labor supply, and fixed factors of production.

Y_m as ζ_k from the following regression:

$$\Delta Y_{mt} = \sum_{k \neq 1991} \zeta_k (\Delta ICE_m \times 1_{t=k}) + \delta_m + \delta_t + \epsilon_{mt} \quad (12)$$

where ΔY_{mt} denotes the long difference in Y_m from year t back to the base year 1991,²⁵ and δ_m and δ_k are local labor market and year fixed effects. As the specification is in stacked differences, note that the fixed effects absorb not only the constant, but also market-level secular trends over the entire period. I estimate this regression using years 1986 to 2000, clustering standard errors by local labor market.²⁶

Since equation 12 is a difference-in-differences regression with shift-share treatment intensity, causal interpretation of ζ_k coefficients depends on two assumptions: a) that the import tariff “shifts” composing ΔICE_m are as good as randomly assigned,²⁷ an assumption discussed in Section 3.2 and which relies on the reform-driven nature of the tariff reductions; and b) that absent trade liberalization, the potential outcomes of markets more exposed to import competition would have followed the same trend those of least exposed markets, an untestable assumption whose reasonableness can be argued by the lack of pre-trends, to which I turn next when discussing my findings.

4.2 Estimates of effect of trade on concentration

Figure 2 and Panel A of Table 1 present my main estimates of the effect of trade on local labor market concentration. A 10 percent increase in import competition exposure increased local labor markets’ (wage premium) payroll Herfindahls by 0.02 points (SE of 0.002), or a 7% increase relative to the pre-liberalization 0.28 average.²⁸

This effect is robust to various alternative specifications. It is robust to the use of wage levels (as opposed to wage premia) to compute payroll Herfindahls, to measuring concentra-

²⁵I follow the same long-differences convention adopted by Dix-Carneiro and Kovak (2017): long differences are taken using 1991 as the base year, and to keep the timing convention (i.e., future minus past) consistent, for the pre-treatment years ΔY_{mt} is the long difference from 1991 back to year t .

²⁶Note that because ΔICE_m was defined with a negative sign, a positive ζ_k indicates that the import tariff reductions had a positive effect on the outcome (e.g., raised wages or expanded employment).

²⁷As in the identification conditions discussed in Borusyak, Hull and Jaravel (2018). While identification could be similarly obtained if payroll shares were as good as random, as discussed in Goldsmith-Pinkham, Sorkin and Swift (2018), the case is stronger for quasi-exogeneity of the shifts as opposed to the shares, as the latter were driven by liberalization.

²⁸Appendix Table A.1 presents pre-liberalization statistics of local labor markets. The wage premium Herfindahl is computed using firms’ estimated wage premia to compute payroll shares, as opposed to wage level. See Appendix B for wage premia estimation details.

tion using the employment (instead of payroll) Herfindahl, to the use of alternative weights to compute ΔICE_m ,²⁹ to two-way clustering by microregion and occupation, and to weighting regressions by market baseline employment, which shows that the effect is not driven by a handful of small markets.³⁰ The effect is also present even when labor markets are defined more broadly by microregions only, and half as large (Appendix Table A.4). Finally, the effect on concentration is also present, and is about half as large, when effective rates of protection – much noisier measures of tariff shocks – are used to construct ΔICE_m (column (4) of Appendix Table A.5).³¹

I also use estimate equation 12 for various other local labor market outcomes, presented in Panels B and C of Table 1 and corresponding Appendix Tables. My estimates for the effect of import competition on employment and wage premia are in line with patterns documented by Dix-Carneiro and Kovak (2017): trade liberalization reduced employment and wages in local labor markets more exposed to import competition relative to less exposed markets, although the effect on wages exhibited positive pre-trends. Given the evidence of pre-trends, I also present effects on wage premia relative to trend.³²

Finally, I address an overrejection concern uncovered by recent literature on shift-share instruments, which arises when regression residuals are correlated across markets with similar sectoral shares independent of market proximity (Adao, Kolesár and Morales, 2019). I address this in two ways. First, by increasing the number of sectors used to construct ΔICE_m to 285 from the 20 to 53 shifts currently used in the literature,³³ and second by replicating the placebo exercise in Adao, Kolesár and Morales (2019) using ΔICE_m . Specifically, I run 1,000 placebo regressions, separately for log employment and log wage premia.³⁴ In these regressions, the dependent variable is the 1997-1991 long-difference in the local labor market outcome,³⁵ and the independent variable is a placebo ΔICE_m , constructed with the same sector payroll shares but with randomly drawn shocks instead of the real tariff shocks.

Appendix Figure A.2 displays histograms of t-statistics associated with each round of

²⁹Consistent with the labor supply framework, using $s_{zm,1991}^2$ as weights gives the most predictive—specifically, the least noisy—estimates of the effect of import competition on market outcomes.

³⁰For all of these robustness estimates, see Panel A in Table 1 and in Appendix Tables A.5-A.7.

³¹Smaller treatment effects are expected when using noisier shocks due to attenuation bias. Effective rates of protection are output tariffs netted out of input tariffs. Effective rates of protection are noisier because they are constructed using Brazil’s 1995 input-output table, which is defined at broader sector levels (43 sectors) than import tariffs on firms’ output (CNAE95, 285 sectors). See Appendix B for details.

³²See Appendix B for details on treatment effects relative to trend.

³³Previous papers used tariffs at either Nível 50 (20 sectors) or Nível 80 (53 sectors) from Kume, Piani and Souza (2003). See Appendix B for details.

³⁴Wage premia are wages conditional on worker observables. See Appendix B for details.

³⁵For simplicity I focus on the 1997-1991 long-difference as 1997 is the mid-point of the post-reform years.

placebo regressions. The figure shows that the roughly 5% of placebo regressions fall beyond the 1.96 standard deviations to the left and right of the distributions, as should be expected. These patterns suggest that ΔICE_m does not suffer from overrejection concerns, a result likely driven by the use of finer-level, and hence more numerous, sectoral shocks relative to what was previously available in the literature.

4.3 Source of increased concentration

What drives the effect of trade on local labor market concentration shown in Figure 2? To study this question, I consider the theoretical prediction discussed earlier that opening to trade tends to reallocate employment towards larger, more productive firms.

Specifically, in the case of a unilateral reduction in import tariffs, such as the one I study, a particular type of large firm towards which employment might be reallocated is exporters. That is because, unlike non-exporting import-competing firms, exporters also sell in foreign markets, whose consumers are unaffected by import tariff reductions in Brazil. This means exporters might be less affected by import tariff reductions than other non-exporting tradable sector firms, which could lead to in the very least a compositional employment reallocation towards exporters within local labor markets.

I therefore test whether import competition exposure reallocated employment towards exporters. Figure 5 presents my year-by-year estimates of the effect of import competition exposure on local labor markets' total exporter employment vs. total employment from non-exporting tradable sector firms, summarized of Appendix Table A.14 by the post-reform mid-point estimates. At the local labor market level, a 10% increase in import competition exposure had no statistically distinguishable effect on total exporter log employment, but reduced log employment at non-exporting tradable sector firms by 12.804 (SE of 1.461) percent.³⁶

Overall, the lack of effect on exporters combined with the large negative effect on import competing firms results in a composition shift in the allocation of local labor market employment away from import-competing firms and towards exporters. This reallocation is the source of increased labor market concentration as exporters had higher payroll shares to begin with: exporters paid more than 3 times as much as all other firms at baseline, and were more than 20 times larger (see Appendix Figure A.13).³⁷

³⁶Another reason why exporters may have been less affected by import competition is that exporters are less dependent on domestic demand for revenues, since they also have revenues flowing in from export markets.

³⁷While I also find that import competition had little effect on total employment by non-tradables (Ap-

Furthermore, the shift in local labor market employment composition towards exporters is not only apparent at the aggregate level as shown in Figure 5, but also at the firm level, where I can further test whether it is a firm’s pre-liberalization export status vs. its size that drove the relative gains in employment and wages. Specifically, I run regressions of the change in a firm’s log employment (and, separately, log wages) on the change in import tariff faced by the firm plus interactions with the firm’s baseline export status and with a dummy indicating the firm was large at baseline.³⁸

Appendix Table A.15 presents my estimates for these firm-level regressions, which shows the reallocation was driven towards exporters specifically and not just towards large firms.³⁹ A 1% increase in import tariffs raised exporter employment by 0.509 percent (SE of 0.155) and its log wage premium by 1.279 percent (SE of 0.333) relative to all other non-large firms, which on average experienced a 0.492 percent (SE of 0.154) reduction in log employment and a 1.176 (SE of 0.270) reduction in their log wage premium. This is not the same for non-exporting large firms, which experienced significant reductions in both log employment and log wage premium. The triple interaction (tariff shock \times exporter status \times large firm) appears to be statistically insignificant.

5 Key labor supply parameters: Empirical strategy

I next describe how I estimate my model’s key parameters: the cross-market inverse elasticity of substitution $\frac{1}{\theta}$, and the within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$. My model provides the regression specifications, and my data and setting the exogenous variation. I leverage within-market cross-firm variation in import tariff reductions to estimate $\frac{1}{\eta}$, and cross-market variation in import competition exposure to estimate $\frac{1}{\theta}$.

pendix Table A.14 and Appendix Figure A.14), compositional reallocation towards non-tradables could not explain increases in labor market concentration because those firms are just as small and pay just as little as the hardest hit firms, as shown in Appendix Figure A.13. Non-tradables might have however absorbed many displaced workers, as suggested by worker-level evidence from Dix-Carneiro and Kovak (2019).

³⁸A firm is “large” if its baseline employment in the local labor market is greater than the 90th percentile of around 20 employees per market. See Appendix Table A.15 for further details.

³⁹Note that total employment reallocation does not necessarily reflect reallocation of the very same workers who were displaced from import-competing firms. Evidence from Menezes-Filho and Muendler (2011) suggests that displaced workers were not reabsorbed by exporters after liberalization.

5.1 Within-market cross-firm inverse elasticity of substitution

5.1.1 Regression specification

To derive the regression equation for estimating $\frac{1}{\eta}$, I start by taking logs of a time-specific version of the model's equation for a firm's inverse residual labor supply function (i.e., equation 3), which gives:

$$\ln w_{zmt} = \frac{1}{\eta} \ln l_{zmt} + \underbrace{\left(\frac{1}{\theta} - \frac{1}{\eta} \right) \ln L_{mt} - \frac{1}{\theta} \ln L_t + \ln W_t + \ln \xi_{mt}^{1+\theta} + \ln \xi_{zmt}^{1+\eta}}_{\text{Market } \times \text{ Year FE}} \quad (13)$$

Which simplifies to:

$$\ln w_{zmt} = \frac{1}{\eta} \ln l_{zmt} + \delta_{mt} + \epsilon_{zmt} \quad (14)$$

where δ_{mt} are market \times year fixed effects (which absorb the constant), and $\epsilon_{zmt} = \ln \xi_{zmt}^{1+\eta}$ is the regression residual, which has a structural interpretation as workers' (scaled) taste shifter ξ_{zmt} for firm z in market m at time t .

Second, anticipating that my empirical strategy for estimating $\frac{1}{\eta}$ will leverage Brazil's trade liberalization, whose key cross-firm exogenous variation is the 1990–1994 long-difference in tariffs, I take long-differences of equation 14, which becomes:

$$[\text{Second Stage}] \quad \Delta \ln w_{zm} = \frac{1}{\eta} \Delta \ln l_{zm} + \Delta \delta_m + \Delta \epsilon_{zm} \quad (15)$$

where $\Delta \delta_m$ is a market fixed effect in the already differenced regression, and its role is to absorb all market-level *changes* that feed into changes in firm z 's wage in market m , shown explicitly in equation 13.

Equation 15 is the regression specification I bring to the data to estimate $\frac{1}{\eta}$. The key threat to identification of $\frac{1}{\eta}$ is that changes in labor supplied to firm z in market m (i.e., $\Delta \ln l_{zm}$) might be correlated with changes in workers' labor supply taste for firm z in market m (i.e., $\Delta \epsilon_{zm}$). I address this identification concern by instrumenting $\Delta \ln l_{zm}$ with a labor demand shock: $\Delta \ln(1 + \tau_z)$, the policy-induced change in import tariffs on firm z 's output sector, using the following first stage regression:

$$[\text{First Stage}] \quad \Delta \ln l_{zm} = \lambda \Delta \ln(1 + \tau_z) + \Delta d_m + \Delta \nu_{zm} \quad (16)$$

where once again Δd_m is a market fixed effect in the already differenced regression, whose role is to similarly absorb all market-level changes that feed into firm z 's hiring decisions in market m .

Identification of $\frac{1}{\eta}$ using instrumental variables relies on two assumptions: a) there is a first stage (i.e., $\lambda \neq 0$), meaning that—conditional on market-level changes, controlled for by the market fixed effect—, the import tariff shock faced by the firm affects its employment decisions; and b) exclusion restriction, meaning that—again, conditional on market-level changes—the import tariff shock faced by the firm affects firm wages only via the firm's employment decision, as opposed to by changing workers' distaste ξ_{zm} for the firm-market pair. The first stage assumption is testable, and exclusion restriction—while not directly testable—might be amenable to exploration by correlating estimates of ξ_{zm} with non-wage firm characteristics that might influence worker tastes, an exercise for future work. Having clarified these key identification assumptions, I next turn to how I measure their corresponding endogenous variables and shocks.

5.1.2 Measurement

In order to estimate equations 15 and 16, I need to measure three model objects: the total units of labor l_{zmt} supplied to firm z in market m at year t , the wage w_{zmt} paid by that firm-pair, and the tariff shock to the firm.

First, I measure l_{zmt} (the total units of labor at firm z in market m in year t) as the total number of workers employed at firm z in market m during the entire month of December of year t .⁴⁰ This is equivalent to assuming that each worker provides one “effective monthly unit” of labor, whereas the model allows l_{zm}^j to be more generally pinned down by worker j 's exogenous reservation earnings y^j .⁴¹

Second, I measure w_{zmt} as the firm z 's wage *premium* in market m for the month of December of year t . That is, the total compensation w_{zm}^j received by worker j for all labor j provided in December *conditional on worker j 's characteristics*.⁴² Wage premia are the

⁴⁰That is, the total number of workers employed as of December 31 and who were also hired by the firm on or before December 1. Employment as of December 31 is the standard variable from Brazil's RAIS datasets used for measuring firm-level employment at a given year. See, for example, Kovak (2013) and Dix-Carneiro and Kovak (2017).

⁴¹Alternatively, one could in principle measure l_{zmt} as total hours of labor provided to firm z in market m , and w_{zmt} as the corresponding hourly wage premium offered by firm z in market m . While data on hours worked are not available for the period I analyze, Dix-Carneiro and Kovak (2017) shows for later years that incorporating hours does not matter for estimates of the effect of trade on wages.

⁴²See Appendix B for details in wage premia estimation. Worker characteristics include flexible controls in education, age, and gender. For each worker, the wages received for the month of December includes all

theory-consistent empirical measure for wages because my model assumes that all workers are equally productive, although I also present robustness to using wage levels instead.

Third, the tariff shock to firm z is the policy-induced change in import tariffs on firm z 's output sector, which I measure as:

$$\Delta \ln(1 + \tau_z) \equiv -\ln\left(\frac{1 + \tau_{z,1994}}{1 + \tau_{z,1990}}\right) \quad (17)$$

where the minus sign is included to facilitate interpretation of regression coefficients (i.e., such that a positive coefficient means that the policy-induced import tariff reduction had a positive effect on the outcome variable).

The identifying variation in equation 16 comes from firms of different output sectors operating in the same local labor market (i.e., hiring in the same microregion \times occupation group pair), including firms in non-tradable sectors, for which the change in import tariffs is zero. Appendix Figure A.11 plots this ample within-market cross-firm exogenous variation in tariff shocks. I estimate equations 15 and 16 clustering standard errors at the firm level, and weighting the regression by the firm's base year employment to focus on variation coming from firms where most workers were located at baseline. I then present robustness estimates to alternative clustering schemes, weighting schemes, labor market boundaries, tariff shocks, and wage measurements.

5.2 Cross-market inverse elasticity of substitution

5.2.1 Regression specification

To derive the regression specification for estimating $\frac{1}{\theta}$, I start by returning to the long-differenced version of the model's logged inverse residual labor supply equation (i.e., equation 15), but this time I pay close attention to the market-level changes that are absorbed into the fixed effect $\Delta\delta_m$:

$$\Delta \ln w_{zm} = \frac{1}{\eta} \Delta \ln l_{zm} + \underbrace{\left(\frac{1}{\theta} - \frac{1}{\eta} \right) \Delta \ln L_m - \frac{1}{\theta} \Delta \ln L + \Delta \ln W + \Delta \ln \xi_m^{1+\theta}}_{\Delta\delta_m} + \Delta\epsilon_{zm} \quad (18)$$

It follows from equation 18 that, given estimates of $\Delta\delta_m$, $\frac{1}{\eta}$, and residuals $\Delta\epsilon_{zm}$ —obtained by first estimating equation 15—, the following regression can be used to estimate the gap

compensation paid to the worker in that month, except the “décimo terceiro salário,” a year-end payment equivalent of one month's earnings paid to all formal sector workers.

$\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$ between workers' key elasticities of substitution, and thus $\frac{1}{\theta}$:

$$[\text{Second Stage}] \quad \Delta\delta_m = \alpha + \left(\frac{1}{\theta} - \frac{1}{\eta}\right) \Delta \ln L_m + \Delta\epsilon_m \quad (19)$$

where the constant α absorbs country-level wage component changes common to all markets (i.e., $\alpha = \frac{1}{\theta} \Delta \ln \left(\frac{1}{L}\right) + \Delta \ln W$), $\Delta \ln L_m$ is the change in the CES market-level labor supply index, whose measurement I describe in Section 5.2.2, and $\Delta\epsilon_m = \Delta \ln \xi_m^{1+\theta}$ is the market-level regression residual, which also has a structural interpretation as the (scaled) change in workers' taste for market m .

The key threat to identification of $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$ in regression equation 19 is that changes in the amenity-adjusted labor supplied to market m (i.e., $\Delta \ln L_m$) are correlated with changes in workers' taste for market m (i.e., $\Delta\epsilon_m = \Delta \ln \xi_m^{1+\theta}$). To address this concern, I instrument the market-level change in labor supply with a market-level labor demand shock introduced earlier: ΔICE_m , the market-level policy-induced import competition exposure shock commonly felt by all firms in market m . My market-level first stage regression is thus:

$$[\text{First Stage}] \quad \Delta \ln L_m = \tilde{\alpha} + \lambda \Delta ICE_m + \Delta\nu_m \quad (20)$$

where $\tilde{\alpha}$ is a constant, and $\Delta\nu_m$ is a regression residual.

The two identifying assumptions are that there is a first stage (i.e., $\lambda \neq 0$), and the instrument is excluded (i.e., ΔICE_m affects $\Delta\delta_m$, the market-level component of firm wages, only via market-level changes in employment, as opposed to change workers' distaste ξ_m for market m). Once again, the first stage assumption is testable, and while the exclusion restriction is not testable it might be amenable to exploration in future work by correlating estimates of ξ_m with market characteristics that might influence worker tastes.

Finally, I estimate $\frac{1}{\theta}$ by summing my estimate of $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$ from equation 19 with my estimate of $\frac{1}{\eta}$ from equation 15, taking into account the standard errors of each estimate in order to assess precision for $\frac{1}{\theta}$.

Overall, my methodology for estimating $\frac{1}{\theta}$ is an adaptation, to a labor supply context, of Costinot, Donaldson and Smith (2016)'s estimation of nested CES demand using micro-shocks. This is a "bottom up" approach (i.e., estimate lowest nest elasticity η first, then upper nest elasticity θ last) whose key leverage is the availability of within-market cross-firm labor demand shocks that allows for η to be directly estimated.

My "bottom up" approach differs from the main "top down" approach used in the lit-

erature for estimating labor supply elasticities under Cournot competition. The latter, introduced by Berger, Herkenhoff and Mongey (2021), uses cross-market shocks only to back out both η and θ . This is done by first obtaining a reduced-form estimate of ε_{zm}^{-1} (the endogenous component of wage markdowns that is a function of η and θ) from shock effect heterogeneity by firm size,⁴³ which produces biased estimates and need to be corrected by simulating firm behavior and adjusting η and θ accordingly via indirect inference. Given within-market cross-firm shocks, my “bottom up” approach is simpler to implement, and is less model-dependent as it does not rely on simulations.⁴⁴

5.2.2 Measurement

To estimate equations 19 and 20, I need to measure three objects: $\Delta\delta_m$, the market-level component of the firm-level wage change; $\Delta \ln L_m$, the market-level change in the CES labor supply index; and ΔICE_m , whose measurement I have already introduced in Section 4.

I measure $\Delta\delta_m$ as the market fixed effect from regression equation 15 in Section 5.1.1, and compute $\Delta \ln L_m$ given my point-estimate for $\frac{1}{\eta}$ as follows:

$$\Delta \ln L_m = \Delta \ln \left\{ \left[\sum_{z \in \Theta_m} (\xi_{zm} l_{zm})^{\frac{1+\eta}{\eta}} \right]^{\frac{\eta}{1+\eta}} \right\}$$

where Θ_m is the set of all firms operating in market m , and the taste-shifters ξ_{zm} are calculated using equation 14 and my point-estimate for $\frac{1}{\eta}$.⁴⁵

I estimate equation 19 clustering standard errors at local labor market level, and present robustness checks to alternative levels of clustering, labor market borders, and wage measurements.

⁴³Specifically, they estimate a regression of firm log wages (and, separately, log employment) on the state’s corporate income tax, the firm’s payroll share, and an interaction between these two variables (plus fixed effects, see Berger, Herkenhoff and Mongey (2021)). The ratio of the coefficients from the regression on log wages to the regression on log employment provides a reduced-form estimate of ε_{zm}^{-1} . However, as the authors explain, because firms are assumed to compete à la Cournot, reduced-form estimates are biased: they only capture firms’ partial equilibrium response to the shock. The bias is then corrected by simulating firms’ response to shocks and matching the simulated outcomes to the reduced-form estimates of ε_{zm}^{-1} until convergence of simulated vs. real payroll shares is achieved.

