Trade, Labor Market Concentration, and Wages

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March 9, 2026

Abstract

I estimate the effect of trade on local labor market concentration and its implications for wages using employer-employee linked data and tariff shocks from Brazil's trade liberalization. Trade increased concentration by 7%, an effect driven by firm exit and worker flows to surviving import-competing firms. Increased concentration reduced wage take-home shares—estimated at 50 cents on the dollar pre-shock—enough to offset small wage gains from reallocation, but did not meaningfully reduce wages on net. Most of the wage declines attributed to Brazil's trade liberalization resulted instead from reductions in the marginal revenue product of labor. Incorporating informality reveals substantial regional heterogeneity.

*Yale University and NBER. Email: mayara.felix@yale.edu. I am indebted to my advisers David Atkin, Arnaud Costinot, and Ben Olken for invaluable guidance and support. I thank Rafael Dix-Carneiro, Dave Donaldson, Hamid Firooz, Federico Huneeus, Amit Khandelwal, and Rohini Pande for detailed comments. For very helpful 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, Naercio Menezes Filho, Peter Morrow, Emanuel Ornelas, Vitor Possebom, Pamela Medina 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 import competition persistently reduces wages in more exposed labor markets relative to less exposed ones. These patterns have been documented in various contexts, including India (Topalova, 2010), Brazil (Kovak, 2013), and the U.S. (Autor, Dorn and Hanson, 2013). Why? This paper tests one potential mechanism: trade-induced increases in firm labor market power.

A robust prediction of trade models with firm heterogeneity is that trade liberalization reallocates labor towards larger, more productive firms. In a *bilateral* liberalization, as in Melitz (2003), exporters expand in response to increased foreign demand, thickening the right tail of the firm size distribution, and kicking out the least productive firms on the left tail in equilibrium. In a *unilateral* liberalization, as in Melitz and Ottaviano (2008), increased import competition directly eliminates the least productive firms, cutting off the left tail of the firm size distribution, with the displaced labor being reallocated towards surviving firms in equilibrium. In either case, trade shifts the firm size distribution rightward, raising average productivity but also increasing labor market concentration. If labor markets are imperfectly competitive, with market power increasing in firm size—consistent with developing country evidence (Amodio et al., 2025)—increased concentration can strengthen surviving firms' wage-setting position, putting downward pressure on wages. How much of trade's negative wage effects can be accounted for by increased labor market power can only be assessed empirically.

This paper is an empirical study of the relationship between trade, labor market concentration, and wages in the context of Brazil's 1990s unilateral trade liberalization. I focus on the labor market power commanded by formal sector firms, and measure the degree of a firm's market power as the firm's wage markdown, the ratio of its marginal revenue product of labor to its wage. Formal firms are a natural focus for several reasons. First, formal workers experienced the most negative effects of import competition on wages (Kovak, 2013), and these effects have persisted for decades (Dix-Carneiro and Kovak, 2017). Second, formal firms are the largest employers in any one labor market, and thus those for which size-related labor market distortions are most relevant (Dix-Carneiro et al., forthcoming).

Using a sufficient statistics approach, employer-employee linked data, and import tariff reduction shocks, I test whether trade increased labor market concentration among formal employers in more exposed markets, and estimate the consequences for formal sector wages. I then quantify how much of trade liberalization's net-negative effect on local formal sector wages is accounted for by increased labor market power. Trade increased concentration by 7%, driven by direct worker reallocation from shrinking to expanding non-exporting tradable sector firms, consistent with the pro-competitive effects of import competition predicted by Melitz and Ottaviano (2008). Higher concentration raised average wage markdowns—estimated at 50 cents on the dollar pre-shock—by enough to offset small reallocation gains, but increased markdowns account for only 6% of trade's overall negative effect on average wages. Within-firm reductions in the marginal revenue product of labor, consistent with reduced output prices, account for the remaining 94%. These conclusions—which concern average effects—are largely unaffected by informal wage work and self-employment, but mask substantial heterogeneity in formal firms' wage markdowns across regions and their response to trade.

I develop a parsimonious model of imperfectly competitive labor markets where firm size matters for wage setting. The model provides the link between local labor market concentration and wage markdowns, a standard measure of firm labor market power defined as the ratio of the marginal revenue product of labor to the wage. On the supply side, workers have idiosyncratic preferences over jobs, yielding labor supply decisions that, when aggregated, follow a nested CES structure, as in Berger, Herkenhoff and Mongey (2022), henceforth BHM. On the demand side, firms maximize profits holding constant local employers' labor demand—namely, competing 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.

This paper's first theoretical result concerns the 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 with the market's payroll Herfindahl index, defined as the sum of its firms' squared payroll shares. This result holds regardless of the shape of firms' production functions or the competition structure in product markets, on which I remain agnostic. Overall, the more concentrated a market is, and the more inelastic the elasticities of substitution are, the larger is the market's average markdown.

The second result concerns the effect of import competition exposure on a local labor market's average wage markdown. A direct implication of my model's expression for a market's average wage markdown is that its response to an increase in import competition can be quantified by just two sufficient statistics: the effect of import competition exposure 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.

My empirical analysis begins by estimating the effect of import competition exposure on local labor market concentration. I define a local labor market as a microregion $\times$ occupational group cell, motivated by substantial and stable job-to-job transitions within these cells throughout the entire period, and report results using microregion-only boundaries as robustness. 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 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 unweighted mean, or a 27% increase relative to the 0.08 payroll-share-weighted mean. The effect is robust to alternative measures of import competition exposure and concentration, to defining labor markets solely as microregions, and to weighting by baseline size, showing that it is not driven by a handful of small markets.

To examine the source of increased concentration, I trace direct worker flows between three firm types—exporters, non-exporting tradable firms, and non-tradable firms—within each local labor market. Import competition primarily reduced employment among non-exporting tradable firms, consistent with Melitz and Ottaviano (2008), with little detectable effect on exporters or non-tradable firms. The key driver of increased concentration is direct within-market cross-firm reallocation of workers from shrinking to expanding import-competing firms (i.e., non-exporting tradable sector firms). Consistent with Melitz and Ottaviano (2008), total employment at exporters did not meaningfully respond to unilateral import tariff reductions, contributing only modestly to the increase in concentration as a larger share of the surviving total employment is located in exporting firms, who are much larger, but not via direct worker reallocation towards exporters.

The next step towards quantifying the effect of import competition 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, 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.

I estimate a within-market cross-firm inverse elasticity of substitution of 0.990, and a cross-market inverse elasticity of substitution of 1.448. Both point estimates are robust to alternative tariff shocks and 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, though consistent with estimates for other developing countries.[1] 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 as inelastic as the US', suggesting that Brazilian workers have a much tougher time making within-market cross-firm substitutions than US workers do.[2] Combined with the estimates for the effect of import competition on labor market concentration, the 0.459 gap between these elasticities implies that a 10% increase in import competition exposure reduced local labor markets' average wage take-home share by 0.24 cents on the dollar, via a statistically significant increase in wage markdowns. However, increased wage markdowns account for only about 6% of the overall negative effect of trade on average wages (Table 6); the remaining 94% was driven by within-firm reductions in the other component of the wage, the marginal revenue product of labor.

These baseline results focus on formal firms alone. However, Brazil's labor market is dual: formal firms co-exist with a large informal sector and substantial self-employment. Section 8 extends the model to incorporate self-employment as an alternative to wage work, informal wage work as a consequence of involuntary separation from formality, and preference heterogeneity across demographics and regions. Self-employment substantially curbs formal firms' market power by providing an attractive outside option, while the threat of involuntary separation into informal wage work slightly increases it. On average, these margins bring the wage take-home share to 51 cents on the dollar—close to the baseline's 50 cents, because most formal sector employment is located in predominantly formal microregions (Figure 1), and most of these microregions are in the Southeast, where the within-market cross-firm elasticity is most inelastic (Appendix Table C.2)—but the extension reveals substantial heterogeneity: 46 to 73 cents depending on local conditions outside the formal sector and workforce composition (Table 7). The effect of trade on markdowns through the extended model is also muted on average, but more heterogeneous across regions, with the North and Northeast experiencing a 1.2 p.p. *increase* in wage take-home shares.

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. Combined with evidence that trade raised firm productivity in Brazil (Muendler, 2004) and that the effects of import

[1] Amodio et al. (2025) apply a production function approach to estimate wage markdowns in a harmonized global panel of firms from 82 low- and middle-income countries. While Brazil is not in their sample, consistent with this paper they find a median wage take-home share of 43 cents on the dollar and that markdowns are increasing in firm size.

[2] These preference parameters might be microfounded in institutional and cultural factors that differ between the two countries and that shape worker preferences. For example, Brazil's inelastic cross-firm substitution might be a result of high valuations for formal sector job amenities combined with high search frictions. Using discrete choice experiments, Felix et al. (2026) find that Brazilian workers, and especially those formally employed, have extraordinarily high willingness to pay for formal sector attributes (i.e., 34% of wages for unemployment insurance, 24% for parental leave, 18% for termination notice). They also find that, conditional on searching for jobs, workers primarily search for formal sector jobs. For comparison, recent estimates of willingness to pay for typical job attributes in the US from Maestas et al. (2023) are substantially smaller. US workers are willing to pay less than 10% for 8 of the 12 attributes they evaluate, the most comparable across the two studies being training opportunities, valued at 5.4% by US workers in Maestas et al. (2023) but at 28.5% by Brazilian workers in Felix et al. (2026).

competition are very similar whether measured using output tariffs or effective rates of protection, within-firm MRPL reductions likely reflect reduced output prices rather than productivity losses—consistent with the pro-competitive effects predicted by Melitz and Ottaviano (2008).

Literature. The analysis speaks to large literatures on the regional incidence of trade, on labor market power in developing countries, and on methods for estimating wage markdowns. Brazil's liberalization has been widely studied for various outcomes (e.g., Muendler (2004), Gonzaga, Menezes Filho and Terra (2006), Krishna, Poole and Senses (2012), Dix-Carneiro and Kovak (2017), Dix-Carneiro, Soares and Ulyssea (2018)). More recently, Dix-Carneiro et al. (forthcoming) study how size-dependent distortions—taxes, regulations, and labor market frictions—change the aggregate gains from trade liberalization in Brazil.

My focus is on mechanisms: I zoom into the wage effects on formal sector workers to test whether trade-induced increases in labor market concentration reduce wages by increasing firm labor market power.[3] While some studies have documented that wages are lower in more concentrated local labor markets (e.g., Azar, Berry and Marinescu (2022); Azar, Marinescu and Steinbaum (2022)), and a few others have estimated that trade increases labor market concentration (e.g., Benmelech, Bergman and Kim (2022); Pham (2023)), 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 concentration and average markdowns, derive the sufficient statistics needed to quantify the effect of shocks to the former on the latter, estimate both the negative (via markdowns) and positive (via reallocation) wage effects of trade through concentration, and extend the model to show how formal sector markdown levels and their response to trade change when self-employment, informal wage work, and demographic heterogeneity are incorporated.

The estimates here are among the first of wage markdowns in a developing country, documenting a take-home share of 50 cents on the dollar. Since an earlier version of this paper was first circulated, this literature has greatly advanced. Amodio et al. (2025) use a production function approach to estimate wage markdowns in a panel of firms across 82 low- and middle-income countries, finding a median take-home share of 43 cents on the dollar and that markdowns increase in firm size, consistent with my findings for Brazil, though Brazil is not in their sample. Amodio, Medina and Morlacco (2025) use a labor supply approach to estimate wage markdowns in Peru, finding that self-employment curbs oligopsony power, with comparative advantage driving worker sorting across sectors. Evidence of strategic competition for workers continues to emerge: Sharma (2024) detects collusion among Indian textile firms.

On methods, the labor supply approach to estimating wage markdowns builds on work in international trade (Goldberg (1995), Atkeson and Burstein (2008)) that leverages nested preference structures to approximate market-level behavior originating from richer preferences. Grigolon and Verboven (2014) show that nested structures can approximate key substitution patterns of richer random coefficients models while remaining tractable. Random utility maximization has been increasingly adopted in labor economics to model and

[3] Segerstrom and Sugita (2015) show that extending Melitz (2003) to a multi-industry setting reverses the model's difference-in-differences prediction for bilateral liberalization: productivity rises more in nonliberalized industries, as cross-industry labor reallocation and wage adjustments offset within-industry selection. This critique does not apply to unilateral liberalization settings such as Brazil's, where the relevant framework is Melitz and Ottaviano (2008) and wages are pinned down by a freely traded outside good, shutting down the cross-industry wage channel driving the reversal.

estimate worker preferences (Mas and Pallais, 2017; Azar, Berry and Marinescu, 2022; Maestas et al., 2023; Felix et al., 2026). Market-level analyses (e.g., Berger, Herkenhoff and Mongey (2022)) follow the micro-to-macro approach now common in other fields. By showing when and how the key elasticities of substitution in models of oligopsony can be identified with IV, as opposed to indirect inference, I also contribute to a broader 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)).

The analysis extension in Section 8 advances this work by embedding both self-employment, as in Amodio, Medina and Morlacco (2025), and informal wage work—which may occur within or outside formal firms (Ulyssea, 2018)—into a model of labor market oligopsony where finitely many formal-sector firms compete for workers in dual local labor markets. Worker preferences—rather than comparative advantage as in Amodio, Medina and Morlacco (2025)—drive sorting and serve as the source of formal firms' market power. Felix et al. (2026) conducts discrete choice experiments in Brazil's largest slum complex, finding that formal workers value formal amenities most, the self-employed least, and informal workers have mixed valuations, consistent with preference-based sorting across sectors. The extension shows that the threat of involuntary separation into informality or unemployment increases formal firms' power, and provides a bias formula for market power estimates when only employer-employee linked data is available. It also delivers heterogeneous markdown estimates by gender, age, education, and region, contributing to the literature on markdowns and gender (e.g., Sharma (2023); Hoang, Mitra and Pham (2024)).

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.[4] 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 to 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.

[4] My model diverges from BHM's on two fronts: (i) I allow for arbitrary production functions and product market structure; and (ii) I allow wages to depend on firm-market-specific distaste shifters, which may reflect amenities. These divergences are possible because I estimate wage markdowns (set on the margin) rather than labor shares (which include infra-marginal revenues), and because my setting allows estimating elasticities via IV rather than indirect inference, which would require restrictions on (i) (see footnote 25). I also focus on relative effects of trade rather than general equilibrium counterfactuals. See Appendix B.2 for how this paper's results map into BHM's.

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

$$\min_{zm} V_{zm}^{j} = \ln l_{zm}^{j} + \ln \xi_{m} + \ln \xi_{zm} - \xi_{zm}^{j}$$
$$\text{s.t. } l_{zm}^{j} w_{zm} \geq y^{j}$$

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_{zm}^{j} is an idiosyncratic worker taste shifter with a General Extreme Value (GEV) distribution:[5]

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

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,[6] whose nesting structure is shown in Figure 2 from the point of view of worker j's decision. These are the two key elasticities of substitution whose estimates drive this paper's empirical findings.

Since ξ_{zm}^{j} follows a GEV distribution, the probability that worker j chooses firm z in market m can be written as a function of wages, taste-shifters, and the elasticities of substitution (see Appendix B for detailed derivations of all results in this section). 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 B.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 pay in market m to

[5] Equation 1 corresponds to the Gumbel distribution, a member of the GEV family. Per McFadden (1978), similar equations to those in this section can be derived for any member of the GEV family.

[6] 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.

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 is in Appendix B.

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:

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

where R_z is the firm's revenue function—capturing both production function and goods market structure, on which 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,[7] 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 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

[7] l_{-zm} denotes labor employed by all other firms or in all other markets. The wage w_{zm} depends on all these components via L_m and L in Equation 3. Similarly, R_z depends on them through firm z's production function (e.g., how it combines labor across markets) and through output equilibrium prices (e.g., competitors' production affects goods market structure).

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.[8] 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 the 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 consistent with optimal firm behavior in granular labor markets.[9] For example, in the face of a negative shock, a firm might find it optimal to change its occupation mix or close a specific establishment. The effect of such restructuring would be captured both on changes in the marginal revenue product of labor (via changes in productivity) and on wage markdowns (via relative sizes). At the local labor market level, Corollary 1 below isolates the effect on markdowns.

[8] Trade's negative effects on local wages could also be rationalized under perfect competition if workers cannot easily move across markets (Dix-Carneiro and Kovak, 2017). My paper instead considers the possibility, suggested by Manning (2003), that imperfect worker mobility is itself an outcome of firms exploiting workers' heterogeneous preferences to mark wages down.

[9] Around 3% of firms are multi-establishment (operating in different microregions) in this context. Appendix Figure A.2 shows near non-existent within-firm cross-region movement in the data.

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 a market's average wage markdown and its concentration level:

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

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

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 B.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 is worker movement in response to wage shocks, and thus the larger is the wage markdown.[10]

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:*

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

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.

[10] Proposition 1 refers to the average *wage markdown* at a *local labor market*, not the *country-level labor share* common in the labor and macro literatures. The wage markdown concerns wage-setting at the margin, whereas the labor share concerns payments to and revenues generated by *all* workers (including infra-marginal), requiring additional assumptions on production functions and goods market structure. Under such assumptions (e.g., Cobb-Douglas production and perfectly competitive goods and capital markets, as in BHM), a country's average markdown is closely related to its aggregate labor share. Appendix B.2.4 shows the country-level wage take-home share from equation 9 is mathematically equivalent to a sub-component of BHM's country-level labor share. Appendix B.2.6 shows that Proposition 1 still holds under these additional assumptions.

Proof. Differentiate equation 9 with respect to X. See Appendix B.2.5. □

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, captured by changes in labor market concentration.

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).

3 Data and setting

This section describes the data and setting I leverage to estimate the sufficient statistics in equation 10. The analysis combines employer-employee linked administrative records (RAIS), product-level import tariffs, firm-level exporting activity, and Brazil's 1991 and 2000 population censuses. Appendix A describes all datasets and mapping procedures.

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. Second, data on tariffs come from UNCTAD TRAINS, downloaded from WITS, which I map to RAIS via the 5-digit economic activity code CNAE95, 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 Section 8, downloaded from the replication data for Dix-Carneiro and Kovak 2017.

3.2 Brazil's formal sector labor market structure

In 1991, 42% of employed individuals held formal sector jobs, 28% informal jobs (i.e., worked for wages but without a formal contract that guarantees formal sector benefits like unemployment insurance), and 30% were self-employed (Appendix Table A.1). By 2000, the formal wage work share had fallen to 36% of 55.6 million employed, while informal wage work rose to 38% and self-employment fell to 25%.

Most formal employment is located in regions where employment is primarily formal (Figure 1). In terms of flows, each year most formal workers remain at their prior year's formal employer and most new formal sector hires come directly from other formal sector firms rather than from outside the formal sector (Appendix Figure C.1 and Appendix Table A.4). Flows also reveal that Brazilian formal labor markets have geographic and occupational components. Conditional on switching jobs, most Brazilian workers remain within the same microregion, and switches within microregion × occupational group cells are the most stable share of firm-to-firm transitions throughout the entire period (Appendix Figures A.2 and A.3). In contrast, most firm switchers change sectors (Appendix Figure A.4).

Based on these patterns, I define a formal sector local labor market as a microregion × occupational group cell,[11] and present effects with local labor markets defined by microregions only as robustness.[12] Appendix Table A.2 presents summary statistics of the roughly 20,000 local labor markets in Brazil. In the baseline year of 1991, the unweighted average payroll Herfindahl across local labor markets was 0.28, and the median was 0.21. Many local labor markets are thus highly concentrated, but because most workers work in larger labor markets, the payroll-share-weighted average concentration is much smaller: 0.08 on a scale from zero (infinitely tiny firms) to one (one firm), equivalent to an average worker being in a market whose equilibrium is pinned down as if only $12.5 = 1/0.08$ equally-sized firms operated it (Appendix Table A.3). Formal sector wages and employment decline with formal sector employment concentration (Appendix Figure A.1), consistent with labor market oligopsony.

While these patterns suggest that an analysis of formal sector wage markdowns can be reasonably conducted using employer-employee linked data on formal firms alone, Section 8 extends the paper's model to provide a comprehensive analysis that explicitly incorporates the informal sector.

[11] The literature on labor market power typically considers granular market boundaries, such as region × occupation (e.g., Azar, Marinescu and Steinbaum (2022); Azar et al. (2020); Schubert, Stansbury and Taska (2021)) or region × 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., Pham (2023)). Section 6 shows that finer boundaries yield similar but more precise estimates of elasticities of substitution.

[12] Given measurement limitations with occupation codes in Census data, Section 8's analysis incorporating the informal sector considers informal sector conditions more broadly at the microregion level, but allows them to vary by age, education, and gender.

3.3 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%,[13] with some sectors experiencing larger reductions than others because they were previously more protected, as shown in Figure 3.

These tariff reductions generated plausibly exogenous variation in labor demand shocks across firms and across markets, which I exploit to estimate the key sufficient statistics in equation 10. Kovak (2013) argues that the striking correlation between pre-liberalization tariff levels and reform-induced tariff cuts, as documented in Figure 3, 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.5 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. As discussed in Section 3, I define a local labor market as a microregion $\times$ occupational group cell, and present robustness to market boundaries defined by microregion only.

4.1 Empirical strategy

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.,

[13] Simple 1990 averages of nominal tariffs at CNAE95 level. See Appendix A.

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

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

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

where Θ_m^T is the set of all tradable sector firms in market m in the baseline year of 1991,[14] $s_{zm,1991}$ is the 1991 payroll share of each of these firms as a fraction of all firms operating in the market, and $\tau_{i(z),t}$ is the import tariff faced by firm z's output sector in year t.

In other words, ΔICE_m is a weighted average of the firm-level shocks experienced by tradable sector firms,[15] where the weight κ_{zm} of each firm z is its contribution to the tradable sector's component of market m's pre-liberalization payroll Herfindahl, $HHI_{m,1991}^T \equiv \sum_{j \in \Theta_m^T} s_{jm,1991}^2$.[16] 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.[17]

Figure 4 displays the variation in ΔICE_m across geography for two example occupations, while Appendix Table A.2 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

[14] Year-end wages and employment for 1990 might reflect the removal of non-tariff barriers in 1990; following Dix-Carneiro and Kovak (2017), I use 1991 as the base year for all analyses.

[15] A small number of microregion × occupation markets have no tradable sector firms in 1991. I set ΔICE_m to zero in those markets, which serve as pure controls in market-level regressions. When markets are defined by microregion only, all markets have at least one tradable sector firm, but results are similar.

[16] By construction, the κ_{zm} weights sum to one, constituting "complete shares" (Borusyak, Hull and Jaravel (2022)).

[17] My measure of import competition exposure serves as a shift-share shock for identification but does not have an independent structural interpretation as in Kovak (2013), which would require assumptions on production functions, product market structure, and the equilibrium entry game.

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,[18] and δ_m and δ_k are local labor market and year fixed effects. As the specification is in stacked differences, note that the fixed effects absorb not only the constant, but also market-level secular trends over the entire period. I estimate this regression using years 1986 to 2000, clustering standard errors by local labor market.[19]

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 (i.e., shock-driven identification, see Borusyak, Hull and Jaravel (2022)), an assumption discussed in Section 3.3 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 as 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 5 and Table 1 present my main estimates of the effect of trade on local labor market concentration. Column (1) shows the main specification: 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 unweighted average, or a 27% increase relative to the 0.08 payroll-share-weighted average.

This effect is large in magnitude and it is robust to various alternative specifications, several of which are presented in the remaining columns of Table 1. Within column (1), the effect is robust to the use of wage levels (as opposed to wage premia) to compute payroll Herfindahls, and to measuring concentration using the employment (instead of payroll) Herfindahl. 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 (2) of Table 1).[20] The effect is also present even when labor markets are defined more broadly by microregions only (column (3)), and when dropping markets with no change in import competition exposure (column (4)).[21]

[18] Following Dix-Carneiro and Kovak (2017): long differences use 1991 as the base year; for pre-treatment years, ΔY_{mt} is the long difference from 1991 back to year t to keep the timing convention consistent.

[19] A positive ζ_k indicates that the import tariff reductions had a positive effect on the outcome.

[20] Effective rates of protection are output tariffs netted out of input tariffs, constructed using Brazil's 1995 input-output table at broader sector levels (43 sectors) than output tariffs (CNAE95, 285 sectors). Smaller treatment effects are expected due to attenuation bias from the greater noise. See Appendix A.

[21] The effect is also robust to alternative weights for ΔICE_m and to weighting by baseline employment, confirming it is not driven by small markets. Consistent with the labor supply framework, $s^2_{zm,1991}$ weights yield the least noisy estimates. Statistical significance is also robust to two-way clustering by occupation and region, and to spatial-correlation-adjusted standard errors following Adao, Kolesár and Morales (2019). See Appendix Tables A.8–A.10.

I also estimate equation 12 for local labor market employment and wage premia, presented in Appendix Table A.5. 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 (see Appendix A). 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 by an order of magnitude, to 285, relative to those currently used in the literature—[22] adding further granularity in tariff shocks that mitigates the spatial correlation— and by reporting standard errors that account for this correlation, computed following the procedure described in Adao, Kolesár and Morales (2019). Column (3) of Appendix Table A.9 shows that, in this context, inference results are similar.

The effect of trade on concentration is pervasive across informality levels. Appendix Table A.6 shows that the effect is present in both above- and below-median informality markets, with somewhat larger point estimates where informal employment is a larger share of total employment. While this confirms that the concentration effect is not confined to one segment of the informality distribution, understanding how informality interacts with wage markdowns requires the full model extension in Section 8, which incorporates self-employment, informal wage work, and preference heterogeneity into labor supply decisions.

4.3 Source of increased concentration

What drives the increase in concentration shown in Figure 5? I leverage the employer-employee linked data to compute direct worker flows between firm types within each local labor market. I classify firms into three groups: exporters (those exporting at any point between 1991 and 1994), non-exporting tradable firms, and non-tradable firms. I then estimate the effect of import competition exposure on total employment by firm type and on within-market (microregion × occupation) worker flows between each pair of firm types.

Figure 6 presents results by firm type. Import competition primarily reduced employment among non-exporting tradable firms in the most affected markets, with little detectable effect on exporters or non-tradable firms. This differential incidence is consistent with Melitz and Ottaviano (2008): under unilateral liberalization, import competition hits non-exporting tradable firms hardest, as they depend entirely on the domestic market.

Where do the displaced workers go? Appendix Figures A.6 and A.7–A.8 trace within-market worker flows between firm types.[23] They reveal that the key source of increased concentration is direct reallocation from shrinking to expanding non-exporting tradable sector firms. Appendix Figure A.6 shows that, in more affected markets, hirings into non-exporting tradable firms increased from all three firm types (Panel a), while separations from non-exporting tradable firms rose differentially towards other non-exporting tradable firms

[22] Previous papers use 20 sectors (Nível 50) or (Nível 80). See Appendix A.

[23] Appendix Figures A.9–A.11 replicate this analysis including flows into and out of the formal sector. Conclusions are unchanged: differential flows into or out of the formal sector cannot explain the increase in concentration.

(Panel b). On net, non-exporting tradables experienced a reallocation of employment towards surviving firms within the group—consistent with import competition generating a pro-competitive push among import-competing firms—while also losing workers to non-tradable firms.[24]

This direct reallocation from shrinking to expanding import-competing firms is labor market evidence of the pro-competitive effects of trade predicted by Melitz and Ottaviano (2008). Topalova and Khandelwal (2011) find that tariff reductions raised firm productivity in India's 1991 unilateral liberalization through both pro-competitive effects and reduced input costs, the latter driving most of the effect. Muendler (2004) documents similar productivity gains among Brazilian manufacturers in response to the same tariff reductions studied here. Combined with my finding that most of the wage reductions attributed to trade operate through within-firm declines in the marginal revenue product of labor, this suggests that the wage losses in more exposed regions were likely driven entirely by reduced output prices rather than productivity losses. Consistent with this interpretation, the effects of import competition on concentration, wages, and employment are very similar whether measured using output tariffs or effective rates of protection (Tables 1 and 2, column (2)), as in Dix-Carneiro and Kovak (2017).

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

[24] Appendix Figure A.7 reveals a different pattern for exporters: both hirings and separations declined, suggesting a near-complete halt in dynamism, possibly reflecting the 1994 Real Plan dollar peg dampening export demand. Appendix Figure A.8 shows non-tradable firms' dominant pattern is non-tradable to non-tradable reallocation.

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 × 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: $\Delta \ln\left(1+\tau_{i(z)}\right)$, the policy-induced change in import tariffs on firm z's output sector, using the following first stage regression:

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

where once again Δd_m is a market fixed effect. 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–Waugh–Lovell 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.[25]

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 threat to exclusion is that worker tastes might be a function of non-wage amenities that a) change in response to trade; and b) are marginal to workers' labor supply decision.[26] 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.).[27]

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.[28] This is equivalent to assuming that each worker provides one "effective monthly unit" of labor, whereas the model allows l_{zm}^{j} to be more generally pinned down by worker j's exogenous reservation earnings y^{j}.[29]

I measure w_{zmt} as the firm z's wage *premium* in market m for the month of December of year t. That is, the total compensation w_{zm}^{j} received by worker j for all labor j provided in December *conditional on worker j's characteristics*.[30] It is important here to clarify that my use of the term "wage premia" follows papers

[25] Under Cournot, ε_{zm}^{-1} cannot be directly estimated via regression, which holds competitors' reactions constant (partial equilibrium), whereas ε_{zm}^{-1} includes full equilibrium responses (BHM). However, its key parameters $\frac{1}{\eta}$ and $\frac{1}{\theta}$ can be identified with IV given within-market cross-firm shock variation. My "bottom up" approach—estimate $\frac{1}{\eta}$ and $\frac{1}{\theta}$ with IV, then compute ε_{zm}^{-1}—contrasts with BHM's "top down" approach: estimate a reduced-form ε_{zm}^{-1}, simulate firms' strategic behavior until model and data shares converge, and recover η and θ. The "top down" approach works without within-market cross-firm shock variation; the "bottom up" approach applies whenever firm-level shocks are available, as in Pham (2023) and Zavala (2022).

[26] For a non-wage amenity to be marginal to workers' labor supply decision, workers must be willing to pay for it (i.e., accept lower wages), not merely prefer it—e.g., schedule flexibility (Bustelo et al. (2023)) or dignity (Dube, Naidu and Reich (2022)). See Kessler, Low and Sullivan (2019) on eliciting willingness to pay.

[27] Orthogonality between firm-specific labor demand shocks and amenities is implicit in most of the modern monopsony literature, where amenities do not enter the wage equation (e.g., Manning (2003), Ashenfelter (2010)).

[28] Workers employed as of December 31 who were hired on or before December 1. This is the standard measure of firm-level employment in RAIS (e.g., Kovak (2013); Dix-Carneiro and Kovak (2017)).

[29] Alternatively, one could measure l_{zmt} as total hours and w_{zmt} as the hourly wage premium. Hours data are unavailable for this period, but Dix-Carneiro and Kovak (2017) shows incorporating hours does not affect estimates of trade's effect on wages in later years.

[30] For each year, I estimate firm wage premia as firm $\times$ market fixed effects in a regression of worker log December earnings on firm $\times$ market fixed effects plus controls for age, education, and gender (see Appendix A). These differ from Abowd, Kramarz and

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).[31]

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

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

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 also report results using effective rates of protection, which include tariff reductions on firm inputs.

The identifying variation for equation 16 comes from firms of different output sectors operating in the same local labor market (i.e., hiring in the same microregion × occupation group pair), including firms in non-tradable sectors, for which the change in import tariffs is zero. Appendix Figure A.12 plots this identifying variation. 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 $\Delta\delta_m$:

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

Margolis (1999) firm fixed effects, which condition on worker fixed effects and may be biased under limited mobility (Bonhomme et al., 2023). Appendix Table A.11 shows that conditioning on worker fixed effects does not substantially change elasticity estimates.

[31] As robustness, I present estimates of the within-market cross-firm elasticity based on alternative wage measures, facilitating comparison with other papers that use average wages, as in BHM and Yeh, Macaluso and Hershbein (2022) for the US, or manufacturing plant data (e.g., Amodio and de Roux (2021); Pham (2023); Tortarolo and Zarate (2018)). To check whether unobservable worker characteristics matter, I present results conditioning on worker fixed effects, as in Abowd, Kramarz and Margolis (1999). To check whether differential sorting might confound estimates, I restrict to the sub-sample of stayers within firm-market pairs.

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 changing 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:

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

where Θ_m is the set of all firms operating in market m, and the taste-shifters ξ_{zm} are calculated using equation 14 and my point-estimate for $\frac{1}{\eta}$.[32] I estimate equation 19 clustering standard errors at local labor market level, and present robustness to alternative clustering 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, and binned scatters of its identifying variation are plotted in Appendix Figure A.12. Column (1) presents the main specification. The first stage in Panel A shows that a 1 percent decrease in the import tariff on firms' output reduced employment by 0.556 percent (SE 0.044). This is a strongly identified first stage, with an F-statistic of 156.771. Panel B shows that the proportional effect on firms' wage premia was roughly of the same magnitude, at a 0.550 percent reduction (SE 0.024). Combined, these effects imply a within-market cross-firm inverse elasticity of substitution of 0.990 (SE 0.089).

A within-market cross-firm inverse elasticity of substitution of 0.990 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 roughly 1 percent. This is a large estimate, nearly seven times larger than BHM's corresponding estimate of 0.14 for the US,[33] 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 $1/(1 + 0.990) \approx 50\%$ on firms' wage take-home shares. In other words, the slow change in firm choice in response to wage changes implies 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, several of which are presented in the remaining columns of Table 2. 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 (4) of Table 2 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 equal to my baseline estimate of 0.990. 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.

I also find similar elasticity estimates when using effective rates of protection as opposed to import tariffs as shocks (column (2) of Table 2), with smaller first stage and reduced form effects consistent with the greater noise in effective rates of protection.[34] Column (3) of Table 2 shows that controlling for worker fixed effects

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

[33] BHM reports an η of 6.96, whose inverse is 0.14, based on local labor markets defined as a commuting zone × NAICS3 pairs.

[34] Effective rates of protection are output tariffs netted out of input tariffs. Smaller effects are expected due to attenuation bias.

and demographic-by-year controls—thereby netting out unobservable worker characteristics and changes in workforce composition—yields a somewhat more elastic inverse elasticity of 0.811 (SE 0.080), placing the implied upper bound on wage take-home shares at 55 cents on the dollar. These results suggest that, at least in the Brazilian context, the labor market power exerted by local firms is rather invariant to worker sorting across firms.[35] One important limitation of the labor supply preference structure in Section 2 is that it assumes preference parameters are homogeneous across worker demographics and across regions, which might not be the case. If firms take advantage of demographic-based preference heterogeneity to set differential markdowns by demographics, the estimates thus far would not capture it. Section 8 addresses this by extending the model to allow for demographic heterogeneity in worker preferences.

Finally, while $\frac{1}{\eta}$ is a preference parameter, and thus assumed stable over the period of study, Appendix Figure A.14 presents estimates of $\frac{1}{\eta}$ estimated one year at a time during the post-liberalization period. Appendix Figure A.13 plots the year by year identifying variation. Estimates are stable, though slightly increasing—meaning labor supply becomes more inelastic—consistent with the estimation sample capturing a growing share of within-firm stayers over time, who are likely more inelastic than recent switchers.[36]

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 0.261 percent (SE 0.032), whereas Panel B shows that the proportional effect on markets' wage premia indices was roughly half as large, at a 0.120 percent reduction (SE 0.043). Combined, the first stage and reduced form produce an IV estimate of 0.459 (SE 0.190) for the difference between $\frac{1}{\theta}$ and $\frac{1}{\eta}$, which implies a cross-market inverse elasticity of substitution of 1.448 (SE 0.168) given the estimate for $\frac{1}{\eta}$ from Section 6.1.

There are three important take-aways from Table 3. The first is that the standard error on the IV estimate allows us to reject that $\frac{1}{\theta}$ and $\frac{1}{\eta}$ are the same (p-value < 0.02), which means that we can reject the model's limiting case of monopsonistic competition. This means increases in labor market concentration do matter for firm labor market power. The second 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 moderate, suggesting that Brazilian workers find it somewhat harder to substitute globally (i.e., across markets) than locally (i.e., within markets, across firms). This matters for quantifying the effect of increased concentration on wage markdowns.

It is helpful to compare my estimate of 1.448 for Brazil's cross-market inverse elasticity to other contexts. A cross-market inverse elasticity of substitution of 1.448 means that a market's wage premium index (i.e., the taste-adjusted wage premium) would have to increase by 1.448 percent before one percent more workers were

See Appendix A.

[35] Using average wages changes the implied upper bound to 51 cents (Appendix Table A.11, column (4)); restricting to stayers within firm-market pairs yields 55 cents (column (3)). Restricting to markets whose tradable firms are the only local producers of their sector yields similar elasticities but smaller first stage and reduced form effects (Appendix Table A.12, column (2)), suggesting sectoral agglomeration exacerbates trade's effects, consistent with Dix-Carneiro and Kovak (2017). See also Appendix Tables A.12 and A.13.

[36] Adding exiting and entering firms to the sample (coding employment and wages as zero outside their active period) yields similar estimates (Appendix Table A.12, column (4)).

attracted from other markets. While relatively inelastic, this point estimate is about two-thirds of BHM's corresponding estimate of 2.2 for the US, suggesting Brazilian workers substitute more swiftly across local markets than US workers do.[37] 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 $1/(1+1.448) \approx 41\%$ on wage take-home shares. That is, during the 1990s Brazilian workers were paid at least 41 cents of every marginal dollar they generated.

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 B.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.3 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,[38] a fact that is taken into account in the country-level average wage markdown.

Combined with Section 6 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 approximately 2, whose inverse gives an average wage take-home share of approximately 50 percent.[39] That is, Brazilian formal sector workers took home 50 cents of every dollar of marginal revenue product of labor they generated. This places Brazil's formal sector as substantially less competitive than US labor markets, where wage take-home shares are estimated at 65% for manufacturing (Yeh, Macaluso and Hershbein, 2022) and 73% for tradables by BHM,[40] but close to estimates for developing countries. Using a production function approach on a harmonized global panel of manufacturing firms across 82 low- and middle-income countries, Amodio et al. (2025) estimate a median take-home share of 43 cents on the dollar. For Peru, Amodio, Medina and Morlacco (2025) find that self-employment substantially curbs formal firms' market power, while Pham (2023) report 47% for Chinese manufacturing.[41] Across these studies, markdowns are consistently found to increase with

[37] BHM reports $\theta = 0.45$, whose inverse is 2.2, based on local labor markets defined as a commuting zone × NAICS3 pairs.

[38] The payroll-share-weighted HHI was also smaller than the median of 0.21: many local labor markets are highly concentrated, but most workers are in less concentrated ones. See Appendix A.2.

