Trade, Labor Market Concentration, and Wages

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October 30, 2022

Abstract

I estimate the effect of trade on local labor market concentration and the consequences thereof to wages using a sufficient statistics approach, employer-employee linked data, and tariff shocks from Brazil's trade liberalization. Trade increased concentration by 7%, an effect driven by firm exit and labor reallocation towards exporters. Increased concentration raised wage markdowns—estimated at 50 cents on the dollar pre-shock—by enough to offset small wage gains from reallocation, but on net did not meaningfully reduce wages. Most of the wage decline due to trade was driven instead by reductions in the marginal revenue product of labor.

*Princeton University. Email: mayara.felix@princeton.edu. I am indebted to my advisers David Atkin, Arnaud Costinot, and Ben Olken for invaluable guidance and support, and I am thankful to Rafael Dix-Carneiro, Dave Donaldson, Hamid Firooz, and Federico Huneeus for detailed feedback on the manuscript. For very helpful comments and suggestions, I thank Rodrigo Adão, Francesco Amodio, David Berger, Matilde Bombardini, Paula Bustos, Andrew Bernard, Fabian Eckert, Teresa Fort, Pinelopi Goldberg, Bruno Ferman, Peter Hull, Xavier Jaravel, Brian Kovak, Gabriel Kreindler, Corinne Low, Naércio Menezes Filho, Peter Morrow, Emanuel Ornelas, Vítor Possebom, Pamela Quispe, Rodrigo Soares, Chengxi Su, Fabian Trottner, Gabriel Ulyssea, Diana Van Patten, Daniel Yi Xu, as well as seminar participants at UC Berkeley, Brown, Chicago Booth, Columbia, Cornell, Duke, FGV-SP, Georgetown, IMF, INSPER-SP, JH-SAIS, Microsoft Research, NYU, Northwestern, PUC-Rio, Tuck, UBC, UCSD, UMichigan, UPF/CREI, USC, UToronto, World Bank, Wharton, Yale, the 2022 Penn State New Faces Conference, the 2022 Northwestern Development Rookiefest Conference, the 2022 UWisconsin Emerging Scholars Conference, and the 2022 NBER ITI and Development meetings. I also thank numerous former colleagues at MIT for helpful feedback.

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 tests 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 labor towards larger, more productive firms. On the one hand, reallocation to these firms raises the average marginal product of labor, increasing wages. On the other hand, the same reallocation increases labor market concentration, which can increase firm labor market power, reducing wages.

Specifically, this paper is an empirical study of the relationship between trade, local labor market concentration, and wages in the context of Brazil's 1990s trade liberalization. Using a sufficient statistics approach, employer-employee linked data, and import tariff reduction shocks, I test whether trade increased local labor market concentration in more exposed markets, and I estimate the consequences thereof to formal sector wages in Brazil.[1] I then quantify how much of the net-negative effect of Brazil's trade liberalization on local wages could be accounted for by increased firm labor market power.

To guide the empirical exercise, I start with a parsimonious model of imperfectly competitive labor markets that provides the link between labor market concentration and wage markdowns, a standard measure of firm labor market power.[2] As in Berger, Herkenhoff and Mongey (2022)—henceforth BHM—workers have nested CES preferences over jobs, and firms compete for workers à la Cournot. In this environment, labor reallocation in response to shocks is governed by two key elasticities: a *cross-market* elasticity of substitution, and a *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 firm's wage markdown.

The first result of this paper concerns the theoretical link between local labor market concentration and the average wage markdown at a specific local labor market. Taking a weighted average of firms' markdowns across all firms in a market, I show that the market-level average markdown is determined by the same two key elasticities of substitution, along

[1] All results in this paper apply to Brazil's formal sector only, for which long-lasting negative relative effects of trade on wages have been documented by Dix-Carneiro and Kovak (2017). Like them, I focus on average effects. See Appendix D for heterogeneity by market (informality, unemployment, union strength), and worker characteristics, as well as guidance on model extensions to explicitly incorporate these features.

[2] The wage markdown is the ratio between the marginal revenue product of labor and the wage.

with the market's payroll Herfindahl index.[3] This result holds regardless of the shape of firms' production functions or the competition structure in product markets, on which I remain agnostic.[4] Overall, the more concentrated a market is, and the more inelastic the elasticities of substitution are, the larger is the market's average markdown.

A direct implication of my model's expression for a market's average 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 inverse elasticities of substitution. To see the intuition for why the *gap* in elasticities is what matters for *changes* in markdowns, consider the following. Trade fundamentally changes firms' relative size. But, if it is just as easy for workers to substitute locally (i.e., within markets) as it is for them to substitute globally (i.e., across markets), then firms effectively operate in a single national market, where their relative size is negligible and inconsequential to market power. Overall, the larger the gap between the key elasticities, and the larger the effect on concentration, the larger the effect on markdowns.

With clear guidance on the key sufficient statistics needed to quantify the effect of trade on firm labor market power, I proceed to estimate them using employer-employee linked data and Brazil's 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, the reform generated substantial cross-sector variation in import tariff changes. This cross-sector variation in 1990-1994 changes in import tariffs is the policy-induced variation I exploit to estimate my model's sufficient statistics.

I begin by estimating the effect of trade on local labor market concentration. I define a local labor market as a microregion $\times$ occupational group cell, motivated by switching patterns from workers' job-to-job transition matrices.[5] 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 the change in its "import competition exposure," a shift-share treatment

[3]A market's payroll Herfindahl is the sum of its firms' squared payroll shares.

[4]Such agnosticism is possible due to this paper's focus and empirical strategy. See footnote 10.

[5]The literature on labor market power typically considers granular market boundaries, such as region $\times$ occupation (e.g., Azar, Marinescu and Steinbaum (2017); Azar et al. (2018); Schubert, Stansbury and Taska (2021)) or region $\times$ sector (e.g, BHM, Lamadon, Mogstad and Setzler (2022), and Alfaro Urena, Manelici and Vasquez (2021)), with few studies using region only boundaries (e.g., Hoang (2021)). Section 6 shows that granular boundaries yield more statistical power and similar point estimates of elasticities of substitution.

intensity measure whose "shift" is the set of tariff reductions experienced by each firm in the local labor market, and whose "share" is each firm's contribution to its 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 quite large: it corresponds to a 7% increase relative to the 0.28 pre-reform mean, or a 33% increase relative to the 0.21 pre-reform median. The effect is robust to alternative measures of import competition exposure and concentration, to defining labor markets solely as microregions, and to weighing by baseline size, showing that it is not driven by a handful of small markets.[6]

To examine the source of increased concentration, I consider how import competition differentially affected the total employment, within each market, of tradable (exporters and non-exporters) and non-tradable sector firms. I find that import competition primarily induced exit and reduced employment of non-exporting firms in the tradable sector, and had no detectable effect on total employment of either exporters or 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 compositional 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 workers' two key elasticities of substitution. My model provides the regression specifications, and my setting the quasi-exogenous variation. The availability of trade shocks that vary across firms within markets allows me to estimate both elasticities using IV, as opposed to BHM's method of indirect inference, adding transparency to the identifying source of variation, and dispensing with assumptions on production functions and product market structure. I estimate the within-market cross-firm elasticity of substitution using within-market cross-firm variation in tariff reductions as shocks to firm wage premia and employment,[7] and the cross-market elasticity using cross-market variation in changes to import competition exposure as shocks to indices of market wage premia and employment.

[6]The statistical significance of the effect is also robust to two-way clustering by occupation and region, and to computing standard errors that take into account the spatial correlation of sectoral shocks, following Adao, Kolesár and Morales (2019). See Section 4.

[7]Wage premia are wages conditional on education, gender, age, and, as robustness, worker fixed effects.

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. Both point estimates are robust to alternative tariff shocks to relevant alternative samples, and are not driven by unobservable worker characteristics or by changes in workforce composition, both of which I can control for in estimating firms' wage premia. These elasticities—along with the pre-liberalization level of labor market concentration—imply that prior to liberalization, Brazilian workers took home only 50 cents for every marginal dollar they generated for the firm.

This suggests substantial levels of firm labor market power in Brazil's formal sector—much higher than, for example, estimates for the US, which range from 65 to 80 cents on the dollar. Comparing to estimates by BHM for the US, the key difference between the two contexts is that Brazil's within-market cross-firm elasticity of substitution is *seven* times more inelastic than the US', suggesting that Brazilian workers have a much tougher time making within-market cross-firm substitutions than US workers do.

Combined with the estimates for the effect of trade on labor market concentration, the 0.272 gap between these elasticities implies that a 10% increase in import competition exposure reduced local labor 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 the compositional cross-firm reallocation towards exporters. However, the magnitude of this market power effect was small, accounting for only 2% of the overall 13.8% negative effect of trade on average wages. The overall effect was driven instead by within-firm reductions in the other component of the wage, the marginal revenue product of labor, potentially reflecting reductions in price markups.

Overall, this paper offers three new take-aways from Brazil's trade liberalization episode concerning the interaction between trade, labor market concentration, and wages: (i) Brazilian firms command substantial firm labor market power, primarily driven by difficult within-market cross-firm substitution relative to contexts such as the US; (ii) Opening to trade increased that labor market power a bit further as it raised concentration, by enough to offset wage gains from cross-firm reallocation, but (iii) on net the magnitude of the market power effect was small, and cannot explain most of the relative wage decline due to trade.

This paper speaks to large literatures on the regional incidence of trade. The effects of Brazil's liberalization in particular has been widely studied for a wide-range of outcomes (e.g., see also Muendler (2004); Gonzaga, Menezes Filho and Terra (2006); Krishna, Poole and Senses (2012); Dix-Carneiro, Soares and Ulyssea (2018); Dix-Carneiro et al. (2021)). This paper zooms into the mechanisms underlying wage effects on formal sector workers to test a theory-driven hypothesis: trade-induced increases in labor market concentration might reduce wages by increasing firm labor market power.

By showing when and how the key elasticities of substitution in models of oligopsony can be identified with IV, as opposed to indirect inference, this paper also contributes to a large literature on methods for estimating firm labor market power (e.g., Manning (2003); Dube et al. (2020); Lamadon, Mogstad and Setzler (2022); Yeh, Macaluso and Hershbein (2022), BHM). Applying this method to effects of trade adds to a growing empirical literature on trade and input market power (e.g., Zarate (2016); Morlacco (2020)).

In addition, while some studies have documented that wages are smaller in more concentrated local labor markets (e.g., Azar et al. (2020); Azar, Marinescu and Steinbaum (2017)), and a few others have estimated that trade increases labor market concentration (e.g., Benmelech, Bergman and Kim (2022); Hoang (2021)), to the best of my knowledge, this is the first paper to provide a comprehensive study of the relationship between trade, labor market concentration, and wages. I provide the theoretical link between local labor market concentration and local average markdowns, derive the sufficient statistics needed to estimate how a shock to the former changes the latter, and quantify both the negative (via markdowns) and the positive (via reallocation) effects that a trade shock in particular would have on wages via labor market concentration.

This paper's findings matter for the literature's current understanding of the extent of and changes to firm labor market power. They not only place Brazil's formal sector amongst the least competitive settings worldwide,[8] but also offer an explanation for why: Brazil's within-market cross-firm elasticity of substitution is very inelastic relative to countries like the US, suggesting that Brazilian workers have a tough time substituting across firms. Thus, more attention needs to be paid to factors that might hinder even within-market substitution, such as search frictions, local transport costs, or reputation concerns, beyond factors already accepted as important for cross-market mobility. Finally, my findings suggest that labor market power can be ruled out as a leading mechanism of trade-induced wage reductions, at least in Brazil's context.[9] Future researchers should focus instead on identifying which components of the marginal revenue product of labor account (e.g., price markups, production function, productivity, etc.) for average wage declines.

[8]For comparison, wage take-home shares have been estimated to be 65%-80% for the US (BHM, Lamadon, Mogstad and Setzler (2022), and Yeh, Macaluso and Hershbein (2022)), 71% for Colombian manufacturing (Amodio and de Roux, 2021), 47% for Chinese manufacturing (Hoang, 2021).

[9]Increases in labor market concentration might have a larger effect on markdowns in contexts like the US, where workers find it much easier to substitute within markets than across. See Section 7.

2 Concentration and markdowns: An empirical model

In this section I introduce an empirical model of Brazilian labor markets that provides the relationship between labor market concentration and wage markdowns. As in BHM, labor supply is nested CES, firms compete for workers à la Cournot, and there is a large number of labor markets.[10,11] 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 BHM'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^j_{zm} 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}:

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

[10] My model diverges from BHM's on two fronts: (i) I do not impose restrictions on firms' production functions or product market structure; and (ii) I allow wages to be a function of firm-market-specific distaste shifters, which might be a function of, for example, amenities. These divergences are possible because I focus on estimating wage markdowns (which are set on the margin), as opposed to labor shares (which includes infra-marginal revenues), and because my setting allows for estimating the model's elasticities of substitution via IV, as opposed to indirect inference, which would require restrictions on (i). See footnote 40 for details. Note also that I focus on estimating relative effects of trade, as opposed to conducting counterfactual exercises in general equilibrium, which similarly require restrictions on (i). See Appendix C.2 for how this paper's results map into BHM's.

[11] This 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 goods 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.

where $\xi_{zm} > 0$ and $\xi_m > 0$ are firm-market- and market-specific taste shifters common to all workers, w_{zm} is the wage paid by firm z in local labor market m to identical workers, and ξ^j_{zm} is an idiosyncratic worker taste shifter with a General Extreme Value (GEV) distribution:[12]

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

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,[13] 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^j_{zm} 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.[14] Aggregating these probabilities to the firm-market level gives the model's equation for residual labor supplied to firm z in market m:

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

where W_m, W, and L are CES wage and labor supply indices (i.e., "taste-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 (dis)taste shifters ξ_{zm} and ξ_m, and larger if there is overall more (taste-adjusted) labor L supplied to all markets.

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

[12]The 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.

[13]BHM 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.

[14]See Appendix C for detailed derivations of all results in this section.

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

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

where L_m is market m's taste-adjusted labor supply 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 (dis)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

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

where R_z is the firm's revenue function—capturing both production function and goods market structure, on I remain agnostic— 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,[15] while X represents any exogenous shock to firm z's revenues.

To maximize profits, firm z looks at all local labor markets and considers, for each one, the effect that increasing employment in that market would have on its total revenues—holding

[15] Note 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).

labor demand at all other markets constant—and contrasts that marginal revenue gain to the marginal cost of this decision. This optimal tradeoff yields firm z's profit-maximizing wage setting formula in market m:

$$\underbrace{\partial R_z/\partial l_{zm}}_{\text{Marginal revenue}} = \underbrace{w_{zm} \times \overbrace{\left(1+\varepsilon_{zm}^{-1}\right)}^{\text{Markdown}}}_{\text{Marginal cost}} \tag{5}$$

where $1+\varepsilon_{zm}^{-1} \equiv \mu_{zm}$ is firm z's markdown in market m, which is a function of $\varepsilon_{zm}^{-1} \equiv \frac{\partial \ln w_{zm}}{\partial \ln l_{zm}}$, the inverse elasticity of residual labor supply the firm faces in that market.

The markdown μ_{zm} 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, $\mu_{zm}^{-1} = \left(1+\varepsilon_{zm}^{-1}\right)^{-1}$, 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:

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

where

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

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

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

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

As in BHM, a nice feature of Equation 8 is that it encompasses perfect competition and monopsonistic competition as limiting cases. If $\frac{1}{\eta} = \frac{1}{\theta} = 0$, 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.[16] When $\frac{1}{\eta} = \frac{1}{\theta} > 0$, 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.

