Monopsony and Gender

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March 22, 2023

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Abstract

I investigate the role of labor market power in driving the gender wage gap in Brazil. I exploit establishment-level demand shocks induced by the end of the Multi-Fiber Arrangement to show that women are substantially less likely than men to separate from their employer following a wage cut. The implied gender difference in monopsony power generates an 18pp wage gap among equally productive workers, explaining half the observed gender wage gap. To study the source of monopsony by gender, I build and estimate a discrete choice model where employers have more monopsony power over women if (i) women strongly prefer their specific employer, all else equal (horizontal difference), or (ii) women have fewer good employers (vertical difference). Of the 18pp gender gap due to monopsony, I estimate 10pp as driven by women's preference for a specific employer and 8pp by the concentration of good jobs for women in the textile industry. This concentration in turn reflects the concentration of amenities/disamenities across sectors rather than gender-specific comparative advantage. My findings demonstrate that although the textile industry provides women desirable jobs, this desirability confers its employers with higher monopsony power. By contrast, desirable jobs for men are not similarly concentrated.

Introduction

Across most labor markets, women are paid less than men. While these gender wage gaps could emerge purely from productivity differences or taste-based discrimination, they could also reflect lower competition in women's labor market. Indeed, when Joan Robinson (1933) first introduced the concept of monopsony, she conjectured that "a type of discrimination may arise when men and women of equal efficiency are paid at different rates ... if their conditions of supply are different". In developing countries, where a lack of safety, sparse job networks, or the notion that certain work is "inappropriate" for women can limit women's mobility even more than in developed economies, we may naturally expect monopsony to be an even more prominent force generating their large observed gender wage gaps (35% in India, 28% in Brazil, and 22% in Mexico, ILO (2018)). There is, however, surprisingly little evidence of either the extent or the sources of differential monopsony by gender in any setting, but especially in developing countries.

To fill this gap, I study gender differences in monopsony power in the Brazilian textile and clothing manufacturing industry. This industry is among men and women's largest industrial employers in the developing world, with over 90 million workers, over half of them women (ILO, 2022). I make three contributions. First, I quasi-experimentally estimate men and women's firm-specific elasticities of labor supply, which govern markdowns in monopsony models. Exploiting firm-specific demand shocks induced by the end of the Multi-Fiber Arrangement, I find that women are substantially less likely than men to leave employers that lower their wage. The resulting gender difference in monopsony power would generate an 18pp gender wage gap among equally productive workers. To diagnose the source of differential monopsony by gender, I next build and estimate a model where higher monopsony power over women has two intuitive sources: (i) women strongly prefer their specific employer, all else equal (such as due to commuting frictions that horizontally differentiate employers) and (ii) women have fewer good employers (vertical differentiation). I find that of the 18pp gender gap due to monopsony, 10pp is driven by women's preference for their specific employer and 8pp by the concentration of good jobs for women in the textile industry. Surprisingly, this concentration reflects the concentration of female-focused amenities in textiles rather than gender differences in productivity. Finally, I study the prospect for policy to remedy the monopsony-induced gender wage gap by calibrating the model with my estimates and counterfactually amending its determinants in turn (amenities, skills, and safety).

For data, I use rich employer-employee linked records covering the universe of formal employment in Brazil, merged with customs records detailing establishment-level exports, and the text of all collective bargaining agreements detailing establishment-level amenities.

I begin with the quasi-experiment. Estimating firm-specific supply elasticities requires a firm-level instrument for the wage (a demand shock). I exploit such variation due to the end of the Multi-Fiber Arrangement in 2005, which lifted decades-long export quotas on very specific textile and clothing products from China to the United States, Canada, and the EU. In a single year, Chinese exports of quota-bound products grew 270% while competing Brazilian exports fell 20%. Because MFA rules deemed virtually identical Chinese products quota-bound and quota-free, the Brazilian

workers producing these products were also virtually identical. For example, while "men's shirts of cotton" and "women's skirts of wool" were quota-bound, "men's t-shirts of cotton" and "women's trousers of wool" remained quota-free. Unsurprisingly, then, the workers manufacturing exposed and unexposed products were indistinguishable at baseline—in wage levels, 4-digit occupations, and geographies (of 557).