[39] The country's average wage take-home share does vary somewhat with alternative measures of labor market concentration due to the gap between the two inverse elasticities of substitution. For example, the country-level take-home share would have been about 47 percent if evaluated at the (unweighted) average payroll Herfindahl of 0.28.

[40] $73\% \approx 1/(1+(1/0.45)*0.11+(1-0.11)*(1/6.96))$ using $\theta = 0.45$, $\eta = 6.96$, and payroll-share-weighted Herfindahl of 0.11 from BHM. See Appendix B.2.4 and B.2.6.

[41] Pham (2023)'s "pass-through" corresponds to the wage take-home share: $0.47 = 1/2.14$, where 2.14 is the average $MRPL_i/w_i$.

firm size.[42]

7 Effect of trade on local wage premia: Markdowns vs MRPL

What does the trade-induced increase in labor market concentration documented in Section 4 imply for average wage markdowns, marginal revenue product of labor, and wage premia? This section answers this question by combining the theoretical results from Section 2 with the estimates of workers' key elasticities of substitution from Section 6 and putting these together into an accounting exercise.

7.1 Effect decomposition

We can decompose the effect of trade on average wages via concentration into its effect on markdowns versus its effect on MRPL by applying the product rule to a simple average wage decomposition. Start by noting that the average wage in a market is the product of the average marginal revenue product of labor in that market and the market's average wage take-home share. The model allows us to estimate the latter, while wages are measured directly in the data, so the residual wage variation corresponds to the market's average MRPL. This already allows us to decompose the effect of trade on average wages into its effect on the average wage markdown and the average MRPL. But we can go one step further: because we observe all firms in the market, we can also decompose the effect on average MRPL into within-firm changes over time versus other changes, which stem from labor being reallocated across firms within markets.

To be precise, 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 is the effect of changes in import competition exposure on the average wage markdown in local labor market m. The effect of trade on the average marginal revenue product

[42] Appendix Table A.14 confirms this: regressing $\ln(\mu_{zm})$ on log employment yields +0.003, robust across specifications. Amodio et al. (2025) find a similar positive relationship (+0.025 with firm FE, Table A.3; +0.079 without, Table 1). I also find a near-zero positive correlation between log markdowns and log wages. This result is different from Amodio et al. (2025)'s negative correlation, which are negative by construction, since the production function method calculates log markdowns as log estimated MRPL minus log wage. In contrast, I estimate markdowns directly from elasticities of substitution and wage bill shares. The near-zero correlation I find suggest that cross-firm wage differentials in Brazil are primarily driven by the marginal revenue product of labor, not by market power. The fact that these correlations are positive also suggests that firms with more market power pay higher wages, not lower, on average, such that these are also firms with higher MRPL.

of labor $\bar{r}_{mt}$ 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.[43] Plugging equation 22 into equation 21 and expressing changes relative to the baseline year ($t = 0$) gives:

$$\overbrace{\frac{d\bar{w}_{mt}}{dICE_m}}^{\text{Effect on avg wage}} = \underbrace{-\frac{\gamma_t}{\mu_0^2}\times\bar{r}_0}_{\text{Via average markdown}} + \overbrace{\left[\underbrace{\frac{d\left(\bar{r}_{mt}|_{s^e_{jm0}}\right)}{dICE_m}}_{\text{Within-firm}} + \underbrace{\frac{d\left(\bar{s}^e_{mt}|_{r_{jm0}}\right)}{dICE_m}}_{\text{Cross-firm reallocation}}\right]\times\mu_0^{-1}}^{\text{Via average MRPL}} \tag{23}$$

where $\bar{r}_0$ and μ_0^{-1} are the baseline average MRPL and wage take-home share, respectively.

7.2 Estimates

Figure 7 presents my estimates of γ_t for all sample years, summarized in Table 4 as the post-reform mid-point estimate. The estimated 0.459 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 0.010 (SE of 0.004) points, an effect driven by the 0.02 point average increase in markets' payroll Herfindahls. This is equivalent to a reduction of the pre-liberalization average wage take-home share of approximately 50 cents on the dollar by 0.24 cents ($\frac{1}{2.027+0.010} - \frac{1}{2.027} \approx 0.24\%$).

This rather muted effect of increased labor market concentration on local labor markets' average wage take-home shares reflects the fact that the 0.459 gap between the inverse elasticities of substitution, while statistically significant, is still moderate in magnitude: Brazilian workers find it somewhat harder to substitute globally (across markets) than locally (within markets, across firms), but the difference is not large. This is in contrast to the 2.08 gap estimate for US local labor markets from BHM—about five 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 0.24 cents—,[44] an effect about 10 times as large.

[43] Changes in concentration do not feature into the within-firm effect because $\bar{r}_{mt}|_{s^e_{jm0}}$ holds firms' relative size constant, both when computing each firm's r_{zmt} and when weighting to obtain $\bar{r}_{mt}$.

[44] 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 ($\theta = 0.45, \eta = 6.96$): $\mu_{0,US} = 1 + (1/0.45) * 0.08 + (1 - 0.08) * (1/6.96)$.

Tables 5 and 6 summarize the implication of this effect to average wages per equation 23. Table 5 presents estimates of the overall effect of import competition exposure on the average wage premium and its components, showing that a 10% increase in import competition exposure reduced the average wage premium by 0.163 multiples of the minimum wage.[45] It also shows that a 10% increase in import competition exposure reduced the average MRPL by 0.361 (SE of 0.067) multiples of the minimum wage. This large negative effect is entirely driven by a within-firm MRPL reduction of 0.369 (SE of 0.095) multiples of the minimum wage, and attenuated slightly by a cross-firm employment reallocation positive average MRPL effect of 0.012 (SE of 0.002) multiples of the minimum wage. Since firm productivity rose during Brazil's liberalization (Muendler, 2004), and results are very similar using output tariffs or effective rates of protection (Tables 1 and 2, column (2)), these within-firm MRPL reductions likely reflect reduced output prices rather than productivity losses—consistent with the pro-competitive effects of import competition predicted by Melitz and Ottaviano (2008) and with productivity gains documented in India's comparable episode by Topalova and Khandelwal (2011).

Table 6 puts these effects in perspective relative to the overall effect of trade on average wages. A 10% increase in import competition exposure reduced the average wage premium by 0.184 multiples of the minimum wage, or roughly 7.40% of the pre-liberalization average of 2.48. Of this total reduction, roughly 6% is accounted for by the decline in the average wage take-home share—i.e., by increased firm labor market power—and roughly 94% is accounted for by the decline in the average marginal revenue product of labor. The within-firm MRPL reduction (−0.178 multiples of the minimum wage, or −7.17% of the baseline average premium) accounts for nearly the entire MRPL effect, with a small positive cross-firm reallocation effect (+0.006, or +0.24%).

8 Self-employment, informal wage work, and heterogeneity

While this paper focuses on the formal sector, a natural question is whether Brazil's large informal sector—where informal wage work and self-employment represent roughly 40%–50% of total employment—affects estimates of formal firms' wage markdowns derived from a model that does not explicitly incorporate informality. Appendix C extends the model on three dimensions: adding self-employment as an alternative to wage work, modeling informal wage work as a possible outcome of involuntary separation from formality (and quantifying how unemployment insurance may curb the market power that involuntary separation concerns confer on formal firms), and allowing elasticities of substitution to vary by age, education, gender, and region. I summarize the extensions and main findings here.

8.1 Extension margins

Self-employment. The extension splits each local labor market into wage work and self-employment, introducing an elasticity of substitution $\tilde{\rho}$ between the two. This embeds the relationship between self-employment and wage markdowns studied in Amodio, Medina and Morlacco (2025) into an oligopsony model where firms are heterogeneous from workers' perspective. Self-employment enters the labor supply

[45] Wage effects are reported relative to trend to account for pre-trends in wage premia, also documented in Dix-Carneiro and Kovak (2017).

curves faced by formal firms through $(L_{\overline{g}m}/L_m)^{1/\tilde{\rho}}$ in equation C.5: the larger the wage work share in a market, the more labor supplied to each formal firm, all else equal. A more elastic $\tilde{\rho}$ means self-employment is a closer substitute for wage work, curbing formal firms' market power. The extended markdown formula (equation C.23) shows how $\tilde{\rho}$ interacts with concentration: the wage work share of total market employment, s_m, mediates the contribution of $\tilde{\rho}$ to markdowns.

Informal wage work. Incorporating informal wage work poses different challenges, because it can occur both inside and outside formal firms (Ulyssea, 2018) and cannot be distinguished in the data with the same granularity as formal employment. Rather than adding informality as a separate nest, the extension models it as a possible outcome of involuntary separation from formality. Workers seeking formal jobs consider both wages and the probability of being fired and, until finding another formal job, working in the local informal sector. The relevant wage for attracting labor supply to firm z becomes the *expected* wage $\bar{w}_{z\overline{g}m} = p_{z\overline{g}m} w^o_m + (1 - p_{z\overline{g}m}) w_{z\overline{g}m}$, where $p_{z\overline{g}m}$ is workers' prior about involuntary separation probability and w^o_m are expected local informal wages. This preserves the aggregation properties of the discrete choice problem while allowing informal sector conditions to influence formal sector labor supply.

Unemployment insurance. Since involuntary separation concerns may amplify formal firms' market power, the extension also quantifies whether unemployment insurance helps curb it by cushioning expected post-separation earnings. Cross-country evidence suggests that markdowns are increasing in self-employment shares in countries with unemployment insurance systems (Amodio et al., 2025), and micro evidence from Brazil shows that workers have high willingness to pay for unemployment insurance (Felix et al., 2026), a potential microfoundation for formal firms' market power. In Brazil, formally separated workers were entitled to roughly four months of salary-based benefits during the 1990s (see Appendix C for details). The extension re-estimates Ω with and without incorporating these benefits (Appendix Table C.5).

Preference heterogeneity. The extension allows elasticities of substitution to vary by age, education, gender, and region. Labor markets are partitioned into demographic cells—defined by gender (2), education (3), and age (3) groups—with cell-specific or group-specific parameters. This contributes the first labor market oligopsony framework inclusive of self-employment and informal wage work to the literature on demographic wage differentials, where evidence linking wage markdowns to gender wage gaps has begun to emerge (Sharma, 2023; Hoang, Mitra and Pham, 2024).

Bias formula. A key result is the decomposition of the within-market cross-firm inverse elasticity into two components (equation C.17): $1/\tilde{\eta} = 1/\eta + \Omega$, where $1/\eta$ is the labor supply response to formal wage changes (as estimated in Section 5), and Ω captures the additional response to changes in expected formal-informal wage gaps. If $\Omega > 0$, workers supply *more* labor to firms with higher expected wage gaps relative to the informal sector—preferring formal employment despite potentially higher informal pay—so the original model *understates* firms' market power. If $\Omega < 0$, the informal sector serves as an attractive outside option that curbs formal firms' power. In either case, Ω directly measures how much the within-market cross-firm elasticity would change if informal wage work conditions were incorporated, and its sign reveals whether informal wage work amplifies or mitigates formal firms' market power.

8.2 Empirical strategy

Measurement. Estimation combines RAIS with Brazil's 1991 and 2000 censuses, which provide informal wage work and self-employment earnings at the microregion × demographic cell level. Appendix C provides all estimating equations and data mappings. The within-market cross-firm elasticity $1/\tilde{\eta}$ is recovered by combining the IV estimate for $1/\eta$ with an estimate of the bias Ω from ignoring informal wage work. Ω is estimated using within-firm cross-demographic-cell variation in expected formal-informal wage gaps, where firm-level separation probabilities are directly observed in RAIS. The wage work–self-employment elasticity $1/\tilde{\rho}$ and cross-market elasticity $1/\tilde{\theta}$ are estimated jointly using census data at the microregion × demographic cell level.

Trade shocks. Identification differs from the baseline in important ways. While $1/\eta$ uses firm-level tariff variation as in Section 5, the elasticities $1/\tilde{\rho}$ and $1/\tilde{\theta}$ are identified using cell-specific Regional Tariff Reductions (RTR) from Dix-Carneiro and Kovak (2017)—shift-share measures of import competition at the microregion level whose shares include *all* workers, formally or informally employed, in tradable industries, making them well-suited for census-based estimation. The within-market cross-sector variation identifying $\tilde{\rho}$ comes from demographic cells with their own wage work and self-employment sectors and differential trade exposure; cross-market variation identifying $\tilde{\theta}$ comes from cross-microregion RTR differences. The bias term Ω is identified from the interaction of firm-level tariff reductions and demographic-specific RTRs, capturing how trade shocks jointly affect separation probabilities and informal sector conditions.

8.3 Findings

Elasticities of substitution. I find that the bias from ignoring informal wage work is positive but small ($\Omega \approx 0.033$; Appendix Table C.4), implying that the original model's $1/\eta$ estimates are affected by only about 3%. Incorporating unemployment insurance benefits into expected post-separation earnings reduces Ω from 0.033 to 0.022 (Appendix Table C.5), indicating that unemployment insurance partially curbs the market power that involuntary separation concerns confer on formal firms, consistent with cross-country evidence from Amodio et al. (2025). Self-employment substantially curbs formal firms' market power ($1/\tilde{\rho} \approx 0.47$; Appendix Table C.6), consistent with Amodio, Medina and Morlacco (2025) for Peru and with Amodio et al. (2025) using markdowns estimated with the production function approach. This curbing is very heterogeneous by demographics: women and less educated workers substitute more elastically between formal wage work and self-employment ($1/\tilde{\rho}$), making self-employment a stronger outside option that limits formal firms' wage setting for these groups. There is little demographic heterogeneity in within-market cross-firm substitution, even when taking into account informal wage work ($1/\tilde{\eta}$). There is substantial regional heterogeneity in the within-market cross-firm elasticity of substitution, however: Southeast estimates (1.029) are nearly twice those for the Northeast (0.458) (Appendix Table C.2), yielding more market power in the former.[46]

Wage markdowns. On average, Brazilian formal sector workers were paid 51 cents of their marginal revenue product once all margins are accounted for, compared to 50 cents in the baseline model (Table 8; Figures 9

[46] The muted cross-firm substitution heterogeneity may reflect wage compression from union bargaining; Appendix Figure A.16 shows a mild positive correlation between union presence and wages.

and 8). This average masks substantial heterogeneity: take-home shares range from 46 to 73 cents depending on local labor market conditions outside the formal sector and workforce composition. Table 7 presents summary statistics for the distribution of wage take-home shares across microregions, separately by year and demographic groups. The dispersion is driven by regional heterogeneity in the within-market cross-firm elasticity $1/\eta$: most microregions cluster around 50 cents on the dollar, while those in the North and Northeast—where cross-firm elasticities are almost half those of the rest of the country—feature take-home shares reaching up to 70 cents on the dollar; the dispersion across occupations is centered between 50 and 55 cents (Appendix Figure C.9). These estimates combine the extended model's elasticities—including the wage work–self-employment elasticity ($1/\tilde{\rho}$) and the informal wage work bias (Ω)—with concentration measures that account for expected informal wages by demographic type and the share of employment in wage work versus self-employment. Most of the demographic heterogeneity in markdowns is driven by the elasticity of substitution between wage work and self-employment, $1/\tilde{\rho}$ (Appendix Table C.8): women substitute more elastically than men ($1/\tilde{\rho}$ of 0.390 vs. 0.660), while young workers (0.850) and the highly educated (0.935) are the least elastic, suggesting self-employment is a weaker outside option for these groups. These differences translate into modest variation in wage take-home shares (Table 7): median take-home shares in 1991 range from 0.480 for tertiary-educated workers to 0.509 for primary-educated workers, from 0.487 for young workers to 0.541 for older workers, and are nearly identical across gender (0.498 for men, 0.500 for women). Regional heterogeneity is considerably larger: workers in the Southeast—where formal labor markets are thicker and self-employment less prevalent—face higher markdowns than those in the Northeast, driven by the substantially more inelastic within-market cross-firm elasticity in the Southeast.

Markdowns and concentration. In the baseline model, equation 9 implies a linear relationship between formal sector concentration and the average wage markdown, with slope $(1/\theta - 1/\eta)$. Incorporating informal wage work, self-employment, and demographic preference heterogeneity introduces non-linearities: the extended markdown formula (equation C.23) depends not only on formal sector concentration but also on its interaction with the local wage work share s_m and on region- and demographic-specific elasticities. Appendix Figures C.9, C.11, and C.12 plot the resulting distributions and the relationship between the formal sector's Herfindahl-Hirschman Index (HHI) and estimated take-home shares. The relationship is non-linear, likely driven by cross-regional differences in elasticities: take-home shares increase with concentration for markets with many similarly sized firms (HHI below 0.2), but past that threshold, higher concentration typically reduces take-home shares.

Effect of trade on markdowns. Combining these estimates with reduced-form effects of RTR on concentration and the wage work share, two channels operate in opposite directions: a *within-market net substitution channel* reduces markdowns by shifting weight toward the more elastic self-employment margin, while a *cross-market substitution channel* increases markdowns by shifting weight toward the least elastic cross-market margin. At the country average, these channels largely offset ($\Delta\mu \approx 0$ percentage points). In low-informality regions the take-home share is essentially unchanged (+0.04 pp), while in high-informality regions it falls modestly (−0.54 pp). Across regions, the North and Northeast see take-home shares rise by +1.2 pp while the Southeast, South, and Center-West see essentially no change (−0.1 pp). Across demographics, differences are small: women and older workers see take-home shares fall by −0.1 pp; tertiary-educated and young workers see slight increases (+0.1 to +0.2 pp) (Table 8; Appendix Section C.3.3). Appendix Table A.6 confirms that trade affects concentration in both high- and low-informality markets. The key demographic heterogeneity takeaway is that the within-market net substitution and cross-market substitution effects nearly cancel for all groups, despite substantial demographic heterogeneity in markdown levels, resulting in similar and muted effects of trade's effect on markdowns across groups at the country level.

Overall, these findings add richness to the baseline analysis, but the qualitative conclusions are largely unchanged: formal sector firms in Brazil command high wage markdowns, and the sufficient statistics framework in Section 2 captures the essential forces. This alignment arises because most formal employment is concentrated in predominantly formal microregions, and most of these microregions are in the Southeast, where the within-market cross-firm elasticity is most inelastic ($1/\eta = 1.029$; Appendix Table C.2) and self-employment and informal wage work represent a small share of total employment, so the additional margins have a modest effect on estimated markdowns. Appendix Figure A.16 further shows that unions are unlikely to be a primary driver of the wage dynamics documented here. The full model, estimation strategy, and detailed results are in Appendix C.

9 Conclusion

This paper is an empirical study of the relationship between trade, local labor market concentration, and wages in the context of Brazil's 1990s unilateral trade liberalization. I showed that the effect of trade on wage markdowns across local labor markets can be quantified by two sufficient statistics: the effect of trade on local labor market concentration, and the gap between workers' cross-market vs. within-market cross-firm inverse elasticities of substitution. I then leveraged Brazil's rich employer-employee linked data and the variation in import tariff reductions 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 labor market power, with workers taking home only 50 cents of every marginal dollar generated—primarily driven by workers' very inelastic within-market cross-firm substitution, nearly seven times as inelastic as in the US; (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, increased wage markdowns account for only about 6% of the overall negative effect of trade on average wages (Table 6); the remaining 94% was driven by within-firm reductions in the marginal revenue product of labor. Since firm productivity rose during Brazil's liberalization (Muendler, 2004)—as in India's comparable episode (Topalova and Khandelwal, 2011)—and the effects of import competition are nearly identical using output tariffs or effective rates of protection, these MRPL reductions likely reflect reduced output prices, consistent with the pro-competitive channel in Melitz and Ottaviano (2008).

Section 8 extends these results to incorporate self-employment, informal wage work, and preference heterogeneity by demographics and regions. These additional margins bring average wage take-home shares to 51 cents on the dollar—close to the baseline—but reveal substantial heterogeneity: take-home shares range from 46 to 73 cents depending on local labor market conditions outside the formal sector and workforce composition (Table 7). Self-employment curbs formal firms' power by providing an attractive outside option, while the threat of involuntary separation into informal wage work slightly increases it—though unemployment insurance partially offsets this effect by cushioning expected post-separation earnings. The effect of trade on markdowns through the extended model is near zero at the country average, with modest heterogeneity across regions and demographics.

Future research should further disentangle the components of the marginal revenue product of labor—price markups, productivity, and production technology—to confirm and refine this output-price interpretation across contexts.

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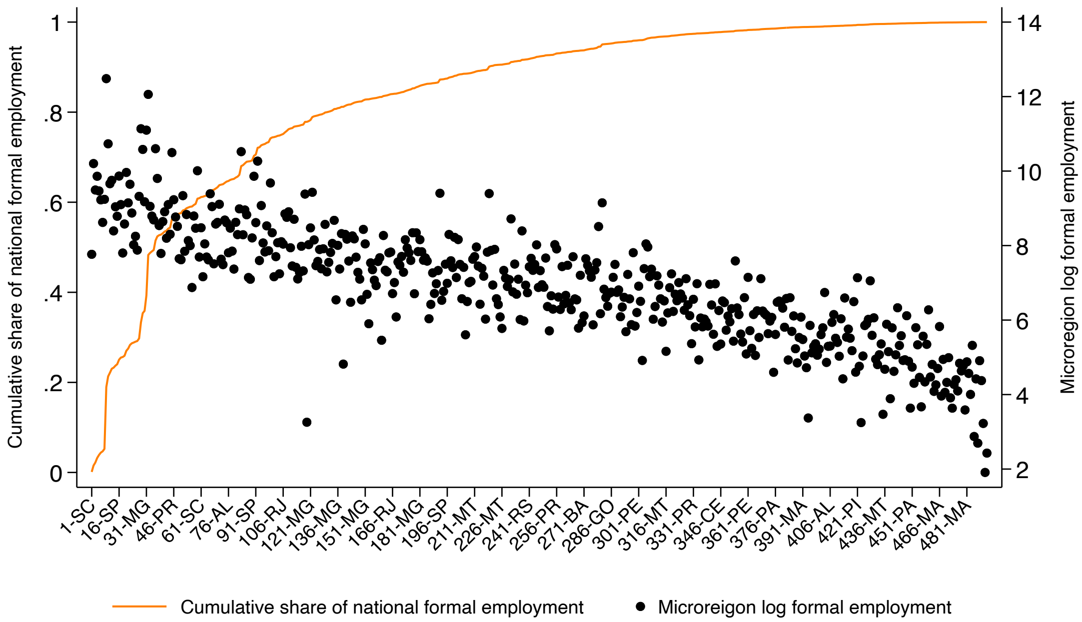
Figure 1: 1991 distribution of formal employment across microregions

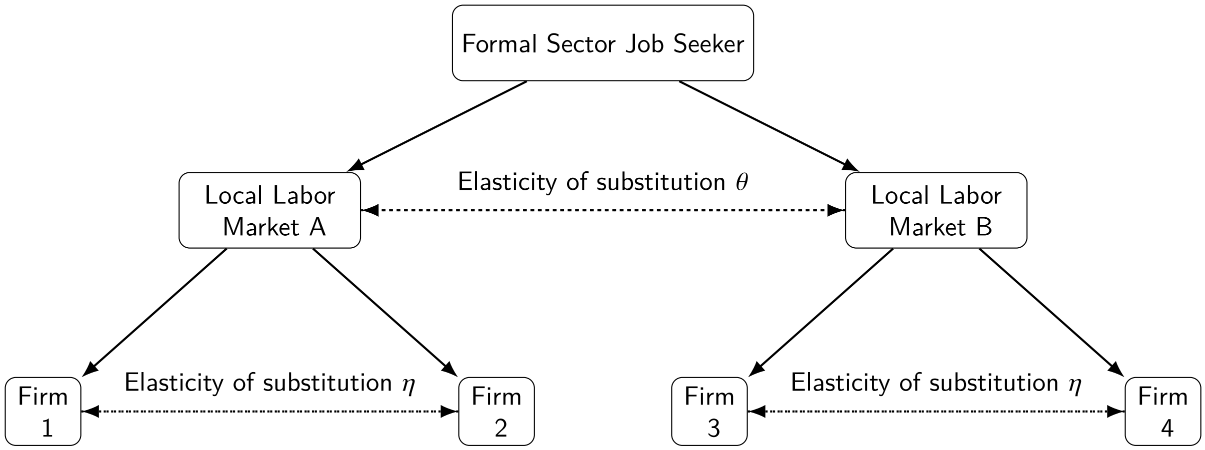
(a) Cumulative distribution of formal employment, from most to least formal regions



(b) Formal wage work, informal wage work, and self-employment

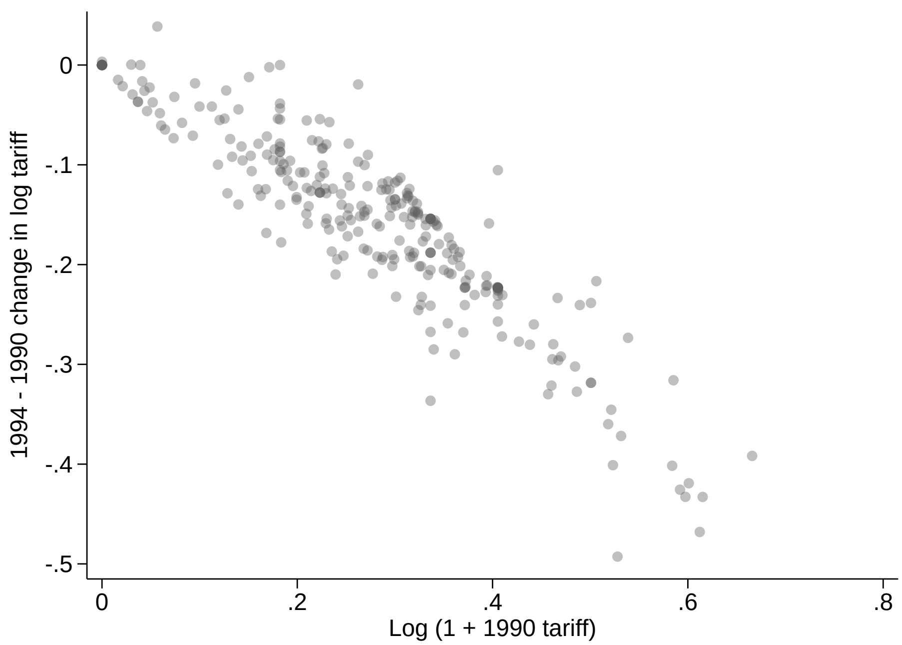
Notes: This figure plots the distribution of formal employment across 486 microregions per the 1991 Population Census. Panel (a) shows the cumulative distribution of formal employment (red line, left y-axis) and log formal employment (black scatter, right y-axis). Labels in the x-axis correspond to different microregions. Panel (a) shows the distribution of formal wage work (black bins, left y-axis), informal wage work (gray bins, left y-axis), self-employment (blue bins, left y-axis), log total employment (yellow scatter, right y-axis), and log formal employment (black scatter, right y-axis). The letters indicate the microregion's state, and the number indicates the microregion's rank in the national sorting (e.g., the country's most formal microregion, labeled 1-SC, is a microregion in the state of Santa Catarina).

Figure 2: Discrete choice microfoundation of nested CES preferences over formal sector jobs



Notes: This figure displays a diagram of workers' labor supply decision, microfounded in discrete choice, as presented in Section 2. In the empirical exercise, a local labor market is defined as a microregion x 2-digit occupation pair based on firm-to-firm flow data in Figures A.2 through A.4. Appendix C extends this setup in three ways: 1) Adds a within-market cross-sector elasticity of substitution into self-employment; 2) Adds informal wage work as a potential outcome of involuntary separation from a formal sector job; and 3) Adds heterogeneity by gender, education, and age groups to all elasticities of substitution, and heterogeneity by regions to the within-market cross-firm elasticity. These extra margins are estimated by combining employer-employee linked data with census data and group-specific trade shocks. See Appendix C.

Figure 3: Brazil's 1990-1994 tariff reduction reform: Variation across 285 sectors

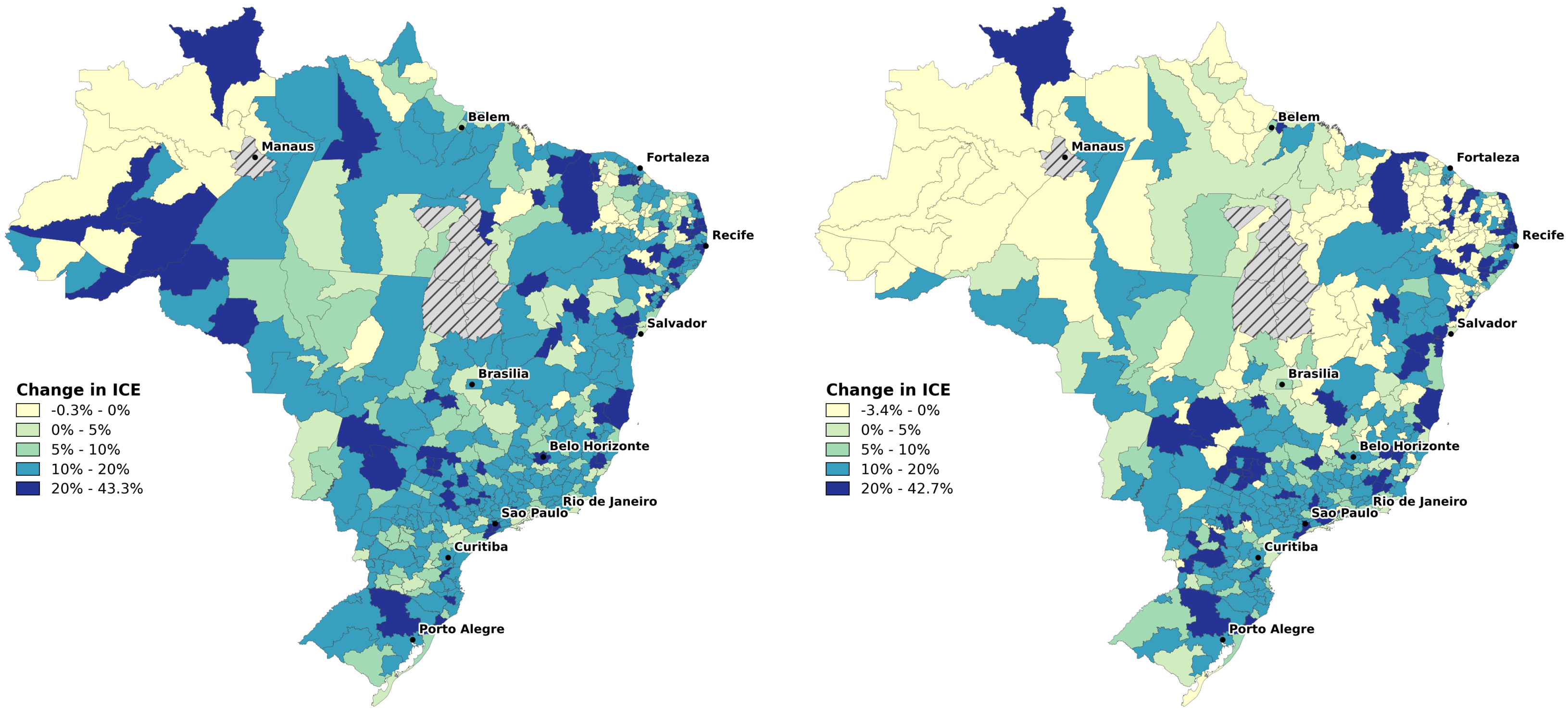


Note: This figure plots import tariff reductions from Brazil's 1990–1994 import tariff reform across RAIS' 5-digit sector variable "CNAE-95", including 285 tradable sectors and 280 non-tradable sectors. Sector-level tariffs are simple averages of product-level tariffs for the products produced in each 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 3.3 for details.

Figure 4: Variation in Import Competition Exposure across local labor markets

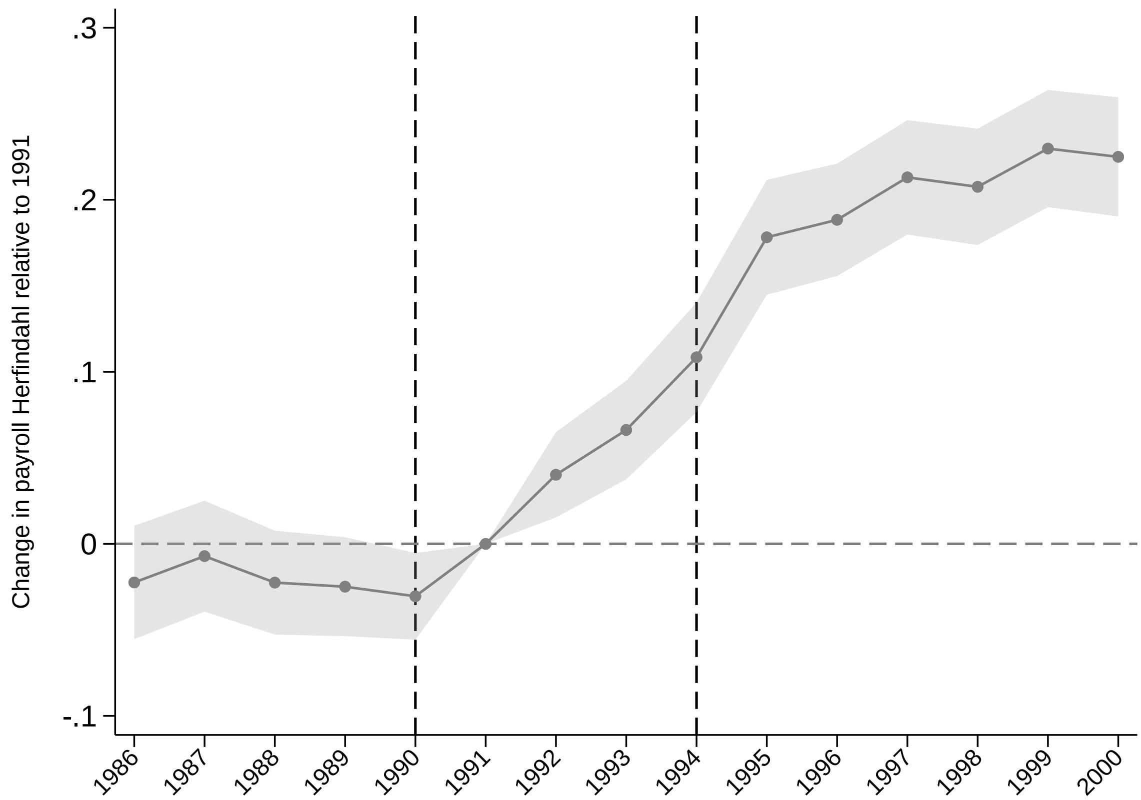
(a) Office administration workers

(b) Managers and supervisors of industrial workers



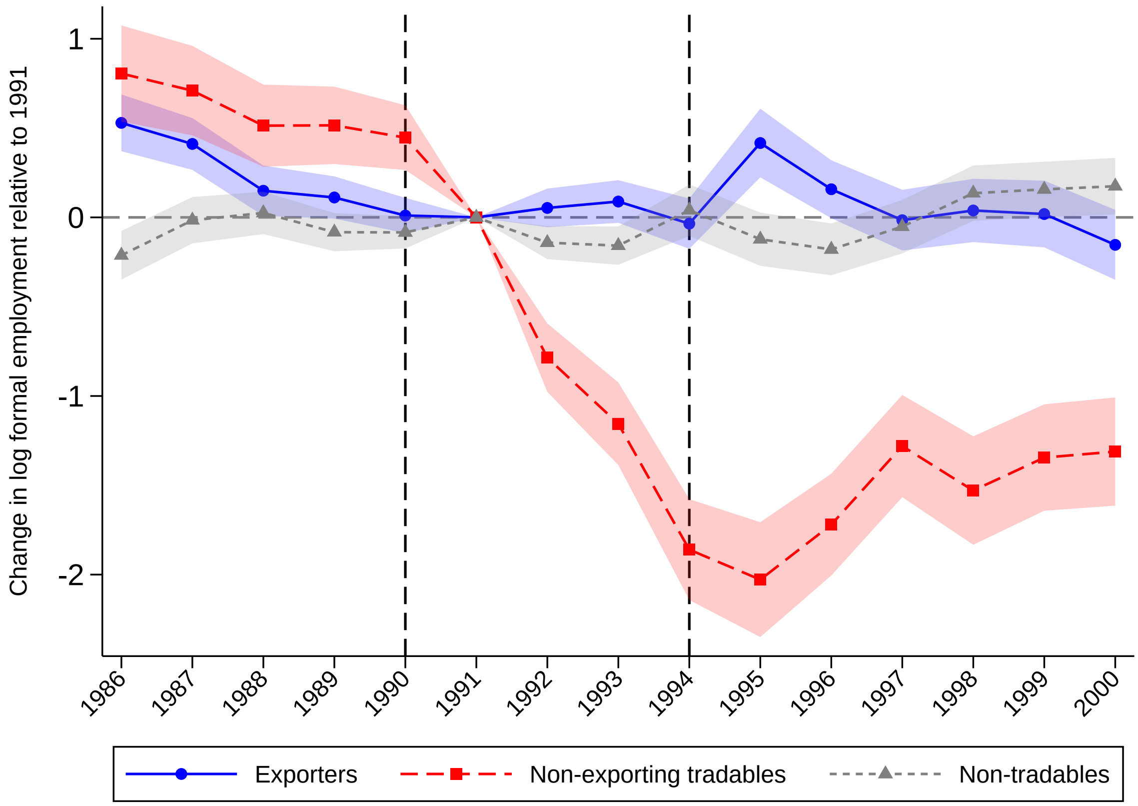
Note: This figure displays variation in ΔICE_m: the change in import competition exposure across local labor markets for two occupation groups. Produced using QGIS with microregion boundaries from Dix-Carneiro and Kovak (2017).