Finally, it is important to highlight that, in this model, the set of markets in which a firm operates is endogenous. This is a consequence of remaining agnostic about firm's revenue function R_z, and specifically of not restricting it to be market-specific. Instead, the set of local labor markets in which a firm operates can be interpreted as part of its production function. This flexibility allows for wage markdowns based on this model to be consistent not only with the existence of multi-establishment firms, but also with optimal firm behavior in granular labor markets, such as those defined by occupation. For example, in face of a negative shock, a firm might find it optimal to change its occupation mix or close a specific establishment. The consequence of this restructuring to wages will be reflected both on the marginal revenue product of labor—since it affects the firm's production function—and on the wage markdown—since it affects firms' relative sizes within each local labor market.

At the local labor market level, upcoming Corollary 1 is what allows us to isolate the effect on markdowns. Since the wage equals the marginal revenue product of labor divided by the markdown, once the effect on markdowns is netted out, the residual effect on wages is accounted for by the marginal revenue product of labor.

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*

[16] Trade'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.

markdown at labor market m is given by:

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

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 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.[17]

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:*

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

[17]Note 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 BHM. 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 BHM. 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.

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. 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

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, downloaded from WITS, which I map to RAIS via the 5-digit economic activity code CNAE95,[18] using product-to-sector concordances from IBGE. Third, exporting activity is mapped to RAIS using firms' unique identifier CNPJ. What I observe in terms of exporting activity is the list of exporting firms for years 1990-1994, which were provided via request by the (extinct as of 2019) Ministry of Development, Industry, and Foreign Trade (MDIC), currently a part of the Ministry of the Economy.

Finally, I use data from the 1991 and 2000 Brazilian census when discussing model extensions and heterogeneity by market characteristics in in Appendix D, downloaded from the replication data for Dix-Carneiro and Kovak 2017.

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%.[19] 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

[18] See Appendix B for details on mapping procedures.

[19] Simple 1990 averages of nominal tariffs at CNAE95 level. See Appendix B for details.

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. The key argument is that, 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 payroll or employment, which could confound the negative estimates of the effect of trade on these outcomes. Reassuringly, Appendix Figure A.2 shows no correlation between sector-level import tariff cuts and sector-level changes in either employment or payroll in the years preceding the tariff cuts (1986-1990). This is different from the pattern observed during liberalization (1990-1994), when employment and payroll shrink more in the sectors with the largest tariff cuts. In the analyses that follow, I further check for pre-trends at the local labor market level by estimating year-specific regression coefficients for all outcomes of interest.

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.[20] My definition is motivated by the striking job-to-job transition patterns

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

presented in Appendix Figures A.3-A.6, and summarized in Appendix Table A.3.[21] 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 × occupational group cells, and present robustness to using microregions only as 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 labor market m's Import Competition Exposure (ICE) shock as

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

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

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 $\tau_{s(z),t}$ 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

[21] These 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)). Aggregate 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.

[22] The literature on firm labor market power typically defines local labor markets more granularly than the literature on the incidence of trade. The most commonly used boundaries in this literature are geography × occupation (e.g., Azar, Marinescu and Steinbaum (2017); Azar et al. (2018); Schubert, Stansbury and Taska (2021)) or geography × sector boundaries (e.g., Alfaro Urena, Manelici and Vasquez (2021) and BHM). A small number of papers examining market power considers geography only as boundaries (e.g., Hoang (2021)), which is more standard in the literature on the regional incidence of trade (e.g., Dix-Carneiro and Kovak (2017); Kovak (2013); Autor, Dorn and Hanson (2013); Topalova (2010)). I find that elasticity point estimates are very similar for finer and broader boundaries, but finer boundaries yield more statistical power. See Sections 6.1 and 6.2.

[23] Because 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.

tradable sector firms,[24] 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, $HHI^T_{m,1991} \equiv \sum_{j \in \Theta^T_m} s^2_{jm,1991}$.[25] 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.[26]

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 Y_m as ζ_k from the following regression:

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

where ΔY_{mt} denotes the long difference in Y_m from year t back to the base year 1991,[27] and δ_m and δ_k are local labor market and year fixed effects. As the specification is in stacked

[24] A small number of local labor markets defined by microregion × occupation have no tradable sector firms in 1991. I consider ΔICE_m to be zero in those markets, as none of their firms experienced a change in import competition exposure. When markets are defined by microregion only, all markets have at least one tradable sector firm. Results are similar in either case.

[25] Note that, by construction, the κ_{zm} weights sum to one, such that the sum of exposure measures do not vary across local labor markets, constituting "complete shares". See Borusyak, Hull and Jaravel (2022) for identification issues arising from incomplete shares.

[26] While my measure of import competition exposure serves as a shift-share shock for identifying 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). This would require making assumptions on production functions, product market structure, and—since my model features finitely many firms within each market—specifying the equilibrium entry game, on which I remain agnostic.

[27] I 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.

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.[28]

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,[29] 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). This is a 7% increase relative to the pre-liberalization 0.28 average, or a 33% increase relative to the pre-liberalization 0.21 median.[30]

This effect is large in magnitude and it 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 concentration using the employment (instead of payroll) Herfindahl, to the use of alternative weights to compute ΔICE_m,[31] and to weighing regressions by market baseline employment, which shows that the effect is not driven by a handful of small markets.[32] The

[28]Note 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).

[29]As 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.

[30]Appendix 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.

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

[32]The statistical significant of the effect is also robust to two-way clustering by occupation and region, and to computing standard errors that take into account the spatial correlation of sectoral shocks, following Adao, Kolesár and Morales (2019). For all of these robustness estimates, see Panel A in Table 1 and in Appendix Tables A.5-A.7.

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).[33]

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.[34]

Finally, I address an over-rejection concern uncovered by recent literature on shift-share instruments, which arises due to spatial correlation in sectoral composition across markets (Adao, Kolesár and Morales, 2019). I address this by increasing the number of sectors used to construct ΔICE_m to 285 from the 20 to 53 shifts currently used in the literature—[35] adding further granularity in tariff shocks that mitigates the spatial correlation— and by reporting standard that account for this correlation, computed following the procedure described in Adao, Kolesár and Morales (2019). column (3) of Appendix Table A.6 shows that, in this context, the spatial-correlation-adjusted standard errors are similar to standard errors clustered by market, if not typically smaller.

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

[33]Smaller 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.

[34]See Appendix B for details on treatment effects relative to trend.

[35]Previous 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.

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.8 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]

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.9 presents my estimates for these firm-level regressions, which shows the reallocation was driven towards exporters specifically and not just towards large firms.[39]

[36]Another 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.

[37]While I also find that import competition had little effect on total employment by non-tradables (Appendix Table A.8 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).

[38]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. See Appendix Table A.9 for further details.

[39]Note 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

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

Section 4.2 showed that local labor markets more exposed to import competition experienced an increase in labor market concentration following Brazil's trade liberalization. How did this affect wage markdowns? Per Corollary 1, the answer to this question depends on the gap between workers' within-market cross-firm elasticity of substitution $\frac{1}{\eta}$, and their cross-market elasticity of substituton $\frac{1}{\theta}$. This Section describes my empirical strategy for estimating these key parameters.

My model provides the regression specifications, and my setting the exogenous variation. I use within-market cross-firm variation in import tariff reductions to estimate $\frac{1}{\eta}$, and cross-market variation in import competition exposure to estimate $\frac{1}{\theta}$. This Section shows how—even in the presence of strategic firm interactions—this empirical strategy can be used to estimate $\frac{1}{\eta}$ and $\frac{1}{\theta}$, so long as within-market cross-firm shock variation is available.[40] The elasticities of substitution can then be combined with data on firm shares to compute firm-specific inverse elasticities of labor supply ε_{zm}^{-1}.

(2011) suggests that displaced workers were not reabsorbed by exporters after liberalization.

[40]BHM showed that, in the presence of strategic firm interactions (as in Cournot), the firm-specific inverse elasticity of labor supply ε_{zm}^{-1} cannot be directly estimated using regression. That is because regression holds competitors' reactions to a firm's shock constant, capturing only partial equilibrium shock responses, whereas ε_{zm}^{-1} is inclusive of full equilibrium responses. While ε_{zm}^{-1} cannot be directly identified by regression, this Section shows that its key parameters $\frac{1}{\eta}$ and $\frac{1}{\theta}$ can, so long as within-market cross-firm shock variation is available. Overall, my empirical strategy is a "bottom up" approach (i.e., estimate $\frac{1}{\eta}$ with IV, then $\frac{1}{\theta}$ with IV, then compute ε_{zm}^{-1}), as opposed to BHM's "top down" approach (i.e., estimate a reduced-form ε_{zm}^{-1}, then feed it into a general equilibrium model of the economy, simulating firms's strategic behavior in response to shocks until model shares and data shares converge, at which point η and θ are obtained, along with the general-equilibrium-corrected estimate of ε_{zm}^{-1}). Despite being more involved, the "top down" approach has the advantage that it can be used even without within-market cross-firm shock variation, as in BHM. The "bottom up" approach could be used whenever firm-level shocks are available, such as in the settings studied by Hoang (2021) and Zavala (2022).

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:

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

Which simplifies to:

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

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.

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:

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

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 use 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 concern by instrumenting $\Delta \ln l_{zm}$ with a labor demand shock: $\Delta \ln\left(1 + \tau_{s(z)}\right)$, the policy-induced change in import tariffs on firm z's output sector, using the following first stage regression:

$$\text{[First Stage]} \quad \Delta \ln l_{zm} = \lambda \Delta \ln\left(1 + \tau_{s(z)}\right) + \Delta d_m + \Delta\nu_{zm} \tag{16}$$

where once again Δd_m is a market fixed effect.[41]

Identification of $\frac{1}{\eta}$ using IV relies on three assumptions: a) the shock is independent of firm potential outcomes, whose validity relies on the policy-driven nature of the shock; b) there is a first stage (i.e., $\lambda \neq 0$); and c) exclusion is satisfied, meaning that—conditional on market-level changes—import tariff shocks only affect workers' labor supply decision by changing wages, as opposed to changing workers' distaste ξ_{zm} for working at the particular firm-market pair.

The main potential violation of exclusion is the possibility that worker tastes might be a function of non-wage amenities a) that change in response to trade; b) are marginal to workers' labor supply decision.[42] Since I cannot test the exclusion restriction, I assume that amenities did not change in response to trade in a way that was marginal to workers' labor supply decision. This is similar to the approach in Lamadon, Mogstad and Setzler (2022), and is more flexible than most papers estimating elasticities of labor supply with labor demand shocks (e.g., BHM, Dube et al. (2020), etc.).[43] I leave the important question of whether trade affects non-wage amenities, and the implications thereof for wage markdowns, for future research.

[41] To see how $\frac{1}{\eta}$ is identified even in the presence of strategic interactions, consider what it means to instrument $\Delta \ln l_{zm}$ in equation 15 conditional on a market fixed effect. By the Frisch-Lowell Theorem, this is equivalent to shocking the partialled-out equation $\Delta \ln \tilde{w}_{zm} = \frac{1}{\eta}\Delta \ln \tilde{l}_{zm} + \Delta\epsilon_{zm}$, where $\tilde{x}$ indicates the residual from regressing x on the market fixed effect $\Delta\delta_m$. Shocking this equation gives $\partial\Delta \ln \tilde{w}_{zm} = \frac{1}{\eta}\partial\Delta \ln \tilde{l}_{zm} + \partial\Delta\epsilon_{zm}$, where ∂ indicates the effect of the shock. But since, by shock independence, $\partial\Delta\epsilon_{zm} = 0$, we have that $\frac{1}{\eta} = \partial\Delta \ln \tilde{w}_{zm}/\partial\Delta \ln \tilde{l}_{zm}$. This means that $\frac{1}{\eta}$ is identified by the effects of a firm-level shock on own-wage and own-employment *holding constant* the effects of the shock on other firms' decisions, which—under the assumption of nested CES—are entirely captured by changes in the market-level CES wage and labor supply indices, absorbed by the market fixed effect. In other words, $\frac{1}{\eta}$ is identified precisely by the *partial equilibrium* effects of a firm-level shock on own-wage and own-employment. This is different than attempting to directly estimate ε_{zm}^{-1}—a general equilibrium object—with regression, which cannot be done for Cournot competition, as shown by BHM.

[42] Note that for a non-wage amenity to be marginal to worker's labor supply decision it is also necessary that workers would be willing to pay for it (e.g., willing to accept lower wages), as opposed to it simply being the case the workers like these firm "traits". These could include, for example, schedule flexibility (e.g., Bustelo et al. (2020)) or dignity (e.g., Dube, Naidu and Reich (2022)). More generally, establishing willingness to pay for a trait is a key issue in the literature focused on measuring preferences (e.g., see Kessler, Low and Sullivan (2019)).

[43] Orthogonality between firm-specific labor demand shocks and firm-specific amenities is an implicit identifying assumption (of the firm-specific inverse elasticity of labor supply) in most papers in the modern monopsony literature, where amenities do not explicitly enter the wage equation (e.g., see Manning (2003) and Ashenfelter (2010)).

5.1.2 Measurement

Estimating equations 15 and 16 requires measuring 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-market pair, and the tariff shock to the firm.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.[44] This is equivalent to assuming that each worker provides one "effective monthly unit" of labor, whereas the model allows l^j_{zm} to be more generally pinned down by worker j's exogenous reservation earnings y^j.[45]

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^j_{zm} received by worker j for all labor j provided in December *conditional on worker j's characteristics*.[46] It is important here to clarify that my use of the term "wage premia" follows papers in the literature on the regional incidence of trade, and is meant to indicate that the confounding effects of worker heterogeneity on wages have been netted out of cross-firm wage differences. Wage premia defined this way are the theory-consistent empirical measure for wages because my model assumes that all workers are equally productive. They still include, however, cross-firm differences in both components of the wage: the marginal revenue product of labor (productivity, production function, product market structure, etc.) and the wage markdown (the market power component).

I then present estimates of the within-market cross-firm elasticity based on alternative wage measures. To better compare my estimates to most other papers estimating firm labor market power,[47] I present results using simple average wages. To check unobservable

[44]That 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).

[45]Alternatively, 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.

[46]For each year, I estimate each firm's wage premium in its local labor market as firm $\times$ market fixed effects in a regression of worker log december earnings on the firm $\times$ market fixed effects plus controls for worker characteristics, including age, education, and gender. See Appendix B for details. Note that these wage premia are different from Abowd, Kramarz and Margolis (1999) firm fixed effects, which condition on worker fixed effects and are therefore estimated off of movers, and might be biased in the presence of limited worker mobility Bonhomme et al. (2020). Appendix Table A.12 shows that conditioning on worker fixed effects does not substantially change elasticity estimates.

[47]This is the case for the US estimates from BHM and Yeh, Macaluso and Hershbein (2022), as well as for all estimates based on manufacturing plant data (e.g., Amodio and de Roux (2021); Hoang (2021); Tortarolo and Zarate (2018)).

worker characteristics matter for elasticity estimates, I present results based on wage premia that are conditional on worker fixed effects, similar to the approach in Abowd, Kramarz and Margolis (1999). Finally, to check whether differential sorting across firm-market pairs might confound elasticity estimates, I present results restricted sub-sample of stayers within firm-market pairs.

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

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

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). I report results using effective rates of protection—which are inclusive of tariff reductions in firm inputs—as robustness.

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 $\Delta\delta_m$:

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

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

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

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 taste-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:

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

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 $\frac{1}{\theta}$.

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:

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

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 $\frac{1}{\eta}$.[48]

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.

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). The is a strongly identified first stage, with an F-statistic of 158.497.[49] 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).

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 BHM's corresponding estimate of 0.14 for the US,[50] suggesting that Brazilian workers substitute a lot less swiftly across firms in response to wage changes than US workers do. This rather inelastic preference parameter places an upper bound of

[48] Following 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.

[49] This is well above Lee et al. (2021)'s recommendation of using a 104.7 cutoff for a true 5 percent significance test in just-identified IV models, which is derived under the assumption of unknown correlation between the error terms in the first and second stages.

[50] BHM 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.