⁴⁴For example, my “bottom up” approach could be implemented in the setting studied by Hoang (2021), who also adopts the “top down” approach to estimate the “endogenous distortion” component of “overall distortions” (i.e., the wage markdown in my paper).

⁴⁵Following equation 14, I compute the taste-shifters for each year as $\xi_{zmt} = (1 + \eta) \exp(\nu_{zmt})$, where ν_{zmt} are the residuals from a regression of $[\ln w_{zmt} - (1/\eta) \ln l_{zmt}]$ on a market fixed effect.

6 Estimates of key elasticities of substitution

6.1 Within-market cross-firm inverse elasticity of substitution

Table 2 presents my estimate of $\frac{1}{\eta}$ based on equations 15 and 16. The first stage in Panel A shows that a 1 percent decrease in the import tariff on firms' output reduced employment by 0.554 percent (SE 0.044). Panel B shows that the proportional effect on firms' wage premia was roughly of the same magnitude, at a 0.545 percent reduction (SE 0.024). Combined, these effects imply a within-market cross-firm inverse elasticity of substitution of 0.985 (SE 0.089). This estimate is also strongly identified, with a first stage F-statistic of 158.497, well above Lee et al. (2021)'s suggested cutoff 104.7 for a true 5 percent significance test in the single IV model.

A within-market cross-firm inverse elasticity of substitution of 0.985 means that if a firm wished to poach from its local competitors 1 percent of its current employment, it would have to increase its wage premium by a little less than 1 percent. This is a large estimate, nearly seven times larger than Berger, Herkenhoff and Mongey (2021)'s corresponding estimate of 0.14 for the US,⁴⁶ suggesting that Brazilian workers substitute a lot less swiftly across firms in response to wage changes than US workers do. In addition, this estimate places an upper bound of $1/(1 + 0.985) \approx 50\%$ on firms' wage take-home shares. In other words, the slow change in firm choice in response to wage changes imply that in the 1990s Brazilian workers were paid at most 50 cents of every marginal dollar they generated.

This point estimate is robust to key alternative specifications. It is robust to defining labor markets as microregions only (i.e., column (3) of Appendix Table A.8); to focusing on the sub-sample of unique producers such that the estimate is identified by unique firm-specific shocks (i.e., column (2) of Appendix Table A.8); to measuring firm wages using wage averages as opposed to wage premia (i.e., column (2) of Appendix Table A.10); and to using effective rates of protection as opposed to import tariffs as shocks (i.e., column (3) of Appendix Table A.10). And while the strength of the first stage and consequent precision of point estimates is sensitive to alternative clustering schemes and to sub-sampling—a point I discuss in more detail in Appendix D—all robustness estimates of $\frac{1}{\eta}$ are reasonably precise.

⁴⁶Berger, Herkenhoff and Mongey (2021) reports an η of 6.96, whose inverse is 0.14, based on local labor markets defined as a commuting zone \times sector (i.e., NAICS3) pairs.

6.2 Cross-market inverse elasticity of substitution

Table 3 presents my estimate of $\frac{1}{\theta}$ based on equation 19. The first stage in Panel A shows that a 1 percent increase in a market’s import competition exposure reduced employment by 0.396 percent (SE 0.032), whereas Panel B shows that the proportional effect on markets’ wage premia indices was only roughly a quarter as large, at a 0.108 percent reduction (SE 0.051). Combined, the first stage and reduced form produce an IV estimate of 0.272 (SE 0.131) for the difference between $\frac{1}{\theta}$ and $\frac{1}{\eta}$, which implies a cross-market inverse elasticity of substitution of 1.257 (SE 0.096) given the estimate for $\frac{1}{\eta}$ from Section 2.

There are three important take-aways from Table 3. The first is that its IV estimate is also strongly identified, with a first stage F-statistic of 150.752. The second is that the standard error on the IV estimate allows us to reject that $\frac{1}{\theta}$ and $\frac{1}{\eta}$ are the same (p-value < 0.02), which means that we can reject the model’s limiting cases of monopsonistically and perfect competition. This means that Brazilian firms not only have market power over workers, but their market power increases with labor market concentration.

A cross-firm inverse elasticity of substitution of 1.257 means that a market’s wage premium index (i.e., the amenity-adjusted wage premium) would have to increase by 1.257 percent before one percent more workers were attracted from other markets. While relatively inelastic, this point estimate is less than 60% of Berger, Herkenhoff and Mongey (2021)’s corresponding estimate of 2.2 for the US, suggesting Brazilian workers substitute more swiftly across local markets than US workers do.⁴⁷ Overall, the main difference in substitution patterns between Brazilian vs. US workers seems to be that US workers substitute a lot more swiftly across firms within markets relative to Brazilian workers. On net, this relatively inelastic cross-market elasticity of substitution places a lower bound of $1/(1 + 1.257) \approx 44\%$ on wage take-home shares. That is, during the 1990s Brazilian workers were paid at least 44 cents of every marginal dollar they generated.

This point estimate is also robust to several alternative specifications. It is robust to defining labor markets as microregions only (column (3) of Appendix Table A.11); nearly identical and nearly as strongly identified as estimates based on average wages as opposed to wage premia (column (2) of Appendix Table A.13); and slightly lower but statistically indistinguishable from estimates focused on the sub-sample of unique producers (column (2) of Appendix Table A.11). However, as in the estimation of $\frac{1}{\eta}$, the strength of the first stage is sensitive to clustering and sub-sampling, a point I discuss in more detail in Appendix D.

⁴⁷Berger, Herkenhoff and Mongey (2021) reports $\theta = 0.45$, whose inverse is 2.2, based on local labor markets defined as a commuting zone \times firm sector (i.e., NAICS3) pairs.

6.3 Pre-liberalization average wage markdown

I now combine my estimates of $\frac{1}{\theta}$ and $\frac{1}{\eta}$ from Section 6 with data on local labor markets' payroll Herfindahl indices to estimate Brazil's pre-liberalization average markdown, along with its (more easily interpretable) inverse, the wage take-home share.

Appendix C.2.4 shows that the country-level average markdown—that is, the country-level ratio of (employment-weighted) average MRPL to (employment-weighted) average wage—is a weighted average of the market-level markdowns in Proposition 1, where the weights are each market's payroll share of the country's total payroll. Appendix Table A.2 shows that in the baseline year of 1991, this weighted average concentration was 0.08 on a scale that ranges from 0 (infinitely tiny firms) to 1 (one firm). This is equivalent to saying that on average Brazilian workers were in labor markets whose equilibria were pinned down as if only $12.5 = 1/0.08$ equally-sized firms operated them. Because most workers work in larger labor markets, note that the payroll-share-weighted average concentration is much smaller, less than one third, of its 0.28 unweighted counterpart,⁴⁸ a fact that is taken into account in the country-level average wage markdown.

Combined with my estimates for $\frac{1}{\theta}$ and $\frac{1}{\eta}$, a 0.08 level of labor market concentration implies per equation 9 that Brazil's formal sector pre-liberalization average wage markdown was 2, whose inverse implies an average wage take-home share of 50 percent.⁴⁹ In other words: Brazilian formal sector workers took home 50 cents of every dollar of marginal revenue product of labor they generated. This places Brazilian local labor markets on the lower end—although not very far off from—currently available estimates of wage take-home shares in other essentially formal sector settings (e.g., 47% for Chinese manufacturing by Hoang (2021);⁵⁰ 65% for US manufacturing by Hershbein, Macaluso and Yeh (2019); 71% for Colombian manufacturing by Amodio and de Roux (2021);⁵¹ and 73% for US tradables

⁴⁸The payroll-share-weighted concentration was also smaller than the median labor market concentration of 0.21. This shows that a large number of local labor markets are highly concentrated, but most workers are in less concentrated markets. See Appendix A.1.

⁴⁹Given the small gap between the two inverse elasticities of substitution, the country's average wage take-home share is nearly identical if alternative measures of labor market concentration are used. For example, at the country-level markdown would have been 49 percent if evaluated at the (unweighted) average payroll Herfindahl of 0.28.

⁵⁰Note that Hoang (2021) refers to this estimate as the pass-through, but it corresponds to the wage take-home share in my paper. Specifically, $0.47 = 1/2.14$, where 2.14 is the author's average estimate for firm i 's "overall distortion," $\tilde{\chi}_i = MRPL_i/w_i$.

⁵¹Based on authors' estimated average wage markdown of 1.4 (i.e., $0.71=1/1.4$). Tortarolo and Zarate (2018) report similarly high implied wage take-home shares for Colombian manufacturing, estimated using a production function approach.

by Berger, Herkenhoff and Mongey (2021)⁵²).⁵³

With the exception of Berger, Herkenhoff and Mongey (2021) and Amodio and de Roux (2021), all of these estimates are based on a production function estimation approach, which does not rely on exogenous labor demand shocks to estimate elasticities of labor supply and, in turn, wage markdowns.⁵⁴ Instead, the production function approach assumes that the markets for non-labor inputs are perfectly competitive, and requires data on these non-labor inputs to estimate the marginal revenue product of labor, from which wage markdowns can then be computed. Since data on non-labor inputs are typically available for manufacturing firms only, estimates based on this approach tend to be based on this subset of essentially formal employment. In contrast, my approach requires detailed data on labor markets and exogenous shocks to labor demand, speaking to the universe of formal employment.

Finally, while studying the universe of formal sector firms and workers is important in its own right (those are the tax-paying firms and workers), it is impossible not to consider the implications that informality might have for the external validity of my findings, especially since nearly 50% of all employment in Brazil is informal (Dix-Carneiro et al., 2021; Ulyssea, 2018). Appendix D.1 provides a detailed discussion on this topic.

Overall, while incorporating informality would have a theoretically ambiguous effect on my estimates for the level of firm labor market power (i.e., 50 cents on the dollar), plenty of evidence suggests that firm labor market power is more prominent in Brazil’s informal sector. Observably equivalent workers are not only paid 29% less under informality than their formal sector counterparts (Ulyssea, 2018), but they are also not covered by labor laws, which assure the right to weekly rest, vacation, etc. More abhorrently, near-slavery working conditions—arguably the most extreme form of firm labor market power—persist until this day under informality. Auditors from Brazil’s Ministry of Labor have freed over 49,816 workers since 1995, the year the Ministry began inspecting locations following anonymous tip-offs, a phenomenon whose relationship to trade liberalization I analyze in Felix (2021b).

⁵²Based on authors’ estimates for $\theta = 0.45$, $\eta = 6.96$, and country-level (payroll-share average) Herfindahl of 0.11. See Section 2.3, Appendix C.2.4, and Appendix C.2.6. The authors also estimate a labor share of 57% based on additional estimates for production function parameters.

⁵³More generally, most current estimates of either firm labor market power or labor market concentration are for developed countries or subsets of what is essentially formal sector employment. Additional examples include Benmelech, Bergman and Kim (2018), Azar et al. (2020), Schubert, Stansbury and Taska (2021), Marinescu, Ouss and Pape (2021).

⁵⁴Leveraging exogenous shocks is likely consequential for any estimates of firm labor market power based on elasticities of labor supply. For example, MacKenzie (2018) estimates labor supply elasticities fully structurally, without any labor demand shocks, and reports much higher implied wage take-home shares than all other estimates from the literature, of nearly 90%, based on two years of Indian manufacturing plant data.

7 Implication for average wages

Given the estimates from Section 6, what does the trade-induced increase in labor market concentration documented in Section 4 imply for average wages?

I address this question by first decomposing the effect of trade on average wages into its subcomponents: the effect on the average wage take-home share, and the effect on the average marginal revenue product of labor. My estimates from Sections 4 and 6 feed directly into the former per equations 9 and 10, while the latter can be estimated by measuring markets' average marginal product of labor using the elasticities estimated in Section 6.

7.1 Decomposition

Recall from equation 9 that market m 's average wage in year t is given by $\bar{w}_{mt} = \mu_{mt}^{-1} \bar{r}_{mt}$, where μ_{mt}^{-1} is the market average wage take-home share and \bar{r}_{mt} is the market average marginal revenue product of labor. Therefore, the effect of trade on average wages can be decomposed as:

$$\frac{d\bar{w}_{mt}}{dICE_m} = \frac{d\mu_{mt}^{-1}}{dICE_m} \bar{r}_{mt} + \frac{d\bar{r}_{mt}}{dICE_m} \mu_{mt}^{-1} = - \underbrace{\frac{d\mu_{mt}}{dICE_m} \frac{1}{\mu_{mt}^2} \bar{r}_{mt}}_{\gamma_t} + \frac{d\bar{r}_{mt}}{dICE_m} \mu_{mt}^{-1} \quad (21)$$

where $\gamma_t = \left(\frac{1}{\theta} - \frac{1}{\eta}\right) \beta_t$ from Corollary 1.

While the relationship between the effect of trade on average wages via increased concentration is explicit in the γ_t component, it is not explicit but still present in $\frac{d\bar{r}_{mt}}{dICE_m}$. To see that, note that $\bar{r}_{mt} = \sum_z s_{zmt}^e r_{zmt}$, where s_{zmt}^e is firm z 's employment share in market m at year t . Therefore, the effect of trade on \bar{r}_{mt} can be further decomposed as:

$$\frac{d\bar{r}_{mt}}{dICE_m} = \sum_{z \in \Theta_{mt}} s_{zmt}^e \frac{dr_{zmt}}{dICE_m} + \sum_{z \in \Theta_{mt}} r_{zmt} \frac{ds_{zmt}^e}{dICE_m} = \underbrace{\frac{d(\bar{r}_{mt}|s_{jmt}^e)}{dICE_m}}_{\text{Within-firm effect}} + \underbrace{\frac{d(\bar{s}_{mt}|r_{jmt})}{dICE_m}}_{\text{Cross-firm reallocation}} \quad (22)$$

where Θ_{mt} is the set of firms operating in market m in year t , $\bar{r}_{mt}|s_{jmt}^e$ is market m 's average marginal revenue product of labor at time t using firms' baseline employment shares as weights for aggregation, and $\bar{s}_{mt}|r_{jmt}$ is market m 's average employment share using firms' baseline marginal revenue product as weights for aggregation.

Trade-induced increases in concentration feature directly into the average marginal product of labor via its cross-firm employment reallocation component. Note that changes in

concentration do not feature into the within-firm effect because $\bar{r}_{mt}|s_{jmt}^e$ holds firms' relative size constant.⁵⁵ Putting it all together gives:

$$\frac{d\bar{w}_{mt}}{dICE_m} = \underbrace{-\frac{\gamma_t}{\mu_0^2}\bar{r}_0}_{\text{Effect via market power}} + \overbrace{\left[\underbrace{\frac{d(\bar{r}_{mt}|s_{jmt}^e)}{dICE_m}}_{\text{Within-firm effect}} + \underbrace{\frac{d(\bar{s}_{mt}^e|r_{jmt})}{dICE_m}}_{\text{Cross-firm reallocation}} \right]}^{\text{Effect via MRPL}} \mu_0^{-1} \quad (23)$$

where \bar{r}_0 and μ_0 are the baseline average marginal revenue product of labor and baseline average wage markdown, respectively. I next estimate each of these sub-components.

7.2 Effect on average wage markdown

Figure 3 presents my estimates of γ_t for all sample years, summarized in Table 4 as the post-reform mid-point estimate.⁵⁶ A 10% increase in import competition exposure increased the average wage markdown by 0.006 (SE of 0.003) points, an effect driven by the 0.02 point average increase in markets' payroll Herfindahls. This is equivalent to a reduction of the pre-liberalization average wage take-home share of 50 cents on the dollar by 0.14 cents.⁵⁷

Tables 5 and 6 summarize the implication of this effect to average wages per equation 23. Table 5 first presents estimates of the overall effect of import competition exposure on the average wage premium — as opposed to on the average log wage premium as in Table 1 — and its subcomponents, showing that a 10% increase in import competition exposure reduced the average wage premium by 0.343 multiples of the minimum wage, which is a roughly 13.8% decline from the pre-liberalization average of 2.48.⁵⁸

Table 6 then presents how much of this effect is accounted for by effects on the average wage take-home share vs. on the average marginal revenue product of labor. A 10% increase in import competition exposure reduced average wages by $0.0014 \times 4.99 = 0.007$ multiples

⁵⁵Firm employment is held constant to compute this statistic, both when computing each firm's r_{zmt} and when weighing r_{zmt} by firm employment to obtain \bar{r}_{mt} .

⁵⁶See Appendix C for standard errors.

⁵⁷This effect would likely be larger if it were inclusive of informality. See Appendix D.1. Interestingly, my small and highly reduced-form-based estimate of the effect of trade on wage markdowns is consistent with counterfactual predictions from the fully structural general equilibrium model developed by MacKenzie (2018). Calibrating a general equilibrium model of trade to two years of Indian manufacturing plant data, MacKenzie (2018) reports that a counterfactual move from autarky to free trade would primarily reduce firms' price markups in product markets, having only a small impact on firms' wage markdowns in labor markets. Those fully structural predictions are not inconsistent with the empirically-driven findings I report in Section 7.3.

⁵⁸Since wages exhibit positive pre-trends (Appendix Figure A.9), these effects are relative to trend.

of the minimum wage via increased firm labor market power, which is roughly 0.29% of the 2.48 pre-liberalization wage premium average. This corresponds to roughly 2% of the overall 13.8% average wage reduction caused by import competition exposure. The remaining effect is accounted by the average marginal revenue product of labor, to which I turn next.

7.3 Effect on average marginal revenue product of labor

Table 5 presents estimates of the effect of import competition exposure on the average MRPL and within-firm effect vs. cross-firm reallocation subcomponents shown in equation 23. A 10% increase in import competition exposure reduced the average MRPL by 0.673 (SE of 0.133) multiples of the minimum wage. This large negative effect is entirely driven by a within-firm MRPL reduction of 0.682 (SE of 0.188) multiples of the minimum wage, and attenuated slightly by cross-firm employment reallocation positive average MRPL effect of 0.013 (SE of 0.002) multiples of the minimum wage.

Table 6 puts these effects in perspective relative to the overall effect of trade on average wages. The negative within-firm effect amounts to a 13.68% reduction in the average wage premia, whereas the positive cross-firm reallocation effect amounts to a 0.27% increase. The overall negative effect of trade on average wage premia is nearly all accounted for by the net negative reduction in the average marginal revenue product of labor. The latter could reflect, for example, changes in price markups, or simply the reduction in prices that Brazilian firms could charge for their goods, once they were no longer as shielded by tariffs from import competition.

8 Conclusion

This paper addressed a key question in the recent literature on the regional incidence of trade: what accounts for trade liberalization’s large negative effects on wages? I studied one potential mechanism: trade-induced increases in labor market concentration, and the consequences thereof to firm labor market power.

I showed that the effect of trade liberalization on firm labor market power can be quantified by two parameters: the effect of trade on local labor market concentration, and the gap between workers’ cross-market vs. within-market cross-firms inverse elasticities of substitution. I then leveraged Brazil’s rich employer-employee linked data and 1990s trade liberalization to estimate these sufficient statistics.

All in all, my findings suggest that while firms commanded substantial labor market power in 1990s Brazil, and while trade liberalization further increased this labor market power by reallocating employment to larger firms, the effect of trade on firm labor market power does not account for the bulk of the negative effect of trade on wages. This effect was driven instead by within-firm reductions in the marginal revenue product of labor.

References

- Adao, Rodrigo, Michal Kolesár, and Eduardo Morales.** 2019. “Shift-share designs: Theory and inference.” *The Quarterly Journal of Economics*, 134(4): 1949–2010.
- Alfaro Urena, Alonso, Isabela Manelici, and Jose Vasquez.** 2021. “The effects of multinationals on workers: evidence from Costa Rican microdata.” Princeton University, Department of Economics, Center for Economic Policy Studies.
- Amodio, Francesco, and Nicolás de Roux.** 2021. “Labor Market Power in Developing Countries: Evidence from Colombian Plants.”
- Atkeson, Andrew, and Ariel Burstein.** 2008. “Pricing-to-market, trade costs, and international relative prices.” *American Economic Review*, 98(5): 1998–2031.
- Autor, David, David Dorn, and Gordon Hanson.** 2013. “The China syndrome: Local labor market effects of import competition in the United States.” *The American Economic Review*, 103(6): 2121–2168.
- Azar, José A, Ioana Marinescu, Marshall I Steinbaum, and Bledi Taska.** 2018. “Concentration in US Labor Markets: Evidence From Online Vacancy Data.” National Bureau of Economic Research.
- Azar, José, Ioana Marinescu, and Marshall I Steinbaum.** 2017. “Labor market concentration.” National Bureau of Economic Research.
- Azar, José, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska.** 2020. “Concentration in US labor markets: Evidence from online vacancy data.” *Labour Economics*, 66: 101886.
- Benmelech, Efraim, Nittai Bergman, and Hyunseob Kim.** 2018. “Strong employers and weak employees: How does employer concentration affect wages?” National Bureau of Economic Research.
- Berger, David W, Kyle Herkenhoff, and Simon Mongey.** 2021. “Labor Market Power.” *University of Chicago, Becker Friedman Institute for Economics Working Paper*, , (2021-58).
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel.** 2018. “Quasi-experimental shift-share research designs.” National Bureau of Economic Research.