Figure 5: Effect of import competition on local labor market concentration



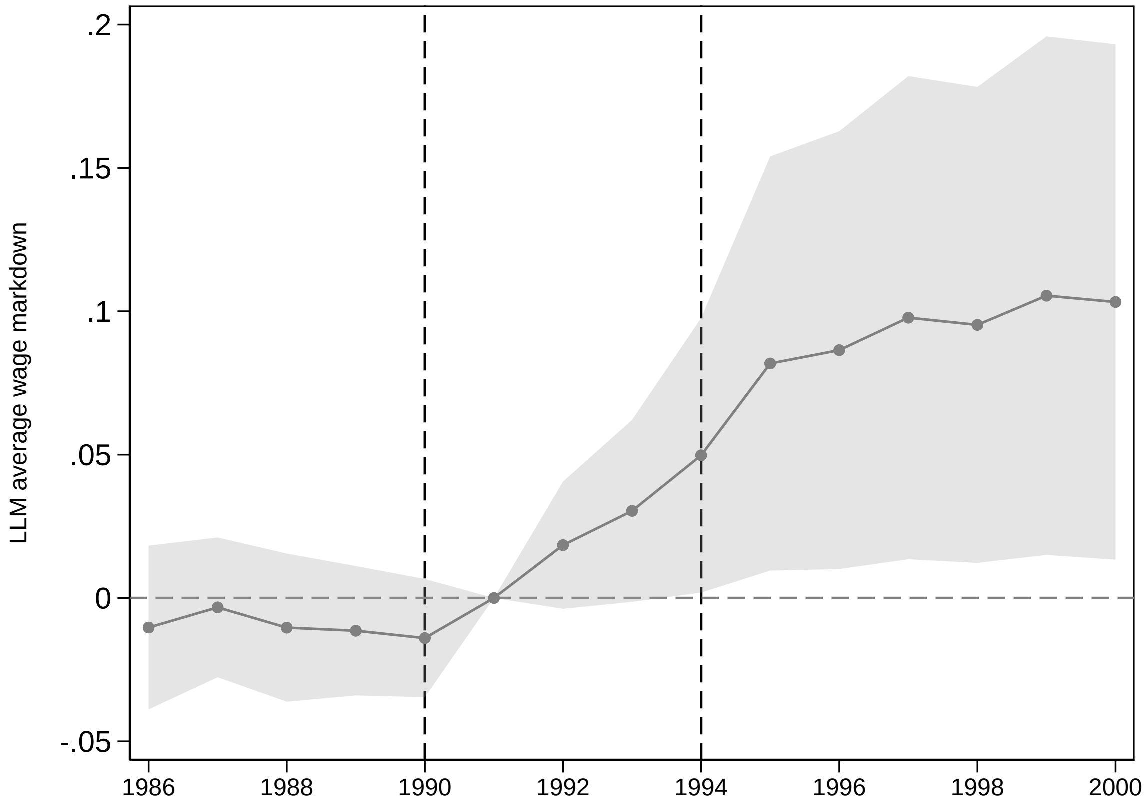
Notes: This figure plots regression coefficients ζ_k on regressor ΔICE_m from equation 12, where the outcome is the change in payroll Herfindahl relative to 1991. Since ΔICE_m is a weighted average log change in import tariffs, note that this is a units-on-logs regression, such that a 10% increase in 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 6: Effect of import competition exposure on employment of non-exporting tradable sector firms, exporting firms, and non-tradable sector 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. To keep the composition of firms fixed, firms exporting any time between 1991 and 1994 are tagged as exporters for the whole period. 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.

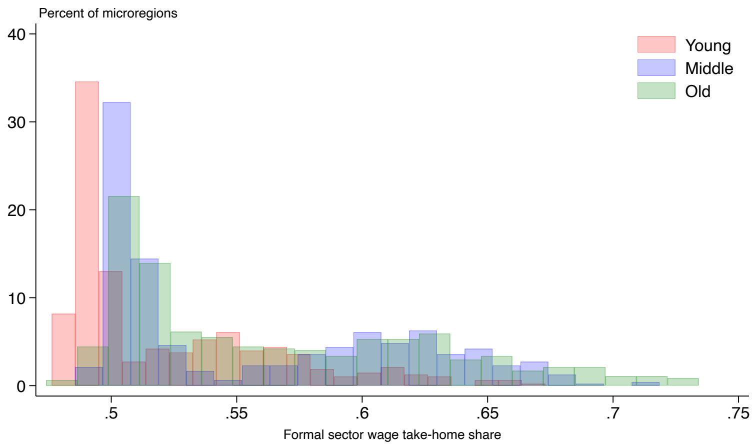
Figure 7: Effect of import competition on local labor market average wage markdowns



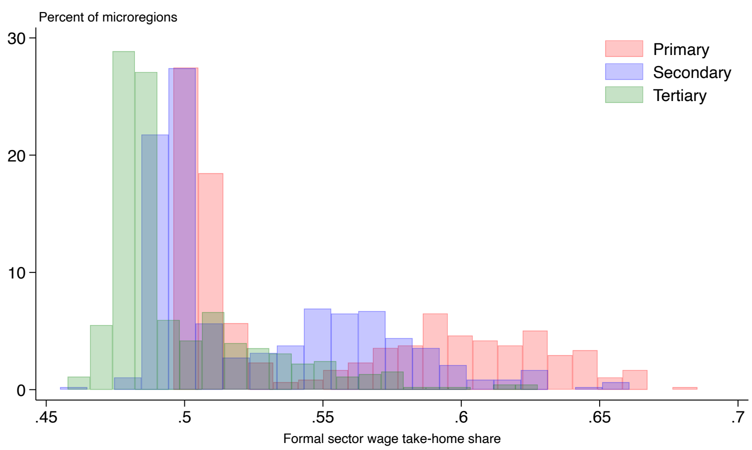
Notes: This figure plots γ_t, the effect of import competition on local labor markets' average wage markdown share at year t, derived in equation 10. The two components of γ_k are $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$, whose estimates are presented in Table 3, and the β_t coefficients that estimate the effect of import competition on labor market concentration, presented in Figure 5. Standard errors are estimated assuming β_t and $\left(\frac{1}{\theta} - \frac{1}{\eta}\right)$ are independent (see Appendix B for details).

Figure 8: Extended model: Formal sector wage take-home share heterogeneity by demographics

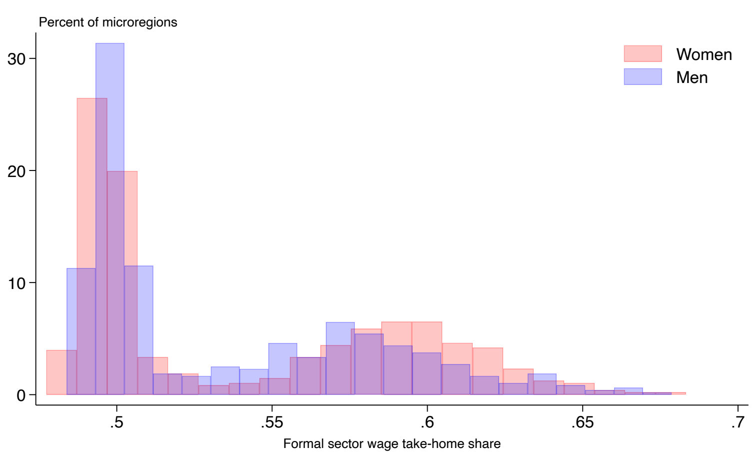
Panel A: By age



Panel B: By education



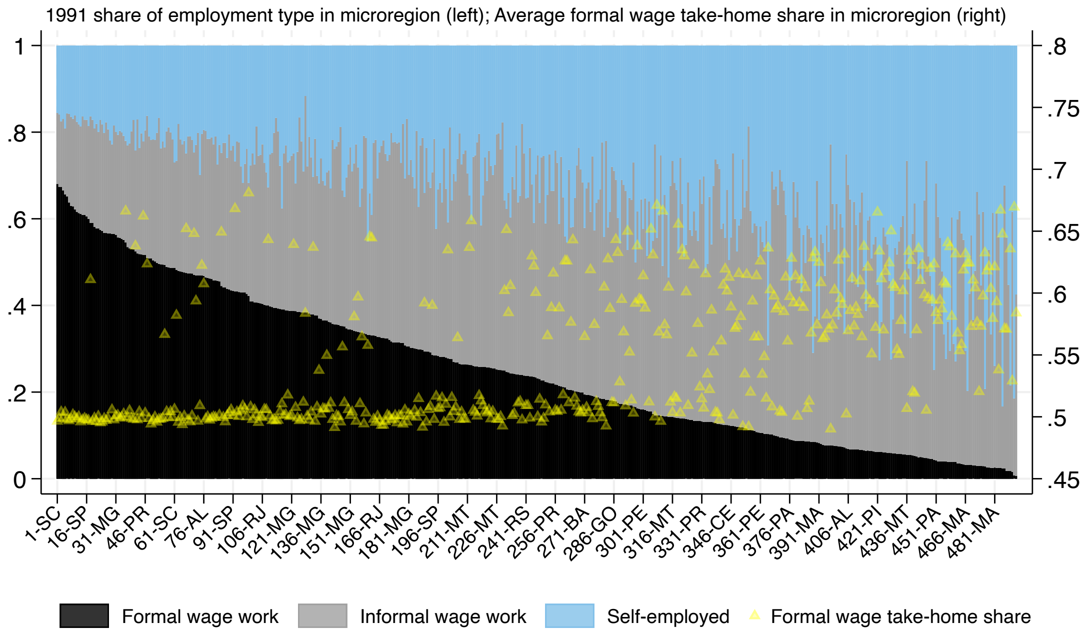
Panel C: By gender



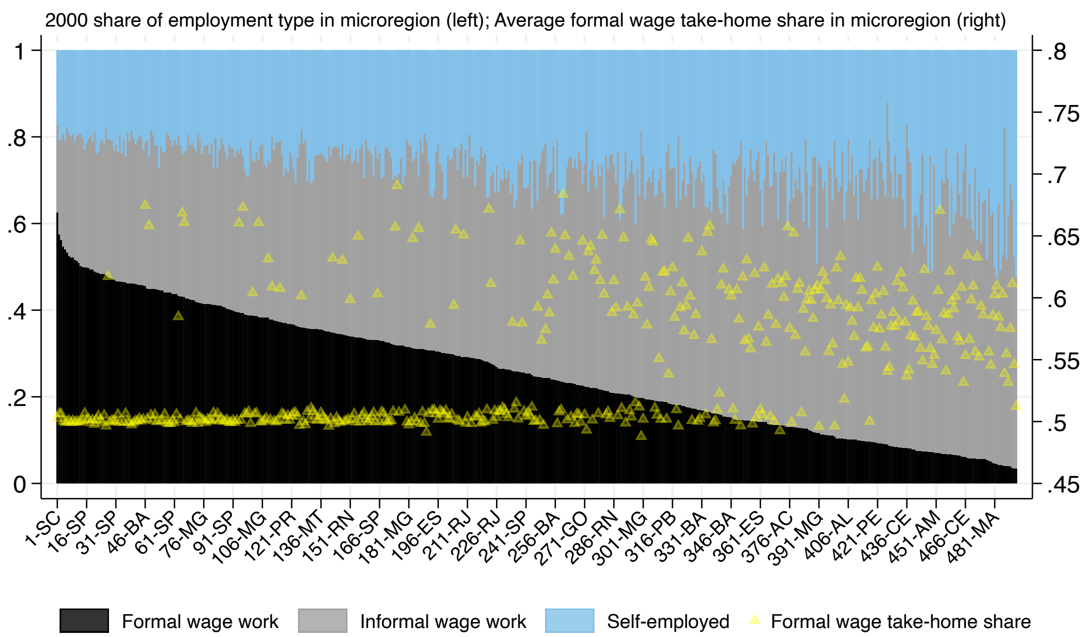
Notes: This figure shows the distribution of average wage take-home shares based on the extended model (Appendix C) across microregions, separately by demographic groups and conditional on year fixed effects. The extended model features heterogeneous (by demographics) substitution to self-employment ($1/\tilde{\rho}$) and formal sector labor supply sensitivity to involuntary separation into informal wage work (Ω). Average wage take-home shares are calculated at the local labor market level (microregion x occupation) using region-specific estimates of $1/\tilde{\eta}$, demographic-specific estimates of $1/\tilde{\rho}$, and the pooled estimate for $1/\tilde{\theta}$.

Figure 9: Extended model: Formal sector wage take-home share heterogeneity by microregion

Panel A: 1991



Panel B: 2000



Notes: This figure plots the distribution of formal wage work (black bins, left y-axis), informal wage work (gray bins, left y-axis), self-employment (blue bins, left y-axis), and estimated average wage take-home shares per the extended model in Appendix C across 486 microregions (yellow scatter, right y-axis). Labels in the x-axis correspond to different microregions. The first two letters indicate the microregion's state, and the number indicates the microregion's rank in the national sorting (e.g., the country's most formal microregion, labeled 1-SC, is a microregion in the state of Santa Catarina).

Table 1: Effect of import competition exposure on local labor market concentration

		Alternative shocks, boundaries, sample			Effect per 10%
	Main specification	ICE constructed with effective rates of protection	Local labor market is microregion	Drop markets where $\Delta ICE = 0$	increase in ICE
	(1)	(2)	(3)	(4)	(5)
Δ Payroll Herfindahl (based on wage premium)	0.213	0.119	0.102	0.036	0.021
	(0.017)	(0.011)	(0.046)	(0.018)	(0.002)
Mean (unweighted), 1991	0.287	0.287	0.038	0.248	0.287
Mean (weighted), 1991	0.079	0.079	0.006	0.076	0.079
Δ Payroll Herfindahl	0.213	0.121	0.110	0.040	0.021
	(0.017)	(0.012)	(0.064)	(0.019)	(0.002)
Mean (unweighted), 1991	0.292	0.292	0.113	0.253	0.292
Mean (weighted), 1991	0.082	0.082	0.026	0.080	0.082
Δ Employment Herfindahl	0.247	0.141	0.058	0.030	0.025
	(0.016)	(0.011)	(0.056)	(0.017)	(0.002)
Mean (unweighted), 1991	0.239	0.239	0.071	0.200	0.239
Mean (weighted), 1991	0.056	0.056	0.011	0.054	0.056
Observations	289,680	289,680	7,124	251,220	289,680
Local labor markets	19,759	19,759	475	16,748	19,759

Notes: Standard errors in parentheses, clustered at the local labor market level. Each cell reports the 1997 coefficient from a stacked differences-in-differences regression of long-differenced outcomes on import competition exposure (ICE) interacted with year dummies, with local labor market fixed effects. Column (1) presents the main specification. Column (2) constructs ICE using effective rates of protection instead of import tariffs. Column (3) defines local labor markets as microregions only. Column (4) drops markets with $\Delta ICE = 0$. Column (5) reports the effect per 10% increase in ICE. HHI is on a 0–1 scale: the coefficient per unit of ICE is multiplied by 10 and divided by 100 to obtain the effect on the 0–1 HHI scale per 10% ICE increase (i.e., $\zeta_{1997}/10$). Weighted means weight by total formal employment in the mmc×cbo942d pair.

Table 2: 2SLS estimates of workers' within-market cross-firm inverse elasticity of substitution $1/\eta$

	Main specification	Shock is effective rate of protection	Premia has worker FE and demo × year FEs	Local labor market is microregion
	(1)	(2)	(3)	(4)
	Panel A: First stage			
Δ Firm log employment in LLM	-0.556	-0.359	-0.604	-0.417
	(0.044)	(0.035)	(0.053)	(0.037)
First stage F	156.771	106.426	130.168	124.666
	Panel B: Reduced form			
Δ Firm wage premium in LLM	-0.550	-0.354	-0.489	-0.404
	(0.024)	(0.019)	(0.030)	(0.017)
	Panel C: 2SLS			
Labor supply within-market cross-firm inverse elasticity of substitution	0.990	0.984	0.811	0.969
	(0.089)	(0.109)	(0.080)	(0.092)
Implied upper bound on wage take-home share	50%	50%	55%	51%
Local labor market (LLM) FE	Yes	Yes	Yes	Yes
Observations	855,104	852,702	463,138	440,966
Firms	344,534	344,027	213,704	420,246
Local labor markets	15,730	15,679	13,627	474

Notes: Standard errors clustered by firm in parentheses. All regressions include local labor market (LLM) fixed effects and are weighted by baseline market employment. The instrument is the change in log import tariff faced by the firm between 1990 and 1994. Column (1): main specification with LLM defined as mmc × occupation, using December wage premium conditional on observables. Column (2): uses effective rate of protection as the instrument instead of TRAINS import tariff. Column (3): wage premium conditional on worker fixed effects and demographic-by-year controls. Column (4): defines LLM as microregion only (no occupation dimension).

Table 3: 2SLS estimate of workers' cross-market inverse elasticity of substitution $1/\theta$

	Δ Import Competition Exposure
	(1)
Panel A: First stage	
Δ LLM employment index	-0.261
	(0.032)
First stage F	66.253
Panel B: Reduced form	
Δ LLM wage premium index	-0.120
	(0.043)
Panel C: 2SLS	
$1/\theta - 1/\eta$	0.459
	(0.190)
Panel D: Cross-market inverse elasticity of substitution	
$1/\theta$	1.448
	(0.168)
Panel E: OLS	
Regression of Δ LLM employment index on	-0.390
Δ LLM wage premium index	(0.015)
Implied lower bound on wage take-home share	0.408
Observations (Local labor markets)	15,730

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. Panel E reports the OLS estimate of a regression of the market employment index on the market wage premium index. Implied lower 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 parentheses are clustered at the local labor market level.

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

	Effect per 10% increase in ICE
Effect of Δ Import Competition Exposure on market average wage markdown	0.0098 (0.0043)
β Effect of Δ Import Competition Exposure on payroll Herfindahl	0.021 (0.003)
$\frac{1}{\theta} - \frac{1}{\eta}$ Difference between key inverse elasticities of labor supply	0.459 (0.190)
Effect of Δ Import Competition Exposure on market average wage take-home share	-0.0022 (0.0010)
Local labor markets	19,759

Notes: This table presents estimates of γ_{1997} per equation 9, listing its two components: β_{1997} taken from Table 1, and $(1/\theta - 1/\eta)$ from Table 3. Standard errors are estimated assuming ζ_{1997} and $(1/\theta - 1/\eta)$ are independent (see Appendix B for details).

Table 5: Effect of import competition on the average wage and its sub-components

	Effect per 10% increase in ICE (1)
Δ Average wage premium	-0.163 (0.030)
Δ Average wage premium take-home share	-0.0023 (0.0010)
Δ Average marginal revenue product of labor	-0.361 (0.067)
Δ Within-firm	-0.369 (0.095)
Δ Cross-firm	0.012 (0.002)
Observations	243,750
Local labor markets	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.

Table 6: Effect of import competition on local average wages: Accounting

	Pre-reform level	Effect of 10% increase in ICE	Change in multiples of min wage per equation 23	Percent change from baseline average wage premium	Effect as percent of total effect on average wage premium
	(1)	(2)	(3)	(4)	(5)
Average wage premium	2.48	-0.163	-0.184	- 7.40%	100%
Average wage take-home share	0.48	-0.0023	-0.012	- 0.47%	6%
Average marginal revenue product of labor	5.15	-0.361	-0.172	- 6.93%	94%
Δ Within-firm	–	-0.369	-0.178	- 7.17%	–
Δ Cross-firm	–	0.012	0.006	+ 0.24%	–

Notes: Column (1) displays the 1991 unweighted average December wage premium across local labor markets from Table A.2, the corresponding unweighted average wage take-home share across these markets, and the implied unweighted average MRPL, computed as their ratio. Note that the unweighted average wage take-home share is slightly different from the country-level average take-home share of 50 cents/dollar, but it is the correct baseline level to align with the effects in column (2), which are based on unweighted market-level regressions. Column (2) repeats the point estimates from Table 5. Column (3) reports the effect of a 10% increase in ICE on multiples of the minimum wage calculated as the sum of the scaled effects on each sub-component, per equation 23, and thus differs slightly from the regression-based estimate column (4), but allows for the accounting decomposition in columns (5)-(6).

Table 7: Extended Model: Distribution of wage take-home shares across microregions

	Min	p10	p25	p50	p75	p90	Max
Panel A.1: All (1991)							
Wage take-home share μ	0.483	0.486	0.489	0.504	0.587	0.616	0.658
N (microregions)				478			
Panel A.2: By age (1991)							
Young (18–29)	0.473	0.479	0.481	0.487	0.542	0.570	0.649
Middle (30–49)	0.483	0.489	0.494	0.513	0.601	0.629	0.718
Old (50–64)	0.474	0.494	0.503	0.541	0.608	0.647	0.731
Panel A.3: By education (1991)							
Primary	0.485	0.490	0.494	0.509	0.588	0.616	0.661
Secondary	0.460	0.483	0.486	0.498	0.552	0.575	0.641
Tertiary	0.462	0.473	0.476	0.480	0.508	0.535	0.610
Panel A.4: By gender (1991)							
Men	0.480	0.484	0.486	0.498	0.567	0.593	0.655
Women	0.475	0.483	0.487	0.500	0.581	0.604	0.670
Panel B.1: All (2000)							
Wage take-home share μ	0.484	0.487	0.490	0.498	0.584	0.609	0.665
N (microregions)				478			
Panel B.2: By age (2000)							
Young (18–29)	0.470	0.479	0.481	0.486	0.558	0.587	0.657
Middle (30–49)	0.485	0.490	0.494	0.506	0.591	0.615	0.666
Old (50–64)	0.488	0.497	0.505	0.523	0.586	0.616	0.668
Panel B.3: By education (2000)							
Primary	0.486	0.489	0.493	0.503	0.585	0.606	0.658
Secondary	0.469	0.485	0.487	0.494	0.562	0.587	0.655
Tertiary	0.459	0.474	0.476	0.480	0.516	0.543	0.622
Panel B.4: By gender (2000)							
Men	0.482	0.486	0.488	0.495	0.572	0.599	0.661
Women	0.475	0.484	0.486	0.494	0.567	0.587	0.647

Notes: This table reports percentiles of the distribution of the wage take-home share μ across microregions, computed from the 1991 and 2000 Brazilian population censuses. Each panel shows the distribution for all workers and by demographic subgroups (age, education, gender). N reports the number of microregions. See Section A for details on sample construction.

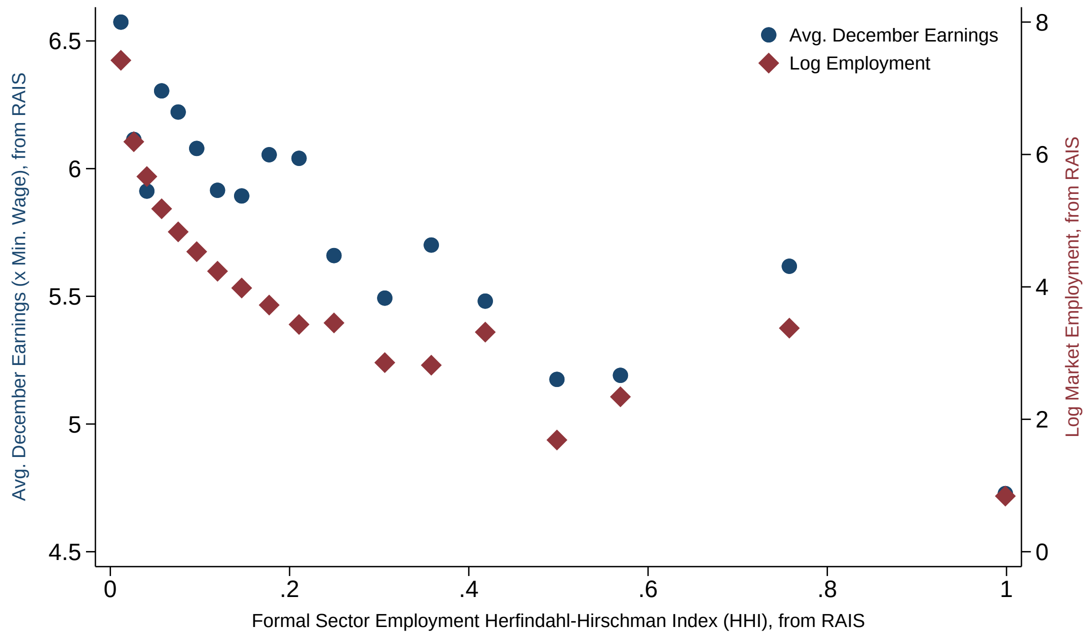
Table 8: Extended model: Effect of 10% increase in Regional Tariff Reductions (RTR) on wage markdowns

	Average	Informality		Gender		Education			Age			Region	
	effect	High	Low	Men	Women	Primary	Second.	Tertiary	Young	Middle	Old	N+NE	SE+S+CW
Panel A: Parameter Estimates													
$1/\eta$ (within-market inverse elast.)	0.990	0.330	0.779	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.385	0.819
	(0.181)												
Ω (separation bias)	0.033	0.033	0.033	0.033	0.035	0.033	0.033	0.033	0.034	0.035	0.033	0.033	0.033
	(0.013)												
$1/\tilde{\eta} = 1/\eta + \Omega$	1.023	0.701	0.991	1.023	1.025	1.023	1.023	1.023	1.024	1.025	1.023	0.484	1.057
$1/\tilde{\rho}$ (wage work vs self-emp)	0.482	0.482	0.482	0.660	0.390	0.482	0.460	0.935	0.850	0.355	0.303	0.482	0.482
	(0.059)												
$1/\tilde{\theta}$ (cross-market)	1.191	1.191	1.191	1.191	1.191	1.191	1.191	1.191	1.191	1.191	1.191	1.191	1.191
	(0.619)												
Panel B: Market Characteristics (1991, wagebill-weighted)													
Average HHI	0.167	0.425	0.156	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.247	0.155
Average s_r	0.785	0.620	0.792	0.785	0.785	0.785	0.785	0.785	0.785	0.785	0.785	0.716	0.796
Average take-home share μ	0.506	0.562	0.504	0.492	0.494	0.494	0.494	0.490	0.490	0.494	0.495	0.627	0.487
Panel C: Reduced-Form Effects of RTR													
β_{HHI} ($\partial HHI/\partial RTR$)	-0.722	-0.910	-0.663	-0.722	-0.722	-0.722	-0.722	-0.722	-0.722	-0.722	-0.722	-0.794	-0.699
	(0.075)	(0.373)	(0.089)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.128)	(0.091)
β_{s_m} ($\partial s_m/\partial RTR$)	0.477	1.585	0.291	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.869	0.329
	(0.069)	(0.496)	(0.072)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.183)	(0.063)
Panel D: Policy Effect of 10% Increase in RTR													
$\partial\bar{\varepsilon}^{-1}/\partial RTR$	0.005	0.028	-0.000	0.000	0.007	0.005	0.005	-0.006	-0.004	0.008	0.009	-0.025	0.004
$\Delta\mu$ (change in take-home share)	0.000	0.001	-0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.001	0.000
Change in take-home share (pp)	-0.051	-0.537	0.042	0.036	-0.100	-0.051	-0.062	0.169	0.126	-0.117	-0.139	1.177	-0.064

Notes: Each column reports the estimated effect of a 10% increase in Regional Tariff Reductions on average wage markdowns for the indicated subgroup. Panel A parameter sources: $1/\eta$ from Table C.2 (region-specific estimates for region columns; pooled for others); Ω from Table C.4 (demographic-specific estimates); $1/\tilde{\eta} = 1/\eta + \Omega$; $1/\tilde{\rho}$ from Table C.6 (demographic-specific estimates where significant; pooled otherwise); $1/\tilde{\theta}$ from Table C.6 (pooled estimate). Standard errors in parentheses. Panel B reports 1991 formal wagebill-weighted averages. Panel C reports reduced-form regressions of market-level changes (1991–2000) on Regional Tariff Reductions, controlling for region fixed effects and clustering standard errors at the microregion level; β_{HHI} and β_{s_m} are from subgroup-specific regressions for informality and region columns, and pooled estimates for demographic columns. Panel D applies the policy effect formula from Section 2. Informality classified by 1991 microregion-level share of non-formal employment above/below the median. Region groups follow the $1/\eta$ heterogeneity: North + Northeast vs Southeast + South + Center West.

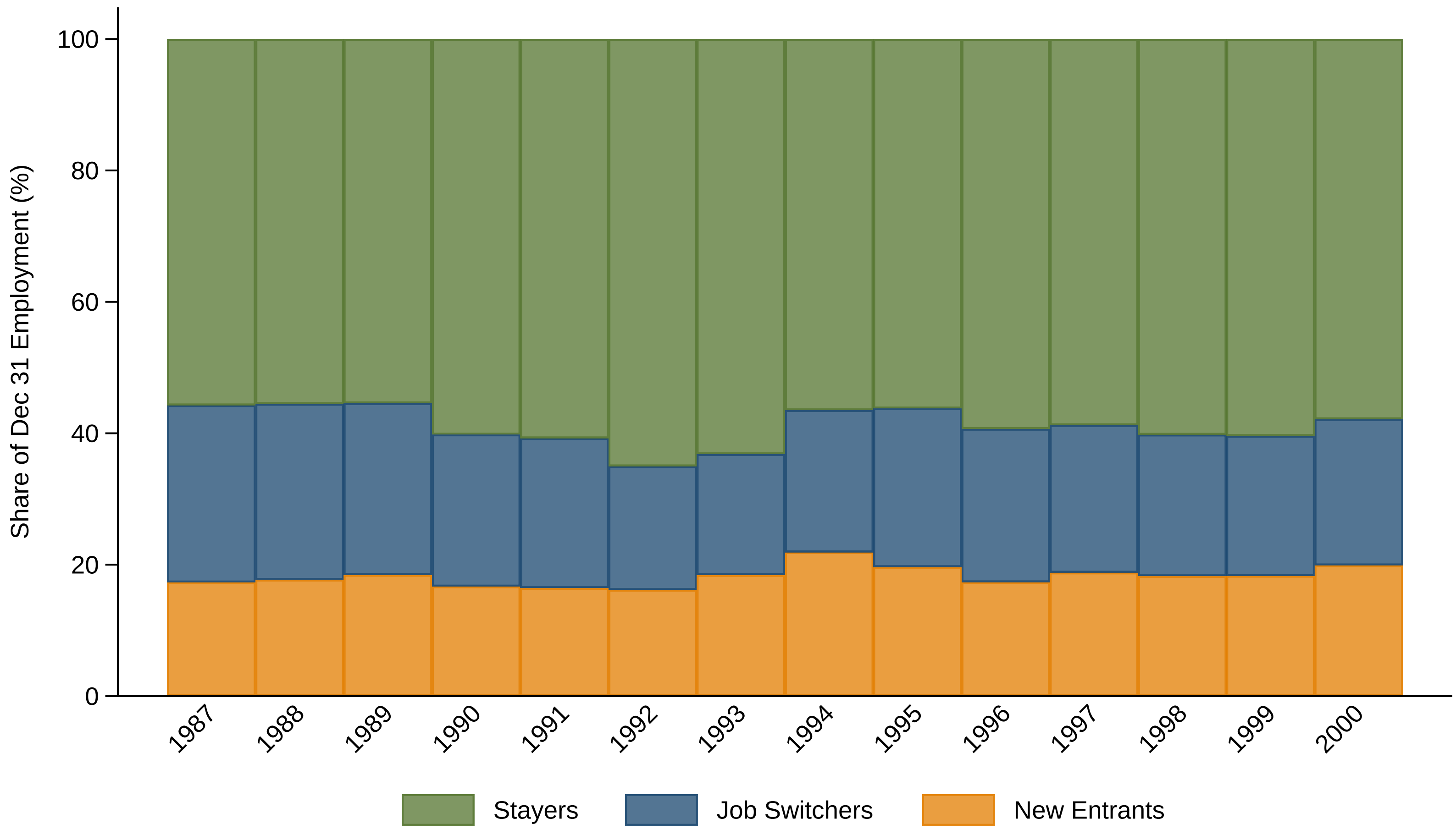
Online Appendix for
"Trade, Labor Market Concentration, and Wages,"
by Mayara Felix

Figure A.1: 1991 wages, employment, and formal sector concentration



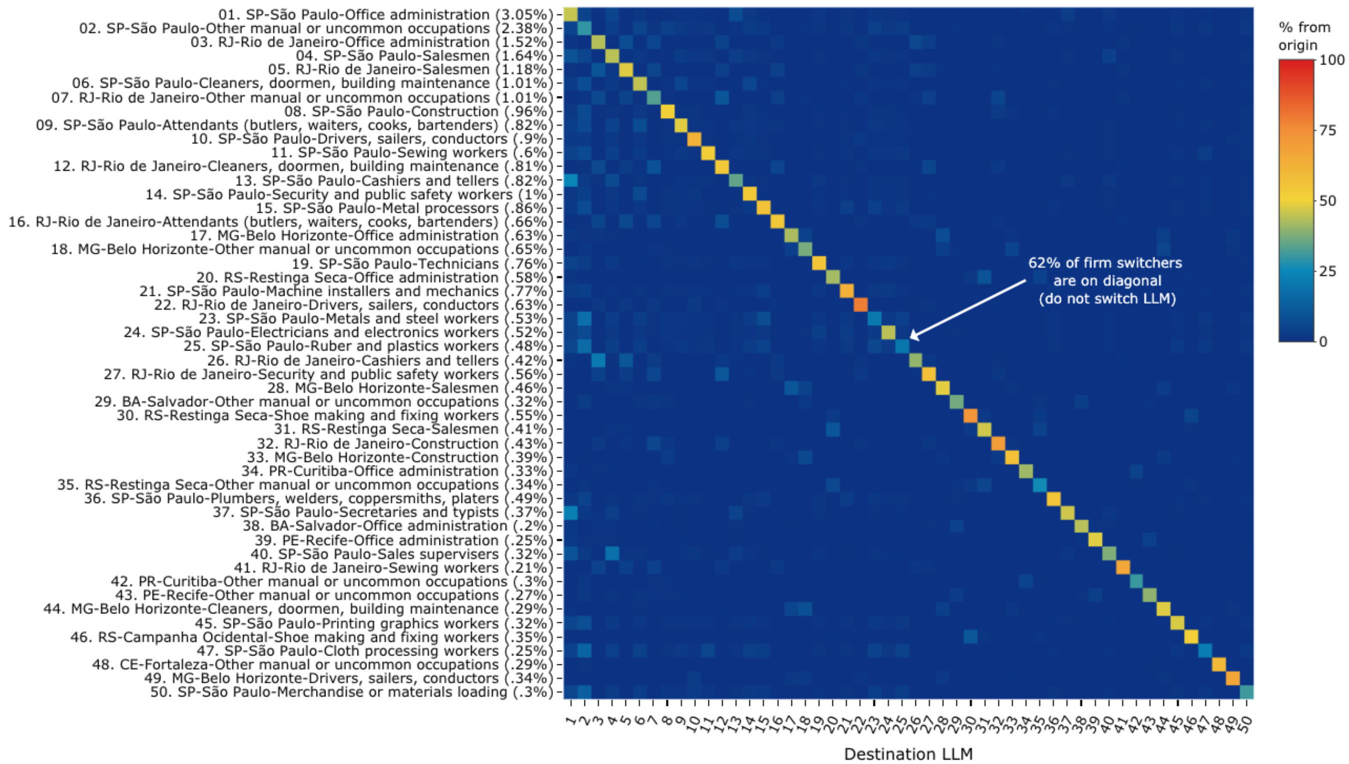
Notes: This figure plots wages and employment as a function of formal sector HHI in microregion x occupation pairs using RAIS data for 1991.

Figure A.2: Formal sector job stayers versus job switchers as of Dec 31 of each year



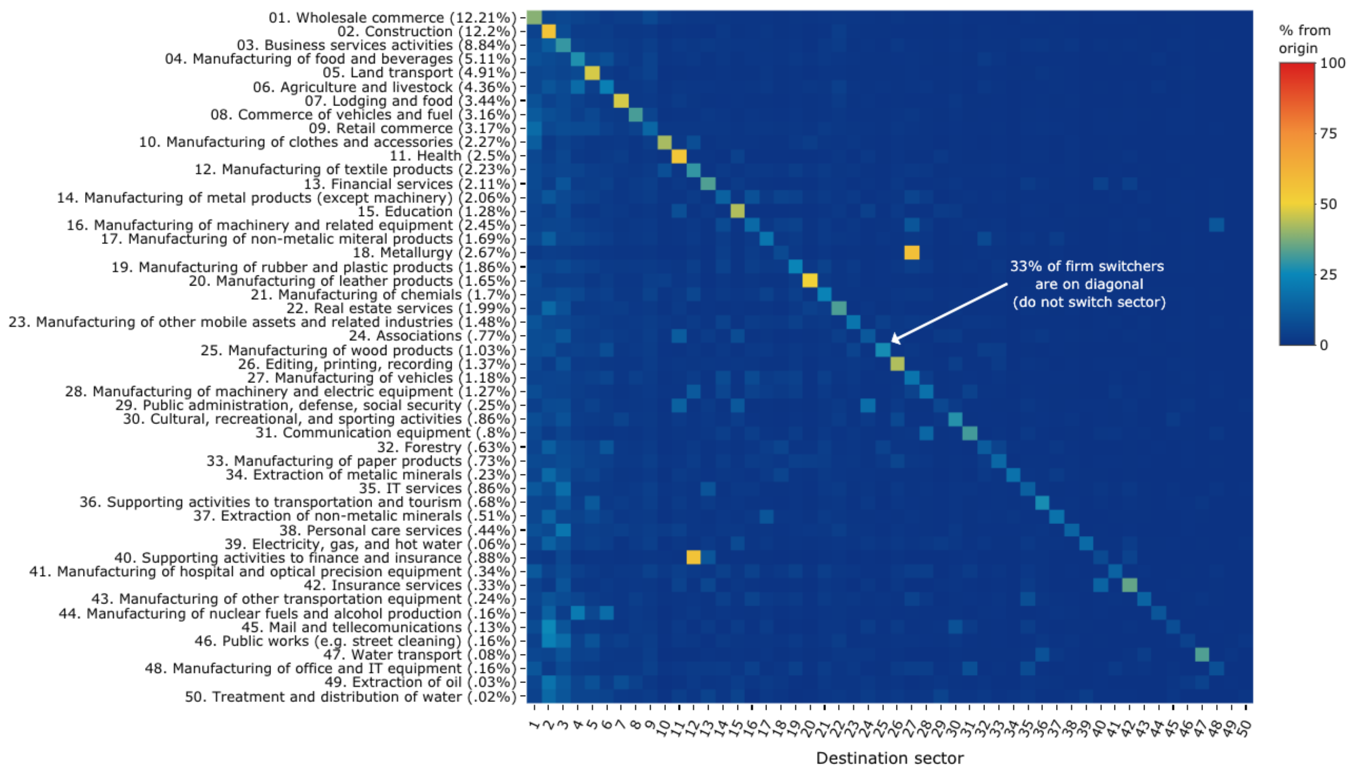
Notes: This figure plots formal private sector employment composition in Brazil from 1986 to 2000 using matched employer-employee data from RAIS. Each bar reports December 31 employment (in millions) decomposed into job stayers (workers employed at the same firm as of December 31 of the previous year) and job switchers (workers employed at a different firm or entering the formal sector). "Hired from Outside" counts workers appearing in the formal sector on December 31 who were not employed in any formal firm on December 31 of the previous year. "Hired from Other" counts workers who switched from one formal firm to another within the year. Flows exclude transitions to/from public administration, retirements, and deaths.

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.