$1/(1+0.985) \approx 50\%$ 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 important alternative specifications. A first concern is that such inelastic within-market cross-firm response might be driven by local labor markets being defined too narrowly, such that within any one market there are too few firms for workers to substitute across. This does not appear to be the case: column (3) of Appendix Table A.10 shows that defining local labor markets more broadly by microregion only yields a very similar within-market cross-firm inverse elasticity of substitution, of 0.969, albeit with a slightly larger standard error than the baseline estimate. I cannot reject that this is different from my baseline estimate of 0.985.[51] Since the latter is only identified by variation within occupations, this suggests that barriers to occupational switching cannot account for Brazilian workers' rather inelastic within-market cross-firm elasticity of substitution.[52]

I also find similar elasticity estimates—though smaller first stage and reduced form effects—when restricting the estimation sample to local labor markets whose tradable sector firms are the only local producers of their sector, such that shocks are firm-specific (i.e., column (3)), and to using effective rates of protection as opposed to import tariffs as shocks (i.e., column (5) of Appendix Table A.10). The smaller first stage and reduced form effects by the former suggests that sectoral agglomeration in a local labor market exacerbates the negative effects of trade on wages and employment—consistent with Dix-Carneiro and Kovak (2017)'s quantitative model—while the smaller first stage and reduced form effects in the latter suggest that tariff reductions in each sector's inputs attenuate such effects.

Perhaps the most surprising result from alternative specifications is seen in columns (2)-(4) of Appendix Table A.10, where the within-market cross-firm elasticity is estimated using alternative wage measures. Column (4) shows that using average wages–instead of wages conditional on worker observables, as in the baseline estimate—only slightly underestimates the within-market cross firm inverse elasticity, and yields an implied upper bound for the wage take-home share of 51 cents on the dollar, as opposed 50 cents. This suggests that, on average, the labor market power exerted by local firms is pretty invariant to differential wage returns across worker types.[53] Controlling for worker fixed effects (i.e.., column (2)) or

[51]Note also that BHM's much more elastic estimate of 0.14 for US workers is estimated for local labor markets of similar granularity.

[52]Barriers to occupational switching are likely an important component of workers' cross-market elasticity of substitution, however, as I will discuss in Section 6.2.

[53]This average result does not imply, however, lack of heterogeneity in wage markdowns across worker groups, a point to which I return in Section A.15.

restricting the wage premia estimation to stayers within firm-market-pairs (i.e., column (3)) matters a bit more for the inverse elasticities, placing the implied upper bound on wage-take home shares at 54-55 cents on the dollar instead. These results suggest that, at least in the Brazilian context, the labor market power exerted by local firms is also rather invariant to worker sorting across firms.

Finally, one might worry that the similarly-proportioned wage and employment response to tariffs might be driven by the fact that the within-market cross-firm inverse elasticity can only be estimated on the subset of firms that survive the opening to import competition, as those are the firms with non-zero wages and employment in the post-period. This could happen, for example, if these firms were simply on strong growth trends relative to least affected firms. Three pieces of evidence suggest that this is not the case. First, Appendix Figure A.12 displays year-by-year estimates of the first stage (effect on employment) and reduced form (effect on wage premia), showing no differential effect of import tariff reductions on either wage premium or employment prior to liberalization. Second, column (4) of Appendix Table A.10 shows a nearly identical inverse elasticity of substitution if exiters were included in the estimation sample (coding wages and employment as zero in the post year and using the inverse hyperbolic sign instead of log). Finally, Panel D of Table 2 shows that—unlike the IV—the OLS coefficient of a regression of changes in firm log wages on changes in firm log employment in is zero. This indicates that the wage and employment growth are uncorrelated among the surviving firms on which the IV is estimated.[54]

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 also has a strong first stage F-statistic, of 150.752. The second is that the standard error

[54]An OLS of zero also shows that, without the appropriate shock, it is not possible to tell whether the coefficient from a regression of log wages on log employment is a supply parameter (positive slope) or a demand parameter (negative slope). Shocking wages and employment with a labor demand shock—as it is done in the first stage and reduced form—is what traces out the labor supply parameter of interest.

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 case of monopsonistic competition. This means increases in labor market concentration do matter for firm labor market power. The third is that, while I can reject the null that the within-market and cross-market elasticities are the same, the magnitude of their gap is very small, suggesting that Brazilian workers find it nearly as hard to substitute locally (i.e., within markets, across firms) than globally (i.e., across markets). This matters for quantifying the effect of increased concentration on wage markdowns.

It is helpful to compare my estimate of 1.257 for Brazil's cross-market inverse elasticity to other contexts. A cross-firm inverse elasticity of substitution of 1.257 means that a market's wage premium index (i.e., the taste-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 BHM's corresponding estimate of 2.2 for the US, suggesting Brazilian workers substitute more swiftly across local markets than US workers do.[55] 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.

Finally, I find that this point estimate is robust to several alternative specifications, although its precision is sensitive to defining markets more broadly by microregion only, and to using alternative samples and clustering. Importantly, the result that the point estimate for the cross-market elasticity of substitution is very similar when local labor markets are defined more broadly by microregion only (column (3) of Appendix Table A.13), suggests that within-microregion barriers to occupational switching might be an important source of labor market power in Brazil. I also find similar cross-market elasticity estimates using average wages as opposed to wage premia (column (2) of Appendix Table A.15) and restricting the estimation sample to the sub-sample of unique producers (column (2) of Appendix Table A.13).

[55] BHM 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 zero (infinitely tiny firms) to one (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,[56] 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 gives an average wage take-home share of 50 percent.[57]

In summary: 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);[58] 65% for US manufacturing by Hershbein, Macaluso and Yeh (2019); 71% for Colombian manufacturing by Amodio and de Roux (2021);[59] and 73% for US tradables

[56]The 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.

[57]Given 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.

[58]Note 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," $\tilde{\chi}_i = MRPL_i/w_i$.

[59]Based 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 BHM[60]). More 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.[61] In contrast, my estimates speak to the universe of formal sector employment.

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. I compute each firm's wage take-home share in their local labor market by combining my estimates of $1/\eta$ and $1/\theta$ with each firm's payroll share in that market. Since the wage equals the wage take-home share times the marginal revenue product of labor, the latter can be computed by dividing the observed wage in the data by the estimated wage take-home share, which is a number between zero and one. Note, therefore, that the marginal revenue product of labor is always greater than the wage, and captures the residual variation in observed wages net of its estimated market power component.

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:

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

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

[60] Calculated as $73\% \approx 1/(1 + (1/0.45) * 0.11 + (1 - 0.11) * (1/6.96))$ based 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.

[61] Additional examples include Benmelech, Bergman and Kim (2018), Azar et al. (2020), Schubert, Stansbury and Taska (2021), and Marinescu, Ouss and Pape (2021).

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 $\bar{r}_{mt} = \sum_z s^e_{zmt} r_{zmt}$, where s^e_{zmt} 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:

$$\frac{d\bar{r}_{mt}}{dICE_m} = \sum_{z\in\Theta_{mt}} s^e_{zmt} \frac{dr_{zmt}}{dICE_m} + \sum_{z\in\Theta_{mt}} r_{zmt} \frac{ds^e_{zmt}}{dICE_m} = \underbrace{\frac{d\left(\bar{r}_{mt}|_{s^e_{jm0}}\right)}{dICE_m}}_{\text{Within-firm effect}} + \underbrace{\frac{d\left(\bar{s}^e_{mt}|_{r_{jm0}}\right)}{dICE_m}}_{\text{Cross-firm reallocation}} \tag{22}$$

where Θ_{mt} is the set of firms operating in market m in year t, $\bar{r}_m|_{s^e_{jm0}}$ is market m's average marginal revenue product of labor at time t using firms' baseline employment shares as weights for aggregation, and $\bar{s}_{mt}|_{r_{jm0}}$ 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 $\bar{r}_{mt}|_{s^e_{jm0}}$ holds firms' relative size constant.[62] Putting it all together gives:

$$\frac{d\bar{w}_{mt}}{dICE_m} = \underbrace{-\frac{\gamma_t}{\mu_0^2}\bar{r}_0}_{\text{Effect via market power}} + \overbrace{\left[\underbrace{\frac{d\left(\bar{r}_{mt}|_{s^e_{jm0}}\right)}{dICE_m}}_{\text{Within-firm effect}} + \underbrace{\frac{d\left(\bar{s}^e_{mt}|_{r_{jm0}}\right)}{dICE_m}}_{\text{Cross-firm reallocation}}\right]\mu_0^{-1}}^{\text{Effect via MRPL}} \tag{23}$$

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.[63] My estimated 0.272 gap between the within-market and cross-market inverse elasticities of substitution implies that 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

[62] Firm 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 $\bar{r}_{mt}$.

[63] See Appendix C for standard errors.

equivalent to a reduction of the pre-liberalization average wage take-home share of 50 cents on the dollar by 0.14 cents.[64]

This rather muted effect of increased labor market concentration on local labor markets' average wage take-home shares is driven by the small 0.272 gap between the inverse elasticities of substitution, which indicates that Brazilian workers find it nearly as hard to substitute locally (within markets, across firms) than globally (across markets) in response to shocks. This is in stark contrast to the 2.08 gap estimate for US local labor markets from BHM—nearly eight times larger— indicating that US workers find it much easier to substitute within markets than across markets. If Brazilian workers had the same within- and cross-market elasticities of substitution as US workers, the average wage take-home share would have declined by 2.3 cents on the dollar—as opposed to 0.14 cents—,[65] an effect over 16 times as large.

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.[66]

Finally, Table 6 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 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.[67] The remaining effect is accounted by the average marginal revenue product of labor, to which I turn next.

[64]Calculated as $\frac{1}{2.00572} - \frac{1}{2} \approx 0.14\%$.

[65]Calculated as $2.3\% \approx \left[\mu_{0,US} + (1/0.45 - 1/6.96) * 0.02\right]^{-1} - \mu_{0,US}^{-1}$, where $\mu_{0,US}$ is the implied pre-liberalization average wage markdown evaluated at Brazil's average Herfindahl-weighted labor market concentration of 0.08 but US elasticities of substitution from BHM ($\theta = 0.45, \eta = 6.96$): $\mu_{0,US} = 1 + (1/0.45) * 0.08 + (1 - 0.08) * (1/6.96)$.

[66]Since wage effects across local labor markets exhibit positive pre-trends (Appendix Figure A.9), as in the wage effects reported by Dix-Carneiro and Kovak (2017), I report wage effects relative to trend. See Appendix B for details..

[67]Despite this paper's highly reduced form approach, the finding that the effect on wage markdowns was small is consistent with MacKenzie (2018)'s fully structural general equilibrium model, calibrated for India's liberalization.

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 almost entirely 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, reduced production capacity if complimentary non-labor inputs were affected, or productivity losses.

8 Conclusion

This paper is an empirical study into the relationship between trade, local labor market concentration, and wages in the context of Brazil's trade liberalization. I showed that the relative effect of trade on wage markdowns across local labor markets can be quantified by two sufficient: 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.

The findings in Sections 4, 6, and 7 can be summarized into three take-aways: (i) In the 1990s, formal sector firms in Brazil commanded substantial firm labor market power, primarily driven by workers' very inelastic within-market cross-firm substitution; (ii) Opening to trade increased that labor market power a bit further as it raised local labor market concentration—by enough to offset wage gains from cross-firm reallocation—but (iii) on net, the magnitude of this market power effect was small, and cannot explain most of the wage decline. The decline was driven instead by the marginal revenue product of labor.

These findings leave unanswered several important questions for future research. Researchers interested in understanding the mechanisms underlying the regional effects of trade should—at least for the Brazilian context— focus instead on identifying which components of the marginal revenue product of labor (e.g., price markups, production function, productivity, etc.) account for the decline. Whether market power was a leading source of wage declines in other contexts remains an open question, however. For example, this channel might be much more important in contexts where workers find it much easier to substitute locally (within markets) than globally (across markets), such as in the US.

Other important avenues for research include zooming into the muted effects on average wage premia to consider heterogeneous market power effects across workers, and the role of labor market features such as informality, unemployment, and unions in mediating these effects, which I discuss in Appendix D. More research is also needed to uncover the microfoundations of workers' very inelastic within-market cross-firm substitution in Brazil, such as information frictions, reputation concerns, or hiring and firing costs.

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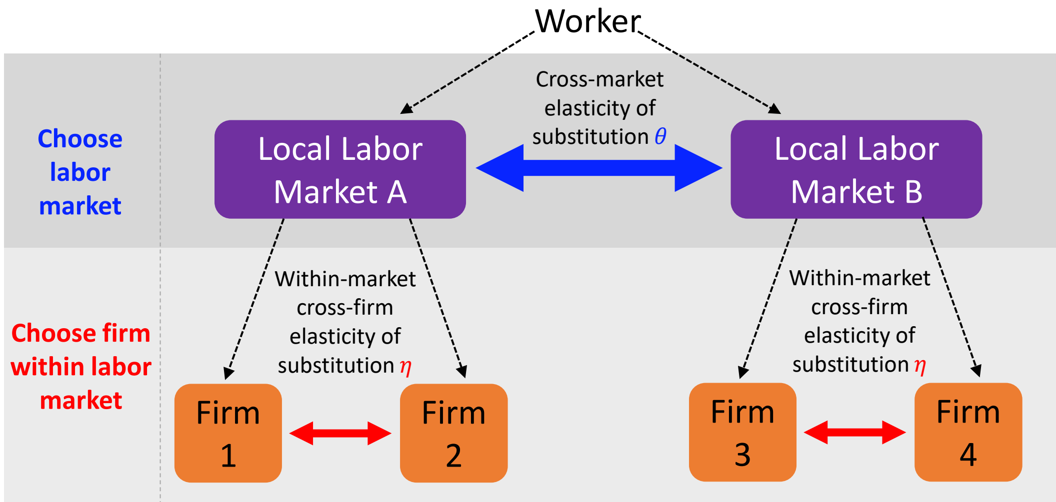
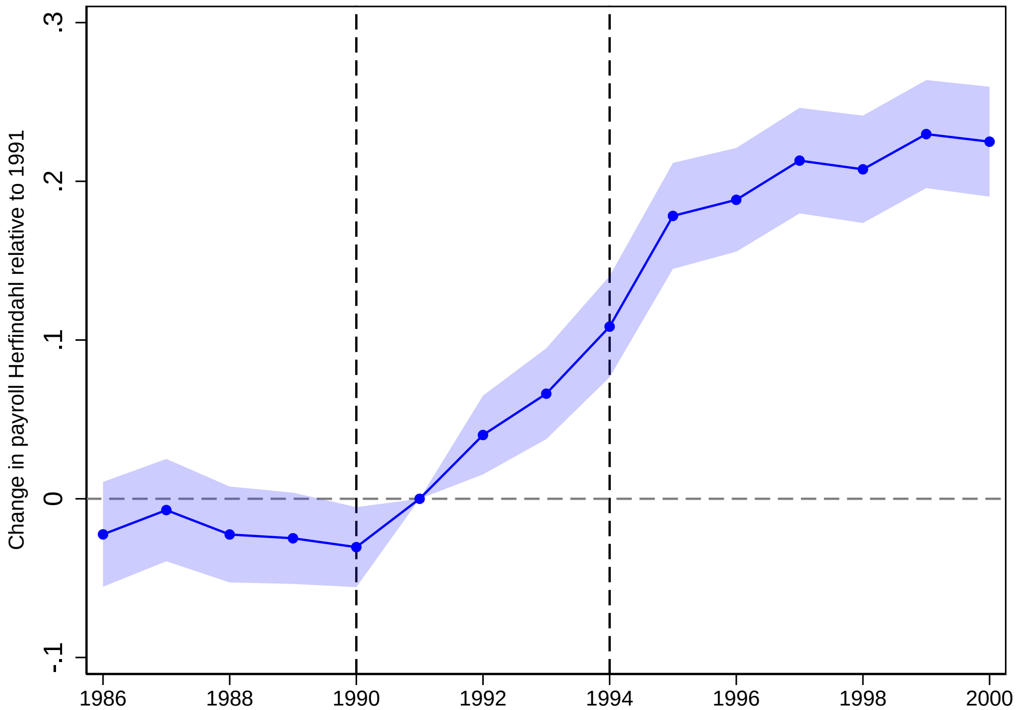
Figure 1: Worker labor supply decision