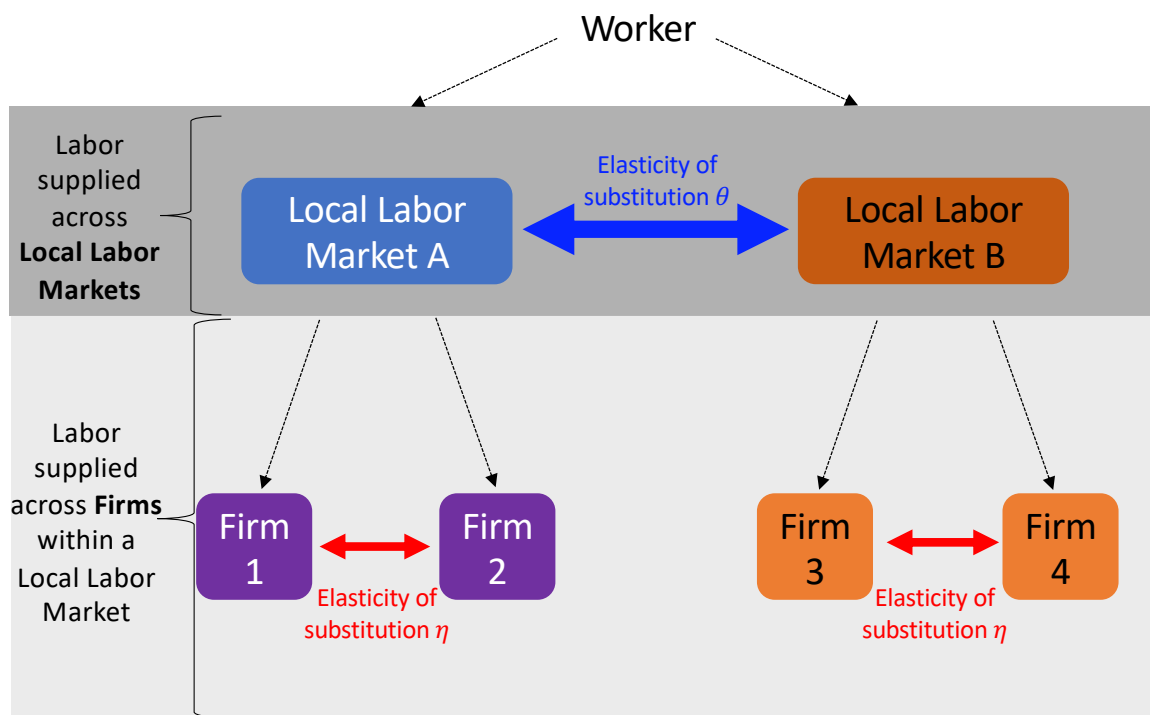
- Costinot, Arnaud, Dave Donaldson, and Cory Smith.** 2016. “Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world.” *Journal of Political Economy*, 124(1): 205–248.
- Dix-Carneiro, Rafael, and Brian K Kovak.** 2017. “Trade liberalization and regional dynamics.” *American Economic Review*, 107(10): 2908–46.
- Dix-Carneiro, Rafael, and Brian K Kovak.** 2019. “Margins of labor market adjustment to trade.” *Journal of International Economics*, 117: 125–142.
- Dix-Carneiro, Rafael, Pinelopi K Goldberg, Costas Meghir, and Gabriel Ulyssea.** 2021. “Trade and informality in the presence of labor market frictions and regulations.” National Bureau of Economic Research.
- Felix, Mayara.** 2021b. “Trade Liberalization and Modern Slavery: Evidence from Labor Inspections in Brazil.” Research in progress.
- Felix, Mayara, and Sean Wang.** 2021. “A Quasi-Experimental Approach to Identifying Labor Market Boundaries: Evidence from Brazilian Workers.” Research in progress.
- Fogel, Jamie, and Bernardo Modenesi.** 2021. “What is a labor market? classifying workers and jobs using network theory.”
- Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift.** 2018. “Bartik instruments: What, when, why, and how.” National Bureau of Economic Research.
- Hershbein, Brad, Claudia Macaluso, and Chen Yeh.** 2019. “Monopsony in US Labor Markets.” Working paper.
- Hoang, Pham.** 2021. “Trade Reform, Oligopsony, and Labor Market Distortions: Theory and Evidence.” Working paper.
- Kovak, Brian K.** 2013. “Regional effects of trade reform: What is the correct measure of liberalization?” *The American Economic Review*, 103(5): 1960–1976.
- Kume, Honório, Guida Piani, and CB Souza.** 2003. “A política de importação no período 1987-1998: Descrição e avaliação.” *Abertura Comercial Brasileira nos Anos Noventa: Impacto sobre Emprego e Salário. MTB/IPEA, Rio de Janeiro.*

- Lee, David S, Justin McCrary, Marcelo J Moreira, and Jack R Porter.** 2021. “Valid t-ratio Inference for IV.” National Bureau of Economic Research.
- MacKenzie, Gaelan.** 2018. “Trade and Market Power in Product and Labor Markets.” Working paper.
- Manning, Alan.** 2003. *Monopsony in motion: Imperfect competition in labor markets.* Princeton University Press.
- Marinescu, Ioana, Ivan Ouss, and Louis-Daniel Pape.** 2021. “Wages, hires, and labor market concentration.” *Journal of Economic Behavior & Organization*, 184: 506–605.
- McFadden, Daniel.** 1978. “Modeling the choice of residential location.” *Transportation Research Record*, , (673).
- Melitz, Marc J.** 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica: Journal of the Econometric Society*, 71(6): 1695–1725.
- Menezes-Filho, Naércio Aquino, and Marc-Andreas Muendler.** 2011. “Labor reallocation in response to trade reform.”
- Nimczik, Jan Sebastian.** 2017. “Job mobility networks and endogenous labor markets.”
- Schmutte, Ian M.** 2014. “Free to move? A network analytic approach for learning the limits to job mobility.” *Labour Economics*, 29: 49–61.
- Schubert, Gregor, Anna Stansbury, and Bledi Taska.** 2019. “Getting labor markets right: Outside options and occupational mobility.” Working paper.
- Schubert, Gregor, Anna Stansbury, and Bledi Taska.** 2021. “Employer concentration and outside options.” *Available at SSRN 3599454*.
- Topalova, Petia.** 2010. “Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India.” *American Economic Journal: Applied Economics*, 2(4): 1–41.
- Tortarolo, Dario, and Roman D Zarate.** 2018. “Measuring Imperfect Competition in Product and Labor Markets. An Empirical Analysis using Firm-level Production Data.”

Ulyssea, Gabriel. 2018. “Firms, informality, and development: Theory and evidence from Brazil.” *American Economic Review*, 108(8): 2015–47.

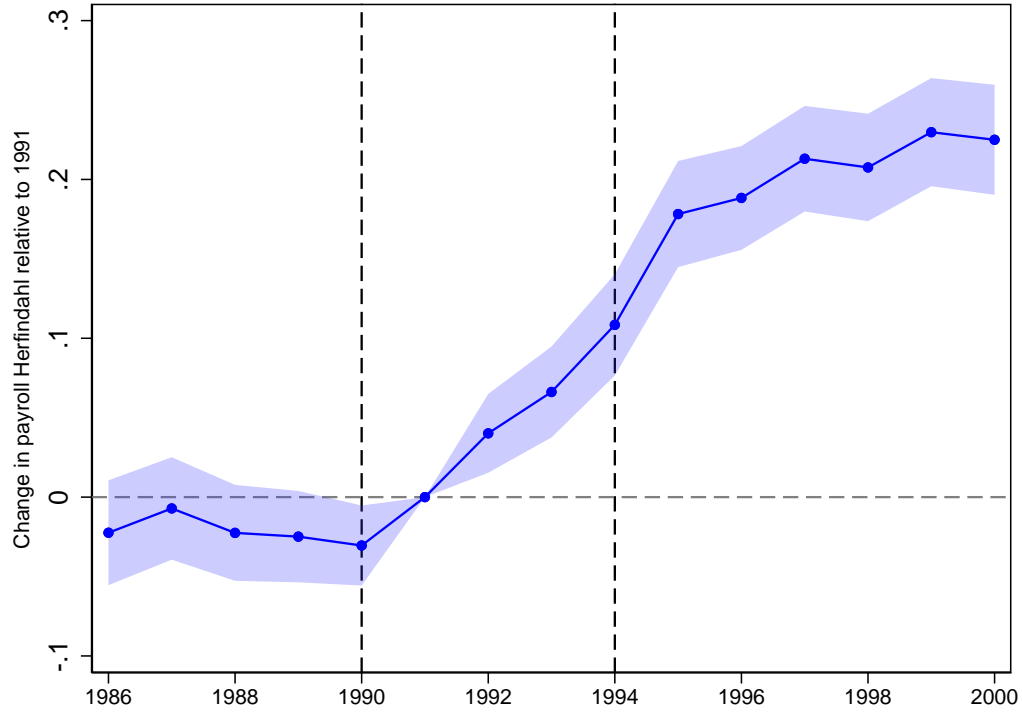
Wooldridge, Jeffrey M. 2015. *Introductory econometrics: A modern approach*. Cengage learning.

Figure 1: Worker labor supply decision



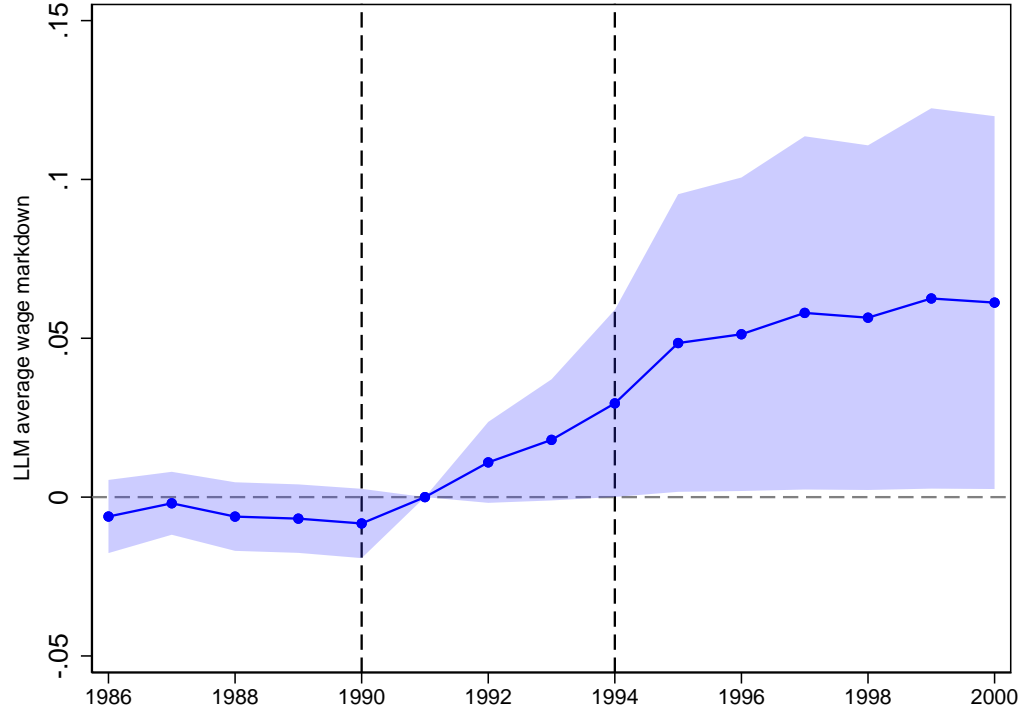
Note: This figure displays a diagram of worker's labor supply decision according to the discrete choice labor supply framework presented in Section 2.

Figure 2: Effect of import competition on local labor market concentration



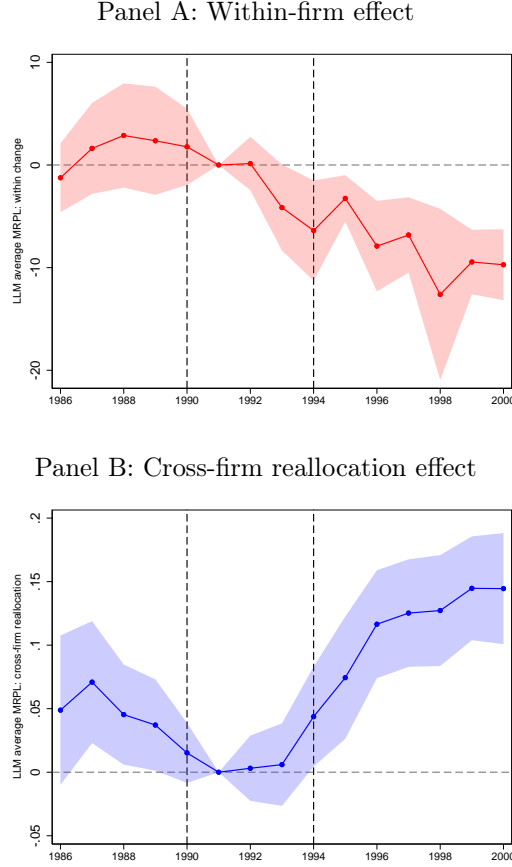
Notes: This figure plots regression coefficients ζ_k on regressor ΔICE_m from equation 12, where the outcome is the change in payroll Herfindahl relative to 1991. Since ΔICE_m is a weighted average log change in import tariffs, note that this is a units on logs regression, such that a 10% increase in import competition exposure changed the outcome by $(\zeta_k/100) \times 10$ units. Shaded areas report the 95% confidence interval based on clustered standard errors at the local labor market level.

Figure 3: Effect of import competition on average wage markdown



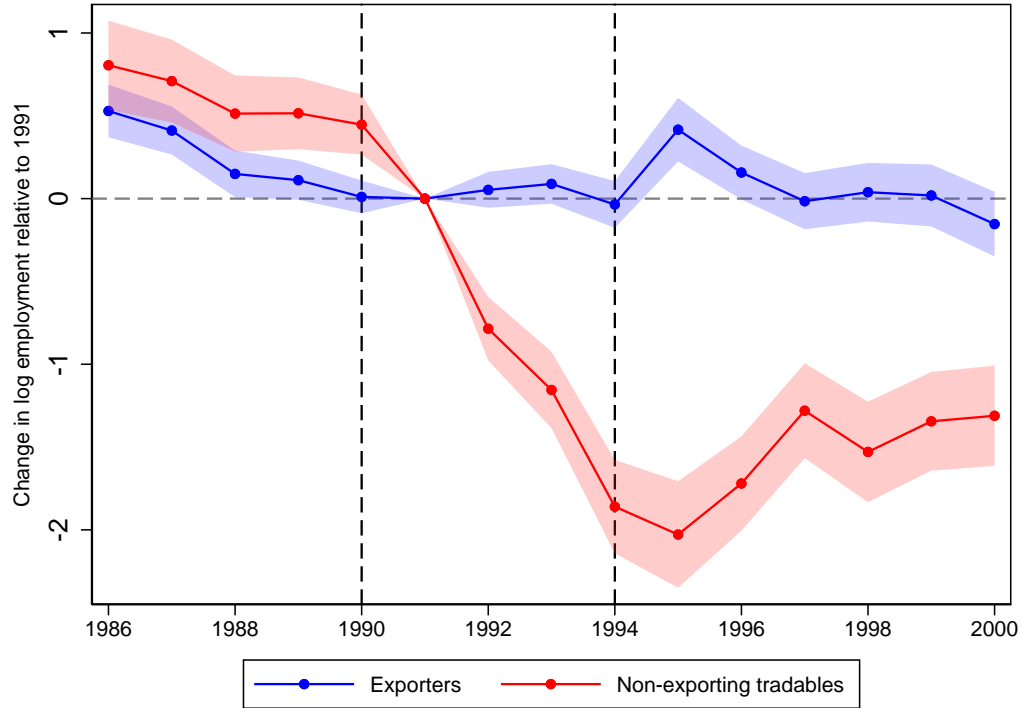
Notes: This figure plots γ_t , the effect of import competition on local labor markets' average wage markdown share at year t , derived in equation 10. The two components of γ_k are $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$, whose estimates are presented in Table 3, and the β_t coefficients that estimate the effect of import competition on labor market concentration, presented in Figure 2. Standard errors are estimated assuming β_t and $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$ are independent (see Appendix C for details).

Figure 4: Effect of import competition on average marginal revenue product of labor



Notes: This table presents estimates of $\tilde{\zeta}_k$, the de-trended specification coefficient equivalent to ζ_k from equation 12, separately estimated for two outcomes. The outcome in Panel A is the change in the within-firm component of the average marginal product of labor relative to 1991. The outcome in Panel B is the change in the cross-firm component of the average marginal product of labor relative to 1991. See equation 23 for the definitions of each component. Since ΔICE_m is a weighted average log change in import tariffs, note that this is a units on logs regression, such that a 10% increase in import competition exposure changed the outcome by $(\zeta_k/100) \times 10$ units. Shaded areas report the 95% confidence interval based on clustered standard errors at the local labor market level.

Figure 5: Nature of employment reallocation: exporters vs. non-exporting tradables



Notes: This figure plots regression coefficients ζ_k on regressor ΔICE_m from equation 12, separately estimated for two outcomes defined at the local labor market level. The blue line plots coefficients where the outcome is the change in log exporter employment for relative to 1991. The red line plots coefficients where the outcome is the change in log employment for non-exporting tradables relative to 1991. Since ΔICE_m is a weighted average log change in import tariffs, note that this is a logs on logs regression, such that a 10% increase in import competition exposure changed the outcome by $\zeta_k \times 10$ percent. Shaded areas report the 95% confidence interval based on clustered standard errors at the local labor market level.

Table 1: Effect of trade on local labor market concentration, employment, and wages

	Δ Import Competition Exposure (1)	Effect per 10% increase in ICE (2)
<i>Panel A: Labor market concentration</i>		
Δ Payroll Herfindahl (based on wage premium)	0.213 (0.017)	0.021 (0.002)
Δ Payroll Herfindahl	0.213 (0.017)	0.021 (0.002)
Δ Employment Herfindahl	0.247 (0.016)	0.025 (0.002)
<i>Panel B: Log number of firms and log employment</i>		
Δ Log number of firms	-0.549 (0.045)	-5.489 (0.447)
Δ Log total employment	-0.440 (0.064)	-4.400 (0.640)
<i>Panel C: Log wage premium</i>		
Δ Log wage premium	0.029 (0.031)	0.293 (0.307)
Δ De-trended log wage premium	-0.206 (0.034)	-2.063 (0.338)
Observations	296,400	296,400
Local labor markets	19,760	19,760

Notes: This table presents estimates of ζ_{1997} from equation 12, separately estimated for each listed outcome. Column (1) presents regression estimates, whereas Column (2) presents the effect per 10% increase in import competition exposure to facilitate interpretation. For the outcomes in Panel A, which are measured in unit changes, $(\zeta_{1997}/100) \times 10$ is the unit change in the outcome per 10% increase in import competition exposure. For the outcomes in Panels B and C, which are measured in log changes, $\zeta_{1997} \times 10$ is the percent change in the outcome per 10% increase in import competition exposure. See Appendix A in Wooldridge (2015) for details on how to interpret unit-on-log vs. log-on-log regressions. See Appendix B for details on how log wage premia are estimated, and for the de-trended log wage premium regression specifications.

Table 2: Estimate of workers' within-market cross-firm inverse elasticity of substitution

	Δ in Log Import Tariff faced by firm (1)
<i>Panel A: First stage</i>	
Δ Firm log employment in LLM	-0.554 (0.044)
First stage F	158.497
<i>Panel B: Reduced form</i>	
Δ Firm wage premium in LLM	-0.545 (0.024)
<i>Panel C: 2SLS</i>	
Labor supply within-market cross-firm inverse elasticity of substitution	0.985 (0.089)
Implied upper bound on wage take-home share	50%
Observations	854,068
Firms	344,066
Local labor markets	15,717

Notes: This table presents first stage, reduced form, and two-stage least squares estimates of $\frac{1}{\eta}$ based on equations 15 and 16. Implied upper bound on wage take-home share is calculated as $\left(1 + \frac{1}{\eta}\right)^{-1}$ per equation 9 under the limiting assumption that each local labor market is composed of infinitely many equally-sized firms (i.e. $HHI_m = 0$ for all m). Standard errors shown in parenthesis are clustered at the firm level.

Table 3: Estimate of workers' cross-market inverse elasticity of substitution

	Δ Import Competition Exposure (1)
<i>Panel A: First stage</i>	
Δ LLM employment index	-0.396 (0.032)
First stage F	150.752
<i>Panel B: Reduced form</i>	
Δ LLM wage premium index	-0.108 (0.051)
<i>Panel C: 2SLS</i>	
$\frac{1}{\theta} - \frac{1}{\eta}$	0.272 (0.131)
<i>Panel D: Cross-market inverse elasticity of substitution</i>	
$\frac{1}{\theta}$	1.257 (0.096)
Implied lower bound on wage take-home share	44%
Observations (Local labor markets)	15,717

Notes: This table presents first stage, reduced form, and two-stage least squares estimates of $\frac{1}{\theta} - \frac{1}{\eta}$, and implied $\frac{1}{\theta}$, based on equations 19 and 20. Implied lower upper bound on wage take-home share is calculated as $(1 + \frac{1}{\theta})^{-1}$ per equation 9 under the limiting assumption that each local labor market is composed of one firm (i.e. $HHI_m = 1$ for all m). Standard errors shown in parenthesis are clustered at the local labor market level.

Table 4: Effect of import competition on the average wage take-home share

	Regression estimate	Effect per 10% increase in ICE
	(1)	(2)
Effect of Δ Import Competition Exposure on market average wage take-home share	-0.014 (0.007)	-0.0014 (0.0007)
Effect of Δ Import Competition Exposure on market average wage markdown	0.058 (0.028)	0.0058 (0.003)
β Effect of Δ Import Competition Exposure on payroll Herfindahl	0.213 (0.017)	0.021 (0.002)
$\frac{1}{\theta} - \frac{1}{\eta}$ Difference between key inverse elasticities of labor supply	0.272 (0.131)	-- --
Local labor markets	19,760	19,760

Notes: This table presents estimates of γ_{1997} per equation 9, listing its two components: β_{1997} taken from Table 1, and $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$ from Table 19. Standard errors are estimated assuming ζ_{1997} and $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$ are independent (see Appendix C for details).

Table 5: Effect of import competition on average wages: decomposition

	Δ Import Competition Exposure	Effect per 10% increase in ICE
	(1)	(2)
Δ Average wage premium	-3.340 (0.454)	-0.334 (0.045)
Δ Average wage premium take-home share	-0.014 (0.007)	-0.0014 (0.001)
Δ Average marginal revenue product of labor	-6.735 (1.334)	-0.673 (0.133)
Δ Within-firm	-6.821 (1.876)	-0.682 (0.188)
Δ Cross-firm	0.132 (0.023)	0.013 (0.002)
Observations	243,750	243,750
Local labor markets	16,250	16,250

Notes: This table presents estimates of $\tilde{\zeta}_{1997}$, the de-trended specification coefficient equivalent to ζ_{1997} from equation 12, separately estimated for the change in average wage premium, the change in average marginal revenue product of labor and its subcomponents. The coefficient for the change in average wage premium wage take-home share is the same as in Table 4. Column (1) presents regression estimates, whereas Column (2) presents the effect per 10% increase in import competition exposure to facilitate interpretation. As outcomes are measured in unit changes, $(\zeta_{1997}/100) \times 10$ is the unit change in the outcome per 10% increase in import competition exposure. See Appendix A in Wooldridge (2015) for details on how to interpret unit-on-log regressions. See Appendix B for details on how log wage premia are estimated, and for the de-trended regression specifications.