My first takeaway is that employers possess higher monopsony power over women than over men. The MFA expiration causes a 6pp decline in both men and women's wages, but men are substantially more likely to switch jobs as a result such that their wages eventually recover whereas women's remain persistently lower. Five years later, treated men are 10pp more likely to have exited their employer compared to 5pp among women. Several pieces of evidence establish monopsony power as driving these findings. An obvious objection is that the findings reveal gender differences in comparative advantage instead of monopsony, i.e., imperfect substitutability between exposed and unexposed women but not men. I rule this out by showing the stability of estimates when leveraging variation in treatment among identically skilled workers — tailors. I rule out gender differences in forced separations by showing that most transitions are to new employers (as opposed to unemployment) and correspond with full wage recovery.

Although the MFA shock is firm-specific, estimating the elasticity of residual labor supply that governs markdowns requires ruling out wage spillovers that in turn alter labor supply to the originally shocked firm (the exclusion restriction).[1] I rule out strategic wage spillovers via a novel test from the exchange rate pass-through literature (Amiti et al., 2019). Its key insight is that spillovers operate by changing markdowns. As workers exit China-competing employers, non-China-competing employers reduce their pay below marginal product. I show that for any structure of competition among employers (including oligopsony) and invertible labor supply system (including nested CES) I can thus estimate spillovers by regressing an employer's wage change on a sufficient statistic for changes to its competitors' wages, controlling for the change in its own marginal product. Using the MFA shock to provide both a market-level instrument for the first and an employer-level instrument for the second, I find no spillovers. I interpret this as evidencing the MFA's small size—it affects fewer than 2% of establishments.[2] Per my elasticity estimates, gender differences in monopsony power generate an 18pp gender wage gap among equally productive workers, explaining half the observed gender wage gap.[3]

To probe the source of differential monopsony by gender, I next develop a model motivated by four empirical results. First, I find that workers in the MFA's aftermath are most mobile across employers within the industry, then across industries, and finally across geography. Second, men exit industries substantially more than women. Third, women are disproportionately employed in fewer industries. Over 30% of women work in only two industries, 60% in their top five, and 80%

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[1]The elasticity of residual labor supply governing markdowns in the firm's FOC is the partial equilibrium elasticity with respect its own wage, holding constant competitor responses.

[2]My evidence remains consistent with oligopsony. As predicted in standard oligopsony models, own marginal product shocks have incomplete pass-through that falls with employer size.

[3]Average elasticities mask heterogeneity by employer size in both the model and data. Aggregating these elasticities to an industry-level average yields the 18pp gender gap.

in their top ten, compared to 10%, 35% and 40% among men. Industries thus seemingly differ in gender-specific amenities or comparative advantage. Finally, gender differences in skill (measured via O*NET or education) fail to explain differential exit by gender, suggesting that comparative advantage does not drive gender differences in monopsony power.

Pursuant to these results, the model features three nests (location, industry, employer) and horizontal and vertical differences across industries as sources of monopsony power. Employers post wages and amenities and workers choose their highest utility employer subject to an idiosyncratic preference draw. Workers are most mobile within an industry, then across industries, and finally across geography, with mobilities governed by three elasticities of substitution: across employers within an industry (η_g), across industries (θ_g) and across geography (λ_g). Because workers flock to relatively desirable (high wage and amenity) employers, these employers are larger in their nest — good textile employers are large in the industry, and good industries large in their geography. Employers compete in a Cournot oligopsony.[4]

Small employers have monopsony power due to workers' match-specific preferences alone whereas large employers have higher monopsony power due to fewer (good) alternatives. Estimated elasticities validate this important prediction— elasticities fall as employers grow large, especially when the textile industry is also large.

A key implication of the model is that a few sufficient statistics quantify the contribution of horizontal and vertical components to the markdown on the average worker's wage. First, the three elasticities of substitution (η_g, θ_g, and λ_g), govern horizontal preferences. Second, within-industry concentration reflects vertical differences and is high when fewer firms in the industry offer good jobs. It lowers markdowns because they compete tightly with less desirable within-industry employers ($\theta_g < \eta_g$). Finally, cross-industry concentration is high when fewer industries offer desirable jobs (vertical amenities or productivity). It lowers markdowns because these industries compete tightly with less desirable industries in their geography ($\lambda_g < \theta_g$). Estimation employs moments from the labor supply system. I directly observe concentration.

My second takeaway is that both match-specific reasons and the concentration of women's jobs in the textile industry generate gender differences in monopsony power. By themselves, match-specific reasons (η_g) prevent workers from exiting atomistic employers even when their local labor market abounds with textile jobs. This generates a 10pp gender wage gap, with the remaining 8pp attributable to concentration. Concentration in turn reflects not within, but, rather, higher cross-industry concentration. Within the industry, markets are similarly concentrated (men's Herfindahl Hirschmann Index across textile firms is, if anything, *higher*). However, the textile industry comprises a much larger share of women's labor market (11% vs 3% for men). In textiles, this concentration contributes 10pp to the monopsony-induced gender wage gap. More broadly in the economy, women's concentration in fewer industries contributes 12pp to the gender wage gap.