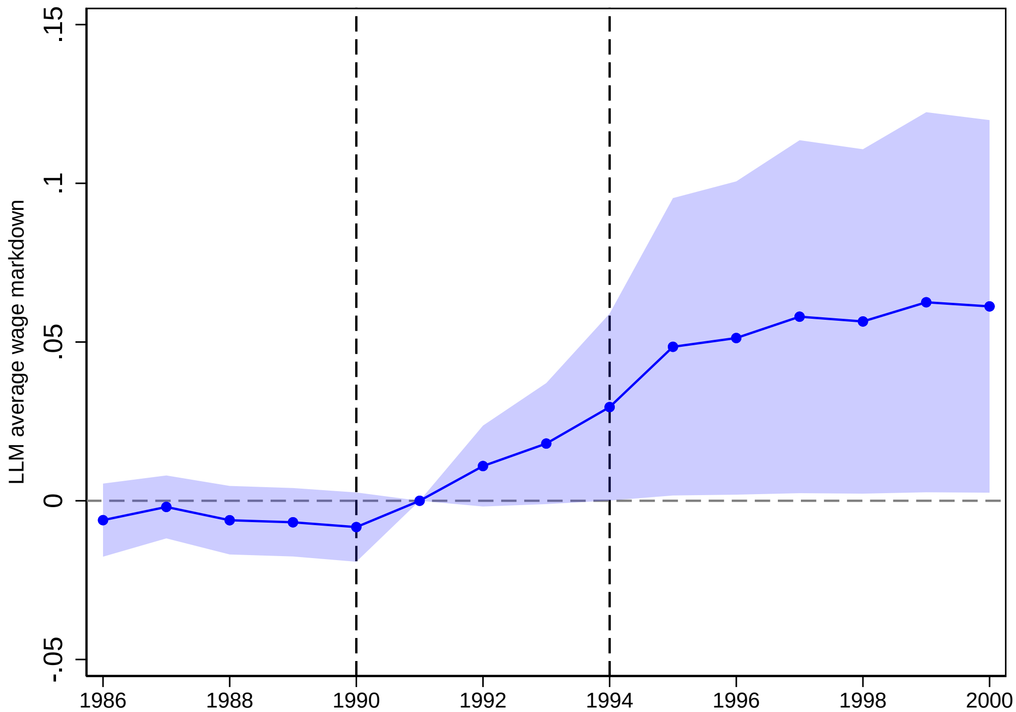
Note: This figure displays a diagram of worker's labor supply decision according to the discrete choice labor supply framework presented in Section 2.

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.

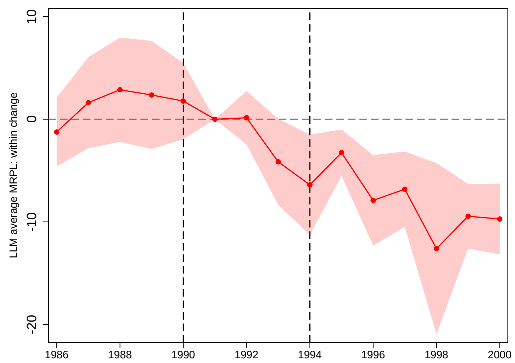
Figure 3: Effect of import competition on average wage markdown



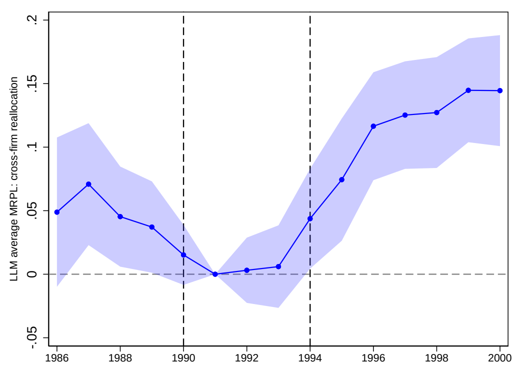
Notes: This figure plots γ_t, the effect of import competition on local labor markets' average wage markdown share at year t, derived in equation 10. The two components of γ_k are $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$, whose estimates are presented in Table 3, and the β_t coefficients that 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

Panel A: Within-firm effect

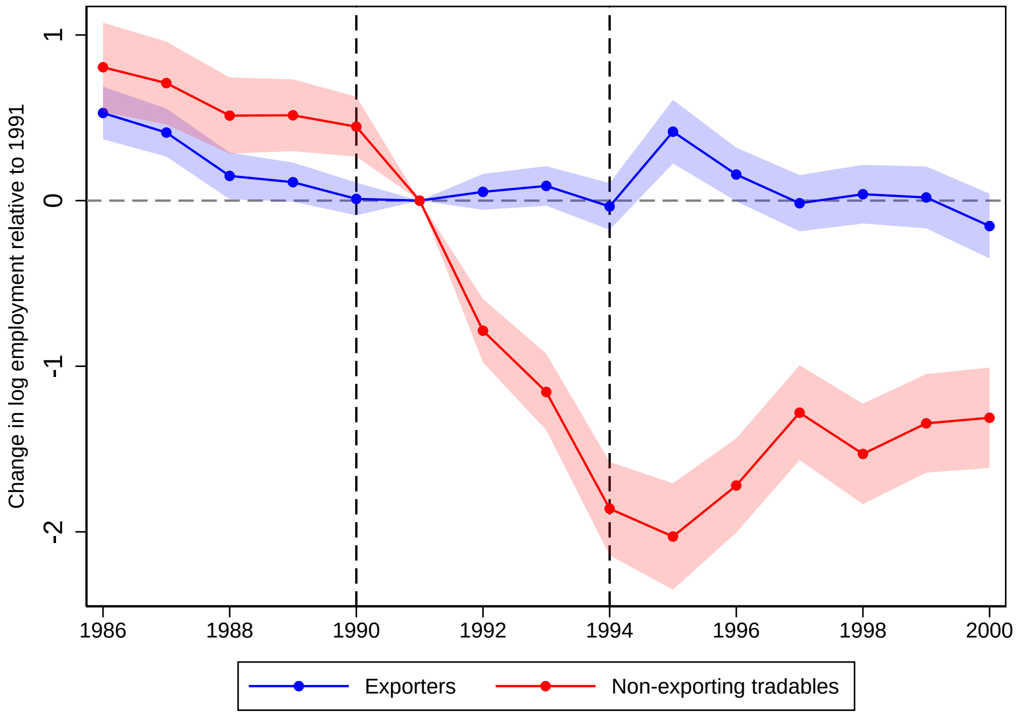


Panel B: Cross-firm reallocation effect



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 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)
Panel A: Labor market concentration		
Δ Payroll Herfindahl (based on wage premium)	0.213	0.021
	(0.017)	(0.002)
Δ Payroll Herfindahl	0.213	0.021
	(0.017)	(0.002)
Δ Employment Herfindahl	0.247	0.025
	(0.016)	(0.002)
Panel B: Log number of firms and log employment		
Δ Log number of firms	-0.549	-5.489
	(0.045)	(0.447)
Δ Log total employment	-0.440	-4.400
	(0.064)	(0.640)
Panel C: Log wage premium		
Δ Log wage premium	0.029	0.293
	(0.031)	(0.307)
Δ De-trended log wage premium	-0.206	-2.063
	(0.034)	(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)
Panel A: First stage	
Δ Firm log employment in LLM	-0.554
	(0.044)
First stage F	158.497
Panel B: Reduced form	
Δ Firm wage premium in LLM	-0.545
	(0.024)
Panel C: 2SLS	
Labor supply within-market cross-firm inverse elasticity of substitution	0.985
	(0.089)
Implied upper bound on wage take-home share	50%
Panel D: OLS	
Regression of Δ Firm log employment in LLM on Δ Firm wage premium in LLM	0.007
	(0.002)
Local labor market (LLM) FE	Yes
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)
Panel A: First stage	
Δ LLM employment index	-0.396
	(0.032)
First stage F	150.752
Panel B: Reduced form	
Δ LLM wage premium index	-0.108
	(0.051)
Panel C: 2SLS	
$\frac{1}{\theta} - \frac{1}{\eta}$	0.272
	(0.131)
Panel D: Cross-market inverse elasticity of substitution	
$\frac{1}{\theta}$	1.257
	(0.096)
Panel D: OLS	
Regression of Δ LLM employment index on Δ LLM wage premium index	-0.018
	(0.016)
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 $\left(1 + \frac{1}{\theta}\right)^{-1}$ 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	-0.0014
		(0.007)	(0.0007)
	Effect of Δ Import Competition Exposure on market average wage markdown	0.058	0.0058
		(0.028)	(0.003)
β	Effect of Δ Import Competition Exposure on payroll Herfindahl	0.213	0.021
		(0.017)	(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	-0.334
	(0.454)	(0.045)
Δ Average wage premium take-home share	-0.014	-0.0014
	(0.007)	(0.001)
Δ Average marginal revenue product of labor	-6.735	-0.673
	(1.334)	(0.133)
Δ Within-firm	-6.821	-0.682
	(1.876)	(0.188)
Δ Cross-firm	0.132	0.013
	(0.023)	(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.

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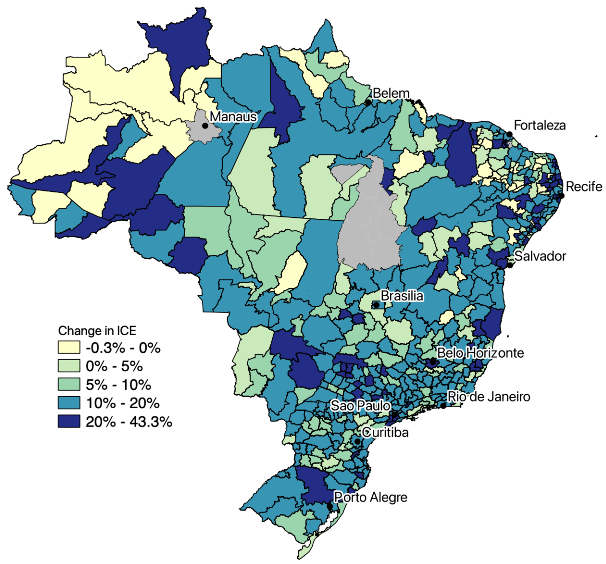
Appendix for "Trade, Labor Market Concentration, and Wages"
Mayara Felix

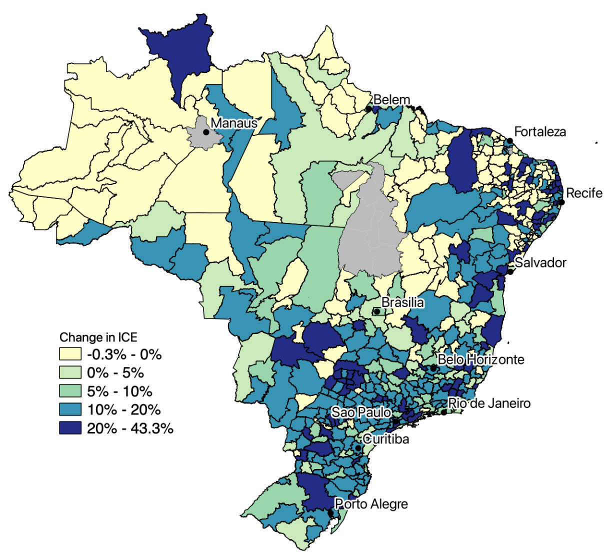
A Appendix Figures and Tables

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

Panel A: Office administration workers



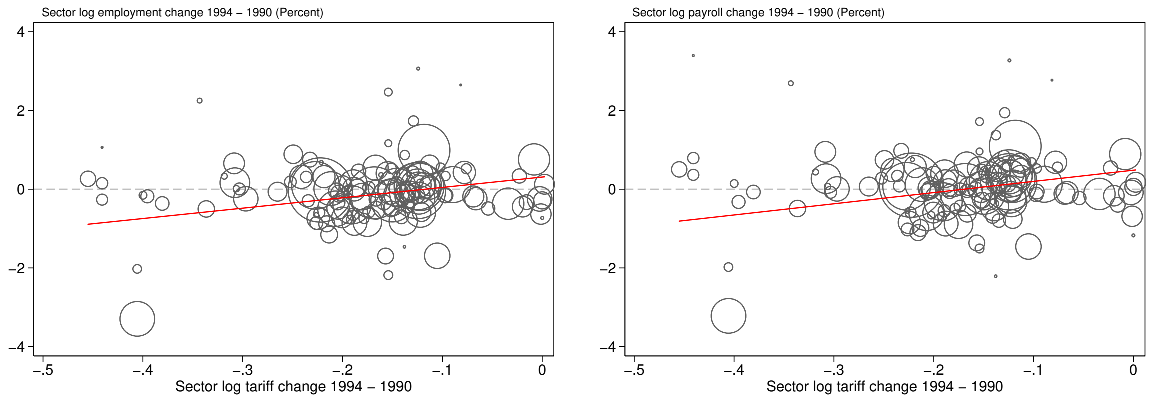
Panel B: Managers and supervisors of industrial workers



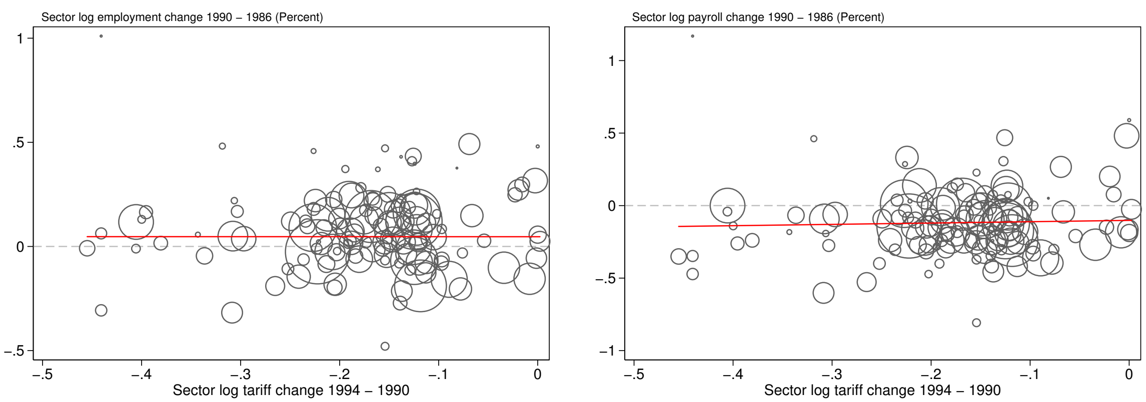
Note: This figure displays variation in ΔICE_m: the change in import competition exposure across local labor markets for two occupation groups. Produced using QGIS using microregion boundaries from (Dix-Carneiro and Kovak, 2017).