Table 6: Effect of import competition on average wages: accounting

	Pre-reform level (1)	Directly affected by increased concentration? (2)	Impact of 10% increase in ICE on average wage premium (3)	Percent change from baseline average wage premium (4)	Effect as percent of total effect on average wage premium (5)
Average wage premium	2.48	--	-0.343	- 13.80%	100%
Average wage take-home share	0.50	Yes	-0.007	- 0.29%	2%
Average marginal revenue product of labor	4.99	--	-0.336	- 13.51%	98%
Δ Within-firm	--	No	-0.340	- 13.68%	--
Δ Cross-firm	--	Yes	0.007	+ 0.27%	--

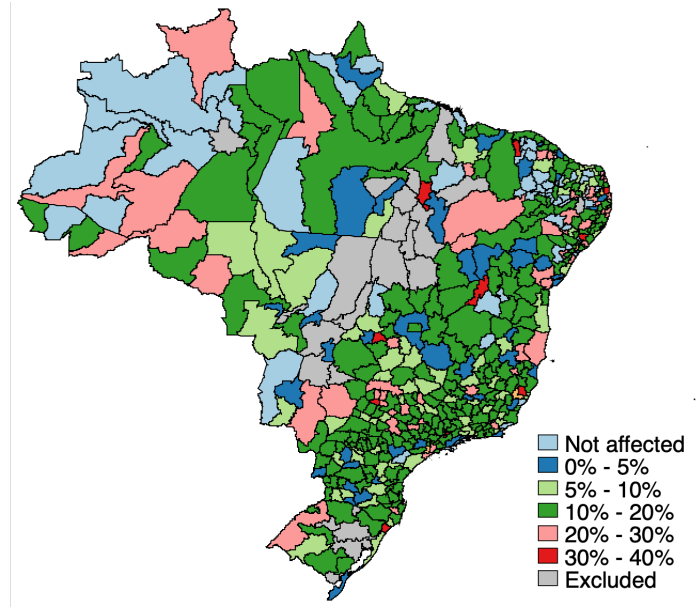
Notes: This table combines pre-reform levels of the average wage premium and its components in column (1), with point estimates of the level effect of trade per 10% increase in import competition exposure from Tables 4 and 5, to compute the effect of trade on each component of the average wage premium in column (3). I then present these effects as percent of the baseline average wage premium in column (4), and how much of each effect accounts for the total effect of trade in column (5). Pre-reform levels in column (1) are from Appendix Tables A.1 and A.2, and are based on the baseline year of 1991.

Appendices

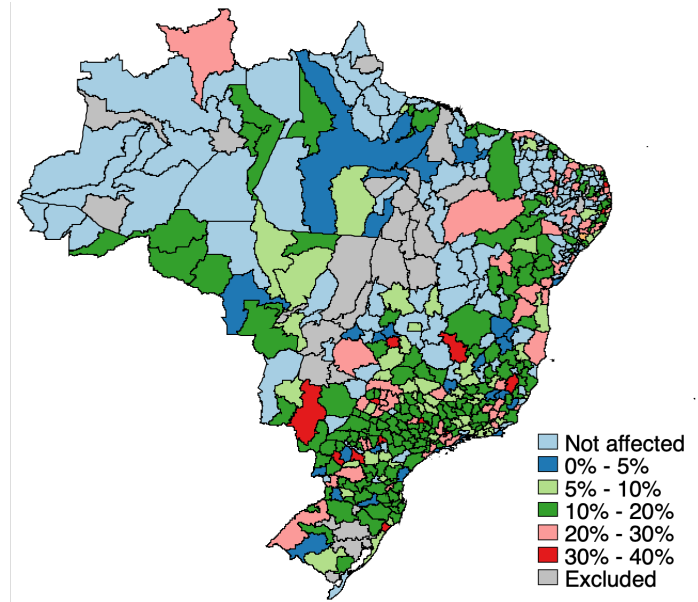
A Figures and Tables

Figure A.1: Variation in Import Competition Exposure across local labor markets

Panel A: Office administration workers



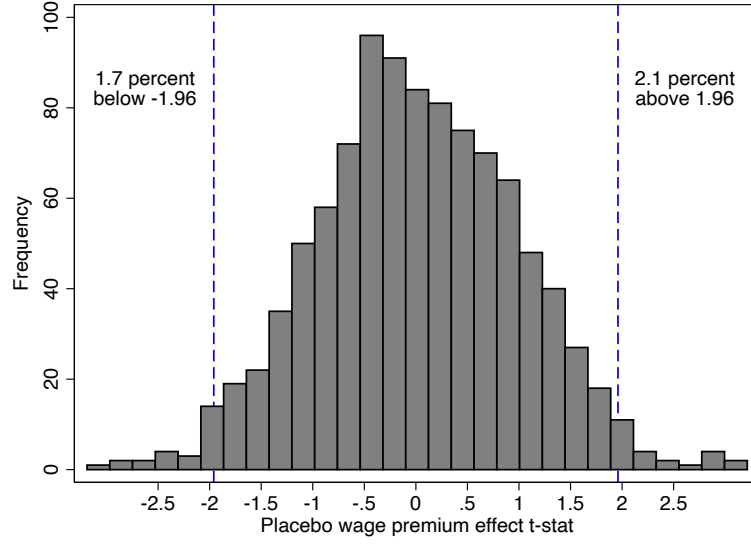
Panel B: Managers and supervisors of industrial workers



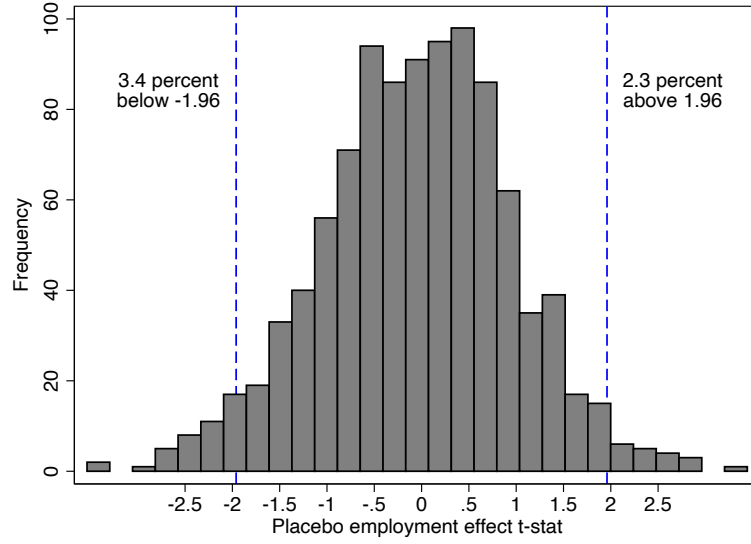
Note: This figure displays variation in ΔICE_m : the change in import competition exposure across local labor markets for two occupation groups. Produced using Stata's maptile program written by Michael Stepler with borders drawn by Stephanie Kestelman.

Figure A.2: Statistical significance across placebo regressions

Panel A: 1,000 placebo shock regressions on 1997-1991 change in wage premia

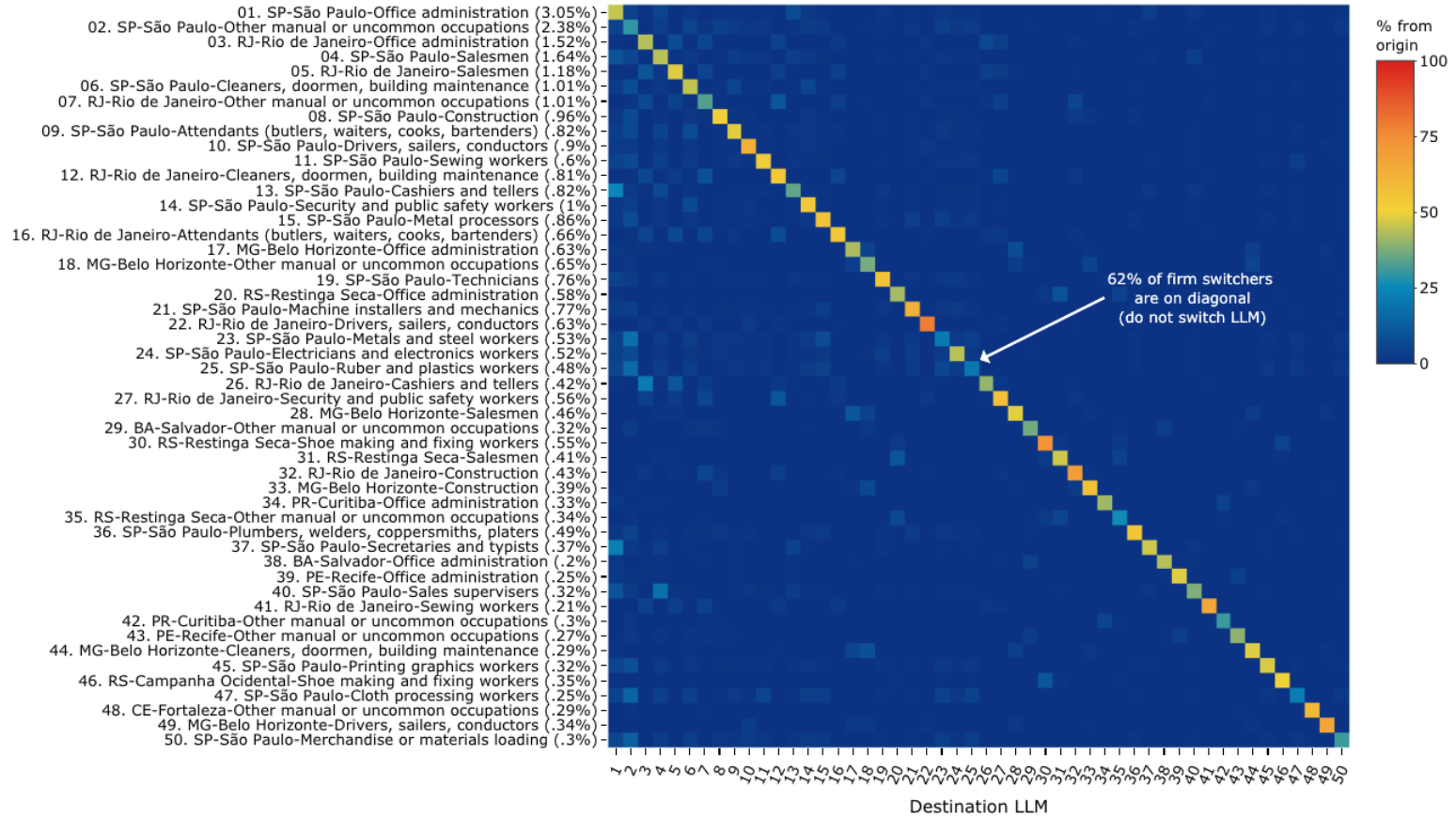


Panel B: 1,000 placebo shock regressions on 1997-1991 change in log employment



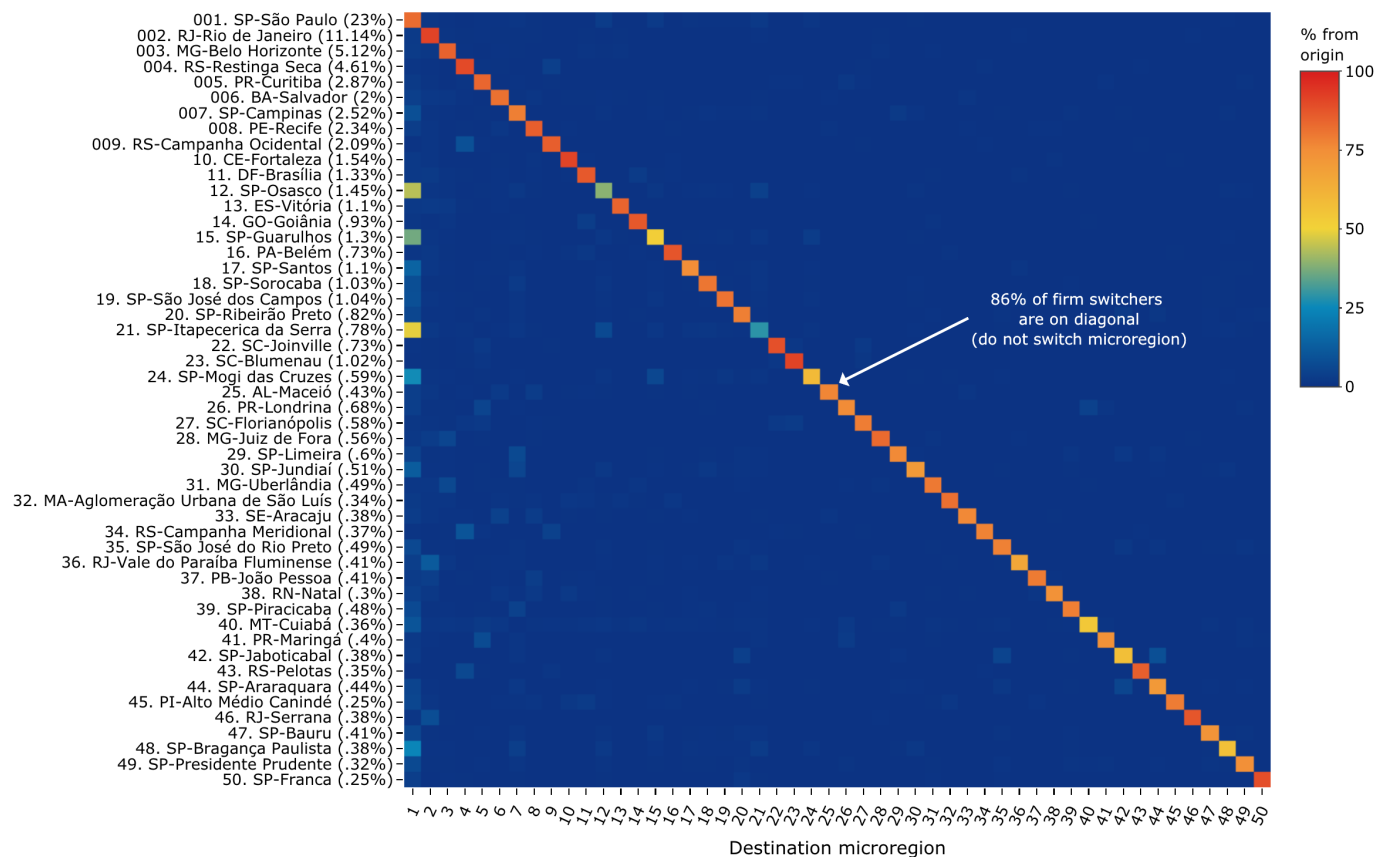
Note: This figure plots the distribution of t -statistics for 1,000 placebo regressions where the regressor is ΔICE_m defined as in equation 11 but using randomly drawn shocks, drawn from a normal distribution centered at zero.

Figure A.3: 1990-1991 local labor market transitions conditional on switching firms (Top 50)



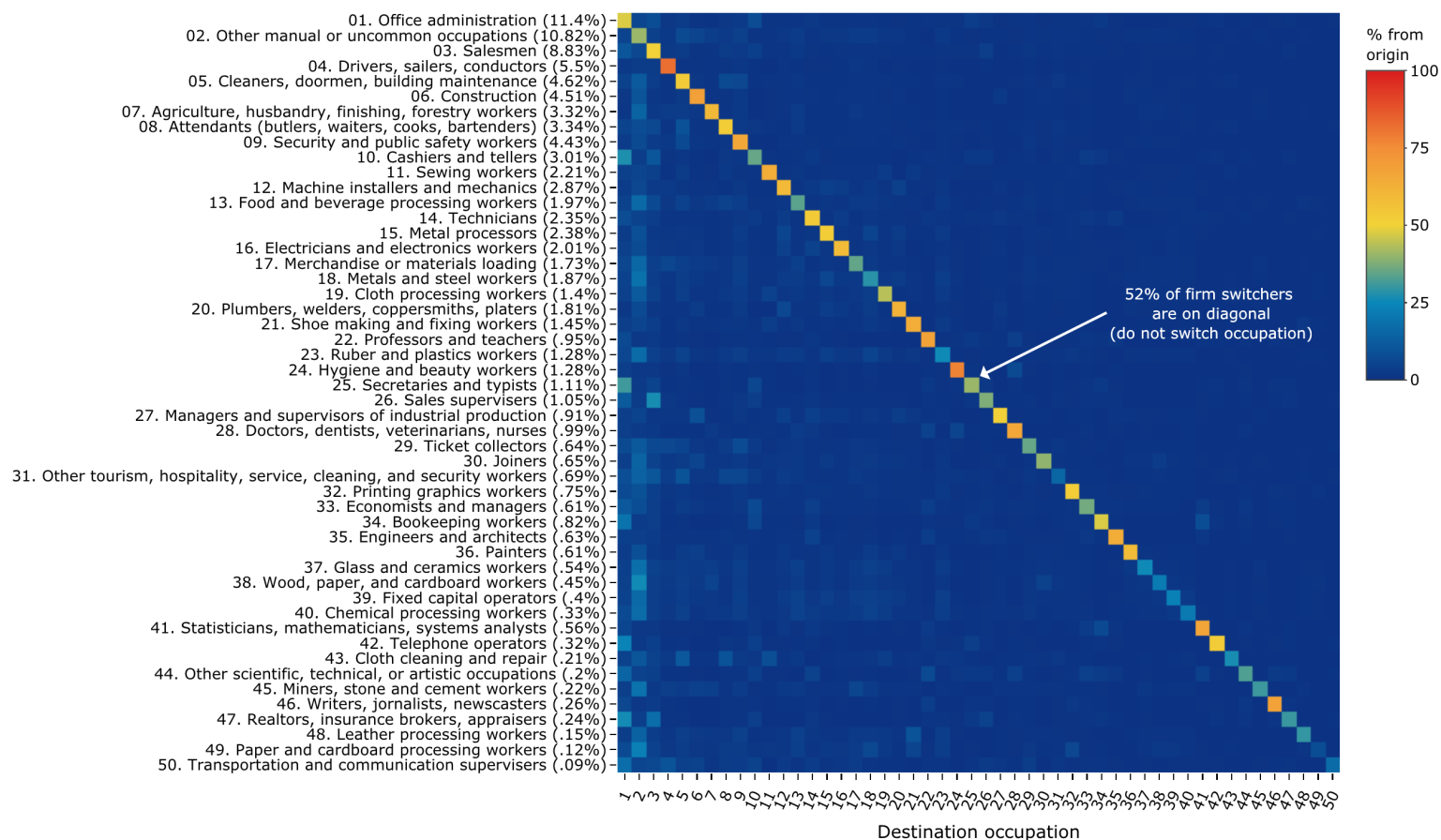
Note: This figure plots worker local labor market to local labor market transitions, among workers who switched employers between 1990 and 1991, for the top 50 local labor markets by number of workers at origin. A local labor market is a microregion × occupational group pair. Each row lists the origin microregion (with percent of total workers indicated in parentheses), while each column lists the destination microregion.

Figure A.4: 1990-1991 microregion transitions conditional on switching firms (Top 50)



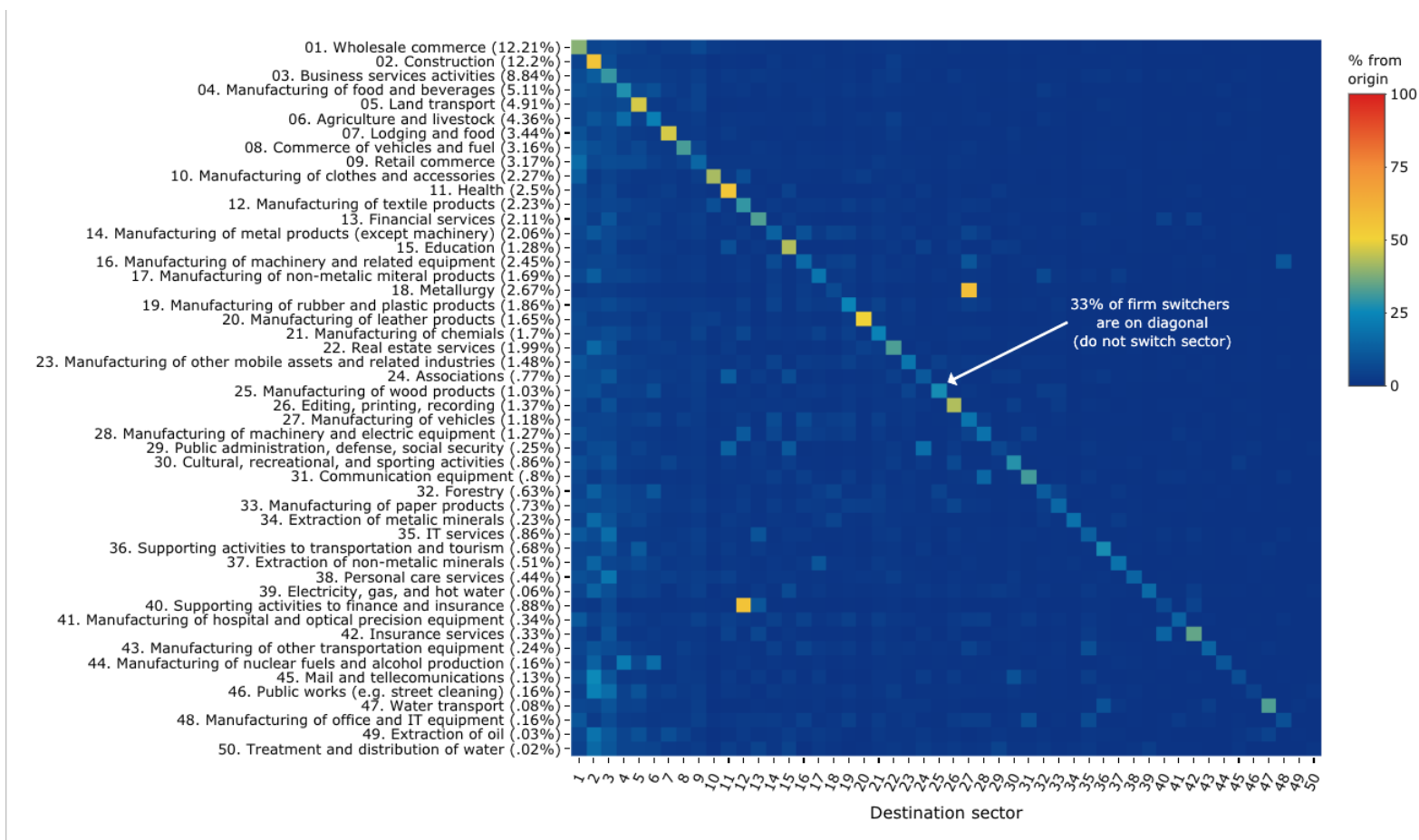
Note: This figure plots worker microregion to microregion transitions, among workers who switched employers between 1990 and 1991, for the top 50 microregions by number of workers at origin. Each row lists the origin microregion (with percent of total workers indicated in parentheses), while each column lists the destination microregion.