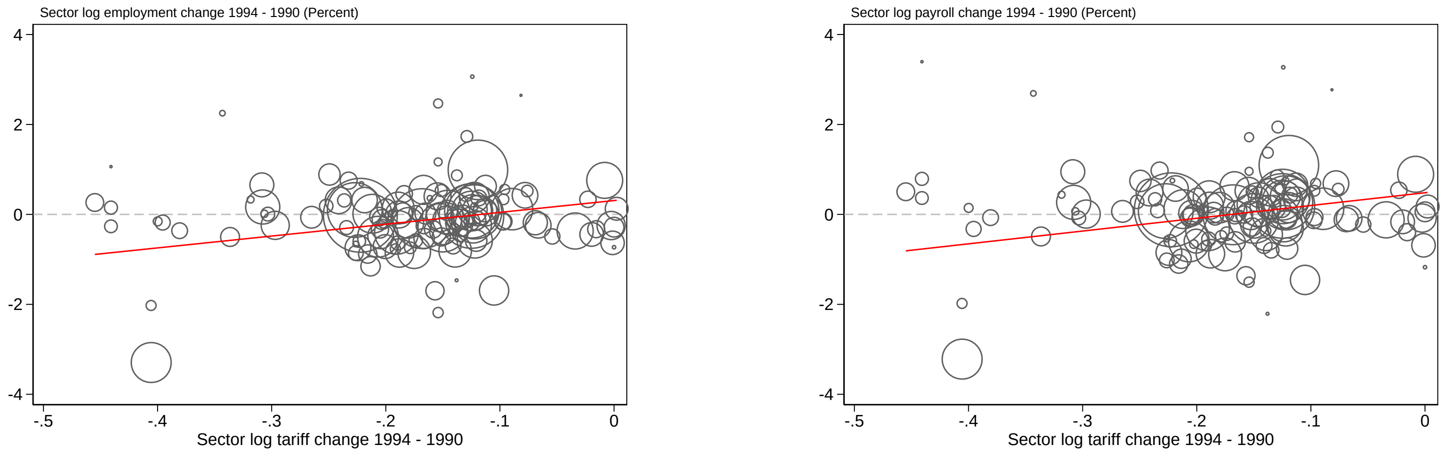
Figure A.4: 1990-1991 sector transitions conditional on switching firms (Top 50)



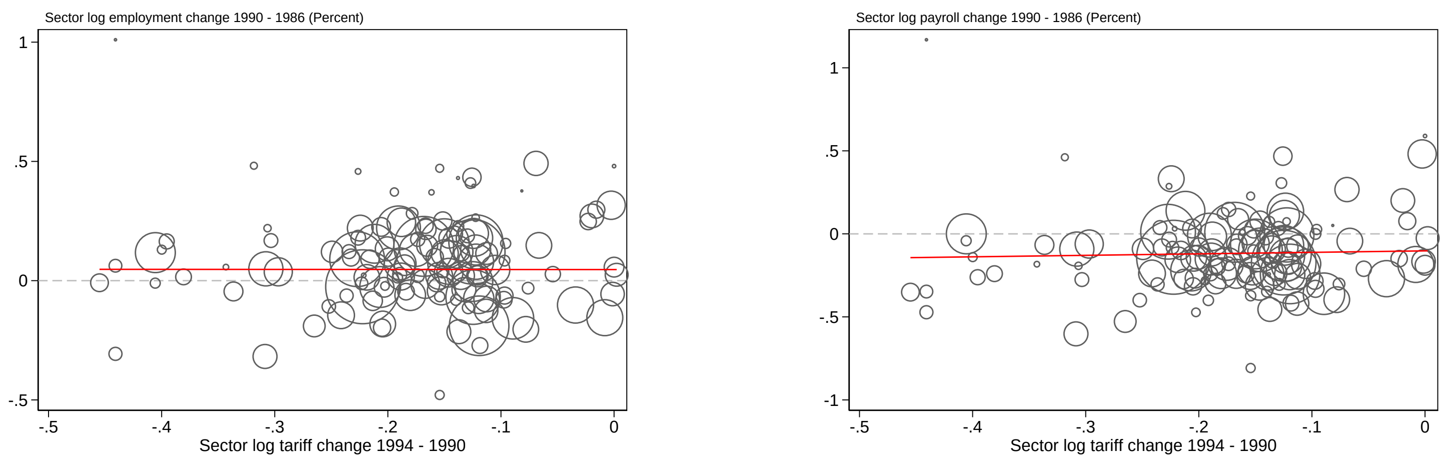
Note: This figure plots worker sector group to sector group transitions, among workers who switched employers between 1990 and 1991, for the top 50 sector (2-digit CNAE95) groups by number of workers at origin. Each row lists the origin sector group (with percent of total workers indicated in parentheses),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

Figure A.5: Changes in sector-level outcomes Before vs. After liberalization

(a) After liberalization (1990–1994)

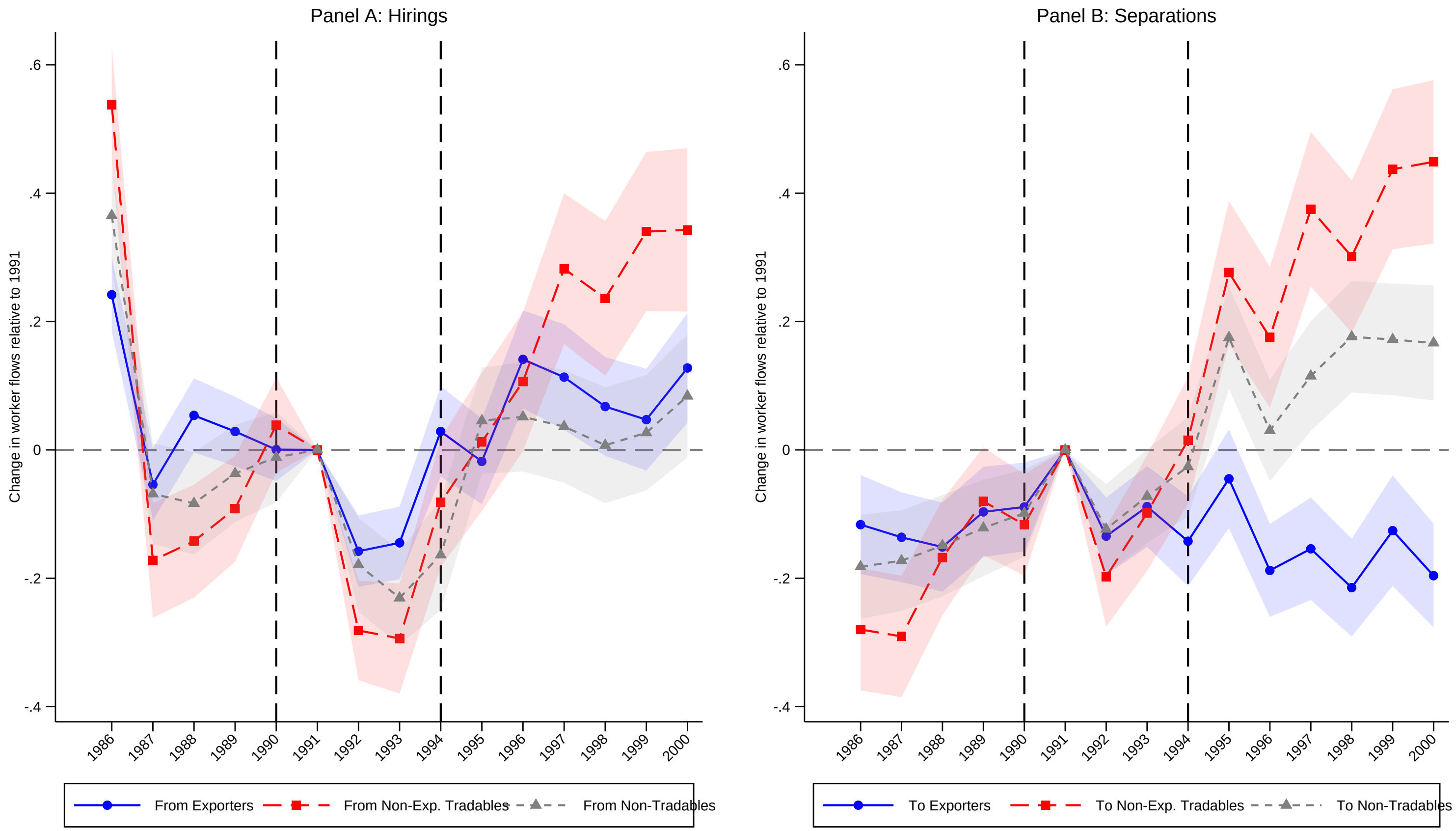


(b) Before liberalization (1986–1990)



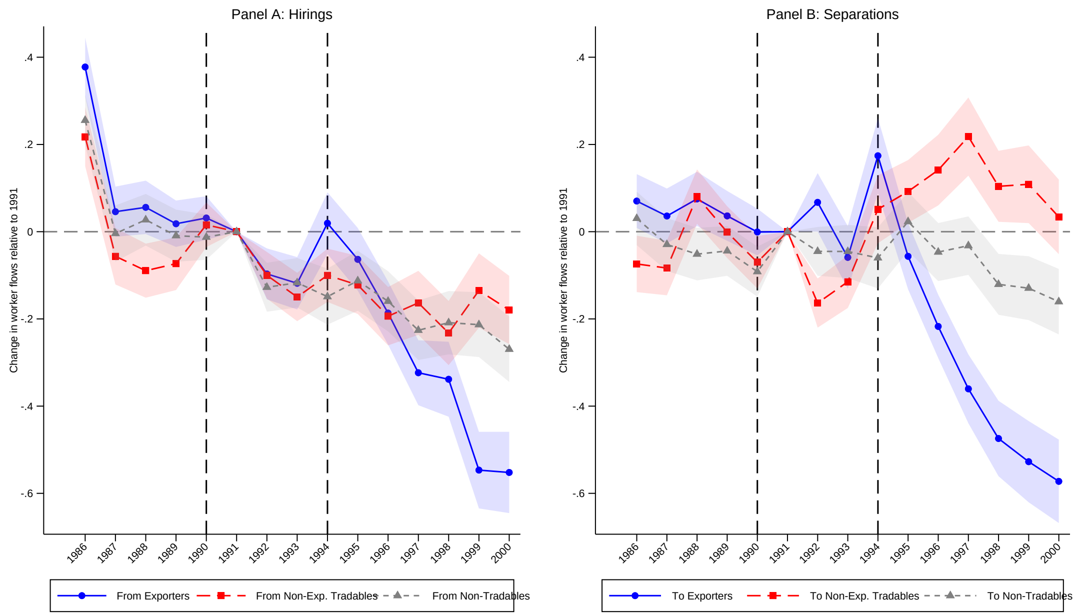
Note: This figure plots changes in sector-level local total employment and sector-level log total payroll for the 4-year periods before versus after liberalization, against the 1990–1994 import tariff reduction on each sector's output. Sector totals are based on data for the entire country and are aggregated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

Figure A.6: Effect of import competition exposure on within-market flows into (Panel A) and out of (Panel B) non-exporting tradable sector firms



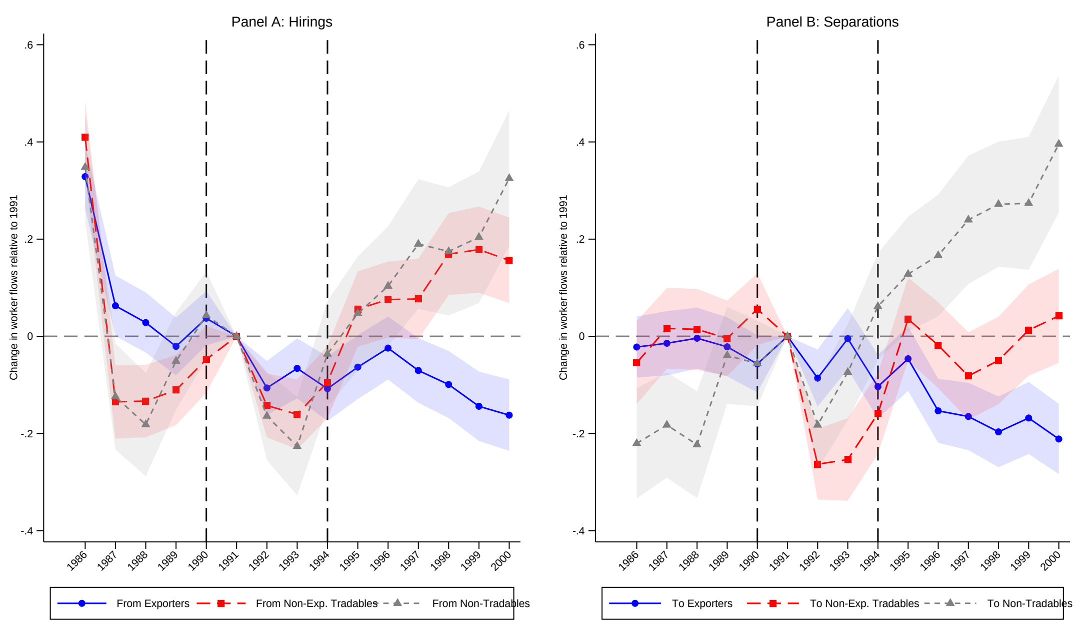
Note: This figure plots year-by-year coefficients from stacked differences-in-differences regressions of within-market cross-firm worker flows on import competition exposure (ICE), with local labor market (mmc × cbo942d) fixed effects, clustering at the local labor market level. Panel A shows hirings into non-exporting tradable firms from exporters, other non-exporting tradable firms, and non-tradable firms within the same local labor market. Panel B shows separations from non-exporting tradable firms to each of these firm types. Outcomes are IHS-transformed long differences relative to 1991. Shaded areas report 95% confidence intervals. Appendix Figures A.7–A.11 present corresponding results for flows into and out of other firm types, including flows into and out of the formal sector.

Figure A.7: Effect of import competition on within-market flows into and out of Exporters



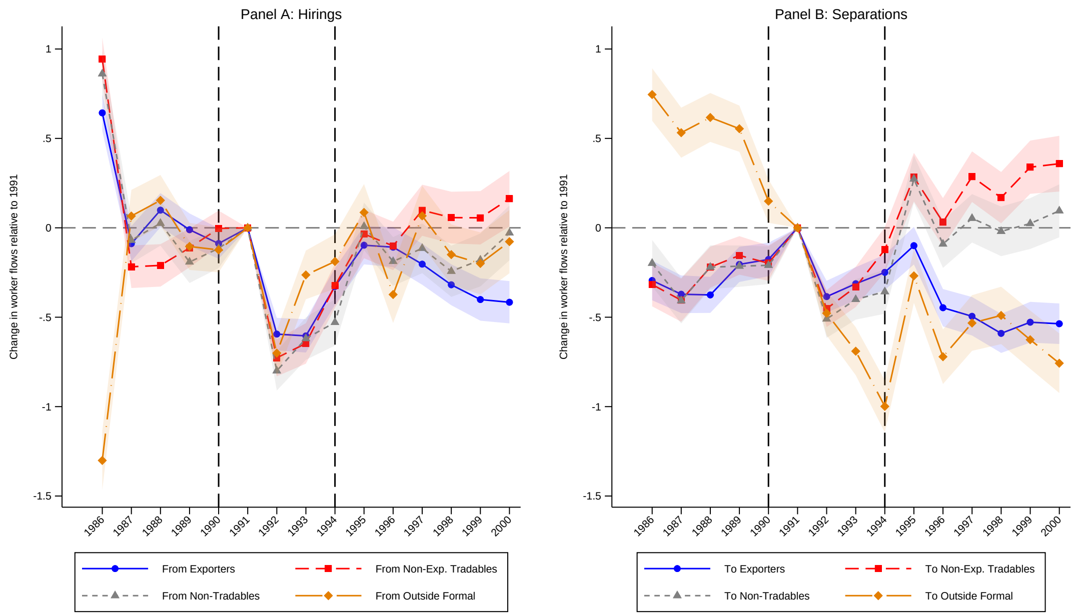
Note: See notes to Figure A.6.

Figure A.8: Effect of import competition on within-market flows into and out of Non-tradables



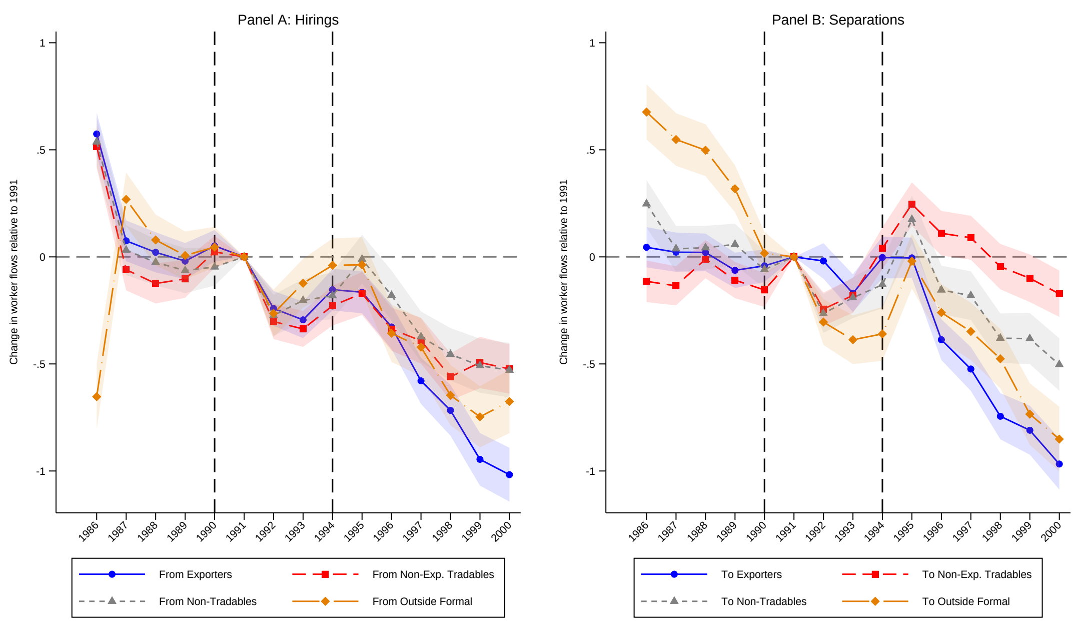
Note: See notes to Figure A.6.

Figure A.9: Effect of import competition on all flows into and out of Non-Exporting Tradable sector firms



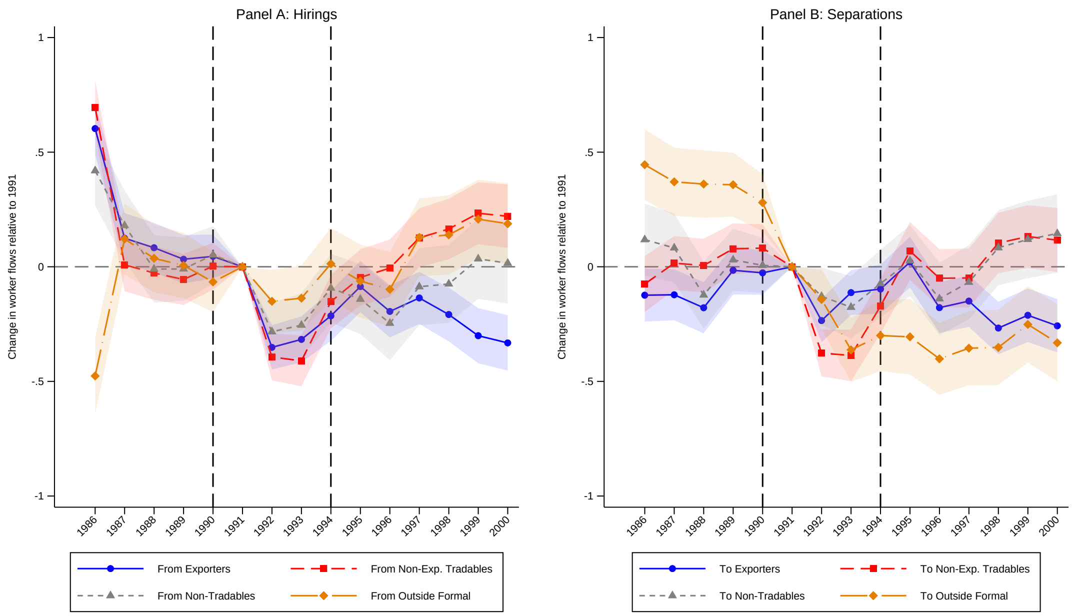
Note: See notes to Figure A.6.

Figure A.10: Effect of import competition on all flows into and out of Exporters



Note: See notes to Figure A.6.

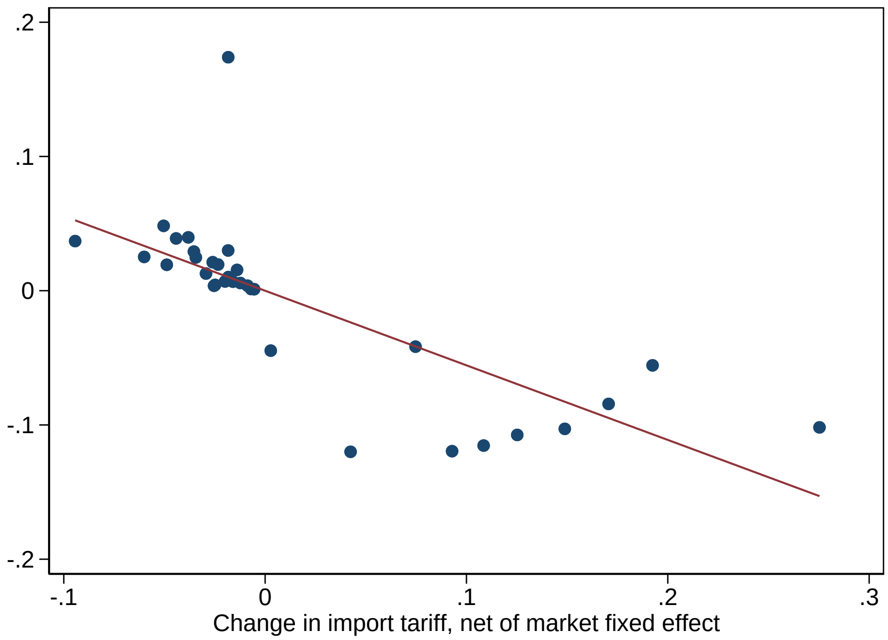
Figure A.11: Effect of import competition on all flows into and out of Non-tradables



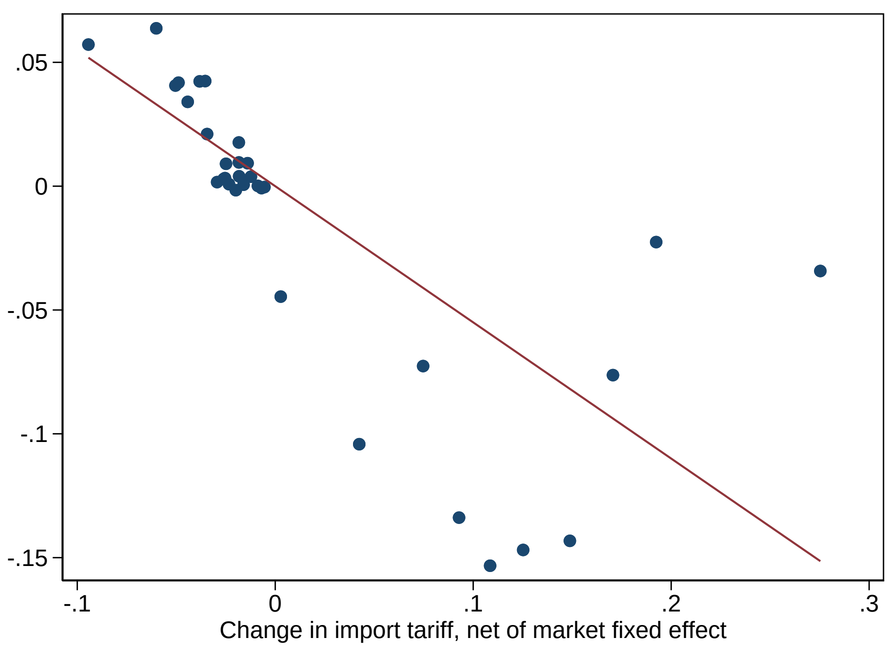
Note: See notes to Figure A.6.

Figure A.12: Identifying variation for within-market cross-firm inverse elasticity of substitution

(a) Panel A: First stage



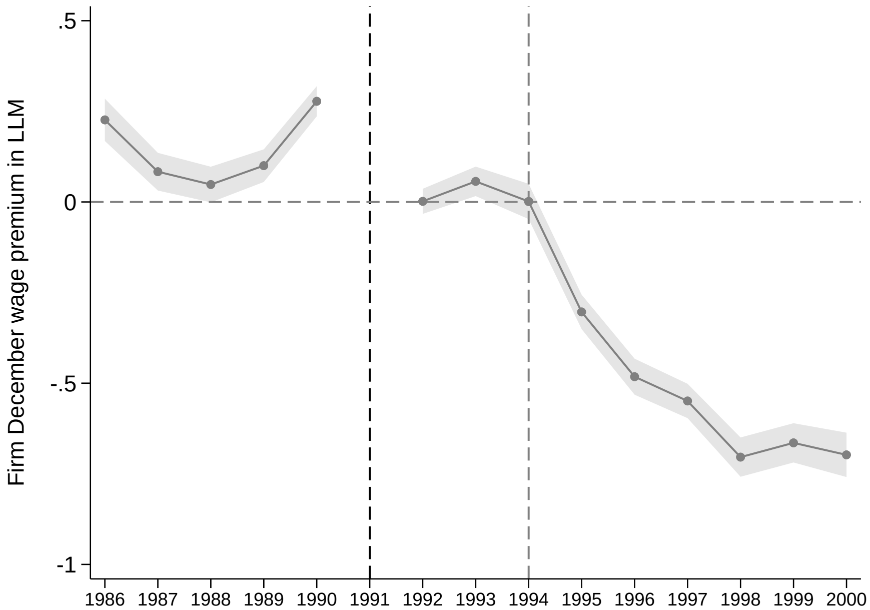
(b) Panel B: Reduced form



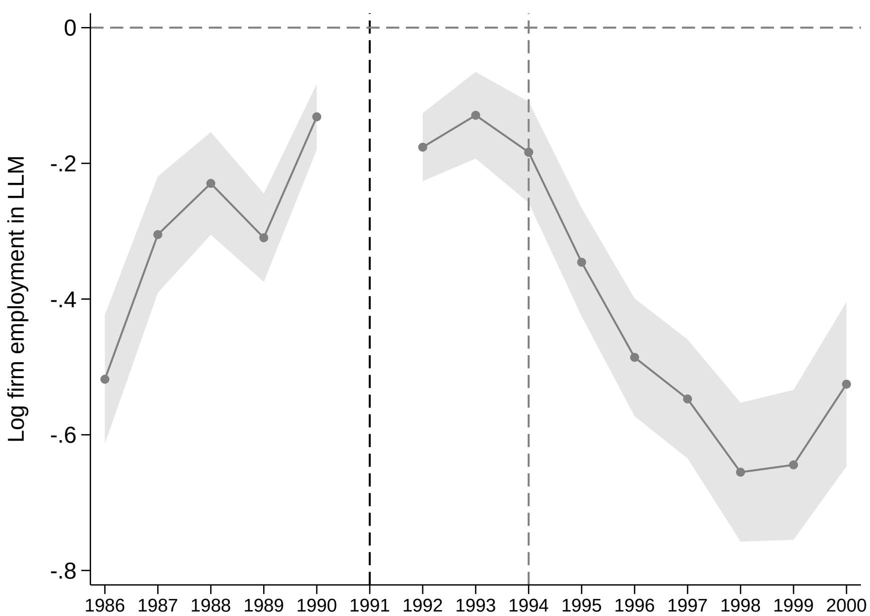
Notes: This figure shows the identifying variation underlying the IV estimate of the within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$. Panel A plots the first stage (firm-level employment against the tariff instrument). Panel B plots the reduced form (firm-level wage premia against the tariff instrument). Both panels show binned scatter plots after partialling out local labor market fixed effects.

Figure A.13: Year by year effects of tariff reductions on firm-market-level wage premia and employment

(a) Wage premia

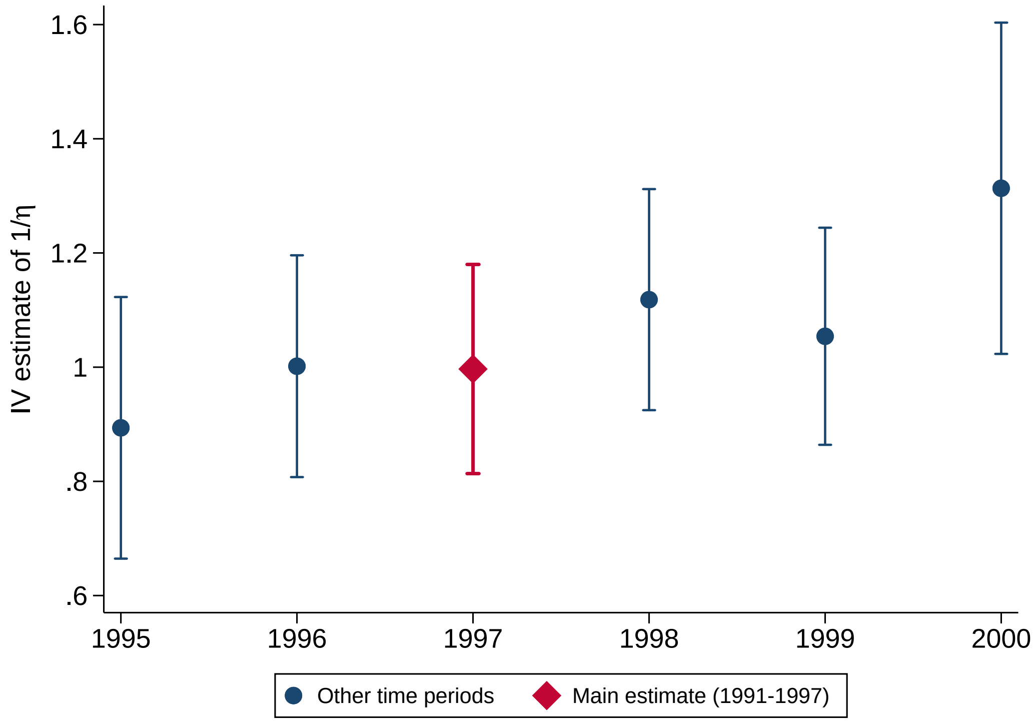


(b) Employment



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

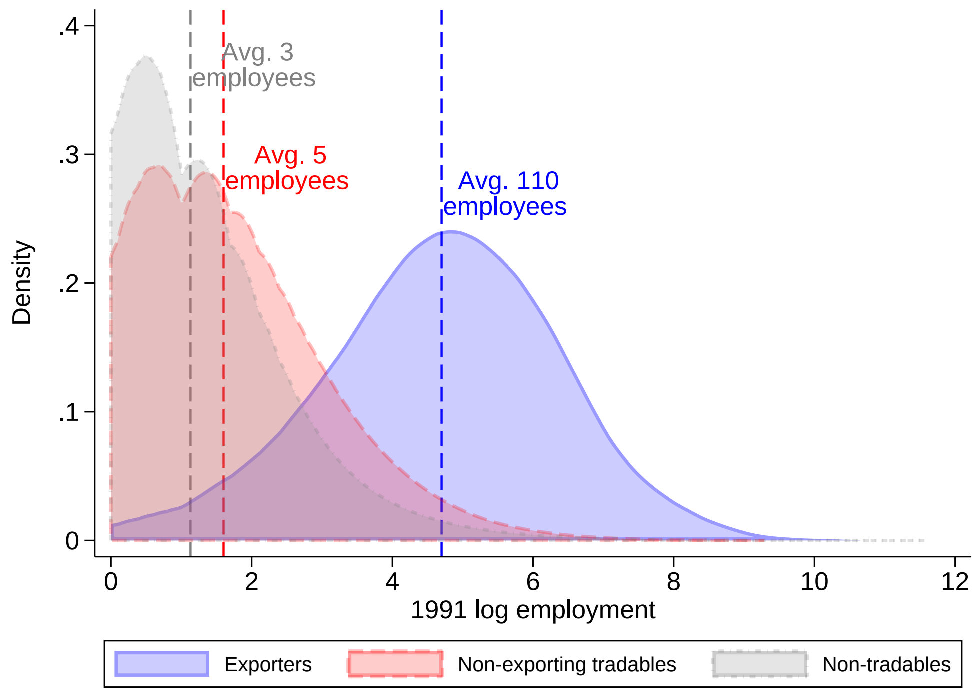
Figure A.14: Year by year estimates of within-market cross-firm inverse elasticity of substitution



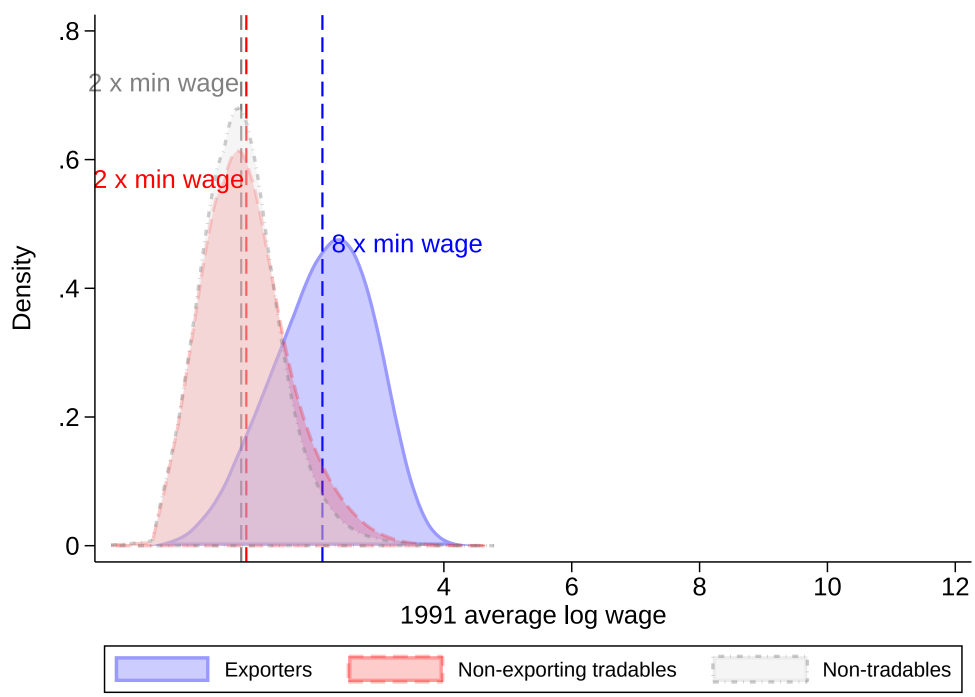
Notes: This figure presents estimates of the within-market cross-firm inverse elasticity of substitution $\frac{1}{\eta}$ estimated separately for each post-liberalization year, using the same specification as in Table 2. The dashed horizontal line indicates the pooled baseline estimate.

Figure A.15: Pre-liberalization distribution of firm size and wages

(a) Distributions of firm log employment



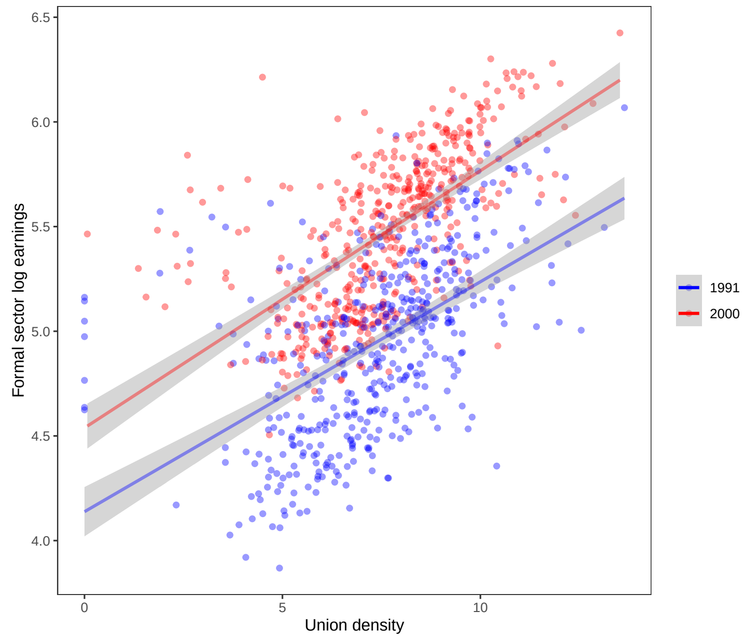
(b) Distributions of firm average log wage



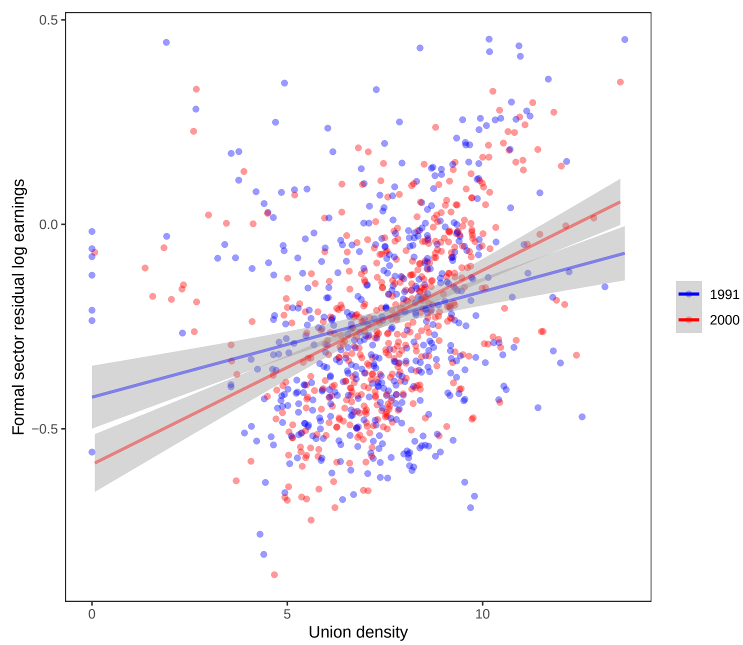
Note: This figure plots pre-liberalization distributions of firm log employment and log December monthly wages for exporters, non-exporters, and non-tradables. Wages are reported as multiples of the national minimum wage.

Figure A.16: Formal sector wage compression and union density

(a) Panel A: Formal sector log earnings and union density



(b) Panel B: Formal sector residual log earnings and union density



Note: This figure examines the relationship between union density and formal-sector wages. Panel A plots average formal-sector log earnings against union density, while Panel B plots residual formal-sector log earnings after netting out observable worker characteristics. Each panel shows two cross-sections, corresponding to 1991 and 2000, with separate linear fits for each year. The horizontal axis reports union density transformed as $\log(1+\text{union density})$ to improve visualization in the presence of skewness. Union density data comes from `https://academic.oup.com/jeea/article/23/1/236/7628306` and was collected for the years 1992 and 2001 to match with wage outcomes in 1991 and 2000.