Figure A.2: Changes in sector-level outcomes Before vs. After liberalization

Panel A: After liberalization (1990-1994)

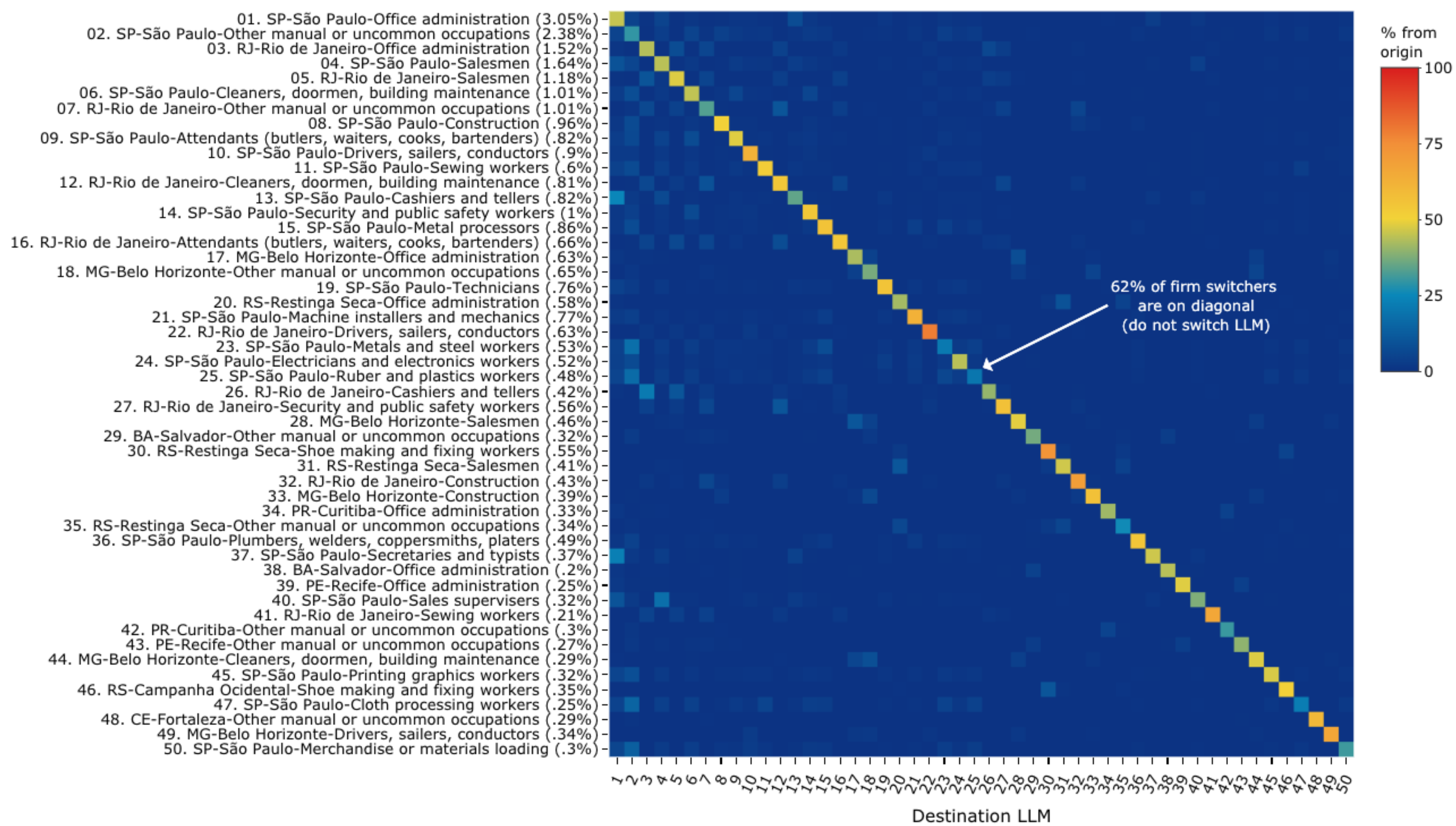


Panel B: Before liberalization (1986-1990)



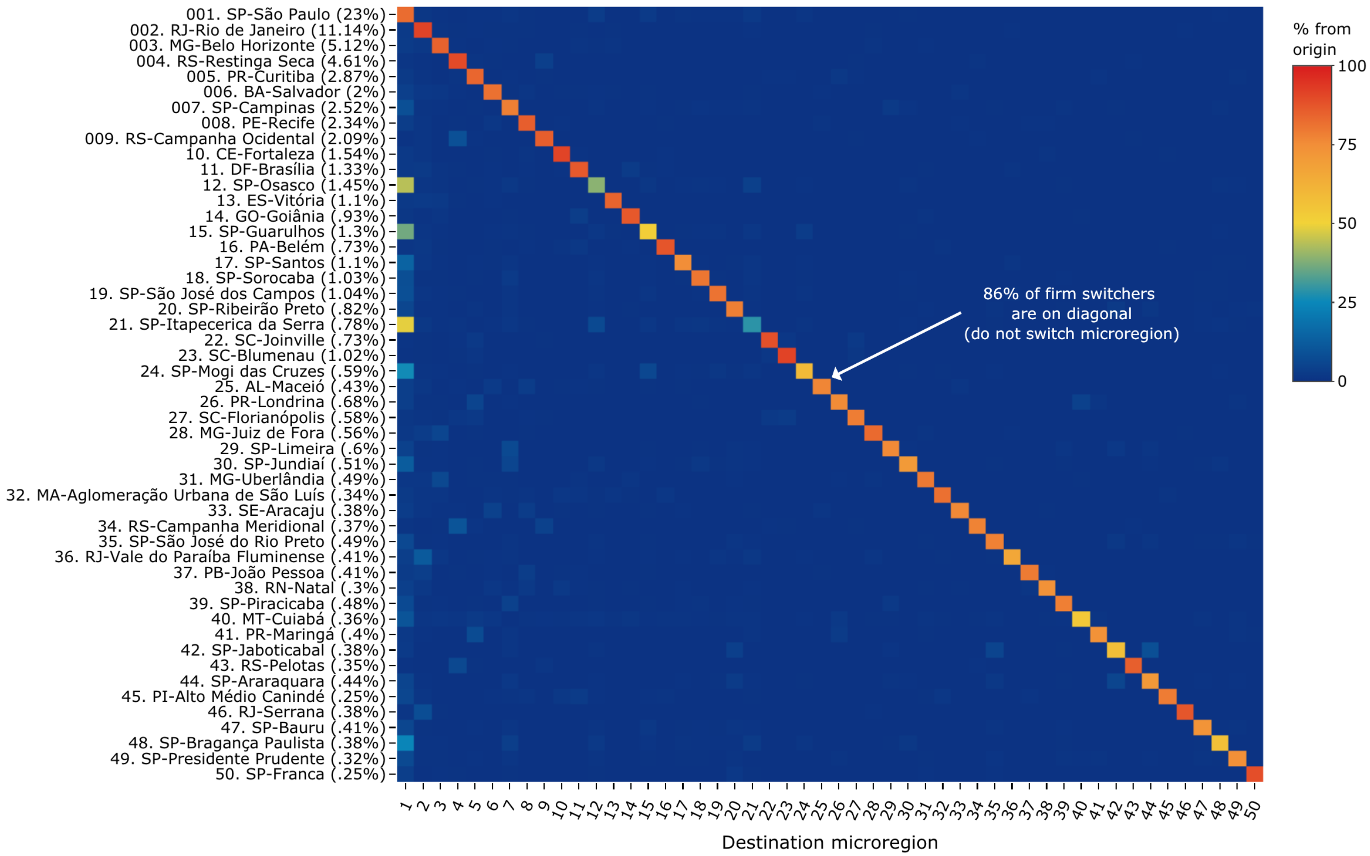
Note: This figure plots changes in sector-level local total employment and sector-level log total payroll for the 4-year periods before versus after liberalization, against the 1990-1994 import tariff reduction on each sector's output. Sector totals are based on data for the entire country and are aggregated into 148 tradable sector codes based on RAIS's 4-digit "ibgesubatividade" sector variable, consistently reported throughout the period.

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



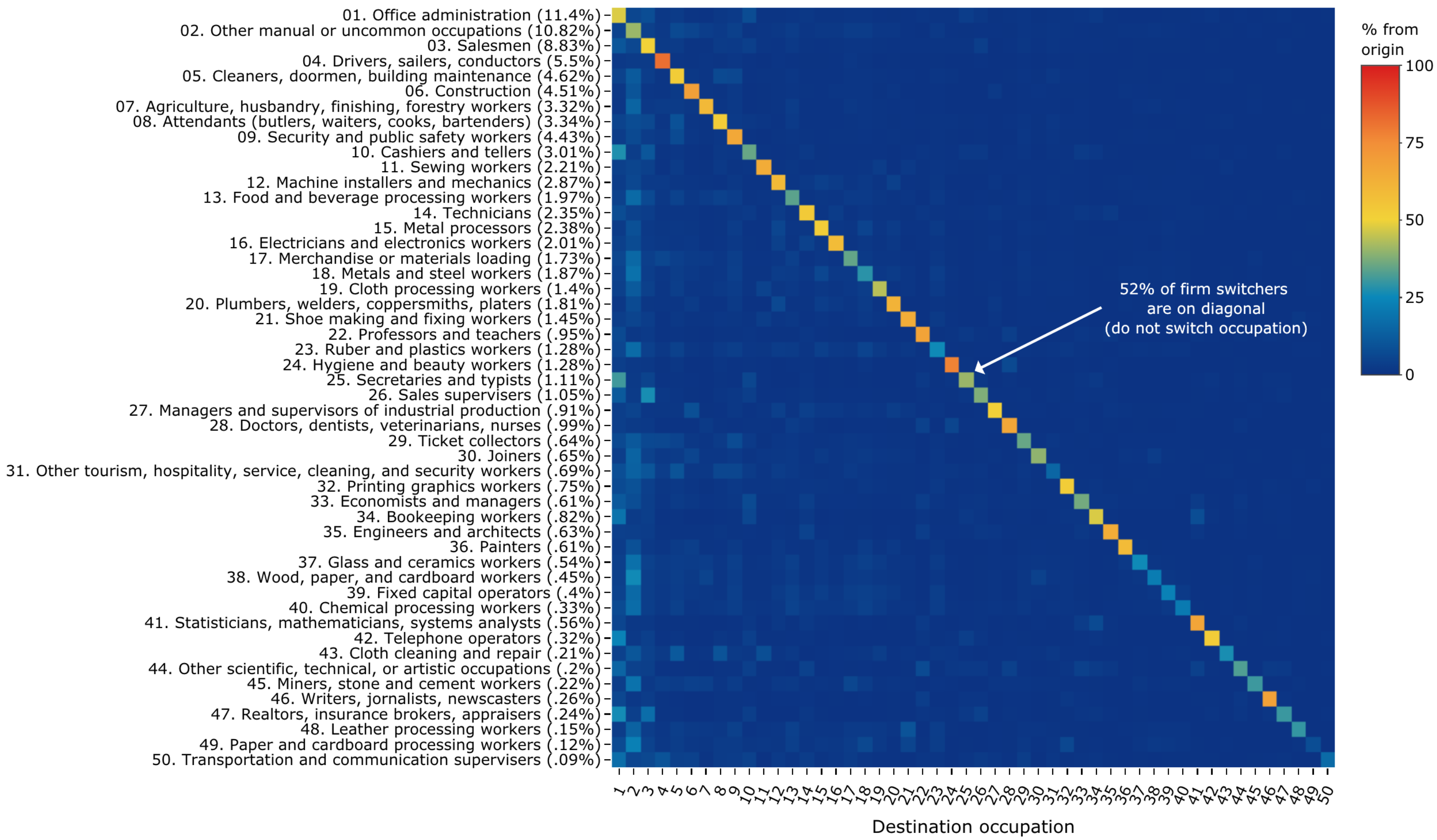
Note: This figure plots worker local labor market to local labor market transitions, among workers who switched employers between 1990 and 1991, for the top 50 local labor markets by number of workers at origin. A local labor market is a microregion × occupational group pair. Each row lists the origin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



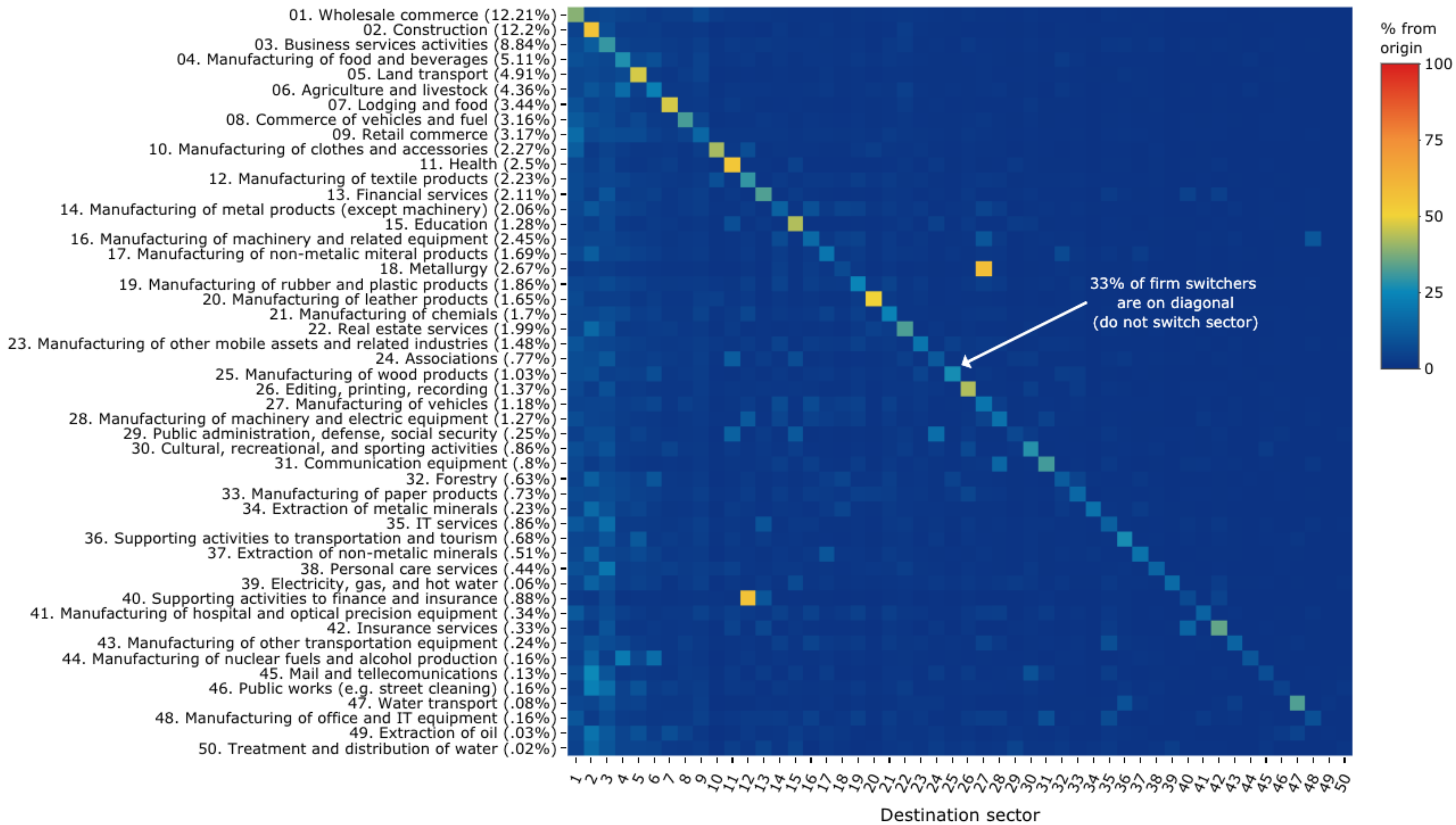
Note: This figure plots worker microregion to microregion transitions, among workers who switched employers between 1990 and 1991, for the top 50 microregions by number of workers at origin. Each row lists the origin microregion (with percent of total workers indicated in parentheses), while each column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