My third takeaway is that women's higher concentration in textiles is almost entirely at-

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[4]The model is similar to Berger et al. (2022), but departs in featuring three nests and amenities, both of which emerge as key features driving differential monopsony by gender.

tributable to non-wage amenities rather than gender differences in comparative advantage. To infer amenities I use the model's insight that high wages or amenities draw workers to an industry. I use this structure to back out non-wage amenities given observed wages and industry size. I separately estimate gender-specific productivity across industries via standard production function methods (Ackerberg et al., 2015).[5] Remarkably, I find that productivity differences and gender wage gaps predict a much smaller fraction of women in the textile industry than observed (by 6 times). Non-wage amenities therefore explain textile's prominence in women's labor market.

Differential monopsony by gender thus has two intuitive sources: women prefer their specific employer even when their labor market abounds with opportunity; they are also tethered to relatively desirable textile jobs. But what drives these match-specific constraints and sector-specific amenities?

I find that safety importantly predicts the former and amenities in collective bargaining contracts importantly predict the latter. Given Brazil's highest rate of violent crime in the world (UNODC), one might expect women's labor supply to be less elastic if unsafe commutes make proximate employers appealing. I show that low safety (above 75th percentile homicide rate) indeed predicts lower labor supply elasticities among women but not men. Exploiting the text of all collective bargaining agreements, I show that female-focused amenities in contracts strongly positively correlate with model-inferred amenities.[6]

Having uncovered key drivers of differential monopsony by gender—amenities, skills, and safety—I finally study the prospect for policy to remedy the monopsony-induced gender wage gap via counterfactual changes to each. Counterfactuals account for the general equilibrium effects that crucially underpin equity and efficiency. Consider, for example, the effect of leveling cross-industry gender gaps in productivity: as non-textile industries raise compensation, women flock to them from textiles, which erodes the monopsony power of large textile employers. Women's wages rise on account of lower monopsony, and because they reallocate to large and productive employers whose monopsony wedge disproportionately falls. Men's wages fall as they reallocate downward.[7] Productive efficiency rises as large employers expand (Baqaee and Farhi, 2020).

By way of benchmark, I estimate an 8pp reduction in the gender wage gap from leveling gender gaps in sector-specific amenities. By contrast, leveling gender gaps in productivity only achieves half this gain (4.1pp). In a policy-relevant counterfactual, I find that leveling gender gaps in contracted amenities reduces the gender wage gap by 4.5pp. Finally, improving safety to enhance women's

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[5]Specifically, I assume a Cobb-Douglas production function in capital and labor, with labor a CES aggregation of male and female workers. I estimate women's CES productivity shifter across industries. As a caveat, pending a Brazilian data application, I estimate productivity in two other developing countries, India and Chile, and use the average β estimate across the two.

[6]I follow Corradini et al. (2022) to define "female-focused" amenities as those predicting women's revealed preference value for an employer. They include provisions governing maternity protections, childcare, and absences, among others. The correlation between contracted and model amenities need not be causal. Therefore, the counterfactuals employ a quasi-experimental estimate of the rate at which Brazilian women flock towards employers that improve contracted amenities (Corradini et al., 2022).

[7]Men reallocate to smaller and less productive employers whenever they are substitutes in production with women, as I assume.

cross-employer mobility reduces the monopsony gap by 3.6pp. Across scenarios, wage gains for women account for 70% of the effect whereas wage losses for men account for 30%.

My fourth and final takeaway is, therefore, that improving non-traditional jobs for women can spur positive spillovers by reducing monopsony in women's current jobs. Per the magnitudes reported above, these improvements must necessarily feature not just within, but, importantly, outside contracts—by combating sexual harassment in the workplace, instituting flexible work arrangements, or expanding maternity protections. While some interventions represent unambiguous improvements (combating sexual harassment), others likely entail costs (enhancing flexibility). I do not speak to the direct costs of these interventions but evidence two offsetting gains. First, I show that equity begets efficiency. Because upgrading non-textile amenities disproportionately erodes the monopsony power of large employers, their expansion increases productive efficiency in textiles. Second, Corradini et al. (2022) evidence an inefficient underprovision of female-focused amenities in Brazil — the authors observe no tradeoffs (in wages, employment, or profits) following a union reform that institutes large improvements in female-focused amenities among 20% of the formal labor force. The costs of reducing differential monopsony by gender may therefore not be prohibitive.[8]