Table A.1: Brazilian workforce during 1990s trade liberalization

	Population Census Year	
	1991	2000
N	51,318,478 (42.6%)	69,279,182 (57.4%)
Formal wage work	0.403 (0.491)	0.313 (0.464)
Informal wage work	0.324 (0.468)	0.344 (0.475)
Self-employed	0.239 (0.427)	0.205 (0.404)
Unemployed	0.044 (0.206)	0.138 (0.345)
Hours worked	43.534 (12.006)	43.950 (14.655)
Earnings (R2000)	331.153 (412.063)	553.811 (704.593)
Earnings (R2000) $- Formal$	383.860 (413.424)	596.340 (653.361)
Earnings (R2000) $- Informal$	279.794 (418.736)	497.524 (725.634)
Earnings (R2000) $- Self-employed$	309.456 (388.220)	568.712 (744.037)
Minimum wage (R2000)	126.514 (0.000)	151.000 (0.000)
Female	0.327 (0.469)	0.404 (0.491)
Age	34.262 (11.490)	34.717 (11.500)
Years of education	5.900 (4.522)	7.033 (4.392)

Note: This table shows descriptive statistics from the Brazilian 1991 and 2000 population censuses, calculated using the 1991 and 2000 census sample extract files from the supplementary materials for Dix-Carneiro and Kovak (2017). Earnings and hours are for main job. All statistics are calculated using individual-level sample extract weights. Earnings statistics exclude top 1% and bottom 1% of earnings distribution. The sample includes all workers employed in the private sector (that is, excludes public administration). Formal wage work follows the standard definition for Brazilian labor markets, which is to have a signed *Carteira de Trabalho* (variables v350 and v0447 in 1991 and 2000 censuses, respectively). Real monthly earnings are based on the IPCA deflator and are expressed in 2000 reais. Minimum wage reports the federal monthly minimum wage for July 1991 and for 2000. Brazil's minimum wage is regulated as minimum monthly earnings for a 44-hour work week.

Table A.2: 1991 descriptive statistics of formal local labor markets (microregion x occupation group pairs)

	Mean	Std. Dev.	p10	p25	Median	p75	p90	N
Number of formal workers	698	5,266	6	16	61	262	1,006	19,514
Number of formal tradable sector workers	293	2,176	0	3	20	101	416	19,514
Number of exporter workers	255	2,076	0	1	10	69	333	19,514
Number of formal non-tradable sector workers	405	3,484	1	6	25	118	496	19,514
Number of formal firms	116	795	3	6	16	55	183	19,514
Number of exporter firms	18	117	0	1	2	8	26	19,514
Payroll HHI (based on wage premia)	0.283	0.248	0.042	0.093	0.207	0.399	0.643	19,513
Payroll HHI (based on wage level)	0.288	0.249	0.044	0.097	0.212	0.406	0.652	19,514
Employment HHI	0.234	0.234	0.027	0.064	0.156	0.333	0.556	19,514
Average December wage (× min. wage)	5.860	5.984	1.672	2.346	3.848	6.922	12.354	19,514
Average December wage premium (× min. wage)	2.484	1.526	1.114	1.474	2.067	3.033	4.395	19,286
Import competition exposure (ΔICE)	0.125	0.091	0.000	0.050	0.130	0.178	0.231	19,514

Note: This table presents descriptive statistics across 19,514 Brazilian local labor markets defined as microregion × occupation group pairs, in the baseline year (1991). Means are unweighted. HHI denotes the Herfindahl-Hirschman Index of employment or payroll concentration. ΔICE is the change in import competition exposure.

Table A.3: Average payroll Herfindahl across local labor markets

	1986 (1)	1991 (2)	1994 (3)	1997 (4)	2000 (5)
Panel A: Payroll Herfindahl (based on wage premia)					
Unweighted average	0.289	0.283	0.274	0.228	0.209
Weighted average (by market employment shares)	0.071	0.078	0.074	0.061	0.058
Weighted average (by market payroll shares)	0.069	0.080	0.077	0.064	0.061
Panel B: Payroll Herfindahl (based on wage levels)					
Unweighted average	0.293	0.288	0.280	0.234	0.214
Weighted average (by market employment shares)	0.073	0.082	0.078	0.065	0.061
Weighted average (by market payroll shares)	0.073	0.084	0.080	0.068	0.065
Panel C: Employment Herfindahl					
Unweighted average	0.246	0.234	0.221	0.184	0.173
Weighted average (by market employment shares)	0.054	0.056	0.053	0.044	0.046
Weighted average (by market payroll shares)	0.049	0.052	0.050	0.041	0.044

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

Table A.4: Formal employment and worker flows by year

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Panel A: December 31 Employment (millions)															
Total	10.64	20.80	21.04	21.74	20.79	19.65	18.25	18.84	20.37	23.54	23.29	24.09	23.93	23.64	25.25
Exporters	1.69	3.97	3.88	4.17	3.88	3.59	3.27	3.35	3.47	3.53	3.06	2.79	2.46	2.21	2.26
Non-Exp. Tradables	2.18	3.67	3.49	3.64	3.52	3.25	2.91	3.14	3.96	4.56	4.56	4.85	4.84	4.94	5.40
Non-Tradables	6.77	13.16	13.66	13.94	13.39	12.81	12.07	12.35	12.94	15.45	15.67	16.45	16.63	16.49	17.59
Panel B: Flows In/Out of Formal Sector (millions)															
Hired from Outside	7.84	3.60	3.73	4.01	3.47	3.23	2.95	3.47	4.46	4.63	4.04	4.53	4.37	4.33	5.03
Into Exporters	1.20	0.50	0.45	0.55	0.40	0.39	0.32	0.40	0.44	0.41	0.29	0.27	0.21	0.22	0.25
Into Non-Exp. Tradables	1.68	0.70	0.68	0.80	0.69	0.61	0.55	0.70	1.03	1.04	0.90	1.03	0.98	1.01	1.18
Into Non-Tradables	4.97	2.40	2.60	2.66	2.38	2.23	2.08	2.37	2.98	3.17	2.85	3.23	3.18	3.10	3.60
Separated to Outside	3.00	3.17	3.17	3.43	4.11	3.92	3.40	2.86	3.16	4.19	3.79	3.89	4.13	3.66	3.71
From Exporters	0.40	0.48	0.41	0.48	0.64	0.57	0.46	0.38	0.41	0.54	0.40	0.38	0.34	0.23	0.21
From Non-Exp. Tradables	0.59	0.66	0.59	0.64	0.78	0.74	0.62	0.53	0.67	0.92	0.82	0.84	0.90	0.81	0.85
From Non-Tradables	2.01	2.04	2.17	2.31	2.69	2.61	2.33	1.94	2.08	2.72	2.57	2.67	2.89	2.62	2.65
Panel C: Flows Between Firms (millions)															
From Exporters	0.88	0.96	0.79	0.82	0.83	0.63	0.51	0.52	0.65	0.74	0.53	0.49	0.41	0.36	0.35
From Non-Exp. Tradables	1.08	1.11	0.97	0.94	0.90	0.71	0.58	0.65	0.94	1.18	1.05	1.08	1.02	1.05	1.19
From Non-Tradables	3.83	3.73	3.75	3.55	3.27	2.80	2.36	2.59	3.19	3.92	3.57	3.58	3.46	3.55	3.92

Notes: This table summarizes formal private sector employment and worker flows in Brazil from 1986 to 2000 using matched employer-employee data from RAIS. Panel A reports December 31 employment (in millions) by firm trading status: exporters, non-exporting tradable firms, and non-tradable firms. Panel B reports annual flows into and out of the formal sector, separately by destination or origin firm type. "Hired from Outside" counts workers appearing in the formal sector on December 31 who were not employed in any formal firm on December 31 of the previous year. "Separated to Outside" counts workers employed in a formal firm on January 1 who are not found in any formal firm on December 31 of the same year. Panel C reports within-year job-to-job transitions between formal sector firms, by origin firm type. All values are in millions of workers.

Table A.5: Effects of import competition exposure on local wages and employment

	Δ Import Competition Exposure	Effect per 10% increase in ICE
	(1)	(2)
Panel A: Log number of firms and log formal employment		
Δ Log number of firms	-0.549	-5.489
	(0.045)	(0.447)
Mean (unweighted), 1991	3.651	3.651
Mean (weighted), 1991	7.645	7.645
Δ Log formal employment	-0.440	-4.400
	(0.064)	(0.640)
Mean (unweighted), 1991	4.918	4.918
Mean (weighted), 1991	9.659	9.659
Panel B: Log formal wage premium		
Δ Log formal wage premium	0.029	0.293
	(0.031)	(0.307)
Mean (unweighted), 1991	0.761	0.761
Mean (weighted), 1991	1.072	1.072
Δ De-trended log formal wage premium	-0.206	-2.063
	(0.034)	(0.338)
Mean (unweighted), 1991	1.225	1.225
Mean (weighted), 1991	1.485	1.485
Observations	289,680	289,680
Local labor markets	19,759	19,759

Notes: Standard errors in parentheses, clustered at the local labor market level. Each cell reports the 1997 coefficient from a stacked differences-in-differences regression of long-differenced outcomes on import competition exposure (ICE) interacted with year dummies, with local labor market (mmc × cbo942d) fixed effects.

Table A.6: Effects of 10% increase in import competition on formal sector labor market concentration: Heterogeneity by baseline formal sector share of total employment

	Main specification (1)	Above median formal share (2)	Below median formal share (3)
Δ Payroll Herfindahl (based on wage premium)	0.021	0.017	0.021
	(0.002)	(0.002)	(0.003)
Mean (unweighted), 1991	0.287	0.244	0.377
Mean (weighted), 1991	0.079	0.072	0.215
Δ Payroll Herfindahl	0.021	0.017	0.021
	(0.002)	(0.002)	(0.003)
Median, 1991	0.216	0.172	0.314
Mean (weighted), 1991	0.082	0.076	0.221
Δ Employment Herfindahl	0.025	0.018	0.028
	(0.002)	(0.002)	(0.003)
Median, 1991	0.158	0.122	0.244
Mean (weighted), 1991	0.056	0.051	0.171
Observations	296,340	195,998	96,833
Local labor markets	19,759	13,068	6,457

Notes: Standard errors in parentheses, clustered at the local labor market level. Each cell reports the 1997 coefficient from a stacked differences-in-differences regression of long-differenced outcomes on import competition exposure (ICE) interacted with year dummies, with local labor market (mmc × cbo942d) fixed effects. Coefficients are divided by 10 to report the effect of a 10 percentage point increase in ICE (HHI variables are on a 0–1 scale; the raw regression coefficient is per unit of ICE, so dividing by 10 converts to a 10 percentage point increase on the 0–1 HHI scale, i.e., $(\zeta_{1997} \times 10)/100$). Column (1) uses all markets. Columns (2) and (3) split mmc×cbo942d markets by whether the microregion's formal employment share (formal employment / (informal wage work + self-employed)) from the 1991 census is above or below the median across microregions. Weighted means weight by total formal employment in the mmc×cbo942d pair.

Table A.7: Effect of import competition exposure on concentration: Microregion boundaries

	Main specification (1)	Local labor market is microregion (2)
Panel A: Formal sector labor market concentration		
Δ Payroll Herfindahl (based on wage premium)	0.213	0.102
	(0.017)	(0.046)
Mean (unweighted), 1991	0.287	0.038
Mean (weighted), 1991	0.079	0.006
Δ Payroll Herfindahl	0.213	0.110
	(0.017)	(0.064)
Mean (unweighted), 1991	0.292	0.113
Mean (weighted), 1991	0.082	0.026
Δ Employment Herfindahl	0.247	0.058
	(0.016)	(0.056)
Mean (unweighted), 1991	0.239	0.071
Mean (weighted), 1991	0.056	0.011
Panel B: Log number of firms and log formal employment		
Δ Log number of firms	-0.549	-0.367
	(0.045)	(0.208)
Mean (unweighted), 1991	3.651	6.646
Mean (weighted), 1991	7.645	10.133
Δ Log formal employment	-0.440	-0.338
	(0.064)	(0.335)
Mean (unweighted), 1991	4.918	9.001
Mean (weighted), 1991	9.659	12.961
Panel C: Log formal wage premium		
Δ Log formal wage premium	0.029	0.116
	(0.031)	(0.131)
Mean (unweighted), 1991	0.761	0.507
Mean (weighted), 1991	1.072	0.895
Δ De-trended log formal wage premium	-0.141	0.106
	(0.031)	(0.131)
Observations	289,680	7,124
Local labor markets	19,759	475

Notes: Standard errors in parentheses. Column 1 clusters at the local labor market level; column 2 clusters at the microregion level. All columns report the 1997 coefficient from stacked differences-in-differences regressions. Weighted means weight by total formal employment in the local labor market.

Table A.8: Effect of import competition exposure on concentration: Alternative exposure measures

	Main specification	ICE weights are firms' base year payroll shares	ICE weights are firms' base year employment shares	ICE tariff shocks are firms' effective tariff protection
	(1)	(2)	(3)	(4)
Panel A: Formal sector 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)
Mean (unweighted), 1991	0.287	0.287	0.287	0.287
Mean (weighted), 1991	0.079	0.079	0.079	0.079
Δ Payroll Herfindahl	0.213	0.259	0.277	0.121
	(0.017)	(0.020)	(0.020)	(0.012)
Mean (unweighted), 1991	0.292	0.292	0.292	0.292
Mean (weighted), 1991	0.082	0.082	0.082	0.082
Δ Employment Herfindahl	0.247	0.303	0.329	0.141
	(0.016)	(0.019)	(0.020)	(0.011)
Mean (unweighted), 1991	0.239	0.239	0.239	0.239
Mean (weighted), 1991	0.056	0.056	0.056	0.056
Panel B: Log number of firms and log formal employment				
Δ Log number of firms	-0.549	-0.673	-0.736	-0.309
	(0.045)	(0.050)	(0.052)	(0.030)
Mean (unweighted), 1991	3.651	3.651	3.651	3.651
Mean (weighted), 1991	7.645	7.645	7.645	7.645
Δ Log formal employment	-0.440	-0.527	-0.577	-0.225
	(0.064)	(0.073)	(0.076)	(0.044)
Mean (unweighted), 1991	4.918	4.918	4.918	4.918
Mean (weighted), 1991	9.659	9.659	9.659	9.659
Panel C: Log formal wage premium				
Δ Log formal wage premium	0.029	0.037	0.046	0.059
	(0.031)	(0.035)	(0.037)	(0.021)
Mean (unweighted), 1991	0.761	0.761	0.761	0.761
Mean (weighted), 1991	1.072	1.072	1.072	1.072
Δ De-trended log formal wage premium	-0.141	-0.156	-0.150	-0.090
	(0.031)	(0.035)	(0.037)	(0.021)
Observations	289,680	289,680	289,680	289,680
Local labor markets	19,759	19,759	19,759	19,759

Notes: Standard errors in parentheses, clustered at the local labor market level. All columns report the 1997 coefficient from stacked differences-in-differences regressions. Weighted means weight by total formal employment in the mmc × cbo942d pair.

Table A.9: Effect of import competition exposure on concentration: Alternative clustering

	Main specification	Two-way clustered by microregion and occupational group	AKM (2019) standard errors
	(1)	(2)	(3)
Panel A: Formal sector labor market concentration			
Δ Payroll Herfindahl (based on wage premium)	0.213	0.213	0.213
	(0.017)	(0.029)	(0.006)
Mean (unweighted), 1991	0.287	0.287	0.287
Mean (weighted), 1991	0.079	0.079	0.079
Δ Payroll Herfindahl	0.213	0.213	0.213
	(0.017)	(0.028)	(0.007)
Mean (unweighted), 1991	0.292	0.292	0.292
Mean (weighted), 1991	0.082	0.082	0.082
Δ Employment Herfindahl	0.247	0.247	0.247
	(0.016)	(0.028)	(0.006)
Mean (unweighted), 1991	0.239	0.239	0.239
Mean (weighted), 1991	0.056	0.056	0.056
Panel B: Log number of firms and log formal employment			
Δ Log number of firms	-0.549	-0.549	-0.549
	(0.045)	(0.131)	(0.010)
Mean (unweighted), 1991	3.651	3.651	3.651
Mean (weighted), 1991	7.645	7.645	7.645
Δ Log formal employment	-0.440	-0.440	-0.440
	(0.064)	(0.153)	(0.019)
Mean (unweighted), 1991	4.918	4.918	4.918
Mean (weighted), 1991	9.659	9.659	9.659
Panel C: Log formal wage premium			
Δ Log formal wage premium	0.029	0.029	0.029
	(0.031)	(0.068)	(0.006)
Mean (unweighted), 1991	0.761	0.761	0.761
Mean (weighted), 1991	1.072	1.072	1.072
Δ De-trended log formal wage premium	-0.141	-0.141	-0.141
	(0.031)	(0.068)	(0.006)
Observations	289,680	289,680	289,680
Local labor markets	19,759	19,759	19,759

Notes: Standard errors in parentheses. Point estimates are identical across columns; only standard errors differ. Column 1 clusters at the local labor market level, column 2 two-way clusters by microregion and occupational group, and column 3 uses AKM (2019) shift-share standard errors. All columns report the 1997 coefficient from stacked differences-in-differences regressions. Weighted means weight by total formal employment in the mmc × cbo942d pair.

Table A.10: Effect of import competition exposure on concentration: Weighting markets

	Main specification	Weighted by local labor market 1991 employment
	(1)	(2)
Panel A: Formal sector labor market concentration		
Δ Payroll Herfindahl (based on wage premium)	0.213	0.156
	(0.017)	(0.032)
Mean (unweighted), 1991	0.287	0.287
Mean (weighted), 1991	0.079	0.079
Δ Payroll Herfindahl	0.213	0.162
	(0.017)	(0.034)
Mean (unweighted), 1991	0.292	0.292
Mean (weighted), 1991	0.082	0.082
Δ Employment Herfindahl	0.247	0.098
	(0.016)	(0.018)
Mean (unweighted), 1991	0.239	0.239
Mean (weighted), 1991	0.056	0.056
Panel B: Log number of firms and log formal employment		
Δ Log number of firms	-0.549	-0.657
	(0.045)	(0.159)
Mean (unweighted), 1991	3.651	3.651
Mean (weighted), 1991	7.645	7.645
Δ Log formal employment	-0.440	-0.187
	(0.064)	(0.142)
Mean (unweighted), 1991	4.918	4.918
Mean (weighted), 1991	9.659	9.659
Panel C: Log formal wage premium		
Δ Log formal wage premium	0.029	-0.004
	(0.031)	(0.071)
Mean (unweighted), 1991	0.761	0.761
Mean (weighted), 1991	1.072	1.072
Δ De-trended log formal wage premium	-0.141	-0.332
	(0.031)	(0.071)
Observations	289,680	289,680
Local labor markets	19,759	19,759

Notes: Standard errors in parentheses, clustered at the local labor market level. All columns report the 1997 coefficient from stacked differences-in-differences regressions. Weighted means weight by total formal employment in the mmc×cbo942d pair.

Table A.11: Estimates of within-market cross-firm inverse elasticity of substitution $1/\eta$

	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	-0.556	-0.604	-0.604	-0.556	-0.359
	(0.044)	(0.053)	(0.075)	(0.044)	(0.035)
First stage F	156.771	130.168	65.315	156.771	106.426
Panel B: Reduced form					
Δ Firm wage premium in LLM	-0.550	-0.489	-0.470	-0.531	-0.354
	(0.024)	(0.030)	(0.042)	(0.025)	(0.019)
Panel C: 2SLS					
Labor supply within-market cross-firm inverse elasticity of substitution	0.990	0.811	0.778	0.956	0.984
	(0.089)	(0.080)	(0.110)	(0.089)	(0.109)
Implied upper bound on wage take-home share	50%	55%	56%	51%	50%
Local labor market (LLM) FE	Yes	Yes	Yes	Yes	Yes
Observations	855,104	463,138	182,757	855,104	852,702
Firms	344,534	213,704	89,252	344,534	344,027
Local labor markets	15,730	13,627	9,505	15,730	15,679

Notes: Standard errors clustered by firm in parentheses. All regressions include LLM fixed effects and are weighted by baseline market employment. Column (1): main specification using December wage premium conditional on observables. Column (2): wage premium conditional on worker fixed effects and demographic-by-year controls (strict stayers). Column (3): further restricts column (2) to workers who stay in the same firm-market pair. Column (4): uses December average wage instead of residualized wage premium. Column (5): uses effective rate of protection as instrument instead of TRAINS tariff.

Table A.12: Estimates of within-market cross-firm inverse elasticity of substitution: 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	-0.556	-0.661	-0.417	-0.556
	(0.044)	(0.151)	(0.037)	(0.044)
First stage F	156.771	19.164	124.666	158.127
Panel B: Reduced form				
Δ Firm's wage premium in LLM	-0.550	-0.347	-0.404	-0.551
	(0.024)	(0.082)	(0.017)	(0.024)
Panel C: 2SLS				
Labor supply within-market cross-firm inverse elasticity of substitution	0.990	0.525	0.969	0.990
	(0.089)	(0.190)	(0.092)	(0.089)
Implied upper bound on wage take-home share	50%	66%	51%	50%
Observations	855,104	696,197	440,966	1,617,416
Firms	344,534	302,514	420,246	720,085
Local labor markets	15,730	13,146	474	18,602

Notes: Standard errors clustered by firm in parentheses. All regressions include local labor market fixed effects and are weighted by baseline market employment. Column (1): main specification with LLM defined as mmc × occupation. Column (2): restricts to markets with a unique producer of each sector. Column (3): defines LLM as microregion (mmc only, no occupation dimension). Column (4): includes firms that exited between 1991 and 1997, coding their exit-year employment and wages as zero (IHS transform). Column (5): restricts to firms in tradable sectors (IBGE subsectors 1–13 and 25).

Table A.13: Estimates of within-market cross-firm inverse elasticity of substitution: Alternative clustering

	Main specification (Clustered by firm) (1)	Clustered by local labor market (2)	Clustered by sector (3)
	Panel A: First stage		
Δ Firm log employment in LLM	-0.556	-0.556	-0.556
	(0.044)	(0.067)	(0.107)
First stage F	156.771	69.608	26.984
	Panel B: Reduced form		
Δ Firm wage premium in LLM	-0.550	-0.550	-0.550
	(0.024)	(0.103)	(0.103)
	Panel C: 2SLS		
Labor supply within-market cross-firm inverse elasticity of substitution	0.990	0.990	0.990
	(0.089)	(0.201)	(0.148)
Observations	855,104	855,104	855,104
Firms	344,534	344,534	344,534
Local labor markets	15,730	15,730	15,730

Notes: Standard errors in parentheses. Column (1) clusters by firm, column (2) by local labor market (mmc × occupation), column (3) by sector (cnae95). All regressions include LLM fixed effects and are weighted by baseline market employment.

Table A.14: Correlates of firm-level wage markdowns

	Dependent variable: $\ln(\mu_{zm})$			
	(1)	(2)	(3)	(4)
Panel A: Employment				
$\ln(\text{Employment}_{zm})$	0.002681	0.002529	0.002425	0.002724
	(0.000623)	(0.000591)	(0.000580)	(0.000636)
Observations	9,683,946	9,683,945	9,578,928	9,683,945
Panel B: Residual wage				
$\ln(\text{Residual wage}_{zm})$	0.000489	0.000410	0.000203	0.002292
	(0.000485)	(0.000384)	(0.000437)	(0.000610)
Observations	9,683,946	9,683,945	9,578,928	9,683,945
Panel C: Average wage				
$\ln(\text{Average wage}_{zm})$	0.000459	0.000336	0.000007	0.001929
	(0.000426)	(0.000345)	(0.000403)	(0.000544)
Observations	9,683,946	9,683,945	9,578,928	9,683,945
Year FE	Yes	Yes	Yes	Yes
Sector FE		Yes		
Firm FE			Yes	
Local labor market FE				Yes
Firms	589,484	589,483	484,466	589,484
Local labor markets	19,054	19,054	19,038	19,053

Notes: This table presents regressions of log firm-level wage markdowns on firm-level employment, residual wages, and average wages. All regressions include year fixed effects. Standard errors in parentheses.

A 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), separately for 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 (https://wits.worldbank.org/). 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 as the change in log one plus the firm's CNAE95 sector code's nominal tariff between years 1990 and 1994.

To map product-level tariffs to CNAE95, I use Brazil's NCM (Nomenclatura Comum do Mercosul) classification, whose first six digits correspond to the HS. NCM codes are mapped to CNAE95 using official IBGE correspondence tables.[47] Over 90% of products map to a single activity code; the remainder are randomly assigned across the handful of activity codes to which they correspond per the concordance tables. CNAE95-level tariffs are weighted averages of product-level nominal tariffs, weighted by the number of tariff lines. For robustness, I compute effective rates of protection (ERP) using the Corden formula: $ERP_j = (t_j - \sum_i a_{ij} t_i)/(1 - \sum_i a_{ij})$, where t_j is sector j's nominal tariff, t_i are input tariffs, and a_{ij} are Leontief coefficients from Brazil's 1985 intersectoral coefficients matrix ("Tabela 20") at Nível 50.[48] Nível 50 sectors are mapped to CNAE95 using CONCLA correspondence tables.

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, Industry, and Foreign Trade, currently a part of the Ministry of the Economy, in October 2018.

Census. I use data from the 1991 and 2000 census, available in the supplementary materials from Dix-Carneiro and Kovak (2017).

Methods: wage premia regressions

For each year, I estimate each firm's wage premium in its local labor market as firm ×market fixed effects in a regression of worker log December earnings on the firm × 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

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

[48] https://www.ibge.gov.br/estatisticas-novoportal/economicas/contas-nacionais/9085-matriz-de-insumo-produto.html?&t=downloads.

worker fixed effects (e.g., columns (2) and (3) of Appendix Table A.11, I estimate each firm's wage premia in 1991 and 1997 as firm ×market × year fixed effects in a regression—containing years 1991 and 1997—of worker log December earnings on worker fixed effects, the firm ×market × 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:[49]

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

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:

$$\Delta Y_{mt} = \varphi\left(\Delta ICE_m \times t\right) + \nu_m + \nu_t + \nu_{mt} \tag{A.2}$$

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.

[49]For didactic purposes, I express the fixed effects in regression equation A.1 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.

B Model Appendix

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

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

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

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

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

and

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

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 $P_{zm}^j = P_{zm}$ for simplicity. Then:

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

Finally, define the following wage indices:

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

Then

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

With equation B.1 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:

$$l_{zm} = \int_0^1 P^j_{zm} \left(\frac{y^j}{w_{zm}}\right) dF(y) = w_{zm}^{-1} P_{zm} Y \tag{B.2}$$

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

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

which together with equation B.2 and previously defined wage indices imply $Y = \sum_{zm} w_{zm} l_{zm} = WL$ and

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

Rearranging:

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

B.2 Other proofs and derivations

B.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 B.3) 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 B.2 to obtain the identity $l_{zm} = l_{zm}$. I show this in two steps.

First, plug in the expression for w_{zm} into equation B.2 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} WL \left(\frac{1/\xi_{zm}}{W_m} \right) \times \left(\frac{W_m/\xi_m}{W} \right) \\
=& l_{zm} \xi_m^{\eta} \xi_{zm}^{\eta} \left(\frac{\xi_{zm}}{L_m} \right) \left[W \left(\frac{L_m \xi_m}{L} \right)^{\frac{1}{\theta}} \right]^{\eta} \left(\frac{1/\xi_{zm}}{W_m} \right)^{\eta} \times \left(\frac{W_m/\xi_m}{W} \right)^{\theta} \left(\frac{L}{\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:

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

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

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

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

B.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, start from the definition of the labor market index L_m in Section 2 to derive $\partial \ln L_m / \partial \ln l_{zm}$ as

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

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

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

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

B.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 $\sum_{z \in \Theta_m} s_{zm} \left(1 + \varepsilon_{zm}^{-1}\right) = \frac{\bar{r}_m}{\bar{w}_m}$. 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:

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

B.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). 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:

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

□

B.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:

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

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

B.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:

$$\max_{k_{zm}, l_{zm}} \pi_{zm} = \underbrace{A_{zm} \left(k_{zm}^{1-\gamma} l_{zm}^{\gamma} \right)^{\alpha}}_{\equiv y_{zm}} - R k_{zm} - w_{zm} \left(\{ l_{zm}, l_{-zm} \} \right) l_{zm} \tag{B.4}$$

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.[50] Computing the definition of market m's average wage markdown holding capital constant gives:

$$\mu_m^{k-fixed} \equiv \frac{\bar{mrpl}_m^{k-fixed}}{\bar{w}_m} = \frac{\left(\sum_z mrpl_{zm}^{k-fixed} l_{zm} \right) / \sum_z l_{zm}}{\left(\sum_z w_{zm} l_{zm} \right) / \sum_z l_{zm}} \tag{B.5}$$

$$= \frac{\sum_z \alpha\gamma \left(y_{zm} / l_{zm} \right) l_{zm}}{\sum_z w_{zm} l_{zm}} \tag{B.6}$$

$$= \alpha\gamma \frac{\sum_z y_{zm}}{\sum_z w_{zm} l_{zm}} \tag{B.7}$$

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

Simplification of equation B.7 can now be done using the equalities in BHM's Proposition 1.1 (with special

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

care given to note the difference in notation across the two papers). Equation B.7 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.

C Extension: Oligopsony in Dual Labor Markets

C.1 Model

I model the labor supply preferences of *people seeking formal employment*. Firms exploit these preferences to set wages below workers' marginal revenue product when maximizing profits while holding local competitors' labor demand decisions constant. The starting point is the labor supply preference structure in Section C.1, which I extend on three dimensions. First, I split each local labor market into two sectors, wage work and self-employment. Second, I allow workers to take into account the probability of involuntary separation into informal wage work—which varies by firm—when making formal sector labor supply decisions. Finally, when bringing the model to the data, whenever possible I allow the model's key elasticities of substitution to vary by age, education, gender, and region.

C.1.1 Discrete choice formal labor supply in dual labor markets

There is a continuum of homogenous workers j, each choosing where to supply l^j effective units of labor.[51] Each worker chooses a single market m from a continuum of local labor markets. Within each market, workers choose a sector s, which is either wage work $\overline{g}$ or self-employment $\underline{g}$. When considering wage work, workers take into account expected earnings from a finite number of formal sector firms z, taking into account their perceived probability of separation into informal wage work o in market m. When considering self-employment, workers take into account expected earnings from starting a small business in market m.

Let l^j_{zgm} denote the effective units of labor that worker j supplies to employment option zsm.[52] Worker j chooses the employment option zsm that minimizes their dis-utility of labor given their preference parameters ξ, expected earnings $\mathbb{E}[l^j_{zgm} w_{zms}|X_{zgm}]$, and their minimum earnings requirement y^j:

$$\min_{zgm} V^j_{zgm} \equiv \ln l^j_{zgm} + \ln \xi_m + \ln \xi_{zgm} - \xi^i_{zgm} \tag{C.1}$$

$$\text{s.t.} \qquad l^j_{zgm} \bar{w}_{zgm} \geq y^j \tag{C.2}$$

where $\bar{w}_{zgm} = \mathbb{E}[w_{zms}|X_{zgm}]$ are expected wages from employment option zsm given firm, sector, and local labor market characteristics. The terms ξ_m, ξ_{gm}, and ξ_{zgm} are market, sector-market, and option-market taste shifters, respectively, while ξ^j_{zgm} is an idiosyncratic worker taste shock for option zsm, drawn from the

[51] I assume that workers are homogenous in both preferences and productivity to center the model discussion around wage differentials driven by worker preferences—the key underlying source of market power—which facilitates exposition and delivers clearer insights. However, both assumptions are easy to relax empirically. I relax the assumption of homogeneous elasticities of substitution in Section C.1, allowing them to vary by gender, education, and age, after presenting the regression equations that I use to estimate model's key elasticities of substitution. As in Section C.1's original model, the assumption of homogenous productivity is straightforwardly mapped to Brazil's rich microdata by focusing on wages conditional on flexible controls for worker gender, education, age, and worker fixed effects when possible.

[52] For formal sector options (i.e., $s = \overline{g}$), $z\overline{g}m$ represents a formal sector firm z in a market m's wage work sector. For self-employment options (i.e., $s = \underline{g}$), the z subscript refers to the worker (as each worker is their own employer).

following nested Generalized Extreme Value (GEV) distribution:

$$G(\xi) = \exp\Big(- \sum_{m} \Big\{ \sum_{s} \Big(\sum_{z} e^{-(1+\tilde{\eta})\, \xi^{j}_{zgm}} \Big)^{\frac{1+\tilde{\rho}}{1+\tilde{\eta}}} \Big)^{\frac{1+\tilde{\theta}}{1+\tilde{\rho}}} \Big]^{\frac{1}{1+\tilde{\theta}}} \Big). \tag{C.3}$$

Equations C.1-C.3 preserve the structure of the original labor supply decision problem in Section C.1, but differ from it in two ways. First, they add self-employment as an alternative to wage work within each market, with elasticity of substitution $\tilde{\rho}$ between the two sectors, as shown in equation C.3. Second, they center workers' labor supply decisions around *expected earnings*.

Introducing earnings uncertainty is a natural way to incorporate both self-employment and informal wage work into the labor supply decisions of people seeking formal sector employment. For self-employment, workers don't know with certainty the returns to starting a small business ex-ante. For wage work, workers might care about the risk of involuntary separation from any formal sector job into informality (and related expected earnings losses)—whether it is inside or outside firms—when making labor supply decisions. I next derive the implications of these extensions to the labor supply curves facing each formal sector firm and, consequently, markdowns.

C.1.2 Labor supply curves faced by individual formal firms

As in the original model, the discrete choice formulation of workers' labor supply decisions with GEV idiosyncratic tastes yield analytic expressions for the probability that worker j chooses formal sector firm z in the wage work sector $\overline{g}$ of market m. Integrating these probabilities over the continuum of workers gives total labor supply to formal sector firm z:

$$l_{z\overline{g}m} = L \left(\frac{\bar{w}_{z\overline{g}m}}{W_{\overline{g}m}} \right)^{\tilde{\eta}} \left(\frac{W_{\overline{g}m}}{W_m} \right)^{\tilde{\rho}} \left(\frac{W_m}{W} \right)^{\tilde{\theta}} \times \left[\xi_{zgm}^{1+\tilde{\eta}} \xi_{gm}^{1+\tilde{\rho}} \xi_{m}^{1+\tilde{\theta}} \right]^{-1}. \tag{C.4}$$

whose inverse is:

$$\bar{w}_{z\overline{g}m} = W \left(\frac{l_{z\overline{g}m}}{L_{\overline{g}m}} \right)^{\frac{1}{\tilde{\eta}}} \left(\frac{L_{\overline{g}m}}{L_m} \right)^{\frac{1}{\tilde{\rho}}} \left(\frac{L_m}{L} \right)^{\frac{1}{\tilde{\theta}}} \xi_{z\overline{g}m}^{1+\frac{1}{\tilde{\eta}}} \xi_{\overline{g}m}^{1+\frac{1}{\tilde{\rho}}} \xi_{m}^{1+\frac{1}{\tilde{\theta}}}. \tag{C.5}$$

These are the labor supply equations for formal sector firms, and—as in the original model—equation C.5 is the key equation whose derivative with respect to formal sector firms' own employment decisions will determine wage markdowns. Importantly, the relevant wage for attracting labor supply to any one formal sector firm is the *expected* wage $\bar{w}_{z\overline{g}m}$ from taking that formal sector job, which takes into account probabilities of separation into informality and local informal sector conditions:

$$\bar{w}_{z\overline{g}m} = p_{z\overline{g}m} w^{o}_{m} + (1 - p_{z\overline{g}m}) w_{z\overline{g}m} \tag{C.6}$$

where $p_{z\overline{g}m}$ is workers' prior about probability of separation from firm z into informal wage work, w^{o}_{m} are expected local informal sector wages, and $w_{z\overline{g}m}$ is firm z's posted formal wage.