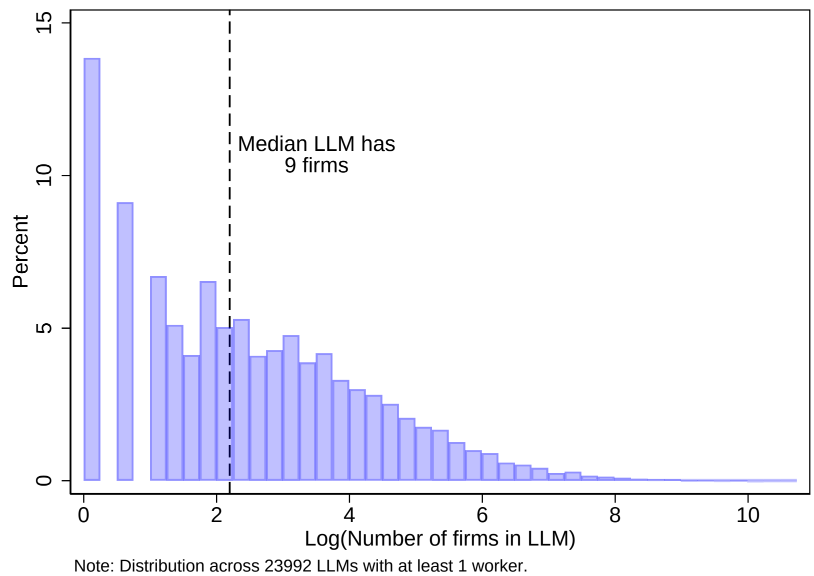
Figure A.6: 1990-1991 sector transitions conditional on switching firms (Top 50)



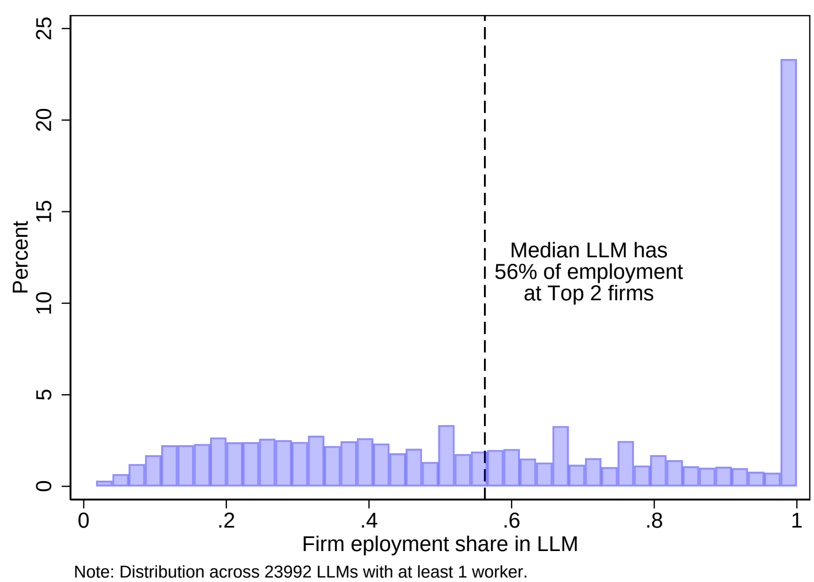
Note: This figure plots worker sector group to sector group transitions, among workers who switched employers between 1990 and 1991, for the top 50 sector (2-digit CNAE95) groups by number of workers at origin. Each row lists the origin sector group (with percent of total workers indicated in parentheses),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

Figure A.7: Local labor market concentration

Panel A: Number of firms

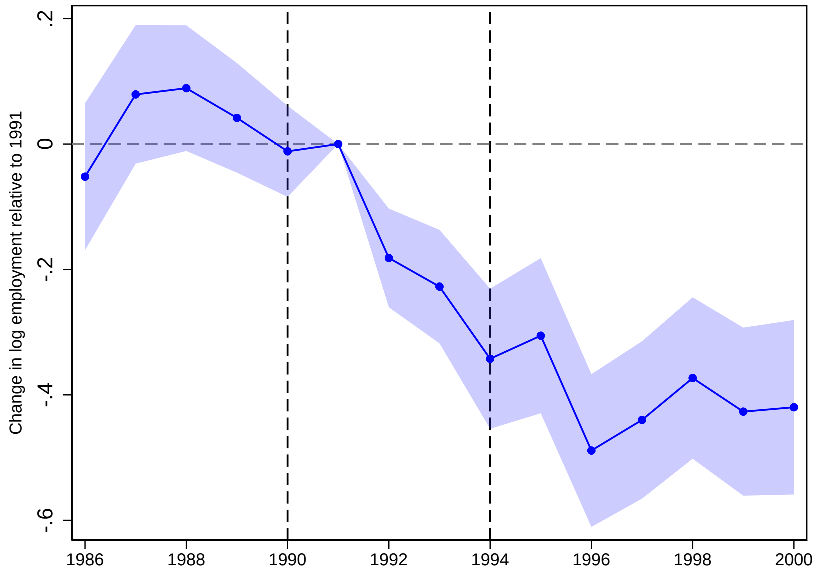


Panel B: Employment share of largest 2 firms



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 × occupation group cell. See Appendix B for details on the definitions of microregion and occupation group.

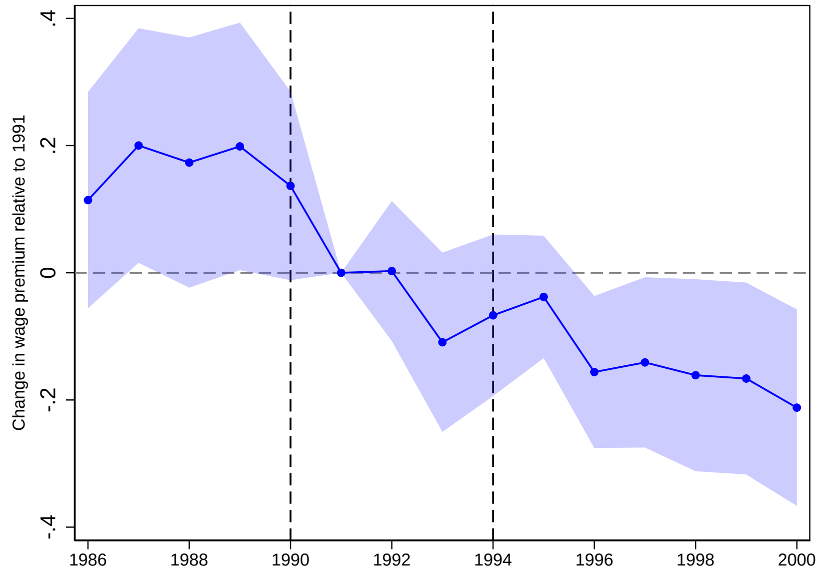
Figure A.8: Effect of import competition on employment



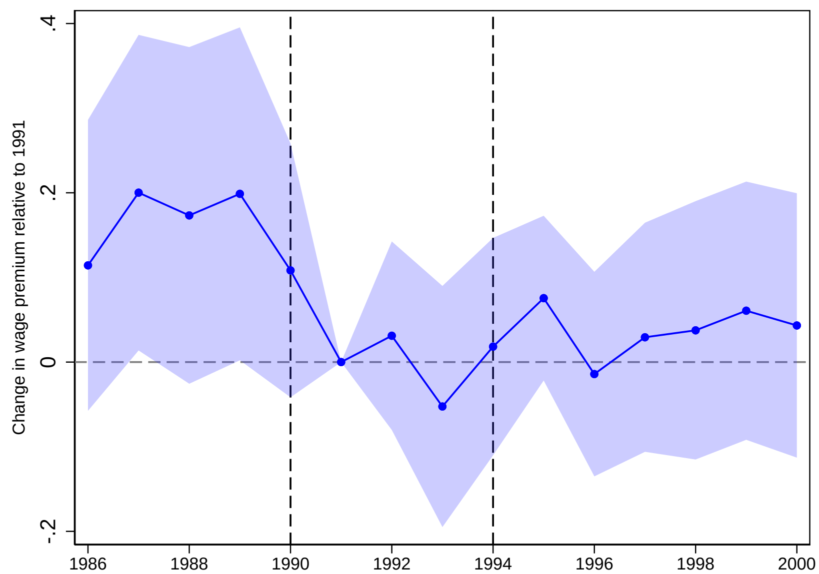
Note: See notes to Figure 2.

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

Panel A: Relative to trend

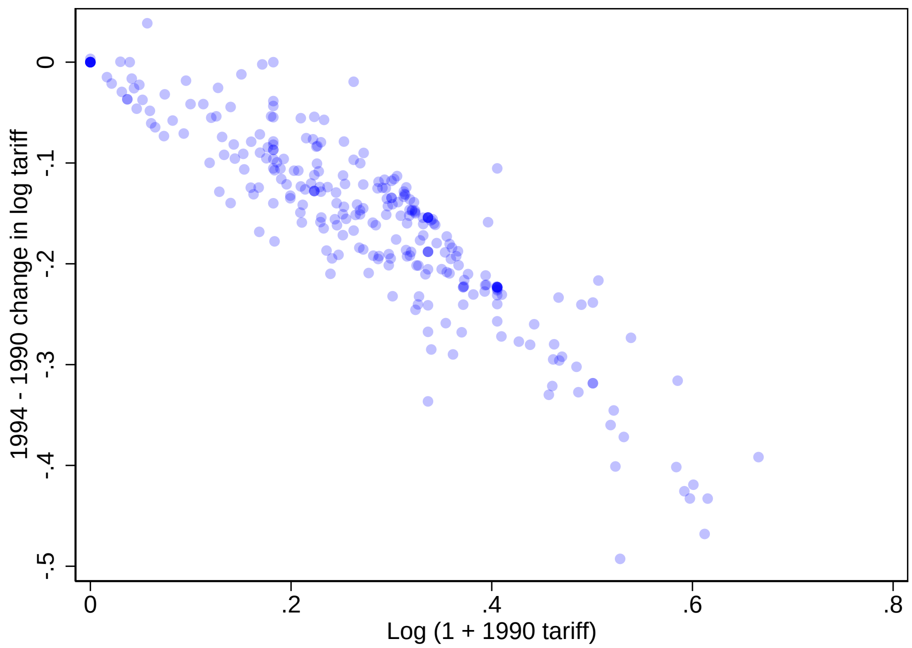


Panel B: Relative to base year



Note: See notes to Figure 2.

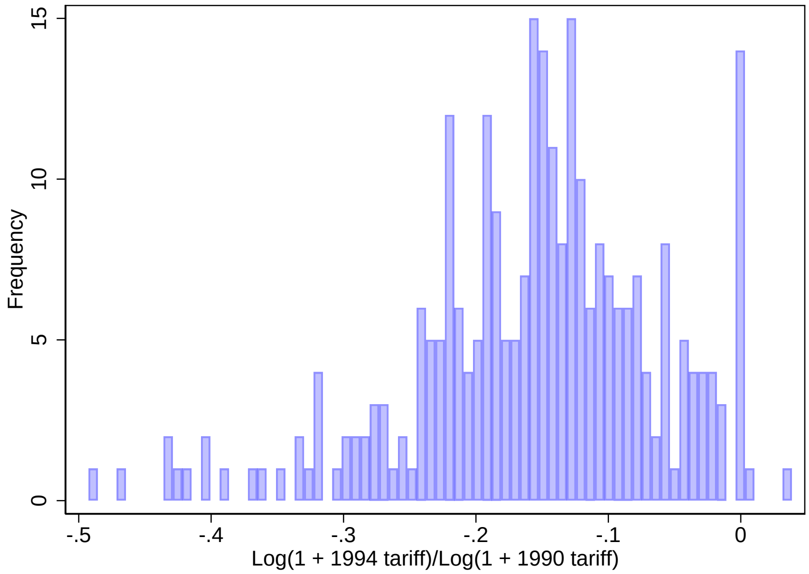
Figure A.10: Brazil's 1990-1994 tariff reduction reform: variation across 285 sectors



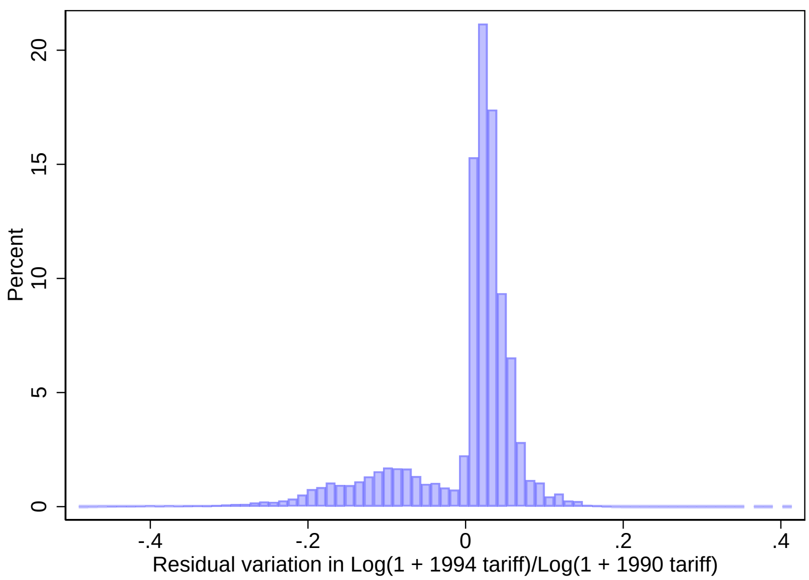
Note: This figure plots import tariff reductions rom Brazil's 1990-1994 import tariff reform across RAIS' 5-digit sector variable "CNAE-95", including 285 tradable sectors and 280 non-tradable sectors. Sector-level tariffs are simple averages of product-level tariffs for the products produced in each sector, and are constructed by mapping 6-digit product-level tariffs from UNCTAD TRAINS to CNAE-95 using Brazil's product-to-sector mappings from IBGE. See Section 3.2 for details.