Related Literature   This paper builds on a large literature studying imperfect competition in labor markets (reviewed in Manning (2003), Manning (2011), Card et al. (2018), Sokolova and Sorensen (2021), Manning (2021), Card (2022)), including in developing countries (Tortarolo and Zarate (2018), Felix (2022)). Most closely related are papers examining gender gaps due to imperfect competition (Card et al. (2016), Morchio and Moser (2021), Caldwell and Oehlsen (2022)), and especially those estimating men and women's firm-specific labor supply elasticities using wage variation at neighboring firms (Barth and Dale-Olsen (2009), Hirsch et al. (2010), Ransom and Sims (2010), Webber (2016)). I make four contributions to this literature. First, I quasi-experimentally show that gender differences in monopsony power can generate large gender wage gaps in an important industrial setting in a developing country (18% of the observed 35%). Relative to prior work, the advantage of a quasi-experiment is that I compare as-if-identical workers (independence condition) and rule out market-level changes in supply as driving results (exclusion restriction). The gap I estimate is substantially larger than found in developed economies (for example, Webber (2016) estimates a 3.3% gap in the US). Second, I identify employer differentiation as importantly driving differential monopsony by gender. Consistent with this, Caldwell and Oehlsen (2022) experimentally find no gender difference in monopsony power among US-based Uber drivers, perhaps owing to its similarity with Lyft. Third, I show that traditional measures of labor market concentration, the within-industry or within-occupation Herfindahl Hirschmann Indices can misdiagnose gender differences (e.g., as measured in Azar et al. (2022), Berger et al. (2022), Felix (2022), Rinz

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[8]Two findings evidence employers exercising their higher monopsony power over women. First, gender wage gaps rise with employer size in industries that are large in women's labor market. Second, shocks to marginal product have lower pass-through to women than men's wages. This is exactly as predicted when large, oligopsonistic textile employers are larger in women's overall labor market.

(2022)). While this HHI is similar by gender (or lower for women) across nearly all Brazilian industries, women's labor market exhibits higher concentration due to their disproportionate clustering in fewer industries. New, data-driven methods may uncover more useful labor market boundaries within which to measure concentration to diagnose market power (e.g., Nimczik (2020), Schubert et al. (2021)). Finally, I bring a test of strategic price spillovers from trade (Amiti et al., 2019) to labor markets. Valid for any structure of competition and invertible labor supply system, it can uncover oligopsony (or its lack thereof) in future work.

I link the study of gender wage gaps (reviewed in Blau and Kahn (2017)), especially in developing countries (Fletcher et al., 2017), to imperfect competition. Several papers decompose these gaps into a component "explained" by gender differences in observable characteristics, thought to reflect competitive explanations, and an "unexplained" component, potentially reflecting discrimination. I show that even among observably different workers, as men and women often are, gender wage gaps can reflect differential monopsony in addition to any productivity difference. Finally, my findings add to a burgeoning literature examining the causes of low female labor force participation in developing countries. Recent work identifies the importance of limited autonomy over own earnings (Field et al., 2021), safety (ILO and Gallup, 2017), and behavioral biases (McKelway, 2018). I highlight the role of a different market failure — disproportionate monopsony power over women — in keeping female employment below its competitive market levels.

Outline   Section 1 describes the MFA shock and data. Section 2 provides empirical evidence of employers' higher monopsony power over women. Section 3 documents several empirical facts to motivate key model ingredients. Section 4 develops the model microfounding differential monopsony by gender. Section 5 estimates elasticities of labor supply that govern gender differences in monopsony power and Section 6 estimates the sufficient statistics diagnosing its sources. Section 7 studies the effect of counterfactual policies on the monopsony-induced gender wage gap. Section 8 concludes.

1   Empirical Setting

1.1   Multi-Fiber Arrangement

For three decades spanning 1974 to 2004, the Multi-Fiber Arrangement (MFA) restricted textile and clothing exports from developing to developed nations (the United States, EU, and Canada) by deeming these products outside the purview of multilateral trade negotiations at the World Trade Organization (WTO). In 1994, however, these quotas were finally abolished as countries gathered at the WTO's Uruguay Round agreed to gradual ease them over four phases beginning respectively on 1 January 1995, 1998, 2002 and 2005. In practice, however, countries reserved the most restrictive quotas for removal in the MFA's 2005 phase, which integrated 49% of trade volume and 60% of 10-digit HS product codes in the textile and clothing categories (Appendix Table C2, Brambilla et al. (2010), Khandelwal et al. (2013)).