In addition, because the elasticity of substitution between self-employment and wage work must necessarily be estimated using census data—which does not include firm boundaries but does include regions—it is useful to introduce the market-level aggregate of equation C.5, the inverse labor supply curve to wage work in each market:

$$W_{\overline{g}m} = W \left(\frac{L_{\overline{g}m}}{L_m}\right)^{\frac{1}{\tilde{\rho}}} \left(\frac{L_m}{L}\right)^{\frac{1}{\tilde{\theta}}} \xi_{\overline{g}m}^{1+\frac{1}{\tilde{\rho}}} \xi_m^{1+\frac{1}{\tilde{\theta}}}. \tag{C.7}$$

Finally, the wage and labor supply indices in equations C.4-C.7 follow the standard nested CES structure:

$$W_{\overline{g}m} = \left[\sum_z \left(\frac{\bar{w}_{z\overline{g}m}}{\xi_{z\overline{g}m}}\right)^{1+\tilde{\eta}}\right]^{\frac{1}{1+\tilde{\eta}}}, \qquad L_{\overline{g}m} = \left[\sum_z \left(\xi_{z\overline{g}m} l_{z\overline{g}m}\right)^{\frac{1+\tilde{\eta}}{\tilde{\eta}}}\right]^{\frac{\tilde{\eta}}{1+\tilde{\eta}}} \tag{C.8}$$

$$W_m = \left[\left(\frac{W_{\underline{g}m}}{\xi_{\underline{g}m}}\right)^{1+\tilde{\rho}} + \left(\frac{W_{\overline{g}m}}{\xi_{\overline{g}m}}\right)^{1+\tilde{\rho}}\right]^{\frac{1}{1+\tilde{\rho}}}, \qquad L_m = \left[\left(\xi_{\underline{g}m} l_{\underline{g}m}\right)^{\frac{1+\tilde{\rho}}{\tilde{\rho}}} + \left(\xi_{\overline{g}m} L_{\overline{g}m}\right)^{\frac{1+\tilde{\rho}}{\tilde{\rho}}}\right]^{\frac{\tilde{\rho}}{1+\tilde{\rho}}} \tag{C.9}$$

$$W = \left[\sum_m \left(\frac{W_m}{\xi_m}\right)^{1+\tilde{\theta}}\right]^{\frac{1}{1+\tilde{\theta}}}, \qquad L = \left[\sum_m \left(\xi_m L_m\right)^{\frac{1+\tilde{\theta}}{\tilde{\theta}}}\right]^{\frac{\tilde{\theta}}{1+\tilde{\theta}}} \tag{C.10}$$

where $W_{\underline{g}m}$ are expected earnings from self-employment in market m.[53]

C.1.3 Firm-specific wage markdowns

Taking logs of Equation C.5 and differentiating it with respect to $l_{z\overline{g}m}$—holding constant labor demand from competing formal firms, priors $p_{z\overline{g}m}$ about the probability of separation, expected returns to self-employment $W_{\underline{g}}$, and expected informal sector wages $\bar{w}_m^o$—gives:

$$\varepsilon_{z\overline{g}m}^{-1} \equiv \frac{\partial \ln \bar{w}_{z\overline{g}m}}{\partial \ln l_{z\overline{g}m}} = \frac{1}{\tilde{\eta}} + \left(\frac{1}{\tilde{\rho}} - \frac{1}{\tilde{\eta}}\right) \underbrace{\frac{\partial \ln L_{gm}}{\partial \ln l_{z\overline{g}m}}}_{s_{z\overline{g}m}} + \left(\frac{1}{\tilde{\theta}} - \frac{1}{\tilde{\rho}}\right) \underbrace{\frac{\partial \ln L_m}{\partial \ln l_{z\overline{g}m}}}_{s_{zm}} \tag{C.11}$$

where

$$s_{z\overline{g}m} \equiv \frac{\bar{w}_{z\overline{g}m} \cdot l_{z\overline{g}m}}{\sum_k \left(\bar{w}_{k\overline{g}m} \cdot l_{k\overline{g}m}\right)} \quad \text{and} \quad s_{zm} \equiv \frac{\bar{w}_{z\overline{g}m} \cdot l_{z\overline{g}m}}{\sum_s \sum_k \left(\bar{w}_{kgm} \cdot l_{kgm}\right)}$$

are formal sector firm z's *expected* wage bill as a fraction of the formal sector's *expected* wage bill (aka, taking into account separation probabilities into informality and local informal sector wages), and as a fraction of each market's overall *expected* wage bill (including self-employment as an alternative to wage

[53] In a nested CES preference structure, $W_{\underline{g}m}$ equals expected log earnings in the limit where the elasticity of substitution between self-employment options is zero. At the micro level, this means that no one worker can provide self-employment for another worker. At the macro level, this is the CES limiting case of Cobb-Douglas preferences over self-employment options. Formally, let $\eta_{\underline{g}}$ denote the elasticity of substitution between self-employment options and let $\mathbb{E}[\pi_{\underline{g}m}^j]$ denote worker j's expected earnings from self-employment in market m. Then $W_{\underline{g}m} = \left(\int_0^1 \mathbb{E}[\pi_{\underline{g}m}^j]^{1+\eta_{\underline{g}}} \, dj\right)^{1/(1\eta_{\underline{g}})}$ is the CES aggregator over self-employment options in a given market. When $\eta_{\underline{g}} \to 0$, we have $W_{\underline{g}m} \to \exp\left(\int_0^1 \log \mathbb{E}[\pi_{\underline{g}m}^j] \, dj\right)$, the Cobb-Douglas form. Note that $W_{\underline{g}m} > 0$ because workers must satisfy their minimum earnings requirement in equilibrium.

work), respectively.[54] Rearranging:

$$\varepsilon_{z\overline{g}m}^{-1} = \left[\frac{1}{\tilde{\rho}} s_{z\overline{g}m} + \frac{1}{\tilde{\eta}}(1 - s_{z\overline{g}m})\right] + \left(\frac{1}{\tilde{\theta}} - \frac{1}{\tilde{\rho}}\right) s_{zm}. \tag{C.12}$$

Equation C.12 differs from its counterpart in Section C.1 in three ways. First, it states that the elasticity of labor supply to any one formal sector firm depends not only on the ease with which workers can substitute between firms within markets $\tilde{\eta}$, and between markets $\tilde{\theta}$, but also on the ease with which they can substitute between wage work and self-employment within markets $\tilde{\rho}$. Second, the relevant wage bill shares for the markdowns are based on expected wages—taking into account probabilities of separation into wage work and local informal sector wages.

Local average wage markdown. As in the original model, the average wage markdown is $\mu_{\overline{g}m} \equiv 1 + \varepsilon_{\overline{g}m}^{-1}$ and the wage take-home share is $\mu_{\overline{g}m}^{-1}$. Taking a weighted average of the firm-specific inverse elasticity of substitution in Equation C.12 using $s_{z\overline{g}m}$ as weights gives the expression for the inverse elasticity of residual labor supplied to each firm:

$$\bar{\varepsilon}_{\overline{g}m}^{-1} = \frac{1}{\tilde{\rho}} HHI_{\overline{g}m} + \frac{1}{\tilde{\eta}}(1 - HHI_{\overline{g}m}) + \left(\frac{1}{\tilde{\theta}} - \frac{1}{\tilde{\rho}}\right) HHI_{\overline{g}m} \cdot s_m. \tag{C.13}$$

where $HHI_{\overline{g}m} \equiv \sum_{z\in\Gamma_{\overline{g}m}} s_{z\overline{g}m}^2$ is the Herfindahl-Hirschman Index for wage work sector $\overline{g}$ in market m, measuring the wage bill concentration in sector $\overline{g}$ in market m, and

$$s_m \equiv \frac{\sum_{z\in\Gamma_{\overline{g}m}} s_{z\overline{g}m}}{\sum_{z\in\Gamma_m} s_{z\overline{g}m}}$$

is the wage bill share of wage work sector $\overline{g}$ in market m.

No dynamic gains from influencing workers' priors. Importantly, these theoretical results assume that firms do not *internalize* that their hiring and firing decisions at time t might influence workers' priors about the probability of separation from the firm at $t + 1$ or after. This assumption of *no dynamic gains from formation of priors* simplifies firms' wage setting problem by shutting off $p_{z\overline{g}m}$ as an additional lever for (future) wage setting. As a result, it preserves the original model's static structure while allowing priors to enter labor supply decisions. While workers may form priors based on past firm-level involuntary separations (observed in the administrative data) and act accordingly, neither workers nor firms consider *future* benefits or costs of labor market decisions made at t. The possibility of dynamic gains to labor market power from firms' ability to influence worker priors about the possibility of separation from formation of priors (and about other within-firm dynamic considerations, such as promotion timelines, tenure benefits, etc) merits further research.

[54] The equivalence between the partial derivatives and market shares can be shown by computing the partial derivatives given the definition of labor supply indices, and then contrasting this result with what we obtain when plugging the inverse labor supply equation into the definition of wage bill market shares.

C.2 Estimation strategy

C.2.1 Substitution Within markets, across firms

I next show how $1/\tilde{\eta}$ can be estimated by combining the IV estimate for $1/\eta$ in Section C.1 with an estimate of the bias introduced into that estimation strategy if the extended model is true instead. That is, under the assumption that workers take into account the probability of involuntary separation into informality when making formal sector labor supply decisions. First, re-arrange the expected wage equation we have:

$$\bar{w}_{z\bar{g}m} = p_{z\bar{g}m} w_m^o + (1 - p_{z\bar{g}m}) w_{z\bar{g}m} = w_{z\bar{g}m} \left(1 + p_{z\bar{g}m}\sigma_{z\bar{g}m}\right) \tag{C.14}$$

where $\sigma_{z\bar{g}m} \equiv (w_m^o - w_{z\bar{g}m})/w_{z\bar{g}m}$ is the wage gap between the local informal sector wage w_m^o (for observationally equivalent workers) and firm z's formal wage. Note that this expected wage gap may be negative (informal sector pays less) or positive (informal sector pays more). Taking logs:

$$\ln \bar{w}_{z\bar{g}m} = \underbrace{\ln w_{z\bar{g}m}}_{\text{Formal wage}} + \underbrace{\ln\left(1 + p_{z\bar{g}m}\sigma_{z\bar{g}m}\right)}_{\text{Expected wage gap}} \tag{C.15}$$

Next, take logs of Equation C.5 and let δ_m denote a market fixed effect to write:

$$\ln \bar{w}_{z\bar{g}m} = \frac{1}{\tilde{\eta}} \ln l_{z\bar{g}m} + \delta_m + \ln \xi_{z\bar{g}m}^{1+\tilde{\eta}} \tag{C.16}$$

Bias formula. Given equation C.16, the within-market cross-firm inverse elasticity of substitution $\frac{1}{\tilde{\eta}}$ in the extended model can estimated as the second-stage coefficient from an IV regression where $\ln l_{z\bar{g}m}$ is instrumented by an exogenous labor demand shock $X_{z\bar{g}m}$. Expanding expected wages per equation C.15 gives and letting $(*)$ denote partialled-out variables to apply the Frisch-Waugh-Lovell theorem, we have:

$$\frac{1}{\tilde{\eta}} = \frac{\operatorname{Cov}(\ln \bar{w}^*_{z\bar{g}m}, X_{z\bar{g}m})}{\operatorname{Cov}(\ln l^*_{z\bar{g}m}, X_{z\bar{g}m})} = \underbrace{\frac{\operatorname{Cov}(\ln w^*_{z\bar{g}m}, X_{z\bar{g}m})}{\operatorname{Cov}(\ln l^*_{z\bar{g}m}, X_{z\bar{g}m})}}_{\frac{1}{\eta}\text{: Supply response to formal wage}} + \underbrace{\frac{\operatorname{Cov}[\ln(1 + p_{z\bar{g}m}\sigma_{z\bar{g}m})^*, X_{z\bar{g}m}]}{\operatorname{Cov}(\ln l^*_{z\bar{g}m}, X_{z\bar{g}m})}}_{\Omega\text{: Supply response to expected wage gap}} \tag{C.17}$$

where $\sigma_{z\bar{g}m} \equiv (w_m^o - w_{z\bar{g}m})/w_{z\bar{g}m}$ is the pay gap between the local informal sector and firm z's formal wage for an effective (namely, equally productive) unit of labor.

The first term in equation C.17—the labor supply response to a firm's change in its formal wage—equals the IV estimate for the within-market cross-firm elasticity of substitution $1/\eta$ in the original model in Section C.1. If the original model were true, workers do not take into account the possibility of separation into informality when making labor supply decisions and, as a result, the second term in equation C.17 is zero and the elasticities in the extended and original models are the same.

However, *if the extended model is true*, then the relevant elasticity of substitution for wage setting is $1/\tilde{\eta}$. The term Ω in equation C.17 is thus the misspecification bias in the original model if the extended model is true. This bias is zero if there is no within-market cross-firm variation in perceived probabilities of involuntary separation into the informal sector at the time workers make decisions. If the bias is non-zero, its sign depends not only on local informal sector wages, but also on the joint distribution (across formal sector firms in the same market) between perceived probabilities of separation and formal sector wages.

Interpretation. If Ω is *negative*, *less* labor is supplied to firms with higher expected wage gaps relative to the same market's informal sector wage. That is, workers dislike firms that in expectation pay less than the local informal sector.[55]. Conversely, if Ω is *positive*, *more* labor is supplied to firms with higher expected wage gaps relative to the same market's informal sector wage. That is, workers prefer to supply labor to a formal firm *despite* higher expected wages in the local informal sector. In this case, the inverse elasticity of substitution $1/\eta$ estimated based on the original model is *too small* relative to the true inverse elasticity $1/\tilde{\eta}$, meaning that *firms have more labor market power* than originally estimated.

Regression. I estimate Ω, the labor supply response to changes in expected formal-informal wage gaps *conditional on firm-level changes in formal wages*, by running the following second stage regression:

$$\Delta \ln(1 + p_{z\bar{g}r}\sigma^{c}_{z\bar{g}r}) = \Omega \Delta \ln l^{c}_{z\bar{g}r} + \delta_z + \delta_r + \delta_c + \epsilon_{z\bar{g}r} \tag{C.18}$$

where the left-hand side are 1991-2000 changes in expected wage gaps for each demographic cell, the right-hand side are 1991-2000 changes in employment at firm z in microregion r for demographic cell c, and the δ terms are firm, region-cell fixed effects. Including a firm fixed effect ensures that Ω captures the supply response to changes in expected wage gaps relative to the informal sector conditional on firm-level changes in wage levels, the identifying variation for η in both the original and extended models.

Measurement. Brazil's employer-employee linked dataset RAIS includes information on separation reason for all separations, discerning between firings and quits. I use this information to proxy for workers' prior about the *probability of involuntary separation* from firm z in microregion r using:

$$p_{z\bar{g}r} = \frac{\text{Fired workers from firm } z\bar{g}r}{\text{Fired workers from + Stayers in firm } z\bar{g}r} \tag{C.19}$$

Since firm employment is measured as of December 31 of each calendar year, I measure priors for year t as of December 31 of year t using separations during that elapsed calendar year. For example, priors as of December 31, 1991 are based on separations between January 1, 1991 and December 30, 1991. Finally, to ensure that the formal-informal wage gaps I measure are not confounded by productivity differences across demographics, I calculate $\sigma_{z\bar{g}m}$ separately for each demographic cell, following the definitions as in the self-employment analysis. I merge RAIS' data for 1991 and 2000 with the census those years at the microregion and demographic cell level, matching on gender, education group, and age group dummies.

Panel A of Figure C.4 plots a binned scatter of firm-level probabilities of involuntary separation distribution against informal-formal wage gaps. The probability is on average 3%. It is highest in local labor markets

[55]The possibility that informal sector options might pay more than formal sector options should not be discarded. Appendix Figure C.4 shows that a non-trivial share of regions exhibit larger monthly earnings for workers of the same demographic composition than monthly earnings at formal sector firms

where the informal sector pays less than the formal sector (for the same demographic cell). This means that workers who are at higher risk of separation would also face lower-paying informal sector jobs. Panel B of Figure C.4 shows that a substantial number of jobs are in local labor markets where the informal sector pays less, but there is a sizable number of jobs for which informal wage work pays higher wages than the formal sector. This is consistent with the residual wage distributions plotted in Figure C.3.

Instruments. Since Ω is a labor supply parameter governing within-market cross-firm substitution in response to formal-informal wage gaps, its identification requires labor demand shocks that vary: (a) across firms within markets, as in the identification of η in the original model; and (b) *within* firm relative to the informal sector, since Ω captures labor supply responses to changes in wage gaps conditional on changes in formal wage levels, captured by η instead. I leverage demographic heterogeneity within firm to construct such an instrument as the interaction between firm-level changes in import tariff reductions $\Delta \ln(1 + \tau_{i(z)})$—the labor demand used to identify η in the original model—and demographic-specific regional tariff reductions ΔRTR_m^c, the labor demand shock used to identify the elasticities of substitution between wage work and self-employment in the extended model.

The key idea is that, conditional on firm-level changes in formal wages, which identify η, the remaining within-market cross-firm labor supply reallocation is driven by cross-firm differences in expected wage gaps relative to the informal sector. Expected wage gaps are, in turn, affected both by the direct import tariff reduction shock to the firm—which change workers' perceived probability of separation from any one firm into informality over the decade—and by regional tariff reductions, which change equilibrium informal sector wages for each demographic group. The exclusion restriction assumes that, conditional on firm, region, and demographic group fixed effects, the only way labor supply is affected by tariff reductions is by changing separation probabilities and equilibrium wages, as opposed to workers' distaste for individual firms or for formal versus informal wage work.

Unemployment insurance. Finally, to test how the prospect of receiving unemployment insurance in the event of involuntary separations affect workers' formal sector labor supply decisions, I consider an alternative measure of the expected wage. I do this by measuring the expected wage after separation as 4/12 the same wage as paid by the formal firm (i.e., the typical unemployment insurance benefit at the time) and 8/12 the local informal sector wage. [56]

C.2.2 Substitution to self-employment and across markets

To arrive at the regression equation to estimate the elasticity of substitution between wage work and self-employment, take logs of equation C.7, express it in long-differences, add a constant to absorb country-level

[56] While Brazil's regulation of unemployment insurance benefits in the 1990s were quite complicated—sometimes featuring earnings brackets to limit benefit amounts, and being contingent on proof of time of service—the typical benefit amount was four-months salary, paid monthly. See Brasil (1990) for the 1990 law that instituted the unemployment insurance system. Details on benefit brackets and how the rules have changed over time are available at https://www.debit.com.br/tabelas/seguro-desemprego?utm_source=chatgpt.com.

changes, and group taste shifters into an error term $\epsilon_{\overline{g}m}$ to get:

$$\Delta \ln W_{\overline{g}m} = \alpha + \frac{1}{\tilde{\rho}} \Delta \ln\left(\frac{L_{\overline{g}m}}{L_m}\right) + \frac{1}{\tilde{\theta}} \Delta \ln\left(\frac{L_m}{L}\right) + \epsilon_{\overline{g}m} \tag{C.20}$$

A challenge in estimating equation C.20 in the context of trade liberalization is that each labor market has a single wage work sector, and import tariff reductions were primarily a labor demand shock to wage work. As a result, $\tilde{\rho}$ cannot be separately identified from $\tilde{\theta}$ unless markets can be partitioned into multiple sub-markets,[57] each with their own wage work and self-employment sectors and their own differential shock to wage work labor demand (the key within-market, cross-sector variation needed to identify $\tilde{\rho}$),[58] but all subject to the same market-level general equilibrium effects of trade liberalization (the key cross-market variation needed to identify $\tilde{\theta}$).

Regression. I overcome this challenge by partitioning labor markets into worker demographic cells, each with their own wage work and self-employment sectors. Let g denote demographic groups defined by gender (men; women), education (primary; secondary; tertiary), and age (young: ages 18-29; middle: ages 30-49; old: ages 50-64) and c denote the fully saturated demographic cells defined by these three groups (e.g., young men with at most primary education). I then estimate:

$$\Delta \ln W^c_{\overline{g}m} = \frac{1}{\tilde{\rho}} \Delta \ln\left(\frac{L^c_{\overline{g}m}}{L^c_m}\right) + \frac{1}{\tilde{\theta}} \Delta \ln\left(\frac{L^c_m}{L^c}\right) + \delta_r + \epsilon^c_{\overline{g}m} \tag{C.21}$$

where Δ denotes long-differences within cell by microregion pairs and δ_r is a region fixed effect (denoting one of Brazil's major 5 regions) to absorb regional general equilibrium effects of trade liberalization.

Measurement. I estimate regression equation C.21 using data from Brazil's 1991 and 2000 censuses and defining markets as microregions.[59] While $W^c_{\overline{g}m}$, $L^c_{\overline{g}m}$, and L^c_m are technically wage and labor supply indices that reflect lower-nest elasticities and taste shifters, to keep the analysis entirely executable with census data I use the corresponding directly observable measures of these objects. Specifically, I measure $L^c_{\overline{g}m}/L^c_m$ as demographic cell c's wage work employment share in microregion m, and $\ln W^c_{\overline{g}m}$ as demographic cell's c's log residual real monthly earnings in microregion m . Log real monthly earnings are residualized conditional on a fully saturated vector of the gender, education, and age variables, so that the variation in wages used to estimate the model's preference parameters are not driven by productivity differences across demographic cells.

[57] Note that identification of lower-nest elasticities also requires that each partition of the wage work sector has within-sector cross-firm variation in tariff reductions, which precludes partitioning the wage work sector by industry.

[58] An alternative approach is to introduce additional cross-market variation in import tariff reductions, such as those generated by interactions between regional tariff reductions and baseline market characteristics. I explore this approach in Appendix Table C.7, where I instrument equation C.20 with regional tariff reductions and its interaction with: (a) each microregion's log maximum distance to the nearest labor law enforcement office, borrowing the estimation strategy from Ponczek and Ulyssea (2022); and (b) each microregion's 1991 share of employment that was formal. The approach lacks power but yields similar point estimates, especially for $\tilde{\theta}$, relative to my preferred specification, which adds within-market cross-group variation to better identify $\tilde{\rho}$.

[59] While the 1991 and 2000 censuses contain occupation codes, they are missing for a large share of observations, and the two years also follow different definitions from each other (and from RAIS). As a result, I define labor markets more broadly as microregions only for the purposes of estimating the extended model's elasticities of substitution between self-employment and wage work and across markets.

Instruments. I instrument the two endogenous variables in equation C.21 with cell-specific regional tariff reductions ΔRTR_m^c and their interaction with: (a) each cell's 1991 formal sector employment share, as tariffs hit formal firms most directly; and (b) demographic group dummies, to soak up variation and allow for heterogeneous effects by groups. The primary instrument ΔRTR_m^c is calculated following the shift-share methodology in Dix-Carneiro and Kovak (2017), featuring exposure shares that are cell-industry-microregion-specific and include *all* workers—formally or informally employed—in tradable sector industries. The exclusion restriction assumption is all cell-specific regional tariff reductions and their interactions with baseline and demographic characteristics are orthogonal to changes in workers' tastes-shifters ξ for wage work and for the market.

Figure C.7 shows that regional tariff reductions reduced *both* employment and earnings in wage work. This same-sign effect is consistent with tariff reductions tracing out labor supply to wage work. The same shock had effects of opposite signs for self-employment: regional tariff reductions *increased* the number of workers in self-employment in more affected regions but, on average, *reduced* their earnings. These opposite-sign effects are consistent with the release of workers from wage work constituting a labor supply shock to the self-employment sector.

Appendix Table C.7 shows a similar pattern for informal wage work as for self-employment, accompanied by a near-zero effect on formal sector residual real monthly earnings. The latter finding differs from the significantly *negative* effects of regional tariff exposure documented based on RAIS-reported earnings in prior literature (e.g., Dix-Carneiro and Kovak (2017), Section C.1). Informality within firms, as studied by Ulyssea (2018) and, more recently, Derenoncourt et al. (2025), is a strong candidate explanation for this near-zero effect. If higher-wage formal sector workers are moved "off the books," they disappear from RAIS,[60] but they might still report that they are formally employed in the Census, as their job is the same as before. This induces a positive selection into the set of workers marked as formally employed in the Census, even if they are in fact informal. In the absence of data that can discern the intensive margin and extensive margin of informality during this period, it is hard to make empirical progress on elasticities of substitution between informal and formal wage work.

C.2.3 Heterogeneous preferences by demographics

An advantage of partitioning markets by demographic cells—and in constructing cell-specific regional tariff reductions— is that it is the first step in estimating demographics-based heterogeneity in elasticities of substitution. I estimate heterogeneity in the elasticity of substitution between wage work and self-employment by demographic groups as follows:

$$\Delta \ln W_{gm}^c = \frac{1}{\tilde{\rho}^g} \Delta \ln\left(\frac{L_{gm}^c}{L_m^c}\right) + \delta_m + \epsilon_{gm}^c \tag{C.22}$$

[60] Moving a worker off the books–potentially tagging their leaving as a quit so that no firing costs are paid—saves the firm nearly 100% the worker's wage in the labor costs that are now evaded, even if the worker keeps the same take-home earnings. See Debaere (2003) for a table listing non-wage labor costs to the firm.

where δ_m is a market fixed effect, absorbing market-level general equilibrium effects of trade common to all demographic cells. I use the same cell-level instruments as for equation $C.21$. The exclusion restriction assumption is that the shocks to wage work labor demand are orthogonal to workers' tastes-shifters ξ for wage work in that market. Unfortunately, there is not enough within-group cross-cell variation in tariff reductions to estimate equation $C.22$ separately by demographic groups, which would yield estimates of heterogeneity in the cross-market elasticity of substitution $\tilde{\theta}$.

If exploited by firms when setting wages, such heterogeneity could generate differential wage markdowns by demographics. Thus, partitioning labor markets by demographic groups effectively extends the original model in Section C.1 in a third direction, contributing the first labor market oligopsony framework inclusive of self-employment and informal wage work to a vast literature on wage differentials by demographics, where evidence on the link between wage markdowns and gender wage gaps has begun to emerge (e.g., see Sharma (2023), Hoang, Mitra and Pham (2024)).

C.2.4 Wage markdowns

I combine estimates of the extended model's parameters with direct measures of labor market equilibrium wage bill shares to compute local labor market m's average wage markdown according to the extended model. The markdown is given by:

$$\mu_{\overline{g}m} \equiv 1 + \varepsilon_{\overline{g}m}^{-1} = \left[\frac{1}{\tilde{\rho}} HHI_{\overline{g}m} + \frac{1}{\tilde{\eta}}(1 - HHI_{\overline{g}m})\right] + \left(\frac{1}{\tilde{\theta}} - \frac{1}{\tilde{\rho}}\right) HHI_{\overline{g}m} \times s_m. \tag{C.23}$$

where $1/\tilde{\eta}$ is calculated as $1/\tilde{\eta} = 1/\eta + \Omega$ using estimates of the bias Ω introduced by expected involuntary separation into informality, $s_{z\overline{g}m}$ and s_{zm} are formal sector firm z's *expected* wage bill as a fraction of the formal sector's *expected* wage bill, and as a fraction of each market's overall *expected* wage bill (including self-employment as an alternative to wage work), respectively. Table **??** summarizes the model parameters and key endogenous objects—which act as weights of these preference parameters in computing workers inverse elasticity of residual labor supply—along with their main estimates and ranges based on detected heterogeneity.

C.2.5 Policy effects on wage markdowns

Let X_m denote an exogenous shock to labor demand in local labor market m. Then this shock's effect on local markdowns is given by its effect on average local inverse elasticities of labor supply, which follows:

$$\frac{\partial \bar{\varepsilon}_{\overline{g}m}^{-1}}{\partial X_m} = \left(\frac{1}{\tilde{\rho}} - \frac{1}{\tilde{\eta}}\right) \times \beta_{\text{HHI}} + \left(\frac{1}{\tilde{\theta}} - \frac{1}{\tilde{\rho}}\right) \left[s_m \times \beta_{\text{HHI}} + HHI \times \beta_{s_m}\right] \tag{C.24}$$

where HHI (short for $HHI_{\overline{g}m}$) market's formal sector's expected wage bill Herfindahl Index, s_m is market m's wage work wage bill share (that is, formal plus informal wage work divided by total work, which includes self-employment), and the β coefficients are the partial (aka, first derivative, reduced form) effects of the labor demand shock on Herfindahl and wage work shares, respectively.

C.3 Results

C.3.1 Elasticities of substitution

Substitution within markets, across firms. Table C.2 reports IV estimates of the within-market cross-firm inverse elasticity of substitution, $1/\eta$, and its regional heterogeneity. Column (1) replicates the 0.990 estimate in Section C.1, which is the relevant within-market cross-firm elasticity of substitution in Section C.1 if workers are indifferent to the threat of involuntary separation to informal wage work (namely, if $\Omega = 0$). The near-unit value of this elasticity is nearly 7 times higher than its corresponding value for the United States, and remains—as in Section C.1—the leading driver of Brazil's high markdown levels.

This near-unit and relatively inelastic value is not homogeneous across Brazil, however. Columns (2)-(5) report heterogeneity by Brazil's major regions. Column (2) shoes that the pooled elasticity is driven by the Southeast— the largest region by employment and where the formal sector made up more than half of total employment share in 1991, as shown in the microregions to the left of Figure 1—where the within-market cross-firm elasticity of substitution is estimated at 1.029.

The picture is very different in the Northeast, Brazil's second largest region by population and employment. Column (2) shows that the within-market cross-firm elasticity of substitution in the Northeast is nearly half of that in the Southeast, at 0.458. Since nearly all employment in the Northeast is informal—these are primarily the microregions to the right of Figure 1, with the exception of a few metropolitan areas (e.g., PE-3 and AL-3), where formality is high—more elastic within-market cross-firm elasticity of substitution in this region suggests raises the interesting possibility of congestion—or larger employer-employee matching frictions within the formal sector—in markets where many more firms are formal and small. Columns (4) and (5) report coefficients pooling with other regions where the first stage of Brazil's firm-level tariff shocks is too weak to yield estimates restricted to the smaller regions of the North, South, and Center West. I pool the North with the Northeast given their similarity in levels of development, and the South and Center West with the Southeast, for similar reasons. Both estimates are attenuated when pooled.

Bias from separation into informal wage work. Panel A of Figure C.8 plots the reduced form and first stage relationships that identify Ω. They are both negative: employment and expected informal-formal wage gaps declined in firms and markets more exposed to import competition. Combined these imply that Ω is positive, such that the threat of involuntary separation from a formal job increases firms' market power. For ease of interpretation, Panel B of Figure shows the OLS relationship between the two variables. The OLS says that firms that grow are also those that distance themselves–in terms of earnings–from local labor market conditions. Some of these firms pay more than local informal jobs, but many pay less, as shown in Panel B of Figure C.3. Table C.4 reports the implied IV coefficients and its heterogeneity by demographic groups.

Table C.4 examines the bias term Ω in the within-market cross-firm elasticity of substitution presented in Table C.2 if the extended model is true, namely, if workers take into account the probability of involuntary separation into informal wage work when making labor supply decisions. The most important take-away is that the magnitude of the bias is very small. At 0.0331 on average per Column (2), Ω shows that the within-market cross-firm inverse elasticity of substitution is roughly 3% *smaller* in Section C.1's model than in the extended model where involuntary separations are considered. In other words, the threat of involuntary separation into informal wage work slightly increases formal firms' labor market power. Columns (2)-(4) then show some heterogeneity in this estimate by demographics, though the magnitudes are not significantly different from each other.

Unemployment insurance. An interesting question is whether the value of unemployment insurance alters workers' attitude towards being fired from a formal sector job. Appendix Table C.4 tests this hypothesis. Consistent with the cross-country evidence Amodio et al. (2025), I find that unemployment insurance makes workers less responsive to the threat of involuntary separation, curbing labor market power. This results from contrasting the magnitude of the Ω bias introduced by involuntary separations if it is estimated with or without the value of unemployment insurance benefits, available in Appendix Table C.5. When Ω is positive, the threat of involuntary separation to the informal sector increases firms' labor market power. When it is negative, the informal sector curbs that market power. While all estimates I find for Ω are positive, adding unemployment insurance to the estimation reduces Ω from 0.0331 to 0.0221. This suggests that unemployment insurance, on average, operates like a substitute to self-employment at Brazil's level of economic development. This is consistent with the findings in Amodio and de Roux (2021). The elasticity of substitution to self-employment is however a much stronger force in curbing labor market power than the contribution of unemployment insurance to its relevant elasticity ($1/\eta$).

Substitution to self-employment. Tables C.6 and C.8 report estimates of inverse elasticities governing substitution between wage work and self-employment, $1/\tilde{\rho}$, as well as cross-market substitution, $1/\tilde{\theta}$. The magnitudes are generally small, indicating highly elastic reallocation between wage work and self-employment and across markets, which limits equilibrium labor market power. Heterogeneity results show that substitution is particularly elastic for demographic groups with stronger outside options, reinforcing the role of self-employment and informal work as key competitive constraints on formal-sector wage setting.

Appendix Figure C.6 plots the first stage of equation C.21—namely, the effect of demographic-specific regional tariff reductions on log share of wage work employment—separately by demographic groups. These figures are demographic-specific versions of Figure C.5, which plots the pooled, across groups, relationship between wage work and regional tariff reductions. The variation in Appendix Figure C.6 is the one I use to estimate the elasticities of substitution, reported in Tables C.6 and C.8.

C.3.2 Wage markdowns and key take-aways

On average, Brazilian formal sector workers were paid 51 cents of their marginal revenue product of labor in 1991. However, this average masks substantial heterogeneity across regions and across demographics. Take-home shares are highest for less educated workers, for whom the minimum wage is a substantial increase relative to their earnings in either informal wage work or self-employment, and for women, for whom self-employment earnings are higher than either formal sector earnings or informal sector earnings at any point of the formal wage take-home share distribution (see, e.g., Figure C.15).

Figure C.9 shows the distributions of average wage take-home shares—the inverse of wage markdowns—

across microregions and across occupations, since a local labor market is defined as a microregion x 2-digit occupation pair. The dispersion is driven by regional heterogeneity in the within-market cross-firm inverse elasticity of susbtitution $1/\eta$. Most microregions have wage markdowns around 50 cents on the dollar, with that mass increasing between 1991 and 2000. Microregions in the North and Northeast of Brazil, for which within-market cross-firm elasticities of substitution are almost half those of the rest of the country, feature higher wage take-home shares. The dispersion across occupations is centered between 50 and 55 cents on the dollar.

Figure 9 displays the microregion-level average markdowns by microregion, along with each microregion's share of employment in formal wage work, informal wage work, and self-employment. A clear pattern is that wage take-home shares are typically higher, though not always, in places where a larger share of the workforce is self-employed. Regions that are primarily formal, such as microregions in the states of São Paulo or Santa Catarina, show little dispersion of average wage take-home shares, though variation still exists as places differ in demographic composition, and demographic groups have different elasticities of substitution to self-employment and respond differently to the threat of separation into informal wage work. Appendix Figures C.13 through C.15 replicate these figures but showing demographic-specific local wage markdowns.

It should also be noted that a substantial share of the earnings gaps between the informal, informal, and self-employment sector is accounted for by the demographics of the workers, as shown in Figure C.3. In fact, the 1991 residual earnings distribution shows that observationally-equivalent workers were paid on average higher earnings in either the informal wage work sector or in self-employment. By 2000, the residual earnings gap between the formal and informal wage work sectors closes, whereas self-employment–primarily composed of women—remained a higher return activity on average.

Wage markdowns and concentration. Since the model in Section C.1 features ample heterogeneity in preference parameters and implies that local labor market conditions outside of the formal sector affect firms' wage setting, the relationship between local labor market concentration and wage markdowns is no longer a linear function of formal sector concentration, as in Section C.1's framework. The relationship is now tied to many more variables, including cross-market variation in demographic composition.

Figure C.11 and its demographic-specific versions (Appendix Figures C.12) plot the relationship between the formal sector's local Herfindahl-Hirschmann Index (HHI)–measured with respect to expected wages—and wage take-home share estimates. It shows a non-linear relationship likely driven by cross-regional differences in elasticities of substitution. Wage take-home shares increase in labor market concentration for markets with numerous similarly sized firms (i.e., HHI below 0.2). Past that threshold, labor market concentration among formal sector firms typically reduces formal sector wage take-home shares.

C.3.3 Policy effect of trade liberalization on wage markdowns

I apply the policy effect formula to compute the effect of a 10% increase in Regional Tariff Reductions (RTR) on average wage markdowns. Table 8 reports the country-average effect and heterogeneity across regions and demographics. All effects are in percentage points (pp) of the take-home share $\mu = w/MRP$. A positive

$\Delta\mu$ means wages moved closer to MRP—reducing employer market power—while a negative $\Delta\mu$ means the wedge widened.

Reduced-form effects of RTR on market structure. The policy effect formula combines the structural elasticities with reduced-form estimates of how trade changed market structure. A unit RTR increase raises formal employer concentration by $\beta_{HHI} = 0.722$ (SE = 0.075), so a 10% RTR increase raises HHI by 7.2 percentage points—large relative to the baseline mean of 16.7%. A unit RTR increase also decreases the formal sector's expected wage bill share by $\beta_{s_r} = -0.477$ (SE = 0.069), so a 10% increase reduces s_r by 4.8 percentage points from a baseline of 78.5%. Both coefficients come from regressions $\Delta Y_m = \alpha + \beta \cdot RTR_m + \gamma_r + u_m$, where ΔY_m is the 1991–2000 change in HHI or s_r, γ_r are region fixed effects, and standard errors are clustered at the microregion level. The HHI regression is estimated at the market (mmc $\times$ cbo942d) level with formal wagebill weights; the s_r regression at the mmc level since s_r varies only across microregions. For informality and region subgroups, both coefficients are re-estimated within each subgroup; for demographic subgroups, pooled coefficients are used.

Average effect: two opposing channels. These reduced-form effects enter the markdown formula through two opposing channels. The *within-market net substitution channel* (-0.0017) reduces markdowns: as trade increases concentration, the formula shifts weight from the less elastic cross-firm margin ($1/\tilde{\eta}$) toward the more elastic wage work–self-employment margin ($1/\tilde{\rho}$), so self-employment disciplines employers even as formal markets become more concentrated. The *cross-market substitution channel* (+0.0058) increases markdowns: as the formal sector shrinks and concentrates, the HHI–s_r interaction shifts weight toward the least elastic cross-market margin ($1/\tilde{\theta}$), so remaining formal employers face workers with fewer cross-market options. At the country average, these channels nearly offset: $\partial\varepsilon^{-1}/\partial RTR = +0.004$, translating into an essentially zero change in the take-home share from a baseline of 50.9%.

Heterogeneity. The near-zero country average masks modest heterogeneity driven by variation in local informality and labor supply elasticities. In high-informality regions—where self-employment is prevalent and baseline concentration is high ($HHI = 0.43$ vs. 0.16 in low-informality regions)—the take-home share falls by -0.54 pp. In low-informality regions, the effect is a small increase (+0.04 pp). Regional heterogeneity is also modest: the take-home share rises by $+1.18$ pp in the North and Northeast, while in the Southeast, South, and Center-West the effect is -0.06 pp.

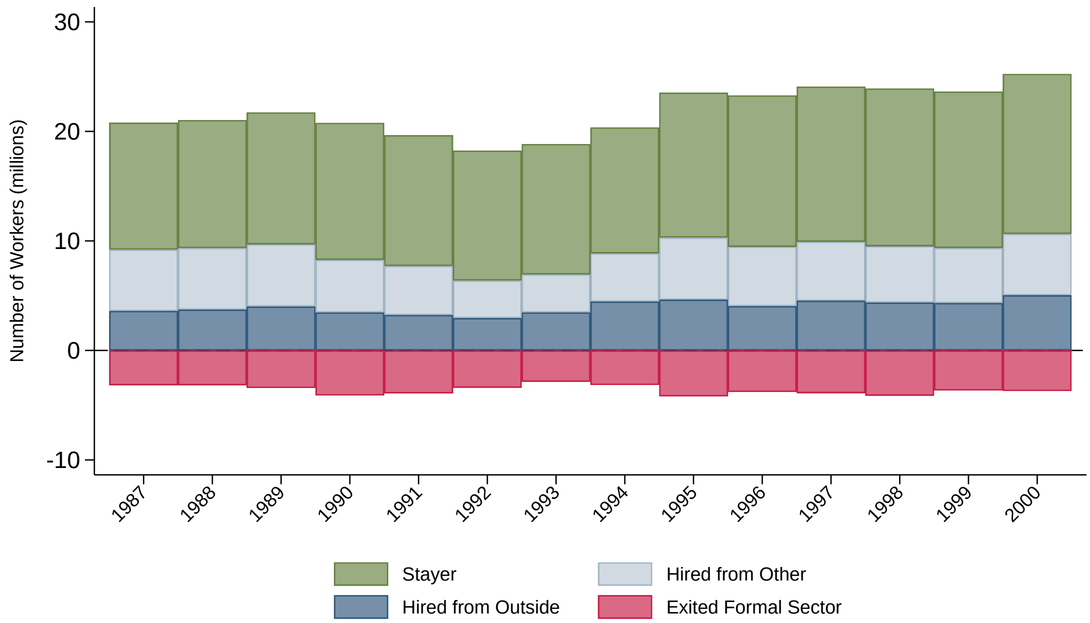
Across demographics, all effects are close to zero. Tertiary-educated workers ($1/\tilde{\rho} = 0.93$, $\Delta\mu = +0.2$ pp) and young workers (0.85, +0.1 pp) see the largest—though still small—positive effects. Middle-aged workers ($1/\tilde{\rho} = 0.35$, $\Delta\mu = -0.1$ pp), older workers (0.30, -0.1 pp), and women (0.39, -0.1 pp) see small decreases, while men (0.66, 0.0 pp) and primary- and secondary-educated workers (-0.0 pp each) are essentially unaffected.