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

Panel A: Cross-sector tariff change variation



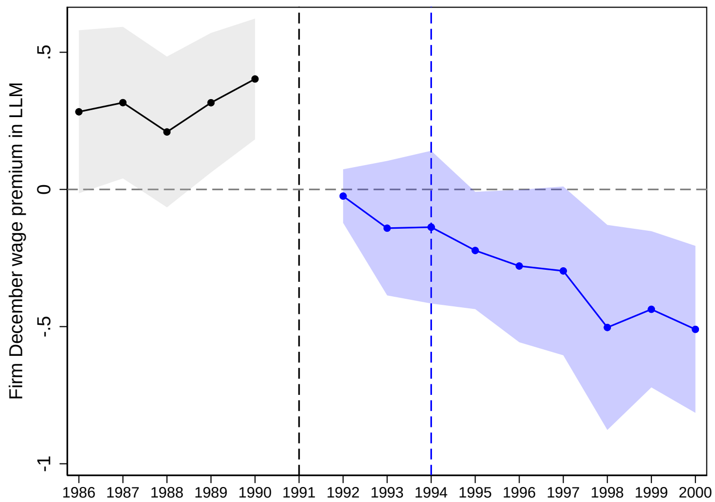
Panel B: Residual cross-firm tariff change variation



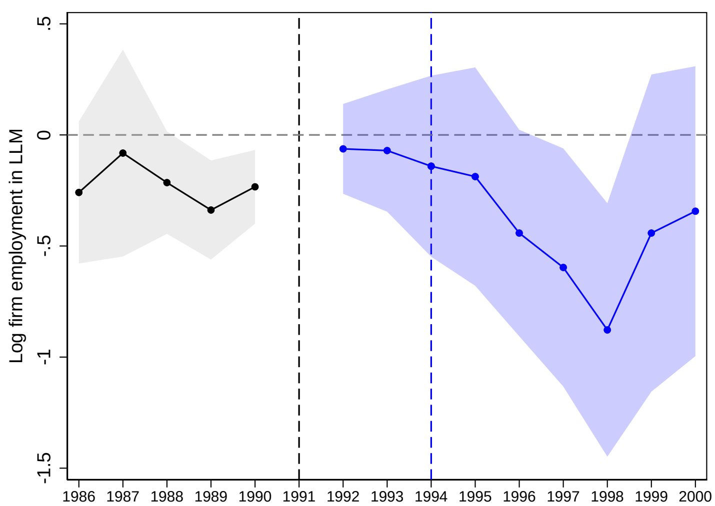
Note: This figure shows the variation in tariff changes at the CNAE95 level (285 tradable sector sectors) induced by Brazil's 1990s import import tariff reform. Panel A displays the raw data, while Panel B displays the residualized changes from a regression of tariff changes for all firms (included non-tradables,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

Panel A: Wage premia



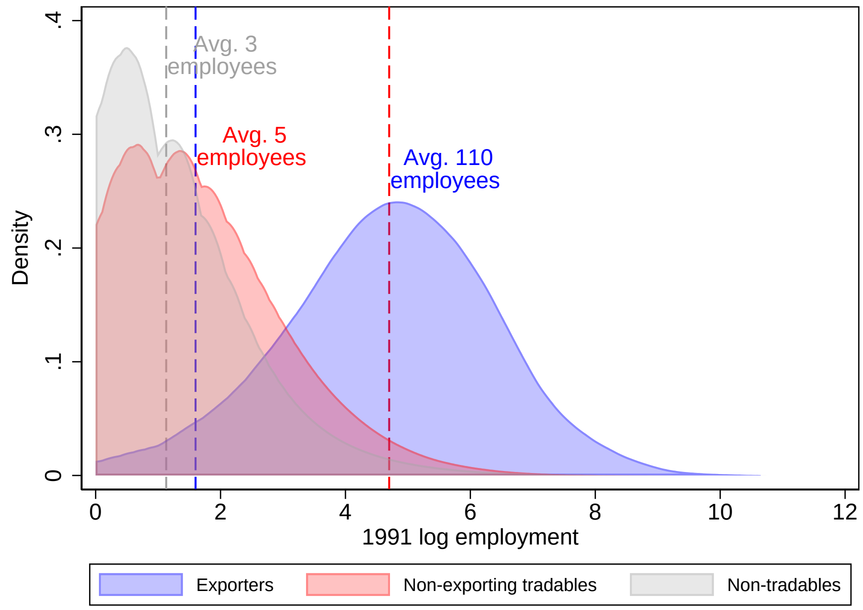
Panel B: Employment



Note: This figure plots coefficients of regressions of firm-level changes in log employment (from each year to the base year of 1991) on minus $\ln\left(\frac{1+\tau_{1994}}{1+\tau_{1990}}\right)$, 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

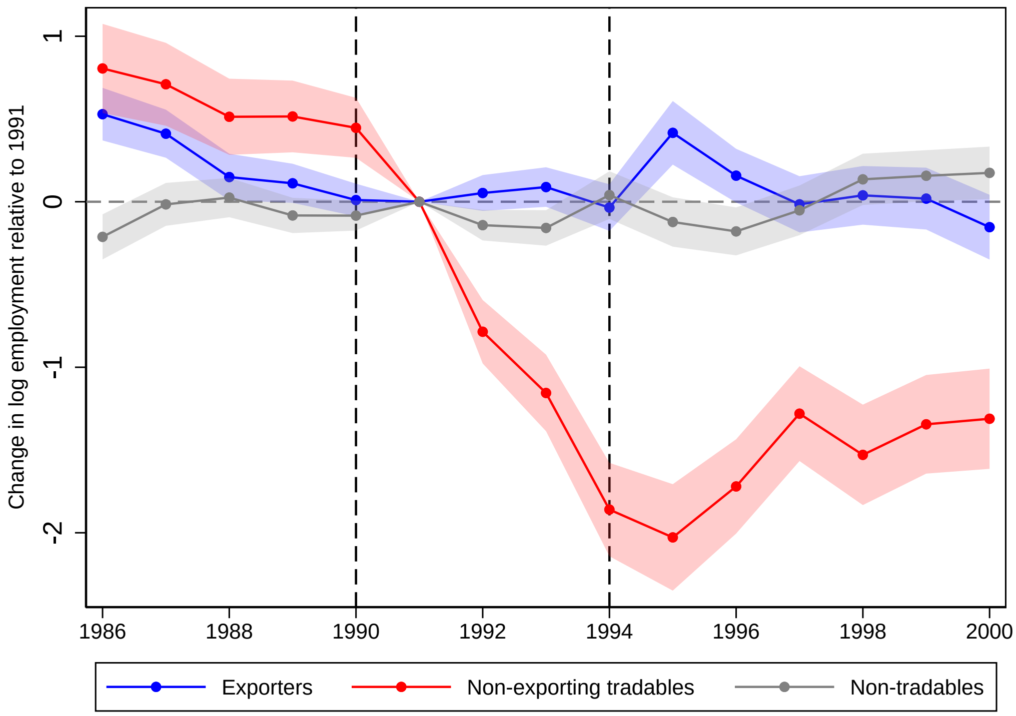
Panel A: Distributions of firm log employment



Panel B: Distributions of firm average log wage

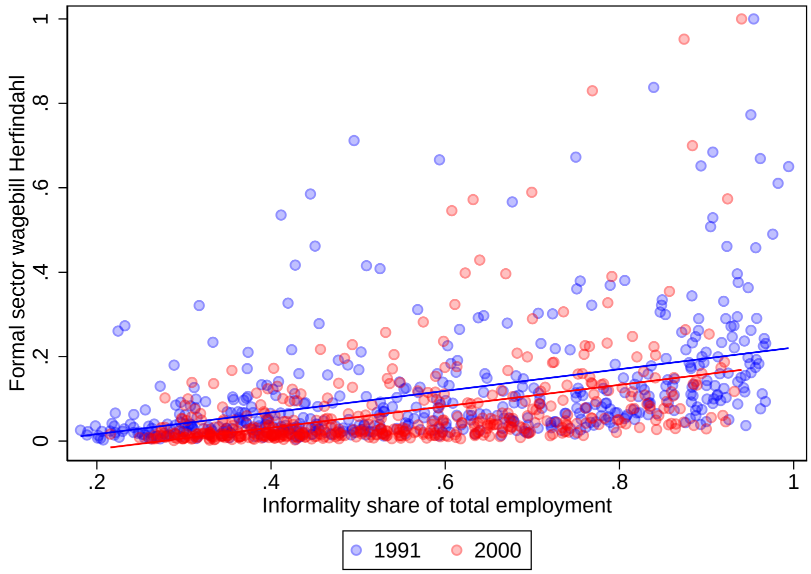
Note: This figure plots pre-liberalization distributors of firm log employment and log December monthly wages for exporters, non-exporters, and non-tradables. Wages are reported as multiples of the national minimum wage.

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
Δ Import Competition Exposure	12%	0%	5%	13%	18%	23%

Note: This table presents descriptive statistics across 21,242 Brazilian local labor markets defined as microregion × 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
Percent staying in...	
Microregion (486 groups of municipalities)	79%
Occupational group (CBO94 / 2-digit / 65 groups)	50%
Local labor market: Microregion x Occupational group cell	40%
Economic sector group (CNAE95 / 2-digit / 59 groups)	33%
Microregion x Economic sector group cell	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)
Panel A: Labor market concentration		
Δ Payroll Herfindahl (based on wage premium)	0.213	0.102
	(0.017)	(0.046)
Δ Payroll Herfindahl	0.213	0.110
	(0.017)	(0.064)
Δ Employment Herfindahl	0.247	0.058
	(0.016)	(0.056)
Panel B: Log number of firms and log employment		
Δ Log number of firms	-0.549	-0.367
	(0.045)	(0.208)
Δ Log total employment	-0.440	-0.338
	(0.064)	(0.335)
Panel C: Log wage premium		
Δ Log wage premium	0.029	0.116
	(0.031)	(0.131)
Δ De-trended log wage premium	-0.141	0.106
	(0.031)	(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)
Panel A: Labor market concentration				
Δ Payroll Herfindahl (based on wage premium)	0.213	0.259	0.278	0.119
	(0.017)	(0.020)	(0.020)	(0.011)
Δ Payroll Herfindahl	0.213	0.259	0.277	0.121
	(0.017)	(0.020)	(0.020)	(0.012)
Δ Employment Herfindahl	0.247	0.303	0.329	0.141
	(0.016)	(0.019)	(0.020)	(0.011)
Panel B: Log number of firms and log employment				
Δ Log number of firms	-0.549	-0.673	-0.736	-0.309
	(0.045)	(0.050)	(0.052)	(0.030)
Δ Log total employment	-0.440	-0.527	-0.577	-0.225
	(0.064)	(0.073)	(0.076)	(0.044)
Panel C: Log wage premium				
Δ Log wage premium	0.029	0.037	0.046	0.059
	(0.031)	(0.035)	(0.037)	(0.021)
Δ De-trended log wage premium	-0.141	-0.156	-0.150	-0.090
	(0.031)	(0.035)	(0.037)	(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)	AKM (2019) standard errors (3)
Panel A: Labor market concentration			
Δ Payroll Herfindahl (based on wage premium)	0.213	0.213	0.213
	(0.017)	(0.029)	(0.008)
Δ Payroll Herfindahl	0.213	0.213	0.213
	(0.017)	(0.028)	(0.008)
Δ Employment Herfindahl	0.247	0.247	0.247
	(0.016)	(0.028)	(0.008)
Panel B: Log number of firms and log employment			
Δ Log number of firms	-0.549	-0.549	-0.549
	(0.045)	(0.131)	(0.024)
Δ Log total employment	-0.440	-0.440	-0.440
	(0.064)	(0.153)	(0.040)
Panel C: Log wage premium			
Δ Log wage premium	0.029	0.029	0.029
	(0.031)	(0.068)	(0.018)
Δ De-trended log wage premium	-0.141	-0.141	-0.141
	(0.031)	(0.068)	(0.019)
Observations	296,400	296,400	296,400
Local labor markets	19,760	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)
Panel A: Labor market concentration		
Δ Payroll Herfindahl (based on wage premium)	0.213	0.156
	(0.017)	(0.032)
Δ Payroll Herfindahl	0.213	0.162
	(0.017)	(0.034)
Δ Employment Herfindahl	0.247	0.098
	(0.016)	(0.018)
Panel B: Log number of firms and log employment		
Δ Log number of firms	-0.549	-0.657
	(0.045)	(0.159)
Δ Log total employment	-0.440	-0.187
	(0.064)	(0.142)
Panel C: Log wage premium		
Δ Log wage premium	0.029	-0.004
	(0.031)	(0.071)
Δ De-trended log wage premium	-0.141	-0.332
	(0.031)	(0.071)
Observations	296,400	296,400
Local labor markets	19,760	19,760

Note: See notes to Table 1.

Table A.8: Nature of employment reallocation: exporters vs. other firms

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

Note: See notes to Table 1.

Table A.9: Nature of employment reallocation: exporters vs. large firms

	Δ Firm log employment (1)	Δ Firm log wage premium (2)
Log tariff shock	-0.492	-1.176
	(0.154)	(0.270)
Log tariff shock x exporter	0.509	1.279
	(0.155)	(0.333)
Log tariff shock x large firm	-1.103	-0.408
	(0.413)	(0.215)
Log tariff shock x exporter x large firm	0.979	-0.212
	(0.553)	(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.

Table A.10: Within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$: alternative samples

		Robustness to key alternative samples		
	Main specification	Unique producers	Local labor market defined as microregion	Including exiting firms, coding employment and wages at exit as zero
	(1)	(2)	(3)	(4)
Panel A: First stage				
Δ Firm log employment in LLM	-0.554	-0.289	-0.417	-0.554
	(0.044)	(0.043)	(0.037)	(0.044)
First stage F	158.497	44.304	124.666	159.847
Panel B: Reduced form				
Δ Firm's wage premium in LLM	-0.545	-0.327	-0.404	-0.546
	(0.024)	(0.044)	(0.017)	(0.024)
Panel C: 2SLS				
Labor supply within-market cross-firm inverse elasticity of substitution	0.985	1.134	0.969	0.986
	(0.089)	(0.224)	(0.092)	(0.088)
Implied upper bound on wage take-home share	50%	47%	51%	50%
Observations	854,068	693,360	440,966	1,616,382
Firms	344,066	301,666	420,246	719,623
Local labor markets	15,717	13,131	474	18,598

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

Table A.11: Within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$: robustness to clustering

	Main specification (Clustered by firm)	Clustered by local labor market	Clustered by sector
	(1)	(2)	(3)
Panel A: First stage			
Δ Firm log employment in LLM	-0.554	-0.554	-0.554
	(0.044)	(0.070)	(0.107)
First stage F	158.497	62.719	26.720
Panel B: Reduced form			
Δ Firm wage premium in LLM	-0.545	-0.545	-0.545
	(0.024)	(0.104)	(0.103)
Panel C: 2SLS			
Labor supply within-market cross-firm inverse elasticity of substitution	0.985	0.985	0.985
	(0.089)	(0.207)	(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.12: Within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$: robustness to wage and shock

	Using December wage conditional on observables (Main specification)	Using December wage conditional on worker FE and demo-by-year controls	Using (2) and further conditioning on stayers in firm-market pair	Using December average wage	Using effective rate of protection
	(1)	(2)	(3)	(4)	(5)
Panel A: First stage					
Δ Firm log employment in LLM	-0.554	-0.609	-0.606	-0.554	-0.358
	(0.044)	(0.054)	(0.074)	(0.044)	(0.035)
First stage F	158.497	129.572	66.895	158.497	107.143
Panel B: Reduced form					
Δ Firm wage premium in LLM	-0.545	-0.497	-0.513	-0.527	-0.351
	(0.024)	(0.028)	(0.041)	(0.025)	(0.019)
Panel C: 2SLS					
Labor supply within-market cross-firm inverse elasticity of substitution	0.985	0.815	0.847	0.952	0.980
	(0.089)	(0.081)	(0.121)	(0.088)	(0.108)
Implied upper bound on wage take-home share	50%	55%	54%	51%	50%
Local labor market (LLM) FE	Yes	Yes	Yes	Yes	Yes
Observations	854,068	433,760	182,610	854,068	851,662
Firms	344,066	195,486	89,130	344,066	343,558
Local labor markets	15,717	12,293	9,501	15,717	15,665

Note: See notes to Table 2.

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

	Main specification	Robustness to key alternative samples: Unique producers	Robustness to key alternative samples: Local labor market is microregion
	(1)	(2)	(3)
Panel A: First stage			
Δ LLM employment index	-0.396	-0.120	-0.224
	(0.032)	(0.042)	(0.133)
First stage F	150.752	8.156	2.819
Panel B: Reduced form			
Δ LLM wage premium index	-0.108	-0.097	-0.034
	(0.051)	(0.065)	(0.122)
Panel C: 2SLS			
$\frac{1}{\theta} - \frac{1}{\eta}$	0.272	0.809	0.153
	(0.131)	(0.602)	(0.536)
Panel D: Cross-market inverse elasticity of substitution			
$\frac{1}{\theta}$	1.257	1.942	1.122
	(0.096)	(0.559)	(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 × occupational group cell. column (2) uses $\frac{1}{\eta}$ estimates based on the set of unique producers in a microregion ×occupational group cell. column (3) expands the definition of a local labor market to microregions only.

Table A.14: Cross-market inverse elasticity of substitution $\frac{1}{\theta}$: robustness to clustering

		Main specification (1)	Two-way clustered by microregion and occupational group (2)
	Panel A: First stage		
Δ LLM employment index		-0.396	-0.396
		(0.032)	(0.076)
	First stage F	150.752	27.008
	Panel B: Reduced form		
Δ LLM wage premium index		-0.108	-0.108
		(0.051)	(0.075)
	Panel C: 2SLS		
	$\frac{1}{\theta} - \frac{1}{\eta}$	0.272	0.272
		(0.131)	(0.190)
	Panel D: Cross-market inverse elasticity of substitution		
	$\frac{1}{\theta}$	1.257	1.257
		(0.096)	(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.15: Cross-market inverse elasticity of substitution $\frac{1}{\theta}$: robustness to wage

	Main specification (1)	Using average December wage (2)
Panel A: First stage		
Δ LLM employment index	-0.396	-0.403
	(0.032)	(0.034)
First stage F	150.752	136.488
Panel B: Reduced form		
Δ LLM wage premium index	-0.108	-0.094
	(0.051)	(0.050)
Panel C: 2SLS		
$\frac{1}{\theta} - \frac{1}{\eta}$	0.272	0.234
	(0.131)	(0.125)
Panel D: Cross-market inverse elasticity of substitution		
$\frac{1}{\theta}$	1.257	1.186
	(0.096)	(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.