Figure A.5: 1990-1991 occupation transitions conditional on switching firms (Top 50)



Note: This figure plots worker occupation group to occupation group transitions, among workers who switched employers between 1990 and 1991, for the top 50 occupation groups (2-digit CBO94) by number of workers at origin. Each row lists the origin occupation group (with percent of total workers indicated in parentheses), while each column lists the destination occupation group.

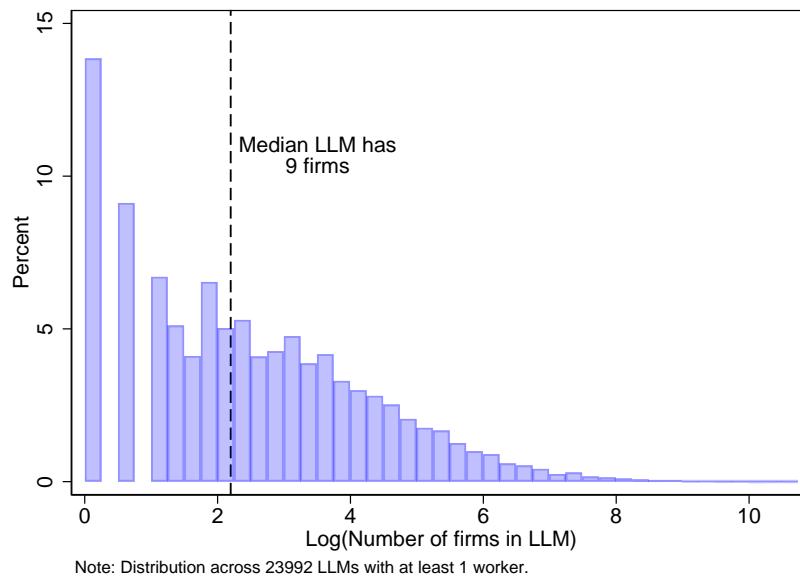
Figure A.6: 1990-1991 sector transitions conditional on switching firms (Top 50)



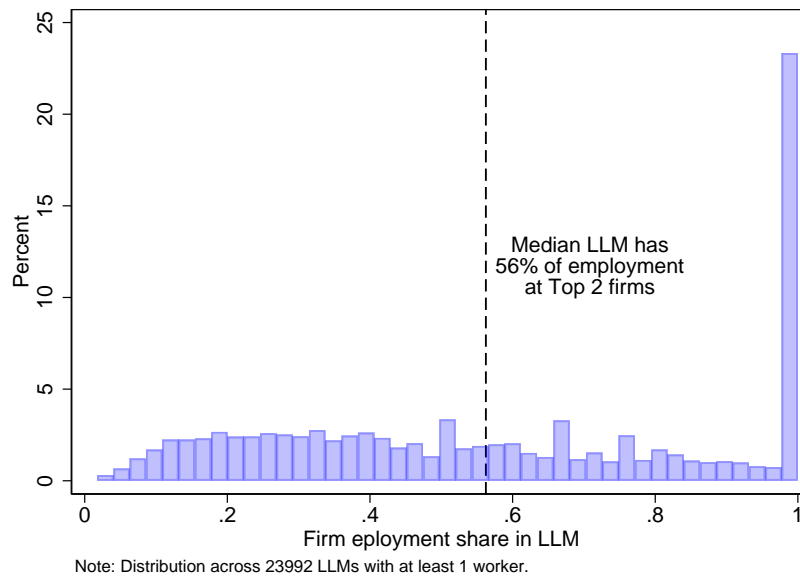
Note: This figure plots worker sector group to sector group transitions, among workers who switched employers between 1990 and 1991, for the top 50 sector (2-digit CNAE95) groups by number of workers at origin. Each row lists the origin sector group (with percent of total workers indicated in parentheses), while each column lists the destination sector group.

Figure A.7: Local labor market concentration

Panel A: Number of firms

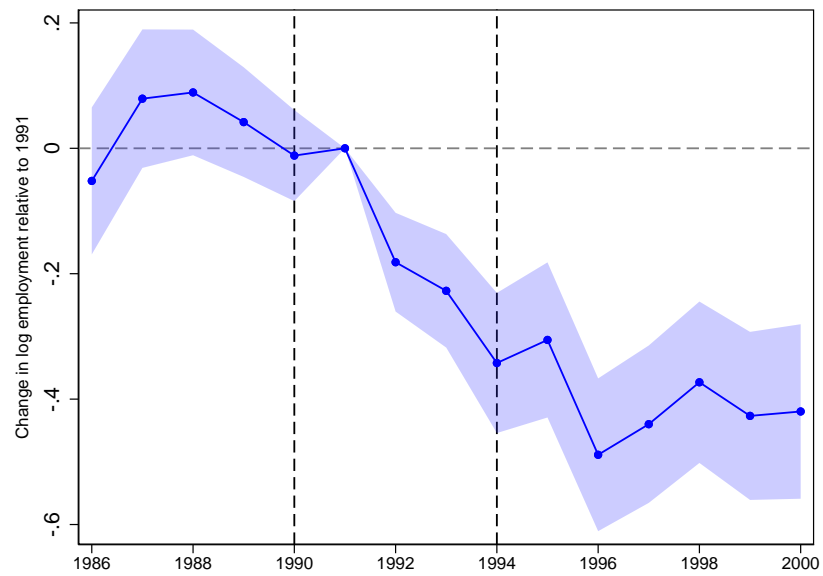


Panel B: Employment share of largest 2 firms



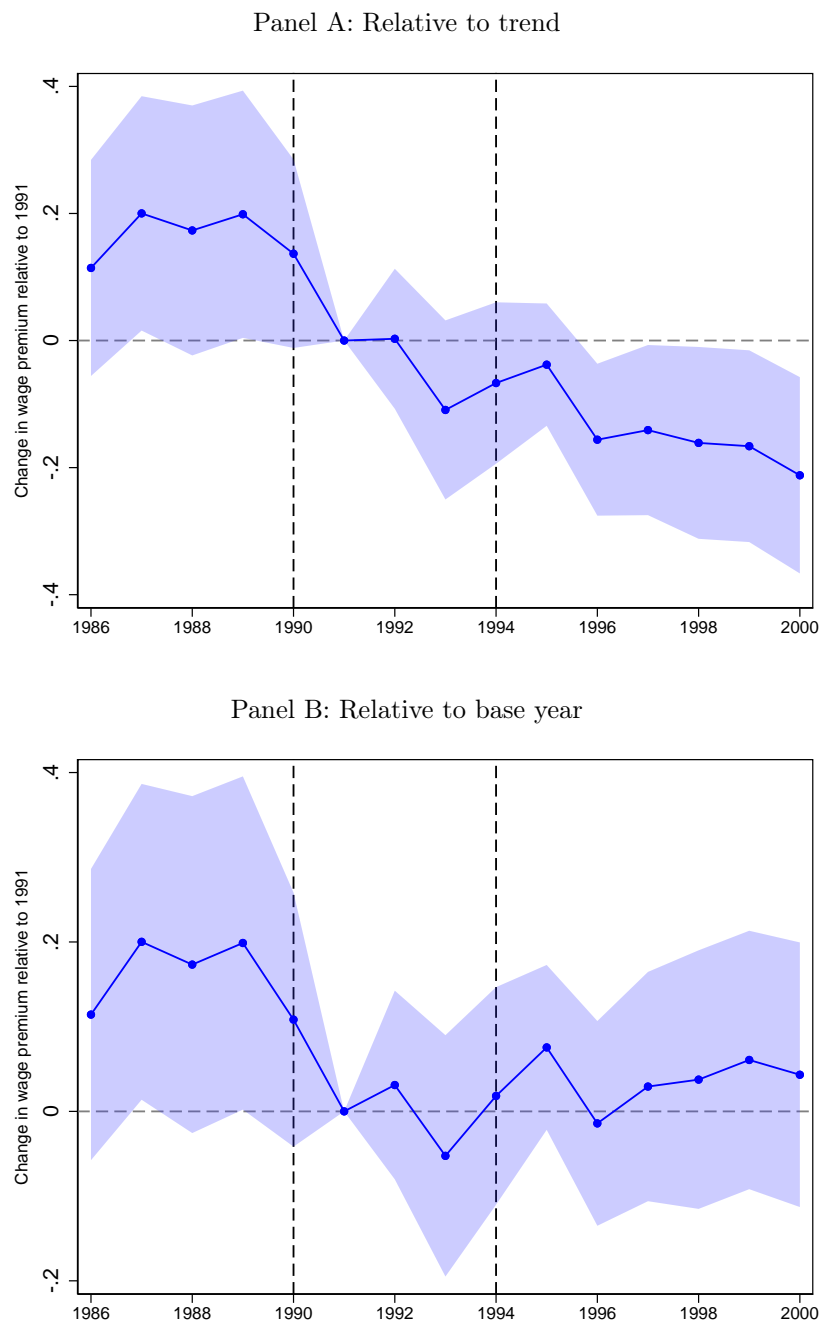
Note: This figure plots the 1991 distributions of number of firms (Panel A), and employment share of the largest 2 firms (Panel B) across local labor markets. Local labor markets are defined as a microregion \times occupation group cell. See Appendix B for details on the definitions of microregion and occupation group.

Figure A.8: Effect of import competition on employment



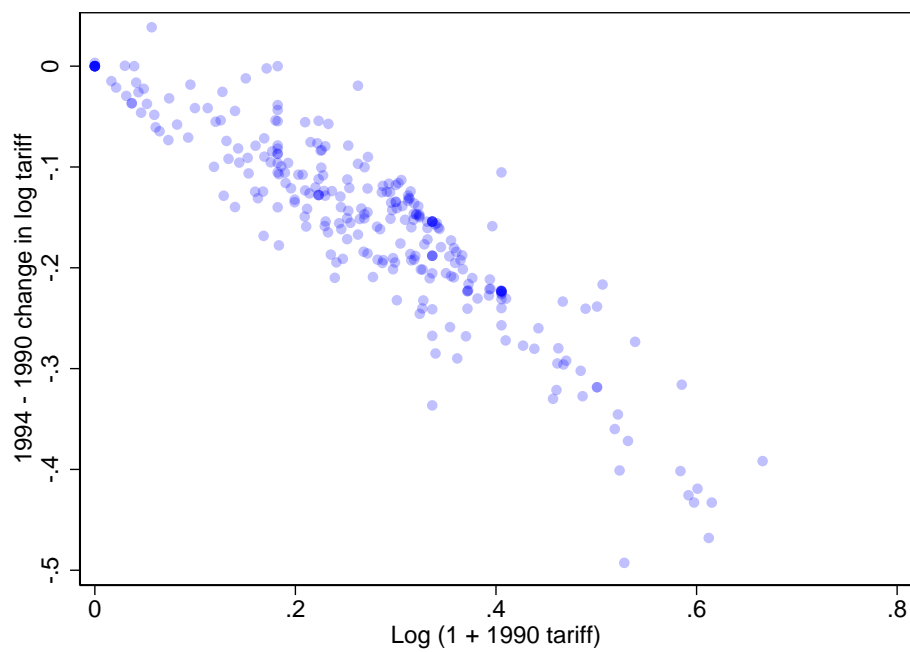
Note: See notes to Figure 2.

Figure A.9: Effect of import competition on local labor market wages



Note: See notes to Figure 2.

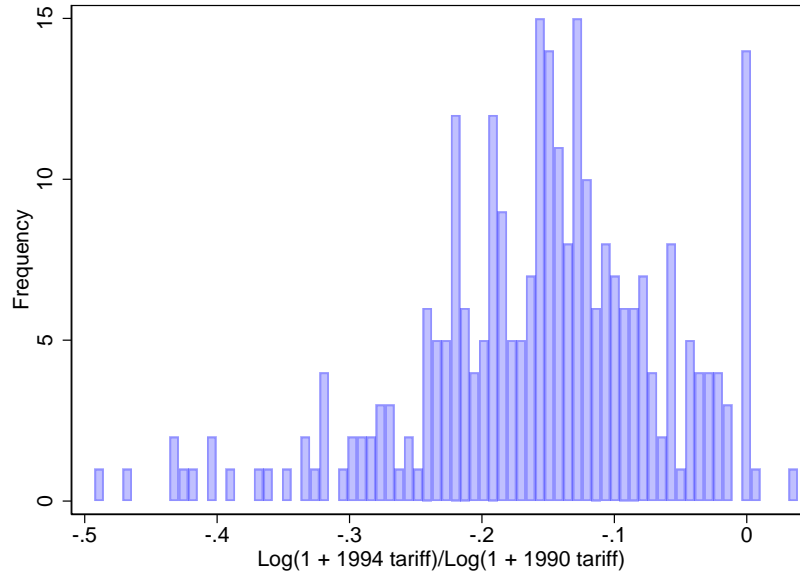
Figure A.10: Brazil's 1990-1994 tariff reduction reform: variation across 285 sectors



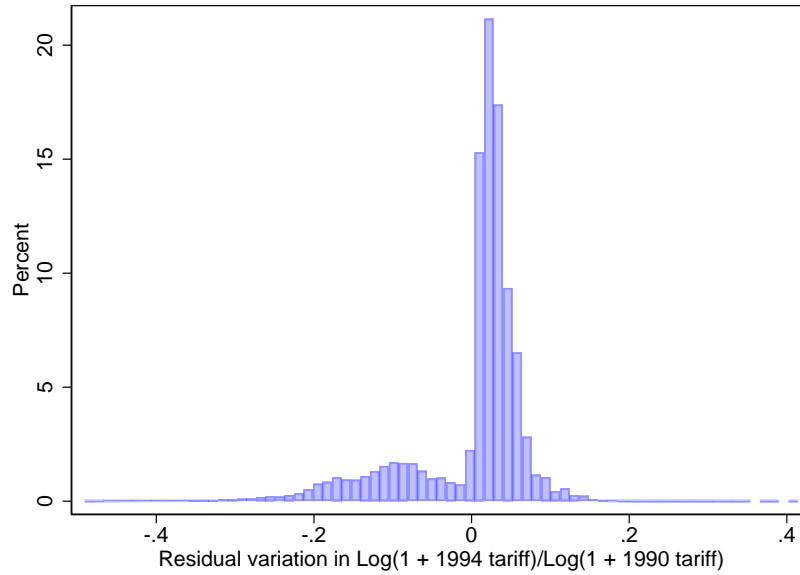
Note: This figure plots import tariff reductions from Brazil's 1990-1994 import tariff reform. See Section 3.2 for details.

Figure A.11: Variation in import tariff reductions across firms

Panel A: Cross-sector tariff change variation

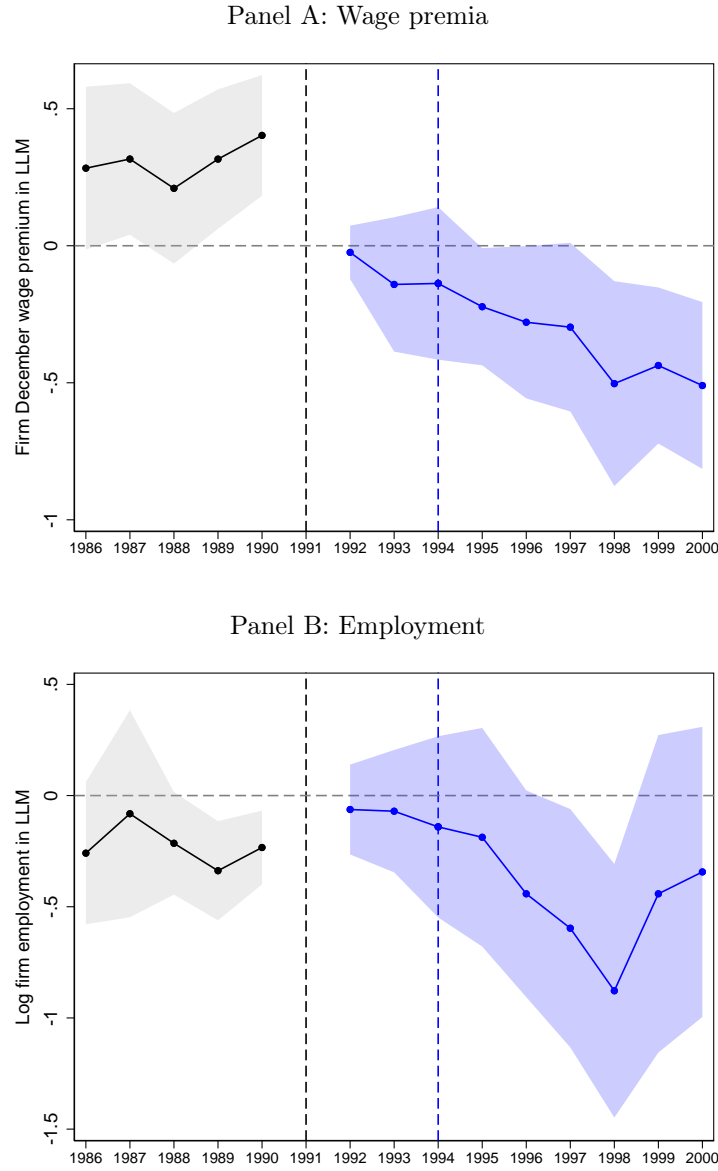


Panel B: Residual cross-firm tariff change variation



Note: This figure shows the variation in tariff changes at the CNAE95 level (285 tradable sector sectors) induced by Brazil's 1990s import import tariff reform. Panel A displays the raw data, while Panel B displays the residualized changes from a regression of tariff changes for all firms (included non-tradables, for whom the tariff change is zero) on market fixed effects.

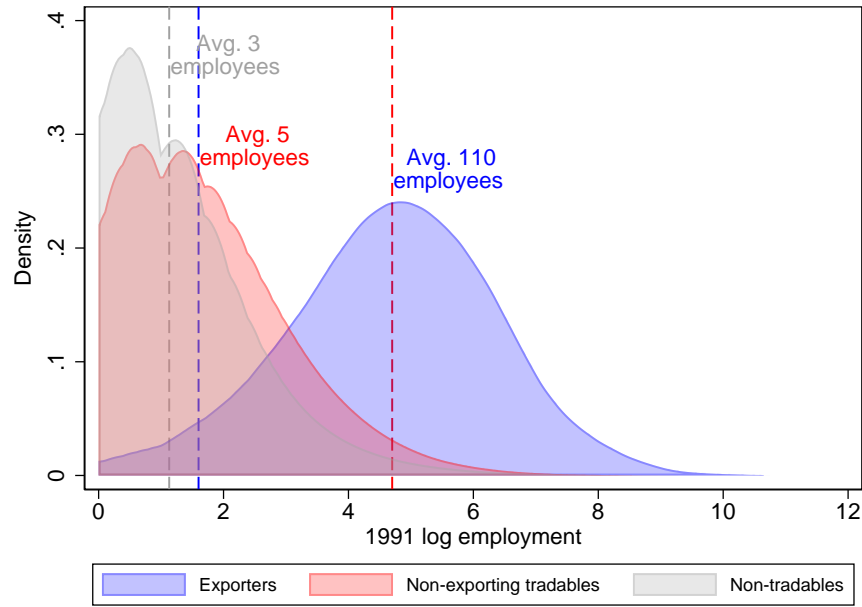
Figure A.12: Effect of tariff reductions on firm-market-level employment and wage premia



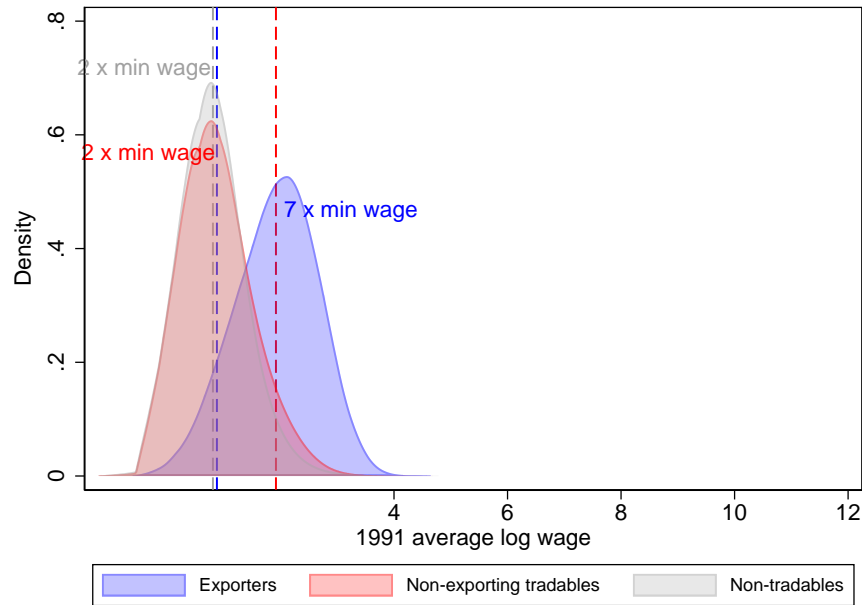
Note: This figure plots coefficients of regressions of firm-level changes in log employment (from each year to the base year of 1991) on $\ln\left(\frac{1+\tau_{1994}}{1+\tau_{1990}}\right)$, which is the firm-level change in import competition exposure, separately estimated for each year. Dotted lines indicate the beginning and end of the tariff reductions reform. So that all differences reflect a change from a future year to a past year, for the pre-liberalization years the outcome is the 1991 log employment minus each respective year's log employment, whereas for the post-reform years the outcome is each respective year's log employment minus the 1991 log employment. All regressions are weighted by 1991 firm employment. Standard errors are clustered at the sector level.