C.4 Summary

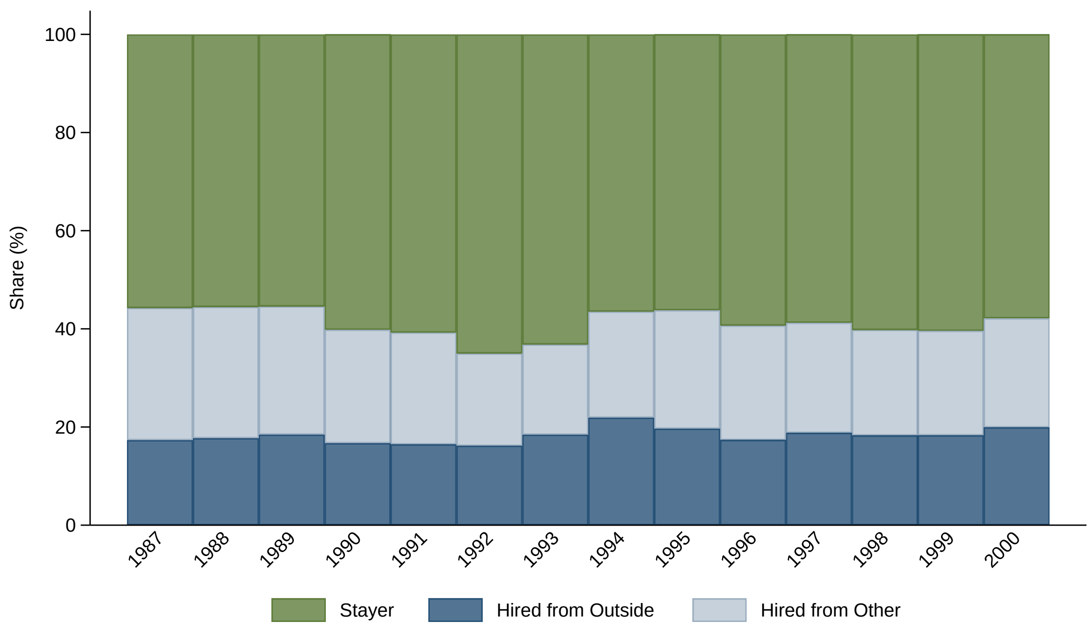
This appendix extends the baseline model to incorporate self-employment, the risk of involuntary separation into informal wage work, and preference heterogeneity by demographics and region. The key findings are: (i) labor supply to formal firms is highly inelastic at the within-market cross-firm margin ($1/\tilde{\eta} \approx 1.01$), with the bias from ignoring informal wage work small ($\Omega \approx 0.02$) and partially offset by unemployment insurance; (ii) substitution between wage work and self-employment is substantially more elastic ($1/\tilde{\rho} \approx 0.47$), confirming that self-employment curbs formal firms' power, especially for women, older workers, and less educated workers; (iii) cross-market mobility is the least elastic margin ($1/\tilde{\theta} \approx 1.19$), indicating large geographic and occupational frictions; (iv) average take-home shares are 51 cents on the dollar—close to the baseline's 50 cents—but range from 46 to 73 cents depending on local informality and workforce composition (Table 7); (v) the effect of trade on markdowns is essentially zero at the country average ($\Delta\mu \approx 0$ pp for a 10% RTR increase), as within-market and cross-market substitution channels nearly offset. Heterogeneity across informality and region is modest: the take-home share falls by -0.54 pp in high-informality regions and rises by +0.04 pp in low-informality regions, while demographic effects are uniformly close to zero.

Figure C.1: Formal sector worker flows

(a) Total firm-to-firm and firm-to-outside flows

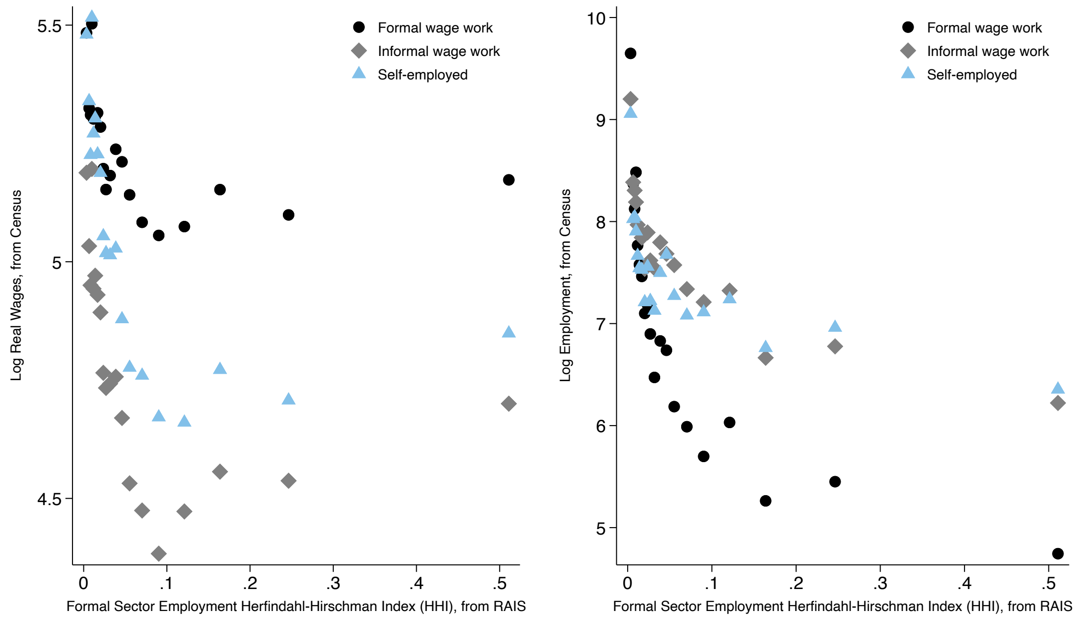


(b) Flow shares



Notes: This figure plots the total number of new hires directly from formal sector firms ("Hired from Other"), workers separated from a formal firm and are matched within one year to another formal firm ("Sep to Other"), new hires from outside the formal sector ("Hired from Outside"), separations to outside the formal sector ("Sep to Outside"), and workers who do not switch employers within the year ("Stayer") as reported by formal sector firms in Brazil's RAIS employer-employee linked dataset. Note that "Hired from Other" and "Separated to Other" match, but are measured separately, the former based on records from the receiving firm, the latter based on records from the origin firm. Flows include within-year transitions and exclude flows to/from public administration, retirements, and deaths.

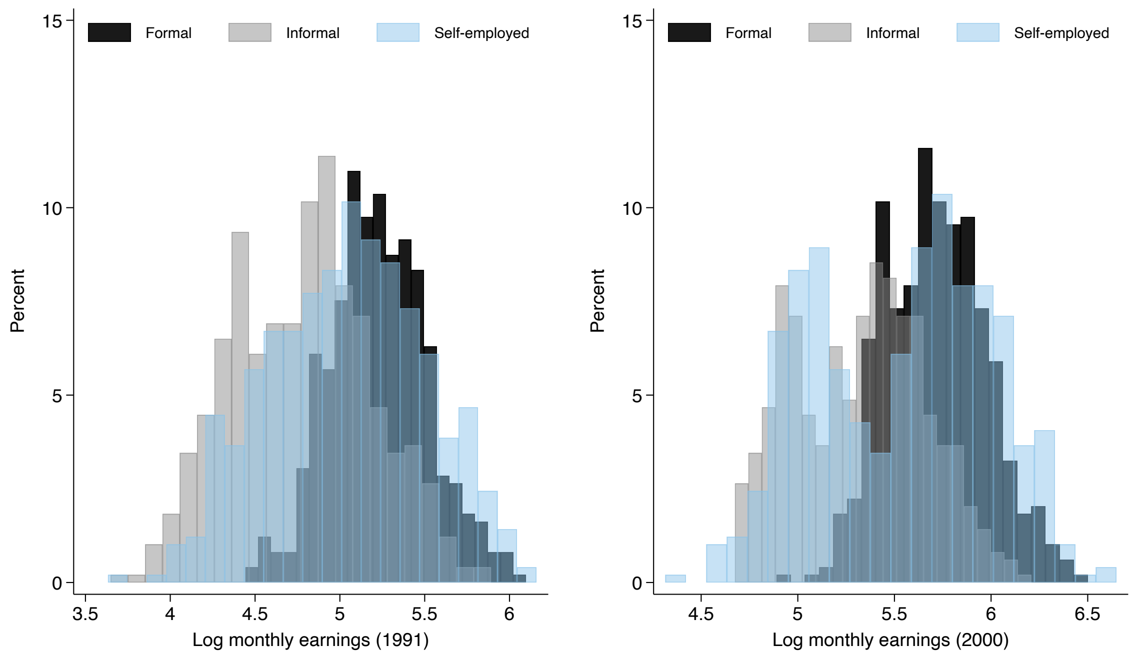
Figure C.2: 1991 wages, employment, and formal sector concentration (Census)



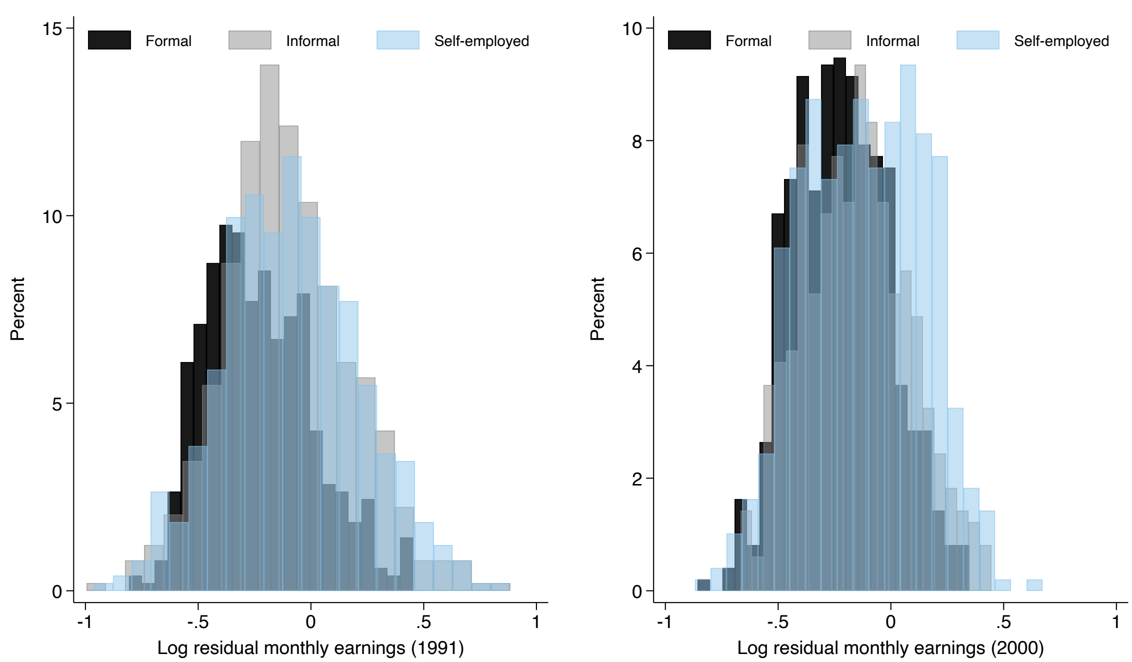
Notes: This figure plots wages and employment as a function of formal sector HHI in microregions using Census data for 1991.

Figure C.3: Formal, informal, and self-employment earnings

Panel A: Raw earnings



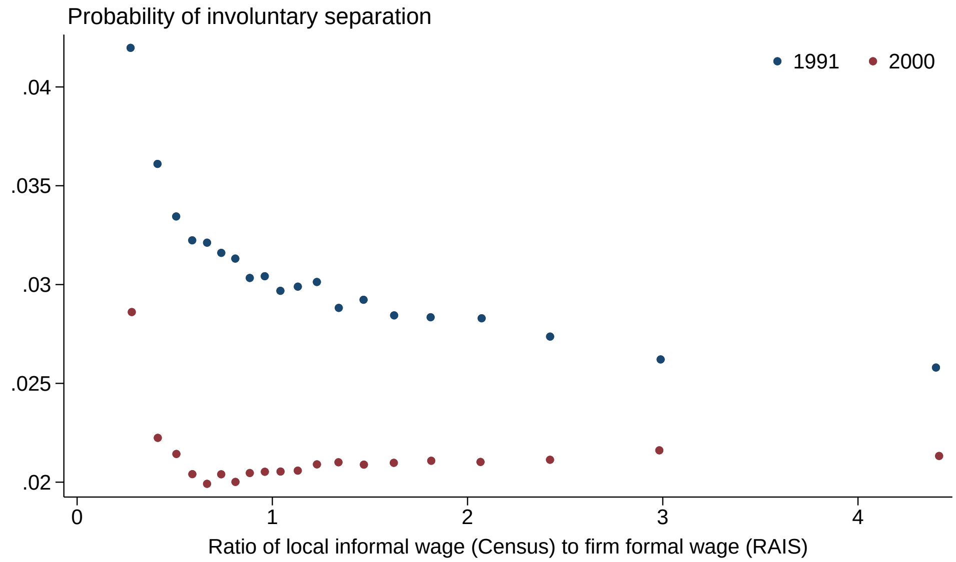
Panel B: Residual earnings



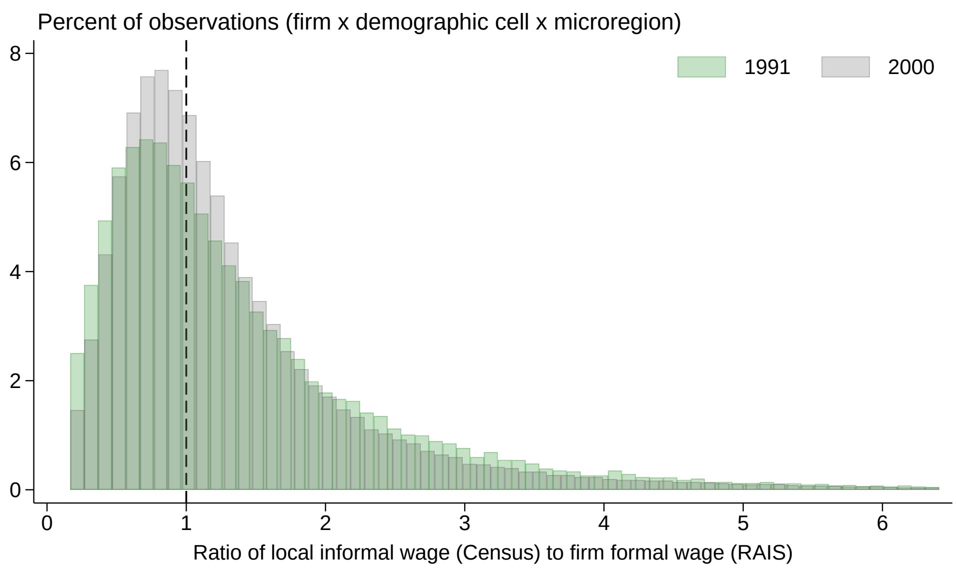
Notes: This figure plots the distribution of raw and residual formal real monthly earnings, informal real monthly earnings, and self-employment real monthly earnings, across 486 Brazilian microregions. Residual real monthly earnings are conditional on a fully saturated vector of dummies for gender, age groups, and education groups. Real earnings are expressed in 2000 reais.

Figure C.4: Probability of involuntary separation from formal firm and informal-formal wage gaps

Panel A: Probability of involuntary separation and wage gap



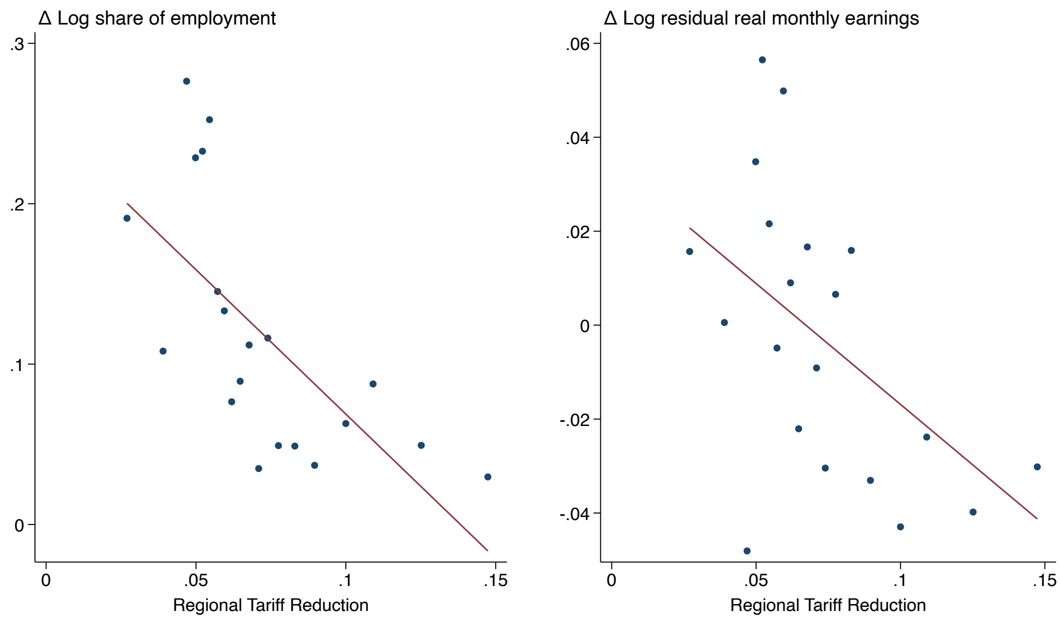
Panel B: Wage gap distribution



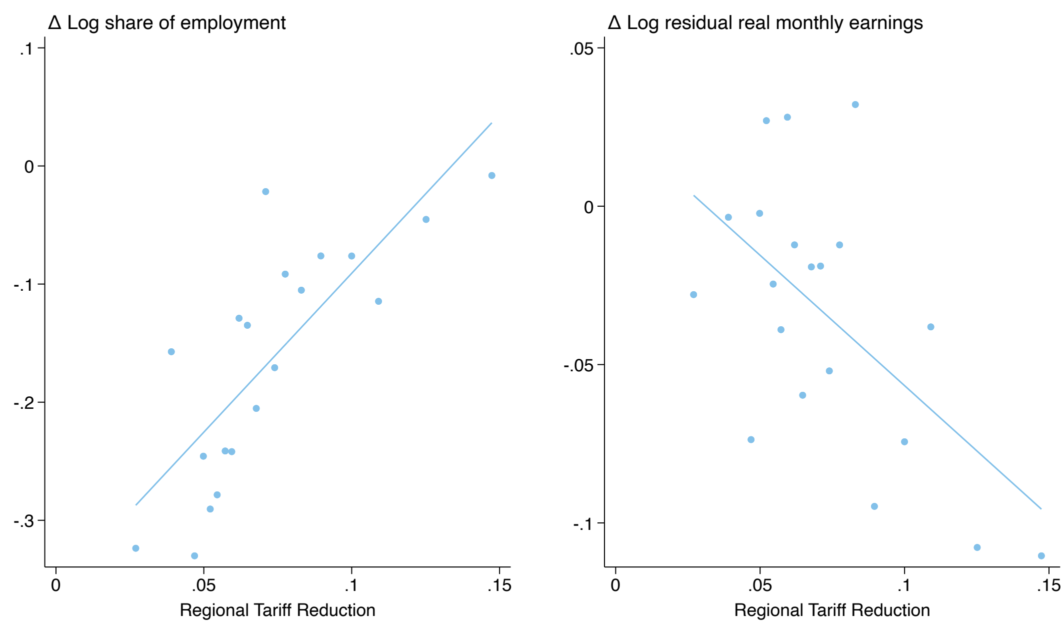
Notes: This figure shows the relationship between probabilities of involuntary separation from a formal sector firm in RAIS and the gap between local informal sector monthly earnings and the firm's formal monthly earnings, separately computed for each demographic cell. The sample includes all formal sector firms in RAIS in 1991 and 2000, merged at the microregion X demographic cell X year level to the corresponding census data. Each observation is a firm X microregion X demographic cell (gender X education group X age group dummies). Monthly earnings gaps are calculated by first converging all reported earnings to 2000 constant Reais. The probability of involuntary separation is calculated using separations between January 1 and December 30 of each year. Firm total formal employment is measured as of December 31 of each year.

Figure C.5: Effect of Regional Tariff Reductions on wage work and self-employment

Panel A: Wage work



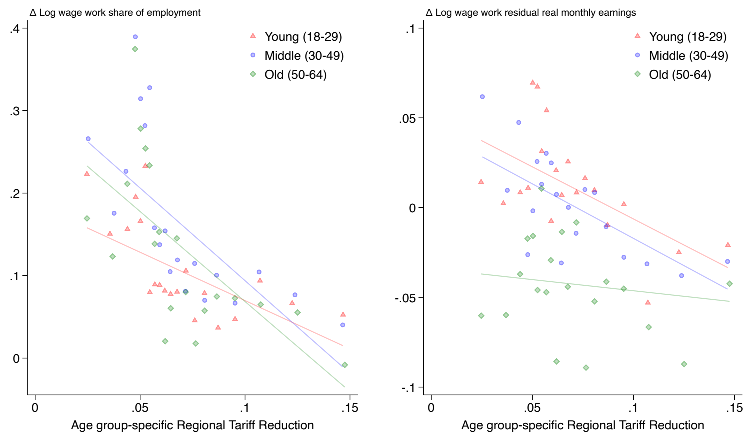
Panel B: Self-employment



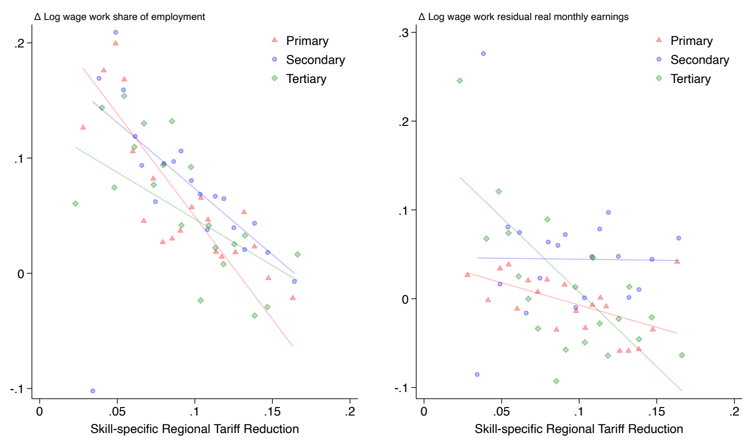
Notes: This figure shows the correlation between Regional Tariff Reductions (i.e., microregion-level exposure to 1990-1994 import tariff reductions from Dix-Carneiro and Kovak (2017)), changes in employment shares (left panel), and changes in log residual real monthly earnings (right panel) between the 1991 and 2000 census, for individuals employed in wage work (formal or informal) (Panel A) versus in self-employment (Panel B) across 486 Brazilian microregions. Log residual real monthly earnings are conditional on flexible controls for gender, age, and education. Real earnings are computed from nominal earnings by expressing all values in 2000 reais.

Figure C.6: Effect of Regional Tariff Reductions on wage work by demographics

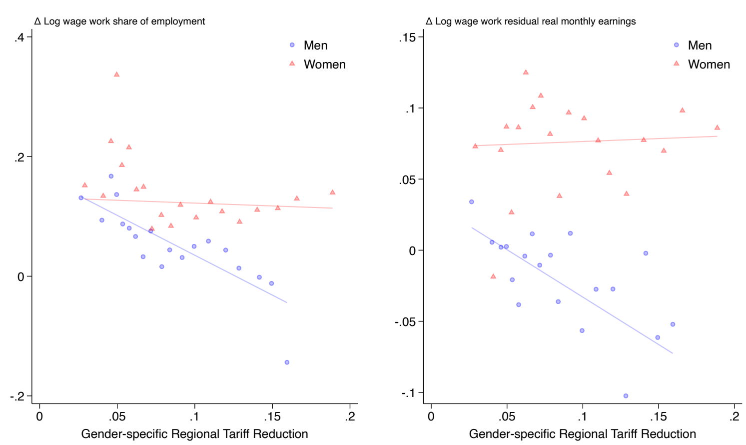
Panel A: By age



Panel B: By education



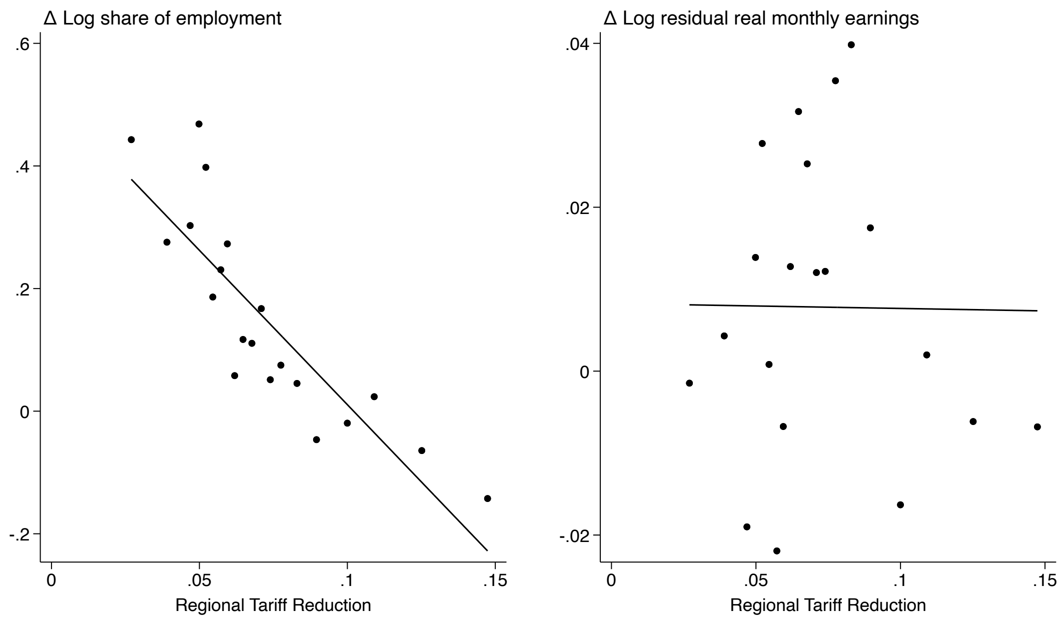
Panel C: By gender



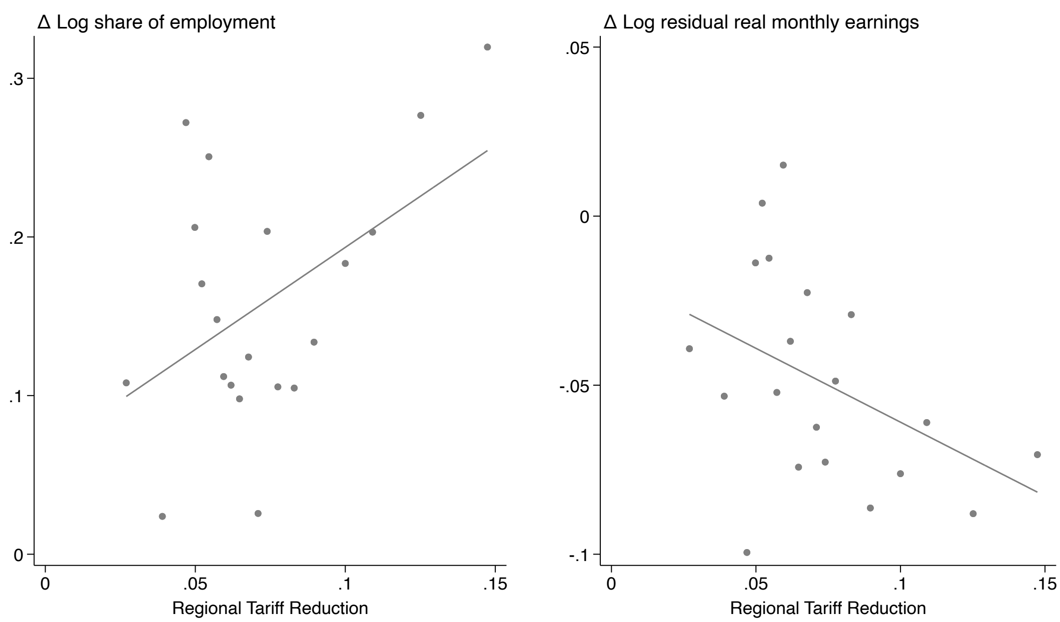
Notes: is figures shows the correlation between Regional Tariff Reductions (i.e., microregion-level exposure to 1990-1994 import tariff reductions from Dix-Carneiro and Kovak (2017)), changes in employment shares (left panel), and changes log residual real monthly earnings (right panel) between the 1991 and 2000 census, for self-employed individuals across 486 Brazilian microregions, separately for different demographic groups. Log residual real monthly earnings are conditional on a fully saturated vector of dummies for gender, age groups, and education groups. Real earnings are computed from nominal earnings by expressing all values in 2000 reais.

Figure C.7: Effect of Import Tariff Reductions on formal versus informal wage work

Panel A: Formal Wage Work



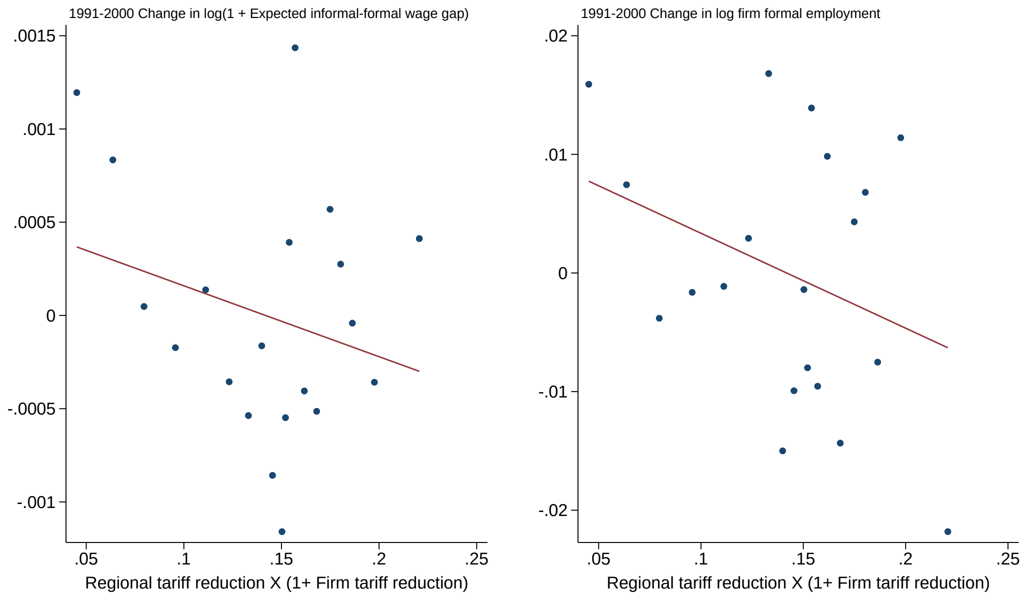
Panel B: Informal Wage Work



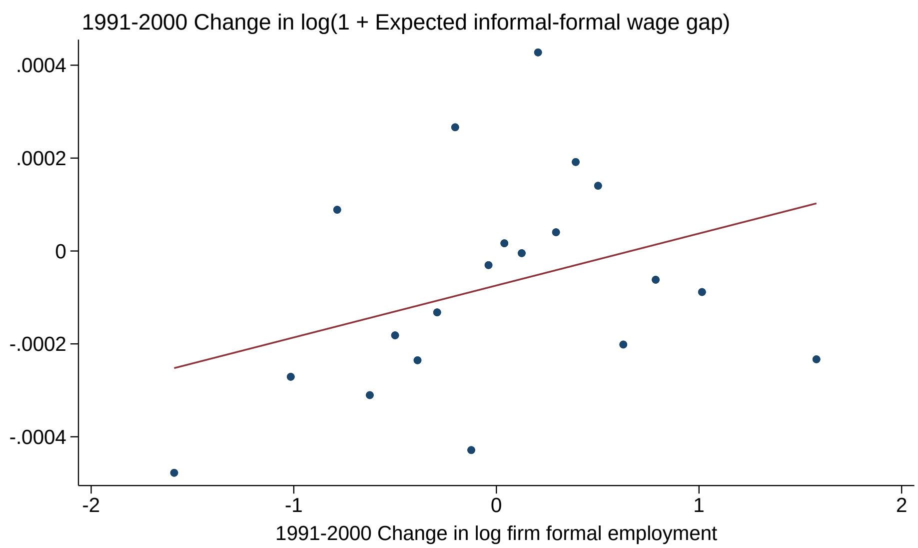
Notes: Each panel shows the correlation between Regional Tariff Reductions (microregion-level exposure to 1990-1994 import tariff reductions from Dix-Carneiro and Kovak (2017)), changes in employment shares (left) and log residual real monthly earnings (right) between 1991 and 2000 across 486 Brazilian microregions. Log residual real monthly earnings are conditional on a fully saturated vector of dummies for gender, age groups, and education groups. Real earnings are expressed in 2000 reais.

Figure C.8: Firm-specific labor supply response Ω to expected informal-formal wage gaps

Panel A: Visual IV: Reduced form (left) and First Stage (right)



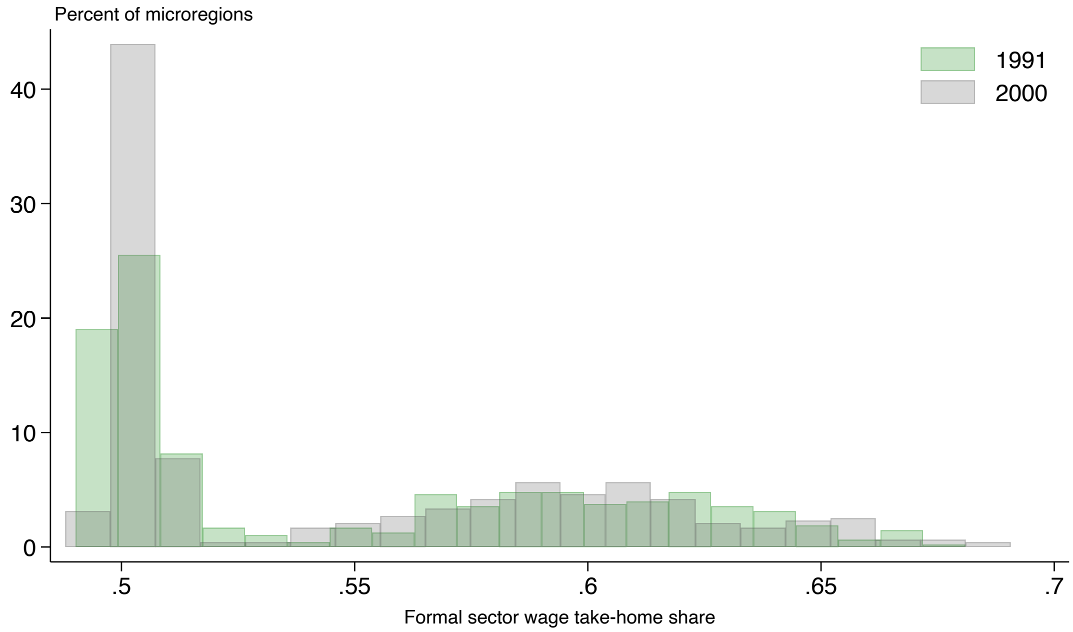
Panel B: Visual OLS



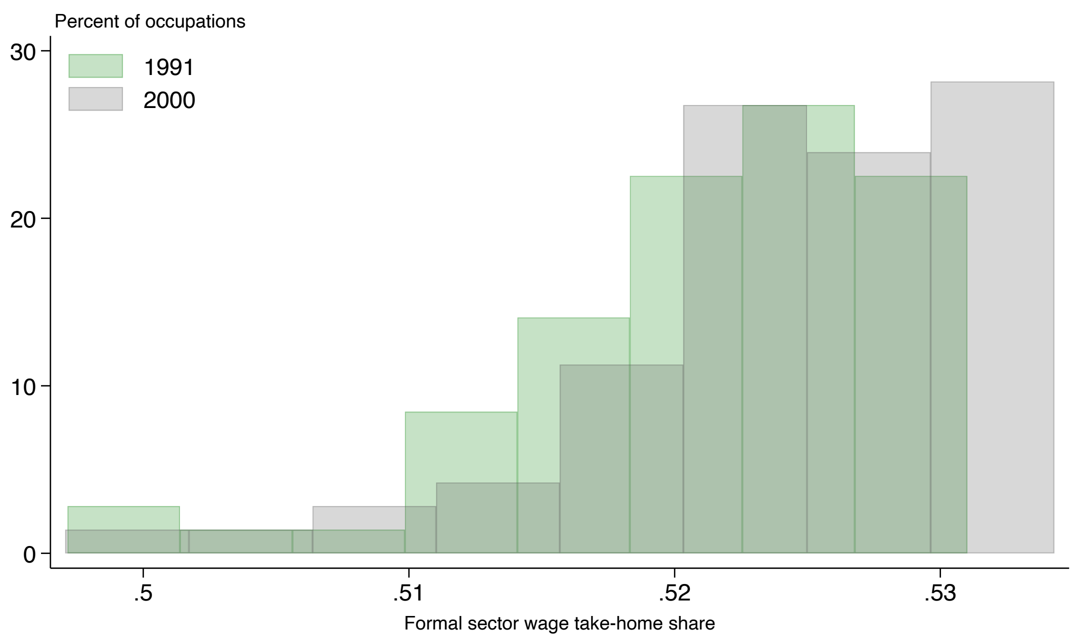
Notes: This figure shows binned scatters of 1991-2000 changes in expected informal-formal wage gaps, firm formal employment, and import tariff reductions. The sample includes all formal sector firms in RAIS in 1991 and 2000, merged at the microregion X demographic cell X year level to the corresponding census data. Each observation is a firm X microregion X demographic cell (gender X education group X age group dummies). All binned scatters show residual variation conditional on firm, microregion, and demographic cell fixed effects. Expected informal-formal wage gap is calculated separately by firm, microregion, and demographic cell as $p_{z\bar{s}r}\sigma^{c}_{z\bar{s}r}$. The first term, $p_{z\bar{s}m}$, is the probability of *involuntary* separation from firm z, measured as the ratio of firings to firings plus stayers in firm z. The second, $\sigma^{c}_{z\bar{s}m} \equiv (w^{o}_{m} - w^{c}_{z\bar{s}m})/w^{c}_{z\bar{s}m}$, is the monthly earnings gap between the local informal sector and firm z's formal wage for that demographic cell. Monthly earnings gaps are calculated by first converging all reported earnings to 2000 constant reais. $p_{z\bar{s}m}$ is calculated using separations between January 1 and December 30 of each year. Firm total formal employment is measured as of December 31 of each year. Regional tariff reductions are microregion-level exposure to 1990-1994 import tariff reductions from Dix-Carneiro and Kovak (2017) and differ by demographic group.