Figure A.16: Heterogeneity of $\frac{1}{\eta}$ by workforce demographic composition at baseline

	Δ firm log wage premium in local market				
	(1)	(2)	(3)	(4)	(5)
Δ Firm log employment in local market	0.985***	1.084***	1.095***	1.003***	1.206***
	(0.089)	(0.142)	(0.087)	(0.087)	(0.147)
Δ Firm log employment in local market x (Baseline female share of employment)		-0.0024			-0.00267
		(0.003)			(0.003)
Δ Firm log employment in local market x (Baseline college-educated share of employment)			-0.0170***		-0.0176***
			(0.003)		(0.003)
Δ Firm log employment in local market x (Baseline over-40-years-old share of employment)				-0.000789	0.000067
				(0.001)	(0.002)
Observations	854,068	854,068	854,068	854,068	854,068

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table shows IV estimates of the within-market cross-firm inverse elasticity of substitution by the demographic composition of the workers in each firm-market cell in the baseline year of 1991. Column (1) reports the main estimate from Table 2. Asterisks denote significance at 5% level and are included to facilitate reading of heterogeneity coefficients. Standard errors are clustered by firm.

Figure A.17: Heterogeneity of $\frac{1}{\eta}$ by microregion characteristics at baseline

	Δ firm log wage premium in local market					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Firm log employment in local market	0.985***	3.636***	3.169***	1.189**	1.809***	3.068***
	(0.089)	(0.617)	(0.459)	(0.409)	(0.405)	(0.869)
Δ Firm log employment in local market x (Baseline informal employment share, excl. self-employment)		-0.127***				0.0905
		(0.028)				(0.093)
Δ Firm log employment in local market x (Baseline self-employment share)			-0.123***			-0.156**
			(0.023)			(0.048)
Δ Firm log employment in local market x (Baseline union employment share)				-0.565		-0.758
				(1.132)		(1.331)
Δ Firm log employment in local market x (Baseline unemployment rate)					-0.103*	-0.118
					(0.049)	(0.077)
Observations	854,068	854,068	854,068	854,068	854,068	854,068

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table shows IV estimates of the within-market cross-firm inverse elasticity of substitution by characteristics of each firm's microregion in the baseline year of 1991. Column (1) reports the main estimate from Table 2. Union employment share denotes the share of formal employment that is employed by sindicates (CNAE code 91200). Asterisks denote significance at 5% level and are included to facilitate reading of heterogeneity coefficients. Standard errors are clustered by firm.

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 (TRAINS), which I download from the World Integrated Trade Solution (WITS)'s website.[68] 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.[69] 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 tecnical coefficients matrix ("Tabela 20"), which is available at Nível 50 from Brazil's national accounts website.[70]

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

[68] See https://wits.worldbank.org/.

[69] See https://concla.ibge.gov.br/classificacoes/correspondencias/atividades-economicas.

[70] See 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

For each year, I estimate each firm's wage premium in its local labor market as firm $\times$market fixed effects in a regression of worker log december earnings on the firm $\times$ market fixed effects and the same worker observable 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. Similarly, for each year, I estimate each market's wage premia as a regression of worker log december earnings on the market fixed effects and the previously mentioned worker observable controls.

For the robustness exercise of the within-market cross firm elasticity using wage premia that condition on worker fixed effects (e.g., columns (2) and (3) of Appendix Table A.12, I estimate each firm's wage premia in 1991 and 1997 as firm $\times$market $\times$ year fixed effects in a regression—containing years 1991 and 1997—of worker log december earnings on worker fixed effects, the firm $\times$market $\times$ year fixed effects, and worker observable-characteristics-by-year controls.

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:[71]

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

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

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

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^j_{zm} units of labor by minimizing their indirect disutility of work V_{zm} subject to making reservation earnings

[71] For 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:

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

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.

$y^j \sim F(y)$:

$$\min_{zm} V^j_{zm} = \ln l^j_{zm} + \ln \xi_m + \ln \xi_{zm} - \xi^j_{zm}$$
$$\text{s.t. } l^j_{zm} w_{zm} \geq y_j$$

where ξ^j_{zm} 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

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

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

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

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 $P\left(\xi^j_{zm} > \ln w_{zm} - \ln y_j - \ln \xi_m - \ln \xi_{zm}\right)$, which can be decomposed as:

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

where $P\left(z|B_m\right)$ is the probability of choosing firm z conditional on choosing market m with set B_m of firms, and $P\left(B_m\right)$ is the probability of choosing market m. By the results in

McFadden (1978), P_{zm} can be computed as:

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

and

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

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 $P^j_{zm} = P_{zm}$ 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

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

With equation 26 at hand, total labor supplied to firm z in market m can be found by integrating probabilities P^j_{zm} (times $h^j_{zm} = y^j/w_{zm}$ supplied by each worker) over the continuum of workers:

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

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:

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

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:

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

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:

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

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:

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

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:

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

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:

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

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 (2022)'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:*

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

where $s_m = \frac{\bar{w}_m l_m}{\sum_m \bar{w}_m l_m}$ is market m's payroll share, $H\tilde{H}I = \sum_m s_m HHI_m$ 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:

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

□

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:

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

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:

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

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

C.2.6 Equation 9 under the setup in BHM

I show that equation 9 holds under the additional assumptions on production function and goods market structure in Berger, Herkenhoff and Mongey (2022), henceforth BHM. 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 BHM. Goods markets are perfectly competitive, with $p_{zm} = 1$ for all firms and markets. Firms compete for labor à la Cournot, solving:

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

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.[72] Computing the definition of market m's average

[72] In BHM, the greek letter μ refers to the wage take-home share (i.e., the inverse of the wage markdown) holding capital constant.

wage markdown holding capital constant gives:

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

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

$$= \alpha\gamma \frac{\sum_z y_{zm}}{\sum_z w_{zm} l_{zm}} \tag{32}$$

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

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:

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

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:

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

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 Extensions and heterogeneity

The findings in Sections 4, 6, and 7 can be summarized into three take-aways: (i) In the 1990s, formal sector firms in Brazil commanded substantial firm labor market power, primarily driven by workers' very inelastic within-market cross-firm substitution; (ii) Opening to trade increased that labor market power a bit further as it raised local labor market concentration—by enough to offset wage gains from cross-firm reallocation—but (iii) on net, the magnitude of this market power effect was small, and cannot explain most of the wage decline. The decline was driven instead by the marginal revenue product of labor.

These findings leave unanswered several important questions for future research, including 1) what components of the marginal revenue product of labor accounts for the decline?; 2) could the muted effect on average wage markdowns be driven by heterogeneous (and offsetting) effects of trade on wage markdowns for different types of workers? and 3) how do features not explicitly modeled in Section 2 (e.g., informality, unemployment, or unions) relate to these findings?

While addressing any one of these question's beyond the scope of this paper, this Section describes how Section 2's model can be extended to make progress on questions 2 and 3,[73] and provides estimates of how the within-market cross-firm elasticity varies by firms' baseline workforce composition as well as by market's baseline characteristics. I focus on heterogeneity for the within-market cross-firm elasticity because it is the key driver underlying the high

[73]Question 1 can be addressed with additional data, such as data on firm sales and non-labor inputs.

levels of market power I estimate for Brazil, as well as the main labor supply parameter that is starkly different between Brazil and the US.

D.1 Adding different types of labor: gender, education, age

In Section 2's model, workers have heterogeneous preferences over jobs, but are otherwise homogenous. The advantage of this simplifying assumption is that it allows for studying the effect of trade on average wage markdowns and, ultimately, average wages, in a parsimonious manner, while still allowing for the wage heterogeneity seen in the data to be taken into account in the empirical exercise. The cost of parsimony is that it does not allow for a richer understanding of the heterogeneity underlying average effects. For example, trade might substantially increase wage markdowns for certain workers while substantially decreasing it for others. Testing this requires a model with type-specific wage markdowns and type-specific marginal revenue products of labor.

Luckily, extending Section 2's model to add different types of labor is relatively straightforward, especially if one is willing to make other simplifying assumptions. Assuming workers cannot change their type, workers' discrete choice problem can be separately specified for each type. Conceptually, this is a *horizontal extension* of the supply side, since each type makes the same the number of nested decisions (two: markets, then firms) as in the baseline model, such that there are now $2 \times k$ elasticities of substitution, where k is the number of types. Similarly, assuming that firms choose type-specific amounts of labor by setting type-specific marginal revenues to type-specific marginal costs, the baseline profit maximization problem can be extended by allowing marginal revenues and marginal costs to vary by type. This extends the demand side. The workforce composition is now determined in equilibrium, with each firm's type-specific wage markdown is a function of the firm's type-specific payroll share in its local market, and the type-specific within-market elasticities of substitution.[74]

Without extending Section 2's model, one way to check how its implied markdowns vary by worker type is to examine how its main driver of market power levels—the within-market cross-firm elasticity of substitution—varies by firms' baseline workforce composition. Appendix Table A.16 provides these estimates. Column (1) reports the baseline estimate for $1/\eta$, based on the IV regression equation 15. Columns (2)–(5) add interactions of the

[74] The expression of the markdown would be different if workers of a given type can only be found in a handful of markets. If this is the case, a profit-maximizing firm would internalize the impact of its type-specific hiring decision on country-level wages and employment, which changes the expression for the firm-type-specific inverse elasticity of residual labor supply. This does not occur in the baseline model because workers are homogenous and there is a large number of markets.

main endogenous variable—the change in firm log employment in the local market—with measures of the firm's baseline workforce composition in the market,[75] in particular: female share, college-educated share, and over-40-years-old share.[76]

Column (5) adds all interactions, and its main effect is identified by firms composed solely of uneducated men under 40. This group is the most inelastic. Column (5) shows that the main dimension diverging from this baseline estimate is education, and suggests that workers in firms with large baseline shares of college-educated workers are the most elastic. This suggests that firms have less market power amongst educated workers. While analyzing the effect of trade on type-specific markdowns requires extending Section 2's model, the empirical presence of this heterogeneity in a baseline model parameter suggests the question merits future research. Differential market power effects by college status might underly, for example, Brazil's reduction in skill premium due to trade (Dix-Carneiro and Kovak, 2015) and increased wage inequality among college-educated workers (Krishna, Poole and Senses, 2012).

D.2 Adding informality, unemployment, and unions

While this paper focuses on the formal sector, an important set of questions concerns how unmodeled labor market features such as informality, unemployment, or unions relate to its findings. I start by discussing heterogeneity estimates of the within-market cross-firm elasticity of substitution to these market features, and then turn to how the model in Section 2 can be extended to explicitly incorporate them.

Without being explicitly modeled, the way in which informality, unemployment, or unions enter Section 2's expression for a firm's wage markdown is as micro-foundations for workers' key elasticities of substitution. For example, high rates of informality or unemployment could make formal sector workers more loyal to their current employer or more risk-averse to quitting a bad formal sector job if they don't already have something else lined up. Through the lens of Section 2's model, this behavior would make elasticities of substitution across firms more inelastic. Alternatively, a strong culture of micro-entrepreneurship might make formal sector workers less risk-averse to quitting, as the possibility of starting something on their own in self-employment may function as a preferable outside option. Finally, strong unions might increase workers' wage take-home share, a force that would be reflected in the

[75] As standard in heterogeneous IV by baseline characteristics, the additional instruments are interactions between the tariff shock to the firm and the corresponding measures of baseline workforce composition.

[76] The age variable is available in five buckets, with over-40 capturing workers in the two oldest buckets.

model as more elastic cross-firm elasticities of substitution.

Appendix Table A.17 presents heterogeneity estimates of the within-market cross-firm inverse elasticity of substitution by these labor market features. Column (1) reports the baseline estimate for $1/\eta$, based on the IV regression equation 15. Columns (2)–(6) add interactions of the main endogenous variable—the change in firm log employment in the local market—with the following microregion baseline characteristics: informality share (excluding self-employment), self-employment share, a proxy for union strength (share of formal sector workers employed by unions), and unemployment rate.

The estimates in Column (6), which add all interactions, suggest that self-employment is the main unmodeled dimension for which the within-market elasticity of substitution is heterogeneous. It suggests that firms in local labor markets where self-employment is more prevalent face more elastic labor supply curves, consistent with the idea that micro-entrepreneurship might work as preferable outside option in these markets. This is not the case for informality excluding self-employment (that is, working for a firm without a signed worker card that guarantees benefits such as unemployment insurance, paid vacation, etc.). The latter appears to make workers more inelastic, though the standard errors on this effect are too large to reject the null. Conversely, union strength appears to make workers more elastic, though I similarly cannot reject the null.

However, a more comprehensive understanding of how informality, unemployment, or unions interact with firm labor market power requires extending the model in Section 2 to explicitly incorporate these features.[77] This would allow not only to expand the analysis beyond effects on the formal sector, but would also link the literatures documenting effects of trade on informality, unemployment, and unions (e.g., Dix-Carneiro et al. (2021); Ogeda, Ornelas and Soares (2021)) to the literature estimating firm labor market power in the presence of self-employment (e.g., Amodio, Medina and Morlacco (2022)) or union bargaining (e.g., Lagos (2019)).

One way to explicitly incorporate either informality or unions—assuming the corresponding data is available to estimate the additional parameters—is to add new nests to workers' discrete choice problem. For example, workers might first choose between the formal and informal sectors, with a new elasticity of substitution φ governing that decision, then markets, and then firms. Conceptually, this is a *vertical extension* of the model, as it adds new layers to workers' decisions. The data requirements—and the consequences for estimates of

[77] See Appendix D.3 for a discussion of informality in particular. In the baseline model, incorporating informality has theoretically ambiguous effects on estimates of the levels of wage markdowns.

firm labor market power—depend on how the decisions are nested.

For example, if workers first choose between formal and informal employment, then the informality margin will not be very important for estimates of the wage markdown because, in general, the lowest nest elasticity is the most important one (as most workers are employed in not-very-concentrated local labor markets). If the decision is made last, then the informality margin will be very important. Therefore, the ideal data for this exercise would be one covering employer-employee links of both formal and informal firms, which would allow for testing which nesting structure is most consistent with the data, as in the exercise by Goldberg (1995) in the context of demand estimation for cars.[78]

Finally, unemployment could be incorporated either on the supply side as an additional nest (i.e., voluntary unemployment, where workers can't find a desirable match), or on the demand side as an exogenous (to the firm) component of the marginal revenue product of labor, capturing the probability that the firm would fire a worker in case the match was not satisfactory ex-post (i.e., involuntary unemployment). In this case, firms would set wage markdowns by setting expected marginal revenues to marginal costs, where the former expectation is taken over the match quality distribution.

D.3 Additional discussion on 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 would be helpful to understand whether these estimates would remain the same if the informal sector were incorporated, 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).[79]

One way to address this question is to understand how omitting data from the informal

[78] As for unions, while all formal sector workers are governed by some union bargaining agreement—typically established at the region $\times$ sector level—some firms have their own bargaining agreements with workers, such as those studied by Lagos (2019). This feature could be incorporated in the model by allowing workers to choose between "high union presence" firms and "low union presence" firms, before choosing among firms within those options.

[79] Liberalization 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)).

sector might impact this paper's main findings. Specifically, consider 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 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.