Figure A.13: pre-liberalization distribution of firm size and wages

Panel A: Distributions of firm log employment

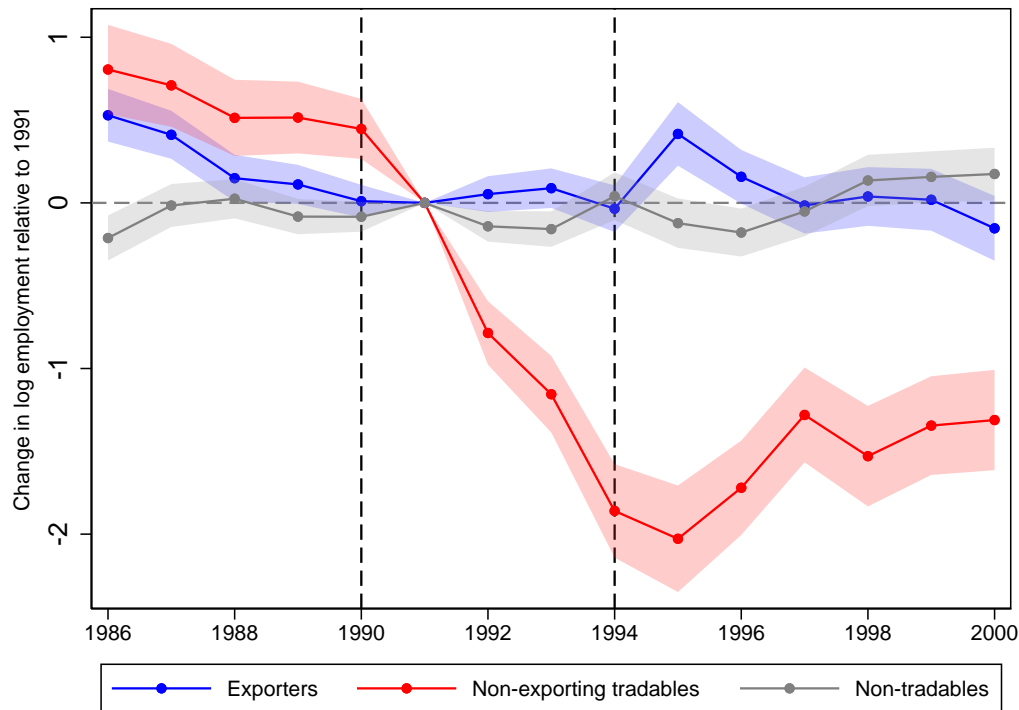


Panel B: Distributions of firm average log wage



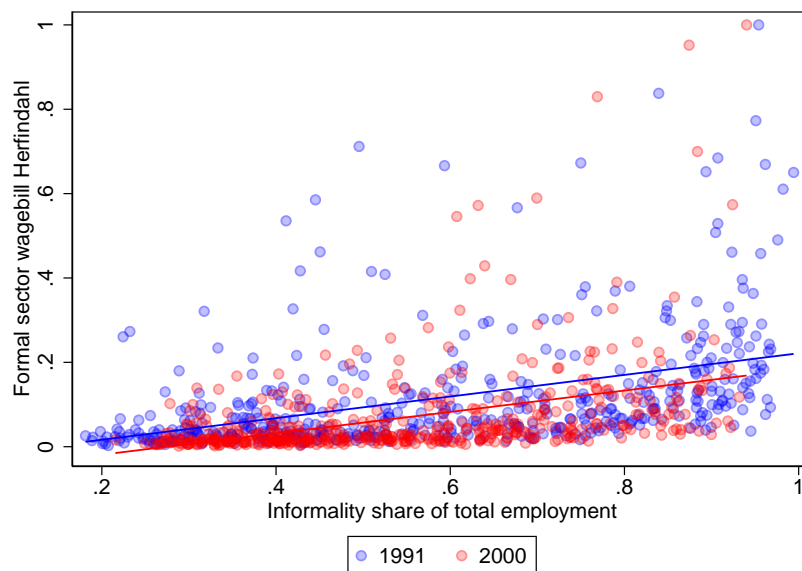
Note: This figure plots pre-liberalization distributors of firm log employment and log December monthly wages for exporters, non-exporters, and non-tradables. Wages are reported as multiples of the national minimum wage.

Figure A.14: Effect of import competition on employment of exporters vs. other firms



Note: This figure plots coefficients of three regressions about the cumulative effect of the change in import competition exposure: on changes in log employment of exporters; on changes in log employment of non-exporting tradables; and on changes in log employment of non-tradables. Each point is a ζ_k coefficient from equation 12. Dotted lines indicate the beginning and end of the tariff reductions reform. So that all differences reflect a change from a future year to a past year, for the pre-liberalization years the outcome is the 1991 log employment minus each respective year's log employment, whereas for the post-reform years the outcome is each respective year's log employment minus the 1991 log employment. All regressions are weighted by 1991 employment. Standard errors are two-way clustered by microregion and occupation group.

Figure A.15: Regional concentration vs. informality



Note: This figure plots microregion-level concentration measures computed from RAIS against microregion-level measures of informality share from the 1990 and 2000 census. Census data was obtained from the supplemental materials to Dix-Carneiro and Kovak (2017).

Table A.1: Local labor market descriptive statistics

	Mean	Market percentile				
		10th	25th	50th	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Total market employment	698	6	16	61	262	1,006
Tradables	293	0	3	20	101	416
Exporters	255	0	1	10	69	333
Non-tradables	405	6	13	41	161	590
Numer of firms	116	3	6	16	55	183
Number of exporters	18	0	1	2	8	26
Payroll Herfindahl (based on December wage premium)	0.28	0.04	0.09	0.21	0.40	0.64
Payroll Herfindahl (based on December wage)	0.29	0.04	0.10	0.21	0.41	0.65
Employment Herfindahl	0.23	0.03	0.06	0.16	0.33	0.56
Average December wage (multiples of min. wage)	5.86	1.67	2.35	3.85	6.92	12.35
Average December wage premium (multiples of min. wage)	2.48	1.11	1.47	2.07	3.03	4.40
<u>Δ Import Competition Exposure</u>	12%	0%	5%	13%	18%	23%

Note: This table presents descriptive statistics across 21,242 Brazilian local labor markets defined as microregion \times occupation group pairs. Means are unweighted.

Table A.2: Average payroll Herfindahl across local labor markets

	1991 (1)	1997 (2)
Payroll Herfindahl (based on December wage premium)		
Unweighted average	0.283	0.228
Weighted average (by market employment shares)	0.078	0.061
Weighted average (by market payroll shares)	0.080	0.064

Note: This table presents country-level weighted average payroll concentration measures for alternative weights.

Table A.3: Workers' labor market transition probabilities conditional on switching firms

Total workers transitioning to different firm in 1990-1991	1,055,205
<i>Percent staying in...</i>	
Microregion (486 groups of municipalities)	79%
Occupational group (CBO94 / 2-digit / 65 groups)	50%
<i>Local labor market: Microregion x Occupational group cell</i>	40%
Economic sector group (CNAE95 / 2-digit / 59 groups)	33%
<i>Microregion x Economic sector group cell</i>	26%
Occupation (CBO94 / 5-digit / 2,357 occupations)	29%
Sub-sector (CNAE95 / 5-digit / 614 sub-sectors)	18%

Note: This table presents statistics on the probability that a worker remains in the same (microregion, occupation group, etc.) conditional on the worker having switched firms. All probabilities are conditional on workers remaining in the formal sector.

Table A.4: Effect of trade on local labor markets: robustness to boundary

	Main specification (1)	Local labor market is microregion (2)
<i>Panel A: Labor market concentration</i>		
Δ Payroll Herfindahl (based on wage premium)	0.213 (0.017)	0.102 (0.046)
Δ Payroll Herfindahl	0.213 (0.017)	0.110 (0.064)
Δ Employment Herfindahl	0.247 (0.016)	0.058 (0.056)
<i>Panel B: Log number of firms and log employment</i>		
Δ Log number of firms	-0.549 (0.045)	-0.367 (0.208)
Δ Log total employment	-0.440 (0.064)	-0.338 (0.335)
<i>Panel C: Log wage premium</i>		
Δ Log wage premium	0.029 (0.031)	0.116 (0.131)
Δ De-trended log wage premium	-0.141 (0.031)	0.106 (0.131)
Observations	296,400	7,125
Local labor markets	19,760	475

Note: See notes to Table 1.

Table A.5: Effect of trade on local labor markets: robustness to shock

	Main specification (1)	ICE weights are firms' base year payroll shares (2)	ICE weights are firms' base year employment shares (3)	ICE tariff shocks are firms' effective tariff protection (4)
<i>Panel A: Labor market concentration</i>				
Δ Payroll Herfindahl (based on wage premium)	0.213 (0.017)	0.259 (0.020)	0.278 (0.020)	0.119 (0.011)
Δ Payroll Herfindahl	0.213 (0.017)	0.259 (0.020)	0.277 (0.020)	0.121 (0.012)
Δ Employment Herfindahl	0.247 (0.016)	0.303 (0.019)	0.329 (0.020)	0.141 (0.011)
<i>Panel B: Log number of firms and log employment</i>				
Δ Log number of firms	-0.549 (0.045)	-0.673 (0.050)	-0.736 (0.052)	-0.309 (0.030)
Δ Log total employment	-0.440 (0.064)	-0.527 (0.073)	-0.577 (0.076)	-0.225 (0.044)
<i>Panel C: Log wage premium</i>				
Δ Log wage premium	0.029 (0.031)	0.037 (0.035)	0.046 (0.037)	0.059 (0.021)
Δ De-trended log wage premium	-0.141 (0.031)	-0.156 (0.035)	-0.150 (0.037)	-0.090 (0.021)
Observations	296,400	296,400	296,400	296,400
Local labor markets	19,760	19,760	19,760	19,760

Note: See notes to Table 1.

Table A.6: Effect of trade on local labor markets: robustness to clustering

	Main specification (1)	Two-way clustered by microregion and occupational group (2)
<i>Panel A: Labor market concentration</i>		
Δ Payroll Herfindahl (based on wage premium)	0.213 (0.017)	0.213 (0.029)
Δ Payroll Herfindahl	0.213 (0.017)	0.213 (0.028)
Δ Employment Herfindahl	0.247 (0.016)	0.247 (0.028)
<i>Panel B: Log number of firms and log employment</i>		
Δ Log number of firms	-0.549 (0.045)	-0.549 (0.131)
Δ Log total employment	-0.440 (0.064)	-0.440 (0.153)
<i>Panel C: Log wage premium</i>		
Δ Log wage premium	0.029 (0.031)	0.029 (0.068)
Δ De-trended log wage premium	-0.141 (0.031)	-0.141 (0.068)
Observations	296,400	296,400
Local labor markets	19,760	19,760

Note: See notes to Table 1.

Table A.7: Effect of trade on local labor markets: robustness to weights

	Main specification (1)	Weighted by local labor market 1991 employment (2)
<i>Panel A: Labor market concentration</i>		
Δ Payroll Herfindahl (based on wage premium)	0.213 (0.017)	0.156 (0.032)
Δ Payroll Herfindahl	0.213 (0.017)	0.162 (0.034)
Δ Employment Herfindahl	0.247 (0.016)	0.098 (0.018)
<i>Panel B: Log number of firms and log employment</i>		
Δ Log number of firms	-0.549 (0.045)	-0.657 (0.159)
Δ Log total employment	-0.440 (0.064)	-0.187 (0.142)
<i>Panel C: Log wage premium</i>		
Δ Log wage premium	0.029 (0.031)	-0.004 (0.071)
Δ De-trended log wage premium	-0.141 (0.031)	-0.332 (0.071)
Observations	296,400	296,400
Local labor markets	19,760	19,760

Note: See notes to Table 1.

Table A.8: Within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$: alternative samples

		Robustness to key alternative samples	
	Main specification (1)	Unique producers (2)	Local labor market defined as microregion (3)
Panel A: First stage			
Δ Firm log employment in LLM	-0.554 (0.044)	-0.289 (0.043)	-0.417 (0.037)
First stage F	158.497	44.304	124.666
Panel B: Reduced form			
Δ Firm's wage premium in LLM	-0.545 (0.024)	-0.327 (0.044)	-0.404 (0.017)
Panel C: 2SLS			
Labor supply within-market cross-firm inverse elasticity of substitution	0.985 (0.089)	1.134 (0.224)	0.969 (0.092)
Implied upper bound on wage take-home share	50%	47%	51%
Observations	854,068	693,360	440,966
Firms	344,066	301,666	420,246
Local labor markets	15,717	13,131	474

Note: See notes to Table 2. Column (1) includes all firms in a microregion \times occupational group cell. Column (2) is restricted to the set of unique producers (plus non-tradable sector firms) in a microregion \times occupational group cell. Column (3) expands the definition of a local labor market to microregions only.

Table A.9: Within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$: robustness to clustering

	Main specification (Clustered by firm) (1)	Clustered by local labor market (2)	Clustered by sector (3)
<i>Panel A: First stage</i>			
Δ Firm log employment in LLM	-0.554 (0.044)	-0.554 (0.070)	-0.554 (0.107)
First stage F	158.497	62.719	26.720
<i>Panel B: Reduced form</i>			
Δ Firm wage premium in LLM	-0.545 (0.024)	-0.545 (0.104)	-0.545 (0.103)
<i>Panel C: 2SLS</i>			
Labor supply within-market cross-firm inverse elasticity of substitution	0.985 (0.089)	0.985 (0.207)	0.985 (0.149)
Observations	854,068	854,068	854,068
Firms	344,066	344,066	344,066
Local labor markets	15,717	15,717	15,717

Note: See notes to Table 2.

Table A.10: Within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$: robustness to wage and shock

	Main specification (December wage premium and tariff) (1)	Using December average wage (2)	Using effective rate of protection (3)
<i>Panel A: First stage</i>			
Δ Firm log employment in LLM	-0.554 (0.044)	-0.554 (0.044)	-0.358 (0.035)
First stage F	158.497	158.497	107.143
<i>Panel B: Reduced form</i>			
Δ Firm wage premium in LLM	-0.545 (0.024)	-0.527 (0.025)	-0.351 (0.019)
<i>Panel C: 2SLS</i>			
Labor supply within-market cross-firm inverse elasticity of substitution	0.985 (0.089)	0.952 (0.088)	0.980 (0.108)
Implied upper bound on wage take-home share	50%	51%	50%
Observations	854,068	854,068	851,662
Firms	344,066	344,066	343,558
Local labor markets	15,717	15,717	15,665

Note: See notes to Table 2.

Table A.11: Cross-market inverse elasticity of substitution $\frac{1}{\theta}$: robustness to alternative samples

		Robustness to key alternative samples	
	Main specification	Unique producers	Local labor market is microregion
	(1)	(2)	(3)
Panel A: First stage			
Δ LLM employment index	-0.396 (0.032)	-0.120 (0.042)	-0.224 (0.133)
First stage F	150.752	8.156	2.819
Panel B: Reduced form			
Δ LLM wage premium index	-0.108 (0.051)	-0.097 (0.065)	-0.034 (0.122)
Panel C: 2SLS			
$\frac{1}{\theta} - \frac{1}{\eta}$	0.272 (0.131)	0.809 (0.602)	0.153 (0.536)
Panel D: Cross-market inverse elasticity of substitution			
$\frac{1}{\theta}$	1.257 (0.096)	1.942 (0.559)	1.122 (0.528)
Implied lower bound on wage take-home share	44%	34%	47%
Observations (Local labor markets)	15,717	13,131	474

Note: See notes to Table 3. Column (1) includes all firms in a microregion \times occupational group cell. Column (2) uses $\frac{1}{\eta}$ estimates based on the set of unique producers in a microregion \times occupational group cell. Column (3) expands the definition of a local labor market to microregions only.

Table A.12: Cross-market inverse elasticity of substitution $\frac{1}{\theta}$: robustness to clustering

	Main specification (1)	Two-way clustered by microregion and occupational group (2)
<i>Panel A: First stage</i>		
Δ LLM employment index	-0.396 (0.032)	-0.396 (0.076)
First stage F	150.752	27.008
<i>Panel B: Reduced form</i>		
Δ LLM wage premium index	-0.108 (0.051)	-0.108 (0.075)
<i>Panel C: 2SLS</i>		
$\frac{1}{\theta} - \frac{1}{\eta}$	0.272 (0.131)	0.272 (0.190)
<i>Panel D: Cross-market inverse elasticity of substitution</i>		
$\frac{1}{\theta}$	1.257 (0.096)	1.257 (0.169)
Implied lower bound on wage take-home share	44%	44%
Observations (Local labor markets)	15,717	15,717

Note: See notes to Table 3. Column (1) clusters standard errors at the local labor market level.

Table A.13: Cross-market inverse elasticity of substitution $\frac{1}{\theta}$: robustness to wage

	Main specification (1)	Using average December wage (2)
<i>Panel A: First stage</i>		
Δ LLM employment index	-0.396 (0.032)	-0.403 (0.034)
First stage F	150.752	136.488
<i>Panel B: Reduced form</i>		
Δ LLM wage premium index	-0.108 (0.051)	-0.094 (0.050)
<i>Panel C: 2SLS</i>		
$\frac{1}{\theta} - \frac{1}{\eta}$	0.272 (0.131)	0.234 (0.125)
<i>Panel D: Cross-market inverse elasticity of substitution</i>		
$\frac{1}{\theta}$	1.257 (0.096)	1.186 (0.089)
Implied lower bound on wage take-home share	44%	46%
Observations (Local labor markets)	15,717	15,717

Note: See notes to Table 3.

Table A.14: Nature of employment reallocation: exporters vs. other firms

	Δ Import Competition Exposure	Effect per 10% increase in ICE
	(1)	(2)
Δ Log total employment	-0.440 (0.064)	-4.400 (0.640)
Δ Exporter log employment	-0.016 (0.087)	-0.156 (0.867)
Δ Non-exporting tradables log employment	-1.280 (0.146)	-12.804 (1.461)
Δ Non-tradables log employment	-0.052 (0.077)	-0.518 (0.765)
Observations	296,400	296,400
Local labor markets	19,760	19,760

Note: See notes to Table 1.

Table A.15: Nature of employment reallocation: exporters vs. large firms

	Δ Firm log employment (1)	Δ Firm log wage premium (2)
Log tariff shock	-0.492 (0.154)	-1.176 (0.270)
Log tariff shock x exporter	0.509 (0.155)	1.279 (0.333)
Log tariff shock x large firm	-1.103 (0.413)	-0.408 (0.215)
Log tariff shock x exporter x large firm	0.979 (0.553)	-0.212 (0.376)
Observations	2,203,009	2,203,009
Firms	792,318	792,318
Local labor markets	25,052	25,052

Note: This table presents estimates from regressions of the long difference in firm outcomes—log employment in column (1) and firm log wage premium in column (2)—on the listed regressors, estimated in the sample of all firms with any employees as of the baseline year of 1991. Long differences are taken from the post-reform mid-point year of 1997 back to the baseline year of 1991, and use the inverse hyperbolic sine instead of log to account for firms that exit by 1997. Log wages of exiters are imputed as the smallest log wage offered in the exiting firms' local labor market. The firm-level log tariff shock is defined in equation 17, such that a positive coefficient indicates an increase in the outcome. A firm is "large" if its baseline employment in the local labor market is greater than the 90th percentile of around 20 employees per market. Export status is measured as of the baseline year of 1991. All regressions include controls for exporter status, large firm status, and local labor market fixed effects. Standard errors are clustered at the firm level.

B Data and Methods Appendix

Data on workers and firms: RAIS

Overview. I use Brazil’s *Relação Anual de Informações Sociais* (RAIS) for years 1986 to 2000 as my source of information on workers and firms. RAIS is an administrative employer-employee linked dataset collected by the federal government for the purposes of administering workers’ social security. Thus, RAIS covers all workers with signed worker cards (*Carteira do Trabalho*), namely the entirety of formal sector employment. Firms report RAIS once a year, reporting all workers who ever worked for the firm in the prior calendar year. Firms are required to report a rich set of information about each employment contract (e.g., occupation, admission date, separation date, etc.), as well as worker demographics (i.e., education, date of birth, and gender), separate by each establishment. The municipality of each establishment as well as the economic sector of the firm are also reported.

Wages. RAIS includes two wage variables for years 1986-2000: average monthly earnings and December monthly earnings. Both variables are reported as multiples of the national minimum wage.

Occupation codes. RAIS’ occupation codes are 5-digit variables “CBO” (prior to 1994) and “CBO94” (1994 onwards). I focus on the first 2 digits to group workers into occupation groups. Both variables share the same data dictionary, with the only difference between them being phased-out and phased-in occupation codes. I have compiled a complete list of all raw occupation codes, along with the total number of workers in each of them, labels, and flags for which codes were either “phased-out” or phased-in, which I identified based on whether the number of workers changing by more than 100 times between any two years. I then re-classified the first two digits of all phased-out and phased-in codes as “99 - Other occupations,” a reclassification that affects roughly 10% of all workers.