Figure C.9: Formal sector wage take-home share in dual labor markets

Panel A: Distribution across microregions

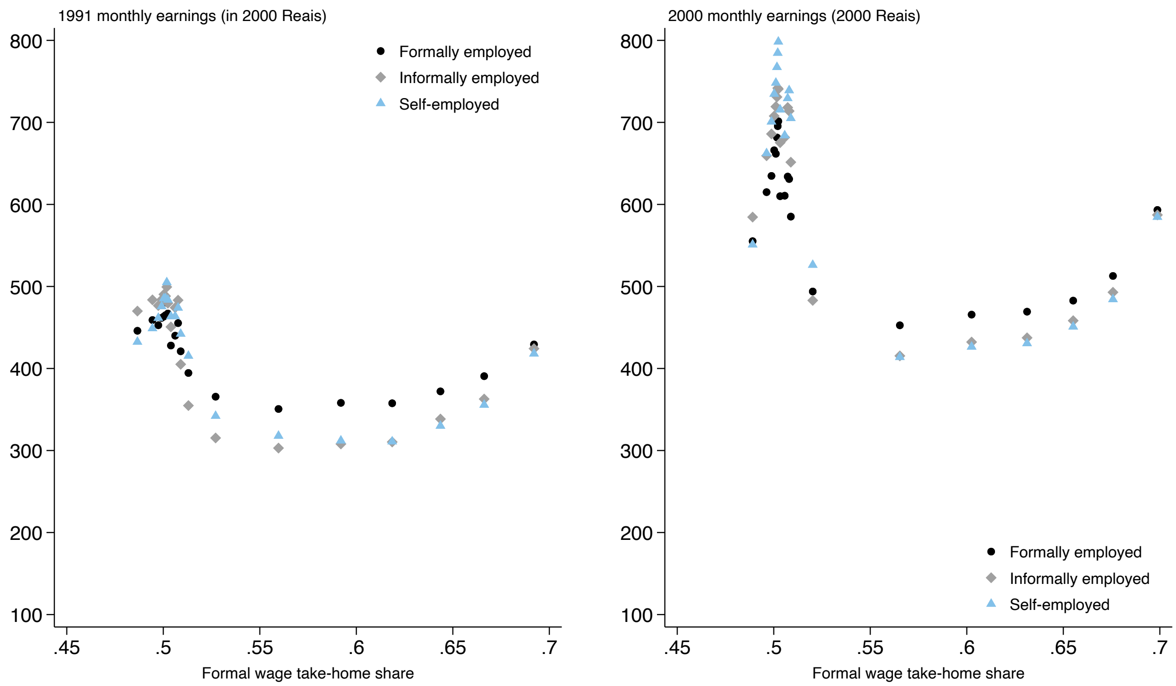


Panel B: Distribution across occupations



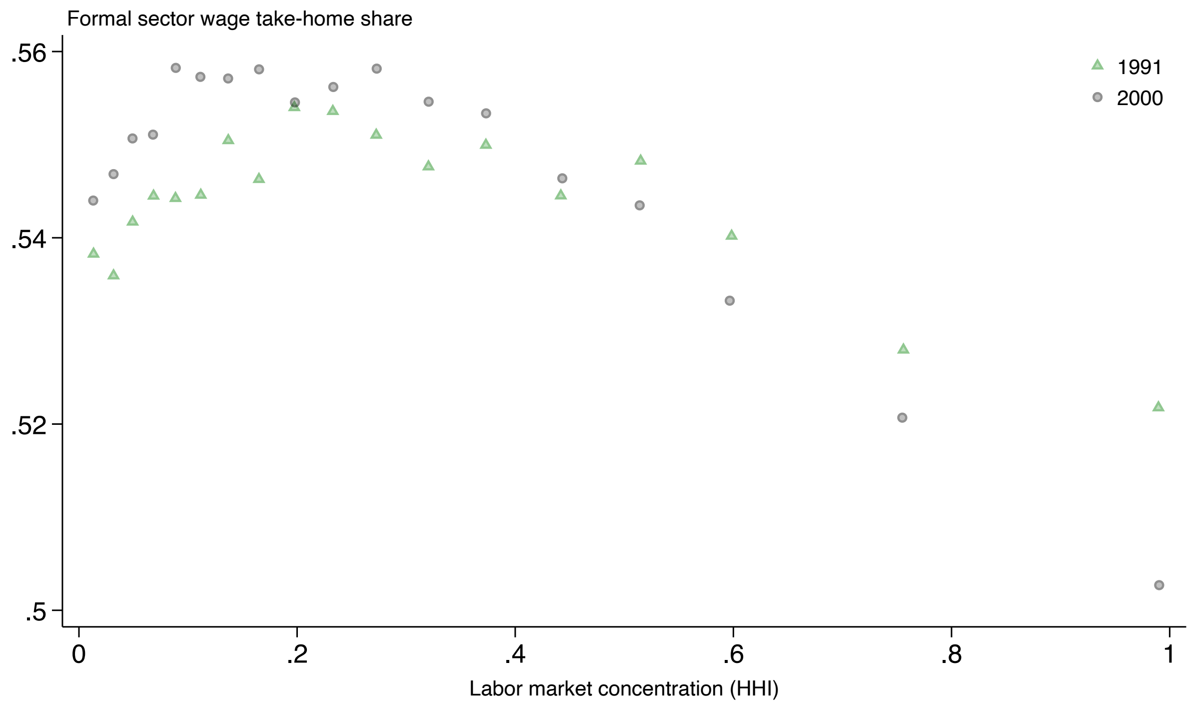
Notes: This figure show the distribution of average wage take-home shares (the inverse of average wage markdown) across microregions (Panel A) and occupations (Panel B), separately by year. Average wage take-home shares are calculated at the local labor market level (microregion x occupation) following equation C.23, using region-specific estimates of $1/\tilde{\eta}$ and pooled estimates of $1/\tilde{\rho}$ and $1/\tilde{\theta}$. Panels A and B aggregate these estimates by microregion and 2-digit occupation, respectively, weighing observations by total formal wage bill.

Figure C.10: Wages and formal sector wage take-home shares



Notes: This figure plots binned scatters between real monthly earnings (separately by employment type) and average formal sector wage take-home shares across microregions. See Figure C.9 for details and Appendix Figures C.12 for demographic-specific binned scatters.

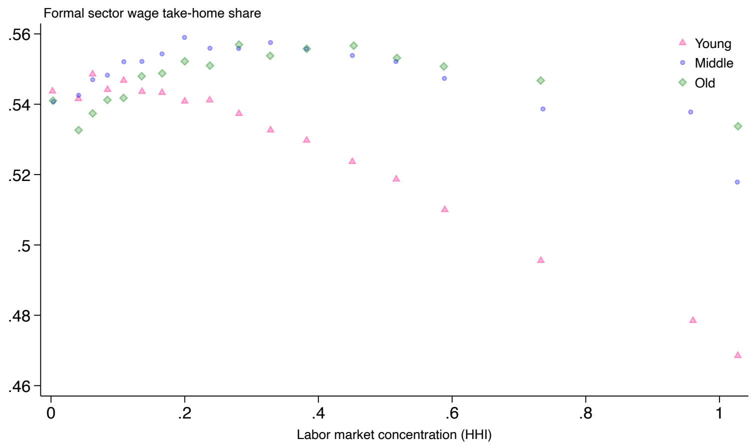
Figure C.11: Concentration and formal sector wage take-home shares



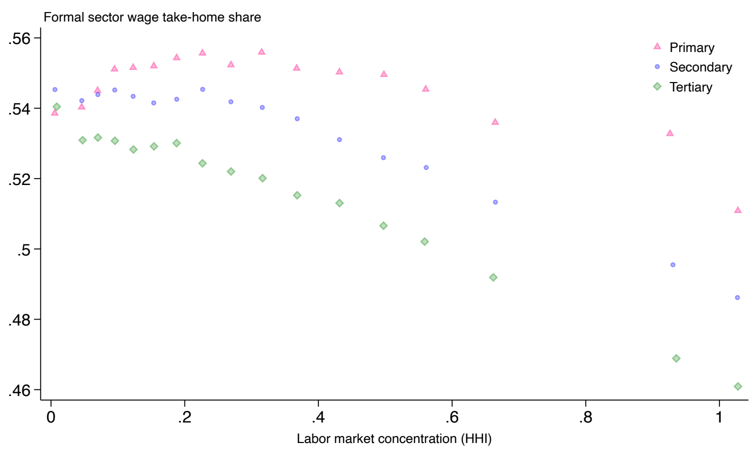
Notes: This figure plots binned scatters between average formal sector wage take-home shares and formal firms' local labor market concentration (HHI), measured in terms of *expected* wage bill shares, which take into account probabilities of separation into informal wage work, across microregion x occupation pairs, separately by year. See Figure C.9 for details and Appendix Figures C.13 through C.15 for demographic-specific distributions.

Figure C.12: Formal sector wage take-home share and labor market concentration

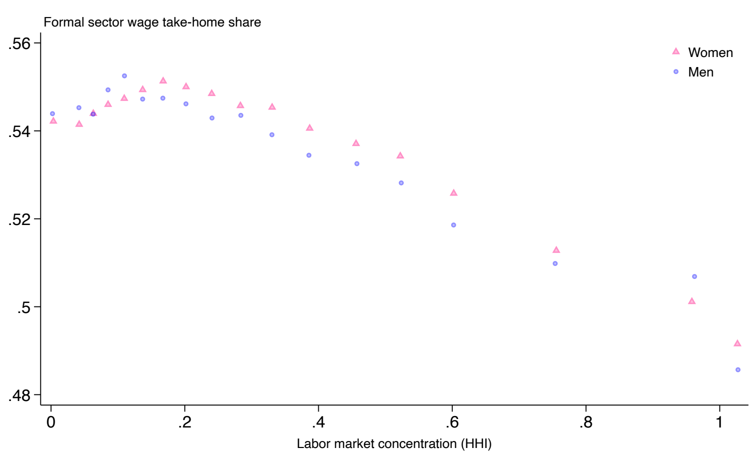
Panel A: By age



Panel B: By education



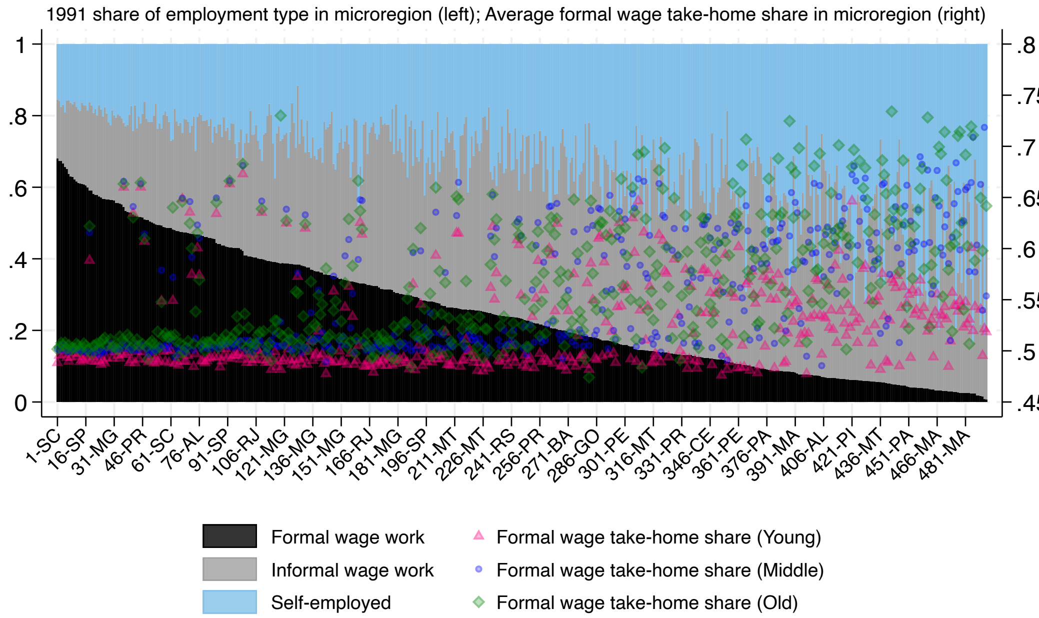
Panel C: By gender



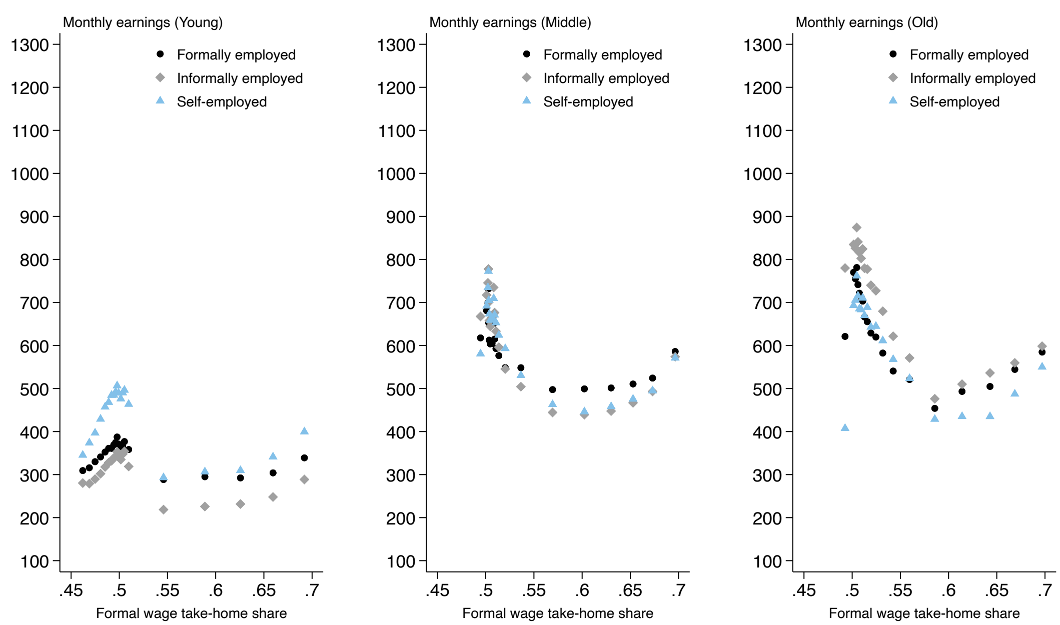
Notes: This figure plots binned scatters between demographic-specific average formal sector wage take-home shares and formal firms' local labor market concentration (HHI). See notes to Figure C.11.

Figure C.13: Formal wage take-home share in dual labor markets: Heterogeneity by age

Panel A: 1991 distribution across microregions



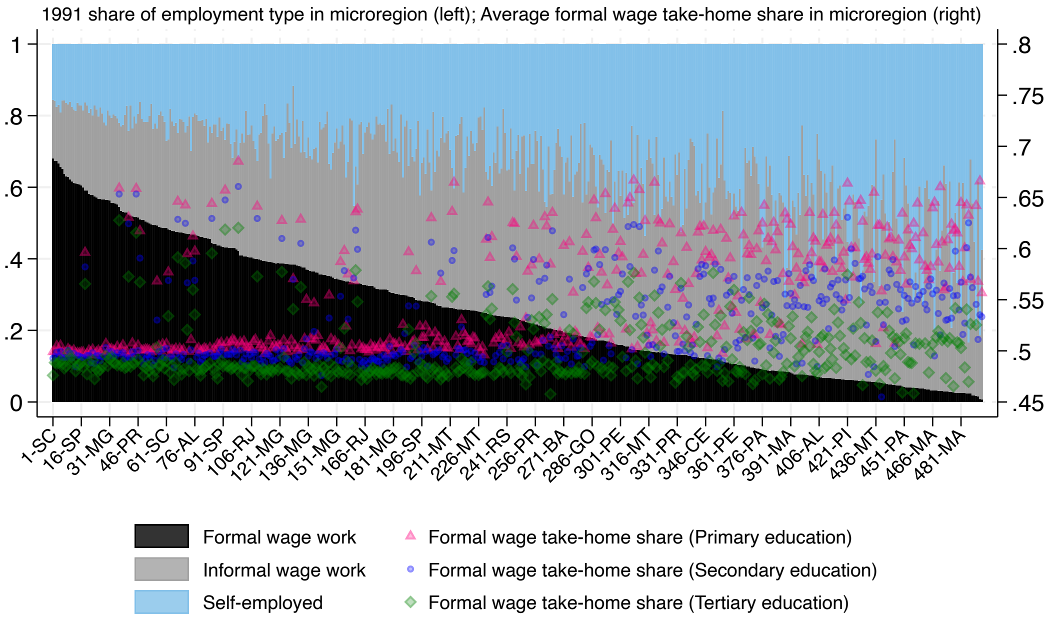
Panel B: Wages and wage take home-shares



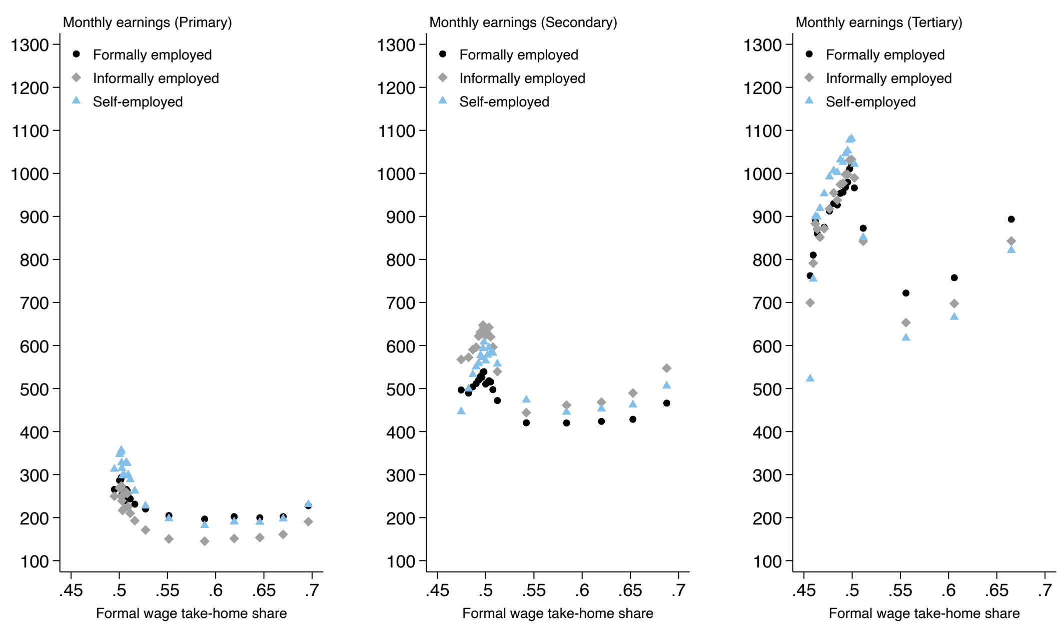
Notes: This figure presents age-specific versions of Figures 9 and C.10. Average wage take-home shares are calculated at the local labor market level (microregion x occupation) following equation C.23, using region-specific estimates of $1/\tilde{\eta}$, demographic-specific estimates of $1/\tilde{\rho}$, and the pooled estimate for $1/\tilde{\theta}$. For Panel A, average take-home shares are aggregated at the microregion level using formal sector wage bill as weights.

Figure C.14: Formal wage take-home share in dual labor markets: Heterogeneity by education

Panel A: 1991 distribution across microregions



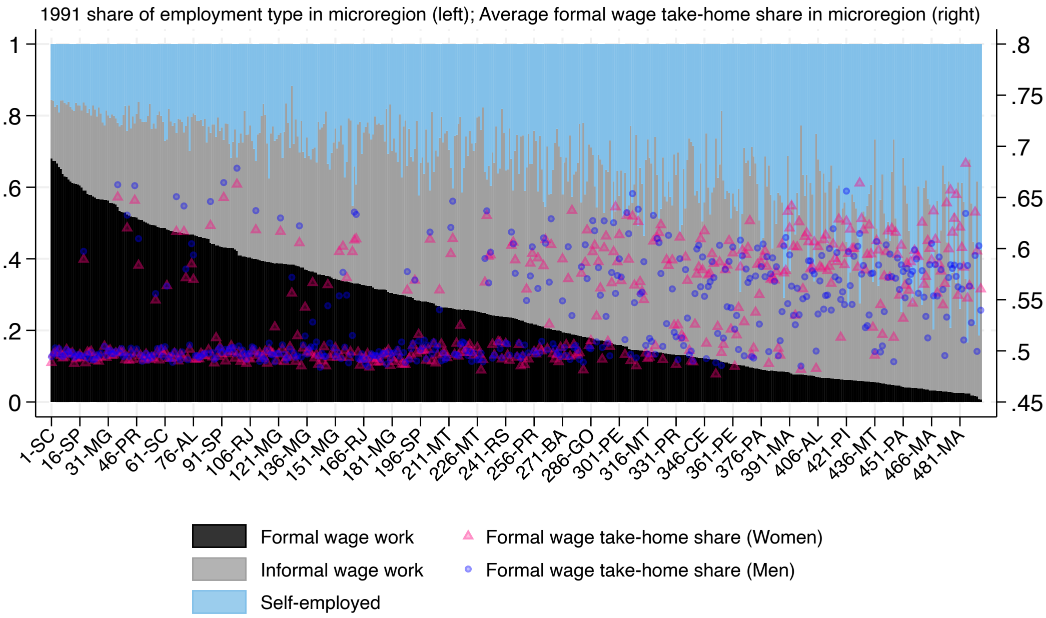
Panel B: Wages and wage take home-shares



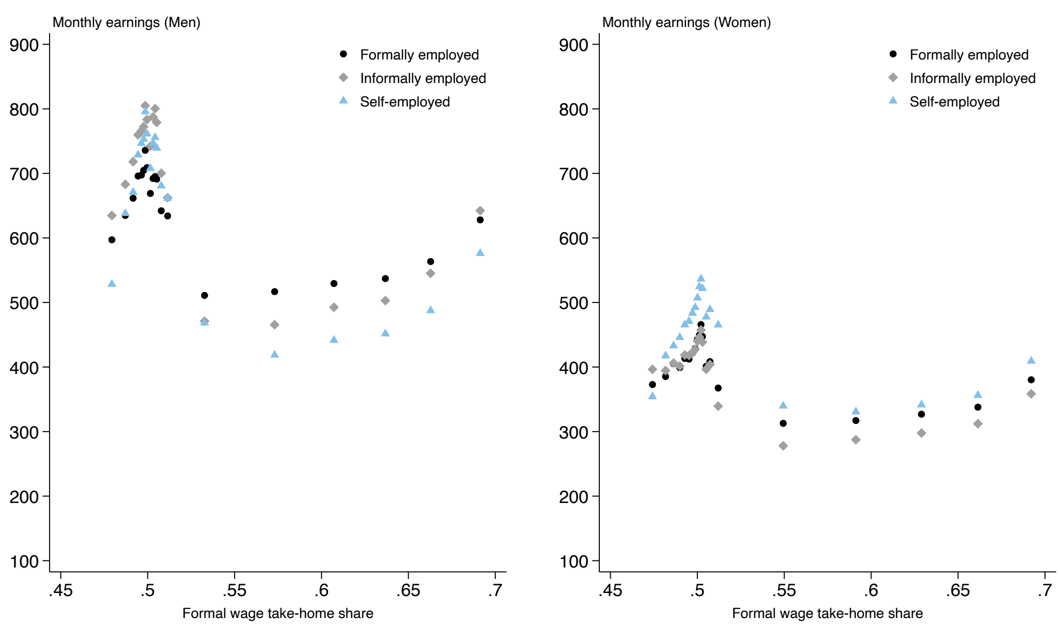
Notes: This figure presents education-specific versions of Figures 9 and C.10. Average wage take-home shares are calculated at the local labor market level (microregion x occupation) following equation C.23, using region-specific estimates of $1/\tilde{\eta}$, demographic-specific estimates of $1/\tilde{\rho}$, and the pooled estimate for $1/\tilde{\theta}$. For Panel A, average take-home shares are aggregated at the microregion level using formal sector wage bill as weights.

Figure C.15: Formal wage take-home share in dual labor markets: Heterogeneity by gender

Panel A: 1991 distribution across microregions



Panel B: Wages and wage take home-shares



Notes: This figure presents gender-specific versions of Figures 9 and C.10. Average wage take-home shares are calculated at the local labor market level (microregion x occupation) following equation C.23, using region-specific estimates of $1/\tilde{\eta}$, demographic-specific estimates of $1/\tilde{\rho}$, and the pooled estimate for $1/\tilde{\theta}$. For Panel A, average take-home shares are aggregated at the microregion level using formal sector wage bill as weights.

Table C.1: Wage markdowns in dual labor markets: Worker preference parameters and weights

Parameter	Definition	Estimation			Statistically signif. heterogeneity	
		Data	Tables	IV estimate	Range	Detected by
(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1/\eta$	Within-market cross-firm inverse elasticity of substitution	RAIS + Tariffs	C.2	0.990	0.458 - 1.029	Region
Ω	Bias in $1/\eta$ due to expected involuntary separation into informal wage work	RAIS + Census + Tariffs	C.4	0.0221	0.0279 - 0.0354	Age, gender
$1/\tilde{\rho}$	Inverse elasticity of substitution between wage work and self-employment	Census + Tariffs	C.6 and C.8	0.469	0.303 - 0.935	Age, educ, gender
$1/\tilde{\theta}$	Cross-market inverse elasticity of substitution	Census + Tariffs	C.6	1.191	-	-
Directly measured labor market equilibrium objects ("weights")						
$HHI_{\overline{g}m}$	*Expected* wage bill concentration among formal firms in market m.	RAIS + Census				
s_m	Wage work sector wage bill share as fraction of overall wage bill in market m.	RAIS + Census				

Notes: Column (3) lists the datasets used; column (6) lists the heterogeneity ranges; column (7) lists the heterogeneity dimensions. A market is a microregion × 2-digit occupation pair.

Table C.2: IV estimates of $1/\eta$ and its heterogeneity across major regions

	$\Delta \ln w_{z\overline{g}m}$				
	(1)	(2)	(3)	(4)	(5)
	Main	NE	SE	NE + N	SE + S + CW
$\Delta \ln l_{z\overline{g}m}$	0.990***	0.458*	1.029***	0.403*	1.005***
	(0.181)	(0.233)	(0.150)	(0.207)	(0.170)
First-stage F	82.10	18.10	112.6	19.84	87.93
Observations	847391	99885	530079	114961	732430

Notes: This table shows IV estimates of $1/\eta$, the within-market cross-firm inverse elasticity of residual labor supply in Section C.1 (and in Section C.1 if $\Omega = 0$) and its heterogeneity by Brazil's major regions. The sample includes all formal sector firms in RAIS in 1991 and 1997. Each observation is a firm X local labor market cell. A local labor market is a microregion x 2-digit occupation pair. All regressions include local labor market fixed effects. The instruments are firm-level import reductions from Section C.1. Column (1) replicates the average elasticity from Section C.1. Column (2) re-estimates Column (1) with a microregion fixed effect instead of a microregion x 2-digit occupation pair fixed effect. Column (3) re-estimates Column (1) with a 2-digit occupation fixed effect instead of a microregion fixed effect. Columns (4)-(7) re-estimates Column (1) limiting the sample to microregions within major regions: NE (Northeast), SE (Southeast), N (North), S (South), and CW (Center West). Limiting the sample to the N, S, or CW alone yields weak first stages and statistically insignificant results, hence why Columns (4)-(5) present results pooling them with Brazil's largest regions in terms of population (Northeast and Southeast). Standard errors are clustered two-ways by microregion and 2-digit occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Heterogeneous inverse elasticity by worker demographics

	Δ firm log wage premium in local market				
	(1)	(2)	(3)	(4)	(5)
Δ Firm log employment in local market	0.990	1.083	1.104	1.008	1.212
	(0.089)	(0.145)	(0.088)	(0.088)	(0.150)
Δ Firm log employment in local market		-0.0023			-0.00263
x (Baseline female share of employment)		(0.003)			(0.003)
Δ Firm log employment in local market			-0.0176		-0.0182
x (Baseline college-educated share of employment)			(0.003)		(0.003)
Δ Firm log employment in local market				-0.000814	0.000129
x (Baseline over-40-years-old share of employment)				(0.001)	(0.002)
Observations	855,104	855,104	855,104	855,104	855,104

Notes: Standard errors clustered by firm in parentheses. All specifications estimated by 2SLS using the change in log tariff and its interaction with the baseline demographic share as instruments. Baseline demographic shares are measured at the firm-market level in 1991 and scaled by 100. All regressions include LLM fixed effects and are weighted by baseline market employment.

Table C.4: IV estimates of Ω and its heterogeneity by demographic groups

	$\Delta \ln(1 + p_{z\bar{s}m}\sigma^c_{z\bar{s}m})$			
	(1)	(2)	(3)	(4)
	All	By gender	By education	By age
$\Delta \ln l^c_{z\bar{s}m}$	0.0331**			
	(0.0130)			
Men		0.0332**		
		(0.0132)		
Women		0.0354**		
		(0.0162)		
Primary education			0.0119	
			(0.0260)	
Secondary education			-0.0409	
			(0.0574)	
Tertiary education			0.0416	
			(0.0383)	
Young (18-29)				0.0344**
				(0.0144)
Middle (30-49)				0.0351***
				(0.0134)
Old (50-64)				0.0279*
				(0.0166)
First-stage F	1.608	3.250	2.757	6.155
Anderson-Rubin F		4.372	24.68	4.124
Observations	395305	395305	395305	395305

Notes: This table shows IV estimates of Ω, the bias term in IV estimates of the within-market cross firm elasticity of substitution in the model in Section C.1 if the extended model is true, and its heterogeneity by worker characteristics. The sample includes all formal sector firms in RAIS in 1991 and 2000, merged at the microregion X demographic cell X year level to the corresponding census data. Each observation is a firm X microregion X demographic cell (gender X education group X age group dummies). All regressions include firm, microregion, and demographic cell fixed effects. Expected informal-formal wage gap is calculated separately by firm, microregion, and demographic cell as $p_{z\bar{s}r}\sigma^c_{z\bar{s}r}$. The first term, $p_{z\bar{s}m}$, is the within-year probability of *involuntary* separation from firm z. The second, $\sigma^c_{z\bar{s}m} \equiv (w^o_m - w_{z\bar{s}m})/w_{z\bar{s}m}$, is the monthly earnings gap between the local informal sector and firm z's formal wage for that demographic cell. Monthly earnings gaps are calculated by first converging all reported earnings to 2000 constant Reais. $p^c_{z\bar{s}m}$ is calculated using separations between January 1 and December 30 of each year. Firm total formal employment is measured as of December 31 of each year. The instrument for the IV estimate is the interaction between firm-level import reductions and regional tariff reductions, interacted with demographic group dummies and firm baseline formal employment. Regional tariff reductions are microregion-level exposure to 1990-1994 import tariff reductions from Dix-Carneiro and Kovak (2017) and differ by demographic group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Sensitivity of Ω and to the value of unemployment insurance

	$\Delta \ln(1 + p_{z\bar{s}m}\sigma^{c}_{z\bar{s}m})$		
	(1)	(2)	(3)
	OLS	Without UI	With UI
$\Delta \ln l^{c}_{z\bar{s}m}$	0.000443***	0.0331**	0.0221**
	(0.000135)	(0.0130)	(0.00856)
First-stage F		1.608	1.608
Observations	407862	395305	395305

Notes: This table shows OLS and IV estimates of Ω, the bias term in IV estimates of the within-market cross firm elasticity of substitution in the model in Section C.1 if the extended model is true, and its heterogeneity by worker characteristics. The sample includes all formal sector firms in RAIS in 1991 and 2000, merged at the microregion X demographic cell X year level to the corresponding census data. Each observation is a firm X microregion X demographic cell (gender X education group X age group dummies). All regressions include firm, microregion, and demographic cell fixed effects. Expected informal-formal wage gap is calculated separately by firm, microregion, and demographic cell as $p_{z\bar{s}r}\,\sigma^{c}_{z\bar{s}r}$. The first term, $p_{z\bar{s}m}$, is the within-year probability of *involuntary* separation from firm z. The second, $\sigma^{c}_{z\bar{s}m} \equiv (w^{o}_{r} - w_{z\bar{s}m})/w_{z\bar{s}m}$, is the monthly earnings gap between the local informal sector w^{o}_{r} and firm z's formal wage for that market and demographic cell. Column (3) substitutes $w^{o}_{r,UI} = (4 * w_{z\bar{s}m} + 8 * w^{o}_{r})/12$ for the informal sector wage to account for unemployment insurance benefits of 4-months salary. Monthly earnings gaps are calculated by first converging all reported earnings to 2000 constant Reais. $p_{z\bar{s}m}$ is calculated using separations between January 1 and December 30 of each year. Firm total formal employment is measured as of December 31 of each year. The instrument for the IV estimate is the interaction between firm-level import reductions and regional tariff reductions, interacted with demographic group dummies and firm baseline formal employment. Regional tariff reductions are microregion-level exposure to 1990-1994 import tariff reductions from Dix-Carneiro and Kovak (2017) and differ by demographic group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6: IV Estimates of $1/\tilde{\rho}$ and $1/\tilde{\theta}$

	(1)
	$\Delta \ln W^c_{\bar{s}m}$
$\Delta \ln(L^c_{\bar{s}m}/L^c_m)$	0.469***
	(0.0805)
$\Delta \ln(L^c_m/L^c)$	1.191*
	(0.619)
First-stage F ($1/\rho$)	66.57
Anderson-Rubin F ($1/\rho$)	60.88
First-stage F ($1/\theta$)	3.207
Anderson-Rubin F ($1/\theta$)	35.33
Observations	8055

Notes: This table shows second stage estimates from an instrumental variables regression that estimates the inverse elasticity of substitution between wage work and self-employment $1/\tilde{\rho}$ as the coefficient on $\Delta \ln(L^c_{\bar{s}m}/L^c_m)$, and the cross-market elasticity of substitution $1/\tilde{\theta}$ as the coefficient on $\Delta \ln(L^c_{\bar{s}m}/L^c_m)$. The sample includes 486 microregions and 18 demographic cells defined by 8 major demographic groups (2 by gender) x (3 by education) x (3 by age). The outcome variable is the 1991-2000 change in log residual real monthly earnings among individuals employed in wage work, either formally or informally, for each demographic group. The dependent variables are (1) the 1991-2000 change in log share of wage work employment in a microregion for each demographic cell; and (2) the 1991-2000 change in the log share of microregion total employment relative to national employment for each demographic cell. The instruments are group-specific Regional Tariff Reductions interacted with demographic group dummies and with the 1991 formal share of employment in the microregion. The regression includes region fixed effects for each of Brazil's five major regions and is weighted by each cell's 1991 microregion population. Log residual real monthly earnings are conditional on flexible controls for gender, education, and age. Real monthly earnings are based on the IPCA deflator and are expressed in 2000 reais. Standard errors in parentheses are clustered by microregion. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7: Estimates of $1/\tilde{\rho}$ and $1/\tilde{\theta}$: Alternative instruments

	(1)
	$\Delta \ln W_{\bar{s}m}$
$\Delta \ln(L_{\bar{s}m}/L_m)$	0.120
	(0.133)
$\Delta \ln(L_m/L)$	1.111***
	(0.405)
First-stage F for $\Delta \ln(L_{\bar{s}m}/L_m)$	38.19
Anderson-Rubin F for $\Delta \ln(L_{\bar{s}m}/L_m)$	49.92
First-stage F for $\Delta \ln(L_m/L)$	1.965
Anderson-Rubin F for $\Delta \ln(L_m/L)$	2.454
Observations	478

Notes: This table shows second stage estimates from an instrumental variables regression that estimates the inverse elasticity of substitution between wage work and self-employment $1/\tilde{\rho}$ as the coefficient on $\Delta \ln(L_{\bar{s}m}/L_m)$, and the cross-market elasticity of substitution $1/\tilde{\theta}$ as the coefficient on $\Delta \ln(L_{\bar{s}m}/L_m)$. The sample includes 486 microregions. The outcome variable is the 1991-2000 change in log residual real monthly earnings among individuals employed in wage work, either formally or informally, in each microregion. The dependent variables are (1) the 1991-2000 change in log share of wage work employment in a microregion; and (2) the 1991-2000 change in the log share of microregion total employment relative to national employment. The instruments are Regional Tariff Reductions interacted with (a) each microregion's log maximum distance to the nearest labor law enforcement office, borrowing the estimation strategy from Ponczek and Ulyssea (2022); and (b) each microregion's 1991 share of employment that was formal. The regression includes region fixed effects for each of Brazil's five major regions and is weighted by each cell's 1991 microregion population. Log residual real monthly earnings are conditional on flexible controls for gender, education, and age. Real monthly earnings are based on the IPCA deflator and are expressed in 2000 reais. Standard errors in parentheses are clustered by microregion. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8: IV Estimates of $1/\tilde{\rho}$ and its heterogeneity by demographic groups

	$\Delta \ln W^c_{\bar{s}m}$			
	(1)	(2)	(3)	(4)
	All	By gender	By education	By age
$\Delta \ln(L^c_{\bar{s}m}/L^c_m)$	0.482***			
	(0.0594)			
Men		0.660***		
		(0.186)		
Women		0.390***		
		(0.122)		
Primary education			0.0686	
			(0.0668)	
Secondary education			0.460***	
			(0.177)	
Tertiary education			0.935***	
			(0.307)	
Young (18-29)				0.850***
				(0.157)
Middle (30-49)				0.355***
				(0.100)
Old (50-64)				0.303***
				(0.104)
First-stage F	52.64	90.64	33.53	30.18
Anderson-Rubin F	52.64	105.1	44.43	44.89
Observations	8055	8055	8055	8055

Notes: This table shows second stage estimates from instrumental variables regressions that estimate the inverse elasticity of substitution between wage work and self-employment $1/\tilde{\rho}$ jointly or separately by demographic groups. The sample includes 486 microregions and 18 demographic cells defined by 8 demographic groups (2 by gender) x (3 by education) x (3 by age). The outcome variable is the 1991-2000 change in log residual real monthly earnings among individuals employed in wage work, either formally or informally, for each demographic cell. The dependent variable is the 1991-2000 change in log share of wage work employment in a microregion for each cell. The instruments are cell-specific Regional Tariff Reductions interacted with group dummies and with each cell's 1991 formal share of employment in the microregion. All regressions include microregion fixed effects. Column (1) reports a pooled regression coefficient. Columns (2)-(4) report coefficients on the dependent variable interacted with dummies for each of the 8 major demographic groups. Columns (1) and (2) are weighted by each cell's 1991 microregion population. Columns (3) and (4) are unweighted due to substantial heterogeneity in workforce composition by education and age across microregions, resulting in larger and noisier estimates. Log residual real monthly earnings are conditional on flexible controls for gender, education, and age. Real monthly earnings are based on the IPCA deflator and are expressed in 2000 reais. Standard errors in parentheses are clustered by microregion. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.