Sector codes. RAIS’ finest sector codes for 1986-2000 are 4-digit “IBGESUBATIVIDADE” (prior to 1995) and 5-digit “CNAE95” (1995 onwards). I focus on the 5-digit CNAE95 codes to map tariff shocks to firms in RAIS. For firms that exit the data prior to reporting any CNAE95 codes, I assign a CNAE95 code using a correspondence table I constructed using the pre-1995 and post-1995 codes of firms in business in both periods. To each IBGESUBATIVIDADE code I assign the most commonly reported CNAE95 code. Finally, throughout all years I use the first CNAE95 code ever reported by a firm as its official CNAE95 code.

Sample restrictions. I focus on workers employed as of December 31 of each year, and aged 18-65, and with positive December earnings. I exclude all workers in the public sector or

with unknown sector. To make sure all public sector workers are excluded, I further exclude workers whose employer’s economic activity was not marked as government, but which exert public sector occupations (i.e., Diplomats, Civil servants, and Post office). Finally, following Dix-Carneiro and Kovak (2017) I exclude from all analyses the free trade zone of Manaus.

Data on tariff shocks: TRAINS

I use tariff data from UNCTAD’s Trade Analysis Information System (TRAITS), which I download from the World Integrated Trade Solution (WITS)’s website.⁵⁹ I focus on the raw tariff data are available for Brazil at the 8-digit HS product level for years 1988 (the first year the data are available) through 2000. As outlined in Section 4, I compute a firm’s tariff reduction shock is the change in log one plus a firms’ CNAE95 sector code’s nominal tariff between years 1990 and 1994. To map the product-level data to CNAE95, which is an economic activity code, I use the following correspondence tables: a) correspondences between 8-digit product-level HS codes and 4-digit economic activity codes ISIC version 3.1 for each year, downloaded from WITS; b) correspondences between ISIC version 3.1 and CNAE95, downloaded from Brazil’s Comissão Nacional de Classificação (CONCLA) website.⁶⁰ The result is a dataset of annual nominal tariffs. CNAE95 level-tariffs are then computed as simple averages of nominal tariffs across all product codes. For robustness exercises, I also compute each CNAE95’s effective rate of protection (ERP), which net out the effect of tariffs on inputs. I calculate ERPs using Brazil’s 1985 intersectoral technical coefficients matrix (“Tabela 20”), which is available at Nível 50 from Brazil’s national accounts website.⁶¹

Other data

List of exporters. I classify firms as exporters during the reform period (1990-1994) by matching the list of exporters during that period to RAIS using firms’ unique identifiers (CNPJ). The list of exporters was provided by the (extinct as of 2019) Ministry of Development, sector, and Foreign Trade, currently a part of the Ministry of the Economy, in October 2018.

Census. I produced Appendix Figure A.15 with data on informality at the microregion

⁵⁹See <https://wits.worldbank.org/>.

⁶⁰See <https://concla.ibge.gov.br/classificacoes/correspondencias/atividades-economicas>.

⁶¹See <https://www.ibge.gov.br/estatisticas-novoportal/economicas/contas-nacionais/9085-matriz-de-insumo-produto.html?&t=downloads>.

level from the 1991 and 2000 census, which I obtained from Dix-Carneiro and Kovak (2017)'s supplemental materials.

Methods: wage premia regressions

I estimate firm wage premia as firm fixed effects from a regression of log december earnings on firm fixed effects and the same controls as Dix-Carneiro and Kovak (2017), namely: a dummy for female; 4 age group dummies (25-29; 30-39; 40-49, 50-64); 8 education group dummies (primary school, incomplete primary school, middle school, incomplete middle school, high school, incomplete high school, college, incomplete college). The omitted category is therefore males aged 18-24 with no formal education. I estimate local labor market wage premia as local labor market fixed effects from a regression of worker log december earnings on local labor market fixed effects and the same demographic controls as in the firm wage premia regressions.

Methods: effects relative to trend

For wage premia, where positive pre-trends are observed, I also report treatment effects of import competition exposure relative to trend. These effects are estimated as the $\tilde{\beta}$ coefficients from the following regression:⁶²

$$\Delta \tilde{Y}_{mt} = \sum_{k \neq 1991} \tilde{\zeta}_k (\Delta ICE_m \times 1_{t=k}) + \tilde{\delta}_m + \tilde{\delta}_t + \tilde{\epsilon}_{mt} \quad (24)$$

⁶²For didactic purposes, I express the fixed effects in regression equation 24 and in its non-detrended counterpart (e.g, equation 12) as simply δ_m and δ_t , which makes it easier for the reader to see how this regression is a stacked difference-in-differences specification. In practice, the (equivalent for ζ_k) regressions I actually estimate are of the form:

$$\Delta Y_{mt} = \alpha + \sum_{k \neq 1991} \zeta_k (\Delta ICE_m \times 1_{t=k}) + \sum_{k \neq 1991} \delta_k (1_{t=k}) + \sum_{m \neq b} \delta_m + \epsilon_{mt}$$

where the constant α is included in the estimation, the base year fixed effect δ_{1991} is omitted, and one market fixed effect δ_b is also omitted. I implement this using the command `reghdfe` in Stata, absorbing market fixed effects only (i.e., no standard errors are estimated for those and one is automatically omitted), and manually add regressors for all year fixed effects except for the base year. While producing identical point estimates for ζ_k as equation 12, this approach has the advantage of giving, via estimates for the constant and year fixed effects relative to base year, a descriptive account of what is happening to the least intensively treated markets over time relative to the base year, which is helpful for interpretation.

where $\Delta\tilde{Y}_{mt} = \Delta Y_{mt} - \hat{\varphi}(\Delta ICE_m \times t)$ is the predicted outcome from the following regression, which I estimate using the pre-treatment years 1986-1990 only:

$$\Delta Y_{mt} = \varphi(\Delta ICE_m \times t) + \nu_m + \nu_t + \nu_{mt} \quad (25)$$

in which ν_m and ν_t are local labor market and year fixed effects, respectively. Causal interpretation of the $\tilde{\beta}_k$ coefficients rely on the identification assumption that more affected markets would have continued to follow the same pre-liberalization growth trend relative to least affected markets.

C Model Appendix

This Appendix provides detailed derivations for various expressions in Section 2.

C.1 Derivation of labor supply equation

Consider an economy consisting of a continuum of homogenous workers j , a large but finite number of local labor markets m , and a finite number of firms z within each local labor market. Each worker chooses to which firm-market pair zm they provide h_{zm}^j units of labor by minimizing their indirect disutility of work V_{zm} subject to making reservation earnings $y^j \sim F(y)$:

$$\begin{aligned} \min_{zm} V_{zm}^j &= \ln l_{zm}^j + \ln \xi_m + \ln \xi_{zm} - \xi_{zm}^j \\ \text{s.t. } l_{zm}^j w_{zm} &\geq y_j \end{aligned}$$

where ξ_{zm}^j is an idiosyncratic taste for working at firm z in market m , and ξ_m and ξ_{zm} are taste shifters common to all workers. This is equivalent to

$$\max_{zm} \ln w_{zm} - \ln y_j - \ln \xi_m - \ln \xi_{zm} + \xi_{zm}^j$$

Now suppose ξ_{zm}^j follows the following Gumbel distribution, a member of the General Extreme Value (GEV) family:

$$G(\{\xi_{zm}^j\}) = \exp \left[- \sum_m \left(\sum_{z \in B_m} e^{-(1+\frac{\sigma}{1-\sigma})\xi_{zm}^j} \right)^{\frac{1+\frac{\varphi}{1-\sigma}}{1+\frac{\sigma}{1-\sigma}}} \right]$$

where $0 \leq \sigma < 1$ is the index of similarity across firms within a market, $0 \leq \varphi < 1$ is the index of similarity across markets, and B_m is the set of firms in market m .

The probability that worker j chooses firm z in market m is $P(\xi_{zm}^j > \ln w_{zm} - \ln y_j - \ln \xi_m - \ln \xi_{zm})$, which can be decomposed as:

$$P_{zm}^j = P(z|B_m) P(B_m) \quad \forall j$$

where $P(z|B_m)$ is the probability of choosing firm z conditional on choosing market m with set B_m of firms, and $P(B_m)$ is the probability of choosing market m . By the results in McFadden (1978), P_{zm} can be computed as:

$$\begin{aligned} P(z|B_m) &= \frac{\exp[(\ln w_{zm} - \ln y^j - \ln \xi_m - \ln \xi_{zm}) / (1 - \sigma)]}{\sum_{k \in B_n} \exp[(\ln w_{km} - \ln y^j - \ln \xi_m - \ln \xi_{km}) / (1 - \sigma)]} \\ &= \frac{\exp \left[\left(\ln w_{zm}^{\frac{1}{1-\sigma}} - \ln y^{j \frac{1}{1-\sigma}} - \ln \xi_m^{\frac{1}{1-\sigma}} - \ln \xi_{zm}^{\frac{1}{1-\sigma}} \right) \right]}{\sum_{k \in B_m} \exp \left[\left(\ln w_{km}^{\frac{1}{1-\sigma}} - \ln y^{j \frac{1}{1-\sigma}} - \ln \xi_m^{\frac{1}{1-\sigma}} - \ln \xi_{km}^{\frac{1}{1-\sigma}} \right) \right]} \\ &= \frac{\left(\frac{w_{zm}}{y^j \xi_m \xi_{zm}} \right)^{\frac{1}{1-\sigma}}}{\sum_{k \in B_n} \left(\frac{w_{km}}{y^j \xi_m \xi_{km}} \right)^{\frac{1}{1-\sigma}}} \\ &= \frac{\left(\frac{w_{zm}}{\xi_{zm}} \right)^{\frac{1}{1-\sigma}}}{\sum_{k \in B_n} \left(\frac{w_{km}}{\xi_{km}} \right)^{\frac{1}{1-\sigma}}} \end{aligned}$$

and

$$\begin{aligned}
P(B_m) &= \frac{\left\{ \sum_{z \in B_m} \exp [(\ln w_{zm} - \ln y^j - \ln \xi_m - \ln \xi_{zm}) / (1 - \sigma)] \right\}^{\frac{1-\sigma}{1-\varphi}}}{\sum_l \left\{ \sum_{k \in B_l} \exp [(\ln w_{kl} - \ln y^j - \ln \xi_l - \ln \xi_{kl}) / (1 - \sigma)] \right\}^{\frac{1-\sigma}{1-\varphi}}} \\
&= \frac{\left[\sum_{z \in B_m} \left(\frac{w_{zm}}{y^j \xi_m \xi_{zm}} \right)^{\frac{1}{1-\sigma}} \right]^{\frac{1-\sigma}{1-\varphi}}}{\sum_l \left[\sum_{k \in B_l} \left(\frac{w_{km}}{y^j \xi_m \xi_{km}} \right)^{\frac{1}{1-\sigma}} \right]^{\frac{1-\sigma}{1-\varphi}}} \\
&= \frac{\left[\left(\frac{1}{\xi_m} \right)^{\frac{1}{1-\sigma}} \sum_{z \in B_m} \left(\frac{w_{zm}}{\xi_{zm}} \right)^{\frac{1}{1-\sigma}} \right]^{\frac{1-\sigma}{1-\varphi}}}{\sum_l \left[\left(\frac{1}{\xi_l} \right)^{\frac{1}{1-\sigma}} \sum_{k \in B_l} \left(\frac{w_{kl}}{\xi_{kl}} \right)^{\frac{1}{1-\sigma}} \right]^{\frac{1-\sigma}{1-\varphi}}}
\end{aligned}$$

Putting them together

$$P_{zm}^j = \frac{\left(\frac{w_{zm}}{\xi_{zm}} \right)^{\frac{1}{1-\sigma}}}{\sum_{k \in B_n} \left(\frac{w_{km}}{\xi_{km}} \right)^{\frac{1}{1-\sigma}}} \times \frac{\left[\left(\frac{1}{\xi_m} \right)^{\frac{1}{1-\sigma}} \sum_{z \in B_m} \left(\frac{w_{zm}}{\xi_{zm}} \right)^{\frac{1}{1-\sigma}} \right]^{\frac{1-\sigma}{1-\varphi}}}{\sum_l \left[\left(\frac{1}{\xi_l} \right)^{\frac{1}{1-\sigma}} \sum_{k \in B_l} \left(\frac{w_{kl}}{\xi_{kl}} \right)^{\frac{1}{1-\sigma}} \right]^{\frac{1-\sigma}{1-\varphi}}} \quad \forall j$$

Let $\eta \equiv \frac{\sigma}{1-\sigma} > 0$, $\theta \equiv \frac{\varphi}{1-\varphi} > 0$, and denote $P_{zm}^j = P_{zm}$ for simplicity. Then:

$$P_{zm} = \frac{\left(\frac{w_{zm}}{\xi_{zm}} \right)^{1+\eta}}{\sum_{k \in B_n} \left(\frac{w_{km}}{\xi_{km}} \right)^{1+\eta}} \times \frac{\left[\left(\frac{1}{\xi_m} \right)^{1+\eta} \sum_{z \in B_m} \left(\frac{w_{zm}}{\xi_{zm}} \right)^{1+\eta} \right]^{\frac{1+\theta}{1+\eta}}}{\sum_l \left[\left(\frac{1}{\xi_l} \right)^{1+\eta} \sum_{k \in B_l} \left(\frac{w_{kl}}{\xi_{kl}} \right)^{1+\eta} \right]^{\frac{1+\theta}{1+\eta}}}$$

Finally, define the following wage indices:

$$W_m \equiv \left[\sum_z \left(\frac{w_{zm}}{\xi_{zm}} \right)^{1+\eta} \right]^{\frac{1}{1+\eta}}, \quad W \equiv \left[\sum_m \left(\frac{W_m}{\xi_m} \right)^{1+\theta} \right]^{\frac{1}{1+\theta}}$$

Then

$$P_{zm}^j = \frac{\left(\frac{w_{zm}}{\xi_{zm}} \right)^{1+\eta}}{W_m^{1+\eta}} \times \frac{\left(\frac{W_m}{\xi_m} \right)^{1+\theta}}{W^{1+\theta}} = \left(\frac{w_{zm}/\xi_{zm}}{W_m} \right)^{1+\eta} \times \left(\frac{W_m/\xi_m}{W} \right)^{1+\theta} \quad (26)$$

With equation 26 at hand, total labor supplied to firm z in market m can be found

by integrating probabilities P_{zm}^j (times $h_{zm}^j = y^j/w_{zm}$ supplied by each worker) over the continuum of workers:

$$l_{zm} = \int_0^1 P_{zm}^j \left(\frac{y^j}{w_{zm}} \right) dF(y) = w_{zm}^{-1} P_{zm} Y \quad (27)$$

where $Y \equiv \int_0^1 y^j dF(y)$ is the country-level labor income. To obtain an expression for l_{zm} that is a function of w_{zm} , parameters, and market-level aggregates, I define the following employment indices:

$$L_m \equiv \left[\sum_z (\xi_{zm} l_{zm})^{\frac{1+\eta}{\eta}} \right]^{\frac{\eta}{1+\eta}}, \quad L \equiv \left[\sum_m (\xi_m L_m)^{\frac{1+\theta}{\theta}} \right]^{\frac{\theta}{1+\theta}}$$

which together with equation 27 and previously defined wage indices imply $Y = \sum_{zm} w_{zm} l_{zm} = WL$ and

$$\begin{aligned} l_{zm} &= w_{zm}^{-1} P_{zm} Y \\ &= w_{zm}^{-1} \left[\left(\frac{w_{zm}}{\xi_{zm} W_m} \right)^{1+\eta} \times \left(\frac{W_m}{\xi_m W} \right)^{1+\theta} \right] Y \\ &= \cancel{w_{zm}^{-1}} \left[\left(\frac{\cancel{w_{zm}}}{\xi_{zm} \cancel{W_m}} \right) \left(\frac{w_{zm}}{\xi_{zm} W_m} \right)^{\eta} \times \left(\frac{W_m}{\xi_m W} \right)^{\theta} \left(\frac{\cancel{W_m}}{\xi_m \cancel{W}} \right) \right] \cancel{W} L \\ &= \xi_{zm} \xi_m \left(\frac{w_{zm}/\xi_{zm}}{W_m} \right)^{\eta} \left(\frac{W_m/\xi_m}{W} \right)^{\theta} L \end{aligned}$$

Rearranging:

$$l_{zm} = L \left(\frac{w_{zm}}{W_m} \right)^{\eta} \left(\frac{W_m}{W} \right)^{\theta} (\xi_{zm}^{1+\eta} \xi_m^{1+\theta})^{-1} \quad (28)$$

C.2 Other proofs and derivations

C.2.1 Equation 3: $w_{zm} = W \left(\frac{l_{zm}}{L_m} \right)^{\frac{1}{\eta}} \left(\frac{L_m}{L} \right)^{\frac{1}{\theta}} \xi_{zm}^{1+\frac{1}{\eta}} \xi_m^{1+\frac{1}{\theta}}$

The inverse function of the residual labor supply equation 2 (same as appendix equation 28) is the wage w_{zm} at which l_{zm} units of labor are supplied to firm z at market m . To check that equation 3 satisfies this criterion, plug it into equation 27 to obtain the identity $l_{zm} = l_{zm}$. I show this in two steps.

First, plug in the expression for w_{zm} into equation 27 to get:

$$\begin{aligned}
l_{zm} &= w_{zm}^{-1} P_{zm} Y \\
&= w_{zm}^{-1} \left(\frac{w_{zm}/\xi_{zm}}{W_m} \right)^{1+\eta} \times \left(\frac{W_m/\xi_m}{W} \right)^{1+\theta} Y \\
&= w_{zm}^\eta \left(\frac{1}{W_m \xi_{zm}} \right)^{1+\eta} \times \left(\frac{W_m/\xi_m}{W} \right)^{1+\theta} Y \\
&= \left[W \left(\frac{l_{zm} \xi_{zm}}{L_m} \right)^{\frac{1}{\eta}} \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m \xi_{zm} \right]^\eta \left(\frac{1/\xi_{zm}}{W_m} \right)^{1+\eta} \times \left(\frac{W_m/\xi_m}{W} \right)^{1+\theta} Y \\
&= \left[W \left(\frac{l_{zm} \xi_{zm}}{L_m} \right)^{\frac{1}{\eta}} \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m \xi_{zm} \right]^\eta \left(\frac{1/\xi_{zm}}{W_m} \right)^\eta \times \left(\frac{W_m/\xi_m}{W} \right)^\theta \cancel{W} L \left(\frac{1/\xi_{zm}}{\cancel{W_m}} \right) \times \left(\frac{\cancel{W_m}/\xi_m}{\cancel{W}} \right) \\
&= l_{zm} \xi_m^\eta \cancel{\xi_{zm}^\eta} \left(\frac{\cancel{\xi_{zm}}}{L_m} \right) \left[W \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \right]^\eta \left(\frac{1/\cancel{\xi_{zm}}}{W_m} \right)^\eta \times \left(\frac{W_m/\xi_m}{W} \right)^\theta \left(\frac{L}{\cancel{\xi_{zm}} \xi_m} \right) \\
&= l_{zm} \left(\frac{\xi_m^\eta}{L_m} \right) \left[W \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \right]^\eta \left(\frac{1}{W_m} \right)^\eta \times \left(\frac{W_m/\xi_m}{W} \right)^\theta \left(\frac{L}{\xi_m} \right) \\
&= l_{zm} \left(\frac{1}{L_m} \right) \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta}{\theta}} \left(\frac{W \xi_m}{W_m} \right)^\eta \times \left(\frac{W_m/\xi_m}{W} \right)^\theta \left(\frac{L}{\xi_m} \right) \\
&= l_{zm} \left(\frac{W \xi_m}{W_m} \right)^\eta \times \left(\frac{W_m/\xi_m}{W} \right)^\theta \left(\frac{L}{L_m \xi_m} \right) \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta}{\theta}} \\
&= l_{zm} \left(\frac{W}{W_m/\xi_m} \right)^\eta \times \left(\frac{W_m/\xi_m}{W} \right)^\theta \left(\frac{L}{L_m \xi_m} \right) \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta}{\theta}} \\
&= l_{zm} \left(\frac{W_m/\xi_m}{W} \right)^{\theta-\eta} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta}{\theta}-1} \\
&= l_{zm} \left(\frac{W}{W_m/\xi_m} \right)^{\eta-\theta} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta-\theta}{\theta}} \\
&= l_{zm} \left(\frac{W}{W_m/\xi_m} \right)^{\eta-\theta} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta-\theta}{\theta}}
\end{aligned}$$

Second, I show that $\left(\frac{W}{W_m/\xi_m} \right)^{\eta-\theta} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta-\theta}{\theta}} = 1$ by expressing the CES wage index W_m as a function of labor and taste shifters, which can be done by first plugging in the expression

for w_{zm} into the definition of W_m :

$$\begin{aligned}
W_m &= \left[\sum_{k \in B_n} \left(\frac{w_{zm}}{\xi_{km}} \right)^{1+\eta} \right]^{\frac{1}{1+\eta}} \\
&= \left[\sum_{k \in B_n} \left(\frac{\left[W \left(\frac{l_{km} \xi_{km}}{L_m} \right)^{\frac{1}{\eta}} \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m \xi_{km} \right]^{1+\eta}}{\xi_{km}} \right)^{\frac{1}{1+\eta}} \right]^{\frac{1}{1+\eta}} \\
&= \left[W^{1+\eta} \left(\frac{1}{L_m} \right)^{\frac{1+\eta}{\eta}} \left[\left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m \right]^{1+\eta} \sum_{k \in B_n} \left(\frac{\left[(l_{km} \xi_{km})^{\frac{1}{\eta}} \xi_{km} \right]^{1+\eta}}{\xi_{km}} \right)^{\frac{1}{1+\eta}} \right]^{\frac{1}{1+\eta}} \\
&= \frac{W}{L_m^{\frac{1}{\eta}}} \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m \left[\sum_{k \in B_n} (l_{km} \xi_{km})^{\frac{1+\eta}{\eta}} \right]^{\frac{1}{1+\eta}} \\
&= \frac{W}{L_m^{\frac{1}{\eta}}} \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m \cancel{L_m^{\frac{1}{\eta}}} \\
&= W \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m
\end{aligned}$$

Thus, $W_m = W \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m$. Recall from the first step that completing the proof requires showing that $\left(\frac{W}{W_m/\xi_m} \right)^{\eta-\theta} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta-\theta}{\theta}} = 1$. Plugging in the expression for W_m into this equation gives:

$$\begin{aligned}
\left(\frac{W}{W_m/\xi_m} \right)^{\eta-\theta} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta-\theta}{\theta}} &= \left(\frac{W}{\left[W \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \xi_m \right] / \xi_m} \right)^{\eta-\theta} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta-\theta}{\theta}} \\
&= \left(\frac{L_m \xi_m}{L} \right)^{-\frac{(\eta-\theta)}{\theta}} \left(\frac{L_m \xi_m}{L} \right)^{\frac{\eta-\theta}{\theta}} \\
&= 1
\end{aligned}$$

which completes the proof that w_{zm} is the inverse function of l_{zm} .

C.2.2 Equation 7: $s_{zm} \equiv \frac{w_{zm}l_{zm}}{\sum_k (w_{km}l_{km})} = \frac{\partial \ln L_m}{\partial \ln l_{zm}}.$

To see why this holds, depart from the definition of the labor market index L_m in Section 2 to derive $\partial \ln L_m / \partial \ln l_{zm}$ as

$$\frac{\partial \ln L_m}{\partial \ln l_{zm}} = \frac{(\xi_{km}l_{km})^{\frac{1+\eta}{\eta}}}{\sum_{j=1}^{N_m} (\xi_{jm}l_{jm})^{\frac{1+\eta}{\eta}}}$$

Now set this aside. Plug in equation 3 to the definition $s_{zm} \equiv w_{zm}l_{zm} / \sum_k (w_{km}l_{km})$ to obtain

$$s_{zm} = \frac{(\xi_{km}l_{km})^{\frac{1+\eta}{\eta}}}{\sum_{j=1}^{N_m} (\xi_{jm}l_{jm})^{\frac{1+\eta}{\eta}}}$$

Therefore, $s_{zm} = \partial \ln L_m / \partial \ln l_{zm}.$

C.2.3 Proposition 1: $\mu_m \equiv \frac{\bar{r}_m}{\bar{w}_m} = 1 + \varepsilon_m^{-1} = 1 + \frac{1}{\theta} HHI_m + \frac{1}{\eta} (1 - HHI_m),$

In this expression, \bar{w}_m and \bar{r}_m are the (employment-weighted) average wage and average marginal revenue product of labor in market m , respectively.

First, I show that $1 + \varepsilon_m^{-1} = 1 + \frac{1}{\theta} HHI_m + \frac{1}{\eta} (1 - HHI_m).$ To see why this holds, let Θ_m denote the set of firms operating in labor market m , and take the (payroll-share-weighted) average of equation 8:

$$\begin{aligned} \underbrace{\sum_{z \in \Theta_m} s_{zm} (1 + \varepsilon_{zm}^{-1})}_{\equiv 1 + \varepsilon_m^{-1}} &= 1 + \sum_{z \in \Theta_m} s_{zm} \left[\frac{1}{\eta} (1 - s_{zm}) + \frac{1}{\theta} s_{zm} \right] \\ &= 1 + \sum_z \left[\frac{1}{\theta} s_{zm}^2 + \frac{1}{\eta} (s_{zm} - s_{zm}^2) \right] \\ &= 1 + \frac{1}{\theta} HHI_m + \frac{1}{\eta} (1 - HHI_m) \end{aligned}$$

Second, I show that $\sum_{z \in \Theta_m} s_{zm} (1 + \varepsilon_{zm}^{-1}) = \frac{\bar{r}_m}{\bar{w}_m}.$ To see that this equality holds, aggregate

the firm-level markdown equation $\frac{r_{zm}}{w_{zm}} = 1 + \varepsilon_{zm}^{-1}$ using payroll shares as weights to get:

$$\begin{aligned}
\underbrace{\sum_{z \in \Theta_m} s_{zm} (1 + \varepsilon_{zm}^{-1})}_{\equiv 1 + \varepsilon_m^{-1}} &= \sum_{z \in \Theta_m} s_{zm} \left(\frac{r_{zm}}{w_{zm}} \right) \\
&= \sum_{z \in \Theta_m} \frac{\cancel{w_{zm}} l_{zm}}{\sum_j w_{jm} l_{jm}} \left(\frac{r_{zm}}{\cancel{w_{zm}}} \right) \\
&= \frac{\sum_{z \in \Theta_m} r_{zm} l_{zm}}{\sum_{j \in \Theta_m} w_{jm} l_{jm}} \\
&= \frac{(\sum_{z \in \Theta_m} r_{zm} l_{zm}) / (\sum_{z \in \Theta_m} l_{zm})}{(\sum_{j \in \Theta_m} w_{jm} l_{jm}) / (\sum_{z \in \Theta_m} l_{zm})} \\
&= \frac{\bar{r}_m}{\bar{w}_m} \equiv \mu_m
\end{aligned}$$

C.2.4 Country-level average wage markdown

I show that a particular country-level average of the market-level average wage markdown (i.e., equation 9) equals the country-level average (employment-weighted) wage markdown. The reader can then directly verify that the resulting expression is the inverse of Berger, Herkenhoff and Mongey (2021)'s expression for the “labor market power adjustment” component of the country-level labor share (see authors' equation 10).

Corollary 2. *Consider the market-level average wage markdown expression from Proposition 1. Then the country-level (employment-weighted) average wage markdown is given by:*

$$\mu \equiv \frac{\bar{r}}{\bar{w}} = \sum_m s_m \mu_m = 1 + \frac{1}{\theta} H \tilde{H} I + \frac{1}{\eta} (1 - H \tilde{H} I)$$

where $s_m = \frac{\bar{w}_m l_m}{\sum_m \bar{w}_m l_m}$ is market m 's payroll share, $H \tilde{H} I = \sum_m s_m H H I_m$ is the country-level payroll-share-weighted average payroll Herfindahl, and \bar{w} and \bar{r} are the (employment-weighted) average wage and average marginal revenue product of labor at the country-level, respectively.

Proof. Having provided a more detailed proof for Proposition 1, I use the same steps to show

the country-level aggregation result more directly. In particular:

$$\begin{aligned}
\mu \equiv \frac{\bar{r}}{\bar{w}} &= \frac{(\sum_m \bar{r}_m l_m) / (\sum_m l_m)}{(\sum_m \bar{w}_m l_m) / (\sum_m l_m)} \\
&= \frac{\sum_m \bar{r}_m l_m}{\sum_m \bar{w}_m l_m} \\
&= \frac{\sum_m \left(\frac{\bar{r}_m}{\bar{w}_m} \right) \bar{w}_m l_m}{\sum_m \bar{w}_m l_m} \\
&= \sum_m \left(\frac{\bar{r}_m}{\bar{w}_m} \right) \frac{\bar{w}_m l_m}{\sum_m \bar{w}_m l_m} \\
&= \sum_m \mu_m s_m \\
&= \sum_m s_m \left[1 + \frac{1}{\theta} HHI_m + \frac{1}{\eta} (1 - HHI_m) \right] \\
&= 1 + \frac{1}{\theta} H\tilde{H}I + \frac{1}{\eta} (1 - H\tilde{H}I)
\end{aligned}$$

□

C.2.5 Corollary 1: $\gamma_t \equiv \frac{d\mu_{mt}}{dX} = \left(\frac{1}{\theta} - \frac{1}{\eta} \right) \beta_t$

In this equation, β_t is the effect of an exogenous shock on the payroll Herfindahl. To derive the expression, plug in $\mu_{mt} \equiv 1 + \varepsilon_{mt}^{-1}$ and differentiate:

$$\begin{aligned}
\gamma_t \equiv \frac{d\mu_{mt}}{dX} &= \frac{d(1 + \varepsilon_{mt}^{-1})}{dX} \\
&= \left[\frac{d(1 + \varepsilon_{mt}^{-1})}{dHHI_{mt}} \cdot \frac{dHHI_{mt}}{dX} \right] \\
&= \left[\frac{d(1 + \varepsilon_{mt}^{-1})}{dHHI_{mt}} \cdot \beta_t \right] \\
&= \left(\frac{1}{\theta} - \frac{1}{\eta} \right) \beta_t
\end{aligned}$$

I then compute standard errors for γ_t under the assumption that the effect on concentration and the labor supply parameters are independent. It follows that:

$$\begin{aligned}\text{Var}(\gamma_t) &= \text{Var} \left[\left(\frac{1}{\theta} - \frac{1}{\eta} \right) \cdot \beta_t \right] \\ &= E \left[\left(\frac{1}{\theta} - \frac{1}{\eta} \right)^2 \right] E[\beta_t^2] - \left[E \left(\frac{1}{\theta} - \frac{1}{\eta} \right) \right]^2 [E(\beta_t)]^2 \\ &= \left[\text{Var} \left(\frac{1}{\theta} - \frac{1}{\eta} \right) + \left[E \left(\frac{1}{\theta} - \frac{1}{\eta} \right) \right]^2 \right] [\text{Var}(\beta_t) + [E(\beta_t)]^2] - \left[E \left(\frac{1}{\theta} - \frac{1}{\eta} \right) \right]^2 [E(\beta_t)]^2\end{aligned}$$

whose components can all be plugged-in using sample estimates.

C.2.6 Equation 9 under the setup in Berger, Herkenhoff and Mongey (2021)

I show that equation 9 holds under the additional assumptions on production function and goods market structure in Berger, Herkenhoff and Mongey (2021). In that environment, μ_m should be interpreted as the ratio of the average marginal revenue (net of expenditures in non-labor inputs) to the average wage. I show this in two steps.

To start, consider the environment in Berger, Herkenhoff and Mongey (2021). Goods markets are perfectly competitive, with $p_{zm} = 1$ for all firms and markets. Firms compete for labor à la Cournot, solving:

$$\max_{k_{zm}, l_{zm}} \pi_{zm} = \underbrace{A_{zm} (k_{zm}^{1-\gamma} l_{zm}^{\gamma})^{\alpha}}_{\equiv y_{zm}} - Rk_{zm} - w_{zm} (\{l_{zm}, l_{-zm}\}) l_{zm} \quad (29)$$

where y_{zm} is firm revenues, k_{zm} is capital, A_{zm} is a general firm-market specific productivity term, R is the rental rate of capital (in perfectly competitive capital markets), and w_{zm} is the wage firm w_{zm} would have to pay to obtain l_{zm} units of labor, given nested CES labor supply preferences that yield the same expression for ε_{zm}^{-1} , the firm-specific inverse elasticity of residual supply, as derived in Section 2.1.

First, I show that equation 9 holds when the firm optimizes labor *holding capital constant*, denoting this corresponding average wage markdown by $\mu_m^{k-fixed}$. To avoid confusion due to differences in notation, let $mrpl_{zm}^{k-fixed}$ denote BHM's expression for the marginal revenue product of labor of firm z in market m *holding capital constant*, and continue to use the greek letter μ to denote the wage markdown.⁶³ Computing the definition of market m 's average

⁶³In BHM, the greek letter μ refers to the wage take-home share (i.e., the inverse of the wage markdown) holding capital constant. See footnote 23 and Proposition 1.1 in Berger, Herkenhoff and Mongey (2021).

wage markdown holding capital constant gives:

$$\mu_m^{k-fixed} \equiv \frac{mrpl_m^{\bar{k}-fixed}}{\bar{w}_m} = \frac{(\sum_z mrpl_{zm}^{k-fixed} l_{zm}) / \sum_z l_{zm}}{(\sum_z w_{zm} l_{zm}) / \sum_z l_{zm}} \quad (30)$$

$$= \frac{\sum_z \alpha \gamma (y_{zm} / l_{zm}) l_{zm}}{\sum_z w_{zm} l_{zm}} \quad (31)$$

$$= \alpha \gamma \frac{\sum_z y_{zm}}{\sum_z w_{zm} l_{zm}} \quad (32)$$

where $mrpl_{zm}^{k-fixed} = \partial y_{zm} / \partial l_{zm}|_k = \alpha \gamma (y_{zm} / l_{zm})$.

Simplification of equation 32 can now be done using the equalities in BHM's Proposition 1.1 (with special care given to note the difference in notation across the two papers). Equation 32 becomes:

$$\begin{aligned} \mu_m^{k-fixed} &= \alpha \gamma \frac{\sum_z y_{zm}}{\sum_z w_{zm} l_{zm}} = \alpha \gamma \left[\frac{1}{\alpha \gamma} \sum_z s_{zm} \mu_{zm}^{k-fixed} \right] \\ &= \sum_z s_{zm} \mu_{zm}^{k-fixed} \\ &= \sum_z s_{zm} \left[1 + \frac{1}{\theta} s_{zm}^2 + \frac{1}{\eta} (s_{zm} - s_{zm}^2) \right] \\ &= 1 + \frac{1}{\theta} HHI_m + \frac{1}{\eta} (1 - HHI_m) \end{aligned}$$

where HHI_m is similarly defined as the payroll Herfindahl of labor market m .

Second, I show that, in equilibrium, $\mu_{zm}^{k-fixed} = \mu_{zm}^{k-adjust}$ for all firms z and markets m . In other words, equation 9 holds whether or not optimization of capital is taken into account, so long as expenditures on capital are netted out of firm revenues. In this case, $\mu_{zm} = \mu_{zm}^{k-adjust}$ should be interpreted as the ratio of the marginal revenue (net of expenditures in non-capital inputs) product of labor to the wage.

To show this, note first that since $\mu_{zm} = mrpl_{zm} / w_{zm}$, it suffices to show that in equilibrium $mrpl_{zm}^{k-fixed} = mrpl_{zm}^{k-adjust}$. Letting y_{zm}^{net} denote total firm revenues net of capital

expenditures, it follows that:

$$\begin{aligned}
mrpl_{zm}^{k-adjust} &\equiv \frac{dy_{zm}^{net}}{dl_{zm}} = \frac{d[f(k_{zm}, l_{zm}) - Rk_{zm}]}{dl_{zm}} \\
&= \frac{\partial f(k_{zm}, l_{zm})}{\partial k_{zm}} \frac{dk_{zm}}{dl_{zm}} + \frac{\partial f(k_{zm}, l_{zm})}{\partial l_{zm}} - R \frac{dk_{zm}}{dl_{zm}} \\
&= \frac{\partial f(k_{zm}, l_{zm})}{\partial l_{zm}} + \frac{dk_{zm}}{dl_{zm}} \underbrace{\left(\frac{\partial f(k_{zm}, l_{zm})}{\partial k_{zm}} - R \right)}_{=0 \text{ by firm's FOC for } k_{zm}} \\
&= mrpl_{zm}^{k-fixed}
\end{aligned}$$

This result, $mrpl_{zm}^{k-fixed} = mrpl_{zm}^{k-adjust}$, also follows directly from the envelope theorem, as the firm is optimizing its non-labor inputs.

D Estimation of model parameters: first stage strength

While the findings presented in Sections 6.1 and 6.2 suggest that point estimates for both $\frac{1}{\eta}$ and $\frac{1}{\theta}$ are consistently robust across several relevant alternative specifications, their first stage strength, and consequent precision, is sensitive to alternative clustering and to alternative samples, as shown in Appendix Tables A.6 and A.8 for $\frac{1}{\eta}$, and Appendix Tables A.12 and A.11 for $\frac{1}{\theta}$.

In this Appendix, I discuss how my strongly identified main regression specifications (i.e., no sub-sampling; standard errors clustered by firm for estimation of $\frac{1}{\eta}$ and by local labor market for estimation of $\frac{1}{\theta}$) are the appropriate specifications for identifying the model-consistent parameters we wish to estimate.

First, consider robustness checks on the alternative sub-sample of firms that are the unique producers in their local labor market. While this check is informative of whether the nesting structure is misspecified too broadly, the model's key elasticities are meant to capture movements across all firms in the local labor market (including non-tradables sector firms), and it is unclear what failing to include all firms would imply for precision. Therefore, my main specification is based on all firms.

Second, consider the robustness check to defining labor market boundaries more broadly, by microregion only. While the model does not directly speak to either the choice of labor market boundary or to the choice of clustering, I make these decisions based on my data and setting. Drawing borders at the microregion \times occupational group level is not only supported

by the job-to-job transition patterns discussed in Section 4, but evidence from ongoing work (i.e., Felix and Wang (2021)) also suggest that occupations are a key component of Brazilian workers’ outside options—even more so than geography—and should therefore be considered when drawing labor market boundaries.

Finally, my main specification’s clustering choices are reasonable given the ample variation in quasi-exogenous shock I observe for estimation of both $\frac{1}{\theta}$ (e.g., see Appendix Figure A.1 for two example occupations) and $\frac{1}{\eta}$ (e.g., see Appendix Figure A.11).

D.1 External validity of main findings to incorporating informality

From a public policy standpoint, studying the universe of formal sector firms and workers is important in its own right: those are the firms that pay taxes and the workers who contribute to social security, so understanding how trade affects their wages matters for future policy. However, it is impossible to ignore the implications that informality might have for the external validity of my findings, especially since nearly 50% of all employment in Brazil is informal (Dix-Carneiro et al., 2021; Ulyssea, 2018), and evidence suggests trade liberalization increased informality in harder hit regions (Dix-Carneiro et al., 2021; Dix-Carneiro and Kovak, 2017).⁶⁴ In this section I discuss how omitting the informal sector might impact my findings.

Consider first how failing to account for informality might effect my estimate for the level of firm labor market power in 1990s Brazil (specifically, my estimates of average wage take-home share) of 50 cents on the dollar pre-liberalization. Equation 9 show that this level depends on: a) the level of labor market concentration; and b) the levels of $\frac{1}{\eta}$ and $\frac{1}{\theta}$. The higher the levels of each component, the larger the wage markdowns, and thus the smaller are wage take-home shares.

I next rely on the 1991 and 2000 census and on findings from the literature on informality in Brazil to sign the bias that unavailability of data on informality at the firm level introduces to each component of average wage take-home shares. While panel data on firm informality at either the extensive margin (i.e., firms without a taxpayer ID) or on the intensive margin (i.e., workers without signed worker cards working for formal sector firms) are not available in the Brazilian context, the key statistics needed on both margins to sign the bias of omitting

⁶⁴Liberalization might have reduced the aggregate level of informality in tradable sectors according to model estimates, however (see Dix-Carneiro et al. (2021)). In terms of wage effects, estimates inclusive of informal sector wages have similar magnitudes as those on formal sector wages only (e.g., see Kovak (2013) and Dix-Carneiro and Kovak (2017)).

informality have been recently uncovered by Ulyssea (2018) using ECINF, a 2003 survey of urban informality for firms with at most 5 employees.

On net, the effect of excluding informality from estimates of the level of firm labor market power is ambiguous. On the one hand, it overestimates firm labor market power by overestimating levels of labor market concentration. This is because both margins of informality decrease sharply with firm size (Ulyssea, 2018), such that small firms are actually larger than their formal sector data suggests, whereas large firms might not be much larger. This overestimation bias likely has bias in the 1990s given the positive correlation I find between formal sector measures of local labor market concentration and census measures of informality, shown in Appendix Figure A.15.

On the other hand, excluding the informal sector likely underestimates the levels of $\frac{1}{\eta}$ and $\frac{1}{\theta}$ because it overestimates their first stage (effect of negative labor demand shock on employment) and underestimates their reduced form (effect of negative labor demand shock on wages). Specifically, the effect on employment is overestimated because firms that appear to shrink in the formal sector might have simply moved workers off the books into informality. Similarly, the effect on wages is underestimated because once workers are moved into informality their wages can fall below the minimum wage. Overall, whether my estimates for the level of firm labor market power would be higher or lower if the informal sector were incorporated depends on the degree to which $\frac{1}{\eta}$ and $\frac{1}{\theta}$ are underestimated vs. the degree to which labor market concentration is overestimated. I leave the important task of quantifying these margins for future research.

Now consider how failing to account for informality might affect my estimates of the effect of trade on firm labor market power. Equation 10 shows that this effect depends on: a) the effect of trade on labor market concentration; and b) the difference between $\frac{1}{\theta}$ and $\frac{1}{\eta}$. While the consequences of excluding informality for the latter are not clear—it depends on the degree to which informal sector workers substitute more strongly across firms vs. across markets relative to formal sector workers—, evidence from the literature suggests it most likely underestimates the effect of trade on firm labor market power.

Specifically, excluding the informal sector underestimates the effect of trade on concentration because: a) informal firms are more likely to exit in response to import competition than formal sector firms are because they are much less productive (Ulyssea, 2018), and productivity is the key driver of exit in face of import competition (Dix-Carneiro et al., 2021; Melitz, 2003); and b) wages in informal sector firms can fall by more than in formal sector

firms, as they are not capped below by the minimum wage.⁶⁵ As a result, the payroll shares of already small informal sector firms likely declines by more than the payroll shares of larger formal sector firms. Failing to take into account this differential effect underestimates the effect of trade on concentration.

Overall, findings from the literature on informality in Brazil suggest that while excluding the formal sector has ambiguous consequences for estimated levels of firm labor market power, it most likely underestimates its response to trade. Finally, even if the consequence for levels is theoretically ambiguous, there is plenty of evidence suggesting that firm labor market power is more prevalent in the informal sector: observably equivalent workers are not only paid 29% less (Ulyssea, 2018), but they are also not covered by labor laws, which assure they have the right to vacation, to weekly rest (i.e., weekends or similar arrangement), to overtime pay, maternity leave, severance, etc. None of that is guaranteed in the informal sector.

It is also important to note the historical context in which labor laws emerged in Brazil, whose economy was extremely reliant on slavery until abolition (on paper) in 1888. Near-slavery working conditions—arguably the most extreme form of firm labor market power—persist until this day under informality. Auditors from Brazil’s Ministry of Labor have freed over 49,816 workers since 1995, the year the Ministry began inspecting locations following anonymous tip-offs.⁶⁶

⁶⁵In addition, Ulyssea (2018) finds that firm fixed effects account for nearly all of the 29% formal sector wage premium, suggesting that the extensive margin of informality is the key driver for wage differences between the two sectors.

⁶⁶Based on data through 2015, the latest year for which data available (see <https://reporterbrasil.org.br/dados/trabalhoescravo/>).