MFA quotas historically bound Chinese exports over those from other developing countries. Whereas over 60% of Chinese products faced quota restrictions from the US, this fraction in Brazil was only 14%. Moreover, the "fill-rate", or share of quota limits actually exported, averaged over 80% in China compared to only 13% in Brazil.[9]

Upon the MFA's expiration, Chinese exports of quota-bound products thus grew dramatically (over 270%) between 2005 and 2006 (Figure 1, Panel A), with competing Brazilian exports declining by 20% (Panel B). This 2005 ending serves as a negative, firm-specific demand shock to the subset of Brazilian employers exporting products that were hitherto-quota-bound in China. I use this demand shock to trace out men and women's firm-specific labor supply elasticities.

The empirical setting offered by the MFA is appealing for several reasons. First, because MFA rules required importers to retire quotas on very similar products in each phase, treated (quota-bound in China) and comparison (quota-free in China) products, and, thereby, the Brazilian workers manufacturing them were indistinguishable at baseline (independence condition). Specifically, in each phase countries had to retire quotas on some products in each major textile and clothing category — yarn, fabrics, made-up textile products, and clothing, comprising a non-trivial fraction of 1990 volumes: 16%, 17%, 18%, and 49%. As a result, quota-bound products in China, such as "men's shirts of cotton" and "women's skirts of wool", required the same skills to manufacture as quota-free products, such as "men's t-shirts of cotton" and "women's trousers of wool". The Brazilian workers manufacturing the two sets of products were as-if-randomly assigned.

Second, the MFA shock plausibly leaves the residual labor supply curve to treated firms unchanged (exclusion restriction) by ushering only a small shock in the local textile and clothing labor market. In the average geography, only 2% of establishments and 10% of employment are exposed to the shock.[10] Importantly, because the MFA's impact varies across geography, I can employ this market-level variation to directly examine the extent of wage spillovers that would alter a firm's residual labor supply curve (Section B).[11]

Finally, because the sheer magnitude of the MFA's effect on Chinese exports was unanticipated, it provides sharp variation in 2005. Expert predictions of Chinese export growth following the MFA expiration ranged from 6 percent (Diao and Somwaru, 2001) to 104 percent (Rivera et al., 2003) still far below the realized 270 percent growth rate. Not anticipating the large positive shock to Chinese and adverse shock to their own exports, treated Brazilian exporters neither systematically changed the composition of their pre-period exports nor their wages and employment (Figure 4).

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[9]Even prior to 2005, quota limits on Chinese exports were eased at a much slower pace than those in other developing countries. In addition, Chinese exporters could not shift quota allocations across years or categories of goods (Brambilla et al., 2010).

[10]Of 557 microregions.

[11]Intuitively, I test for strategic wage spillovers by comparing wages at non-MFA-treated establishments in geographies with many versus fewer MFA-treated establishments.

1.2 Data

I link three rich sources of data: (i) bindingness of MFA quotas at the product-level from a database compiled by the US Office of Textiles and Apparel; (ii) exports at the establishment-level from customs records at Brazil's foreign trade department; and (iii) worker outcomes from linked employer-employee records on the universe of formal sector workers.

For product-wise information on MFA quotas in China, I use two datasets from the US Office of Textiles and Apparel (OTEXA).[12] The first report quota limits, "fill-rates" or how much of the limit was actually exported, and the date of quota removal for each country with which the United States had bilateral quota arrangements. These data span the period from 1984 and 2004. MFA quotas either fully or partially cover 194 different MFA product groups each lying in one of four possible textile and clothing segments: yarn, fabrics, made-ups, and clothing. Examples of MFA groups include "yarns of different colors" and "women's and girls' trousers, breeches, and shorts (cotton)". A companion dataset links every 10-digit HS textile and clothing product with its corresponding MFA subgroup.

For establishment-level information on Brazilian exports I use customs data from the Brazilian foreign trade ministry known as *Secretaria Comércio Exterior* (SECEX). These data span the period between 2000 and 2009 and report annual information on each product exported by an establishment, including its value and destination. Product information is recorded at the 6-digit level, which encodes both product type and material, for e.g. "women's or girls' track suits of cotton" and "men's or boys' shirts of man-made fibers". I link exports to MFA quotas using HS codes and to employer-employee records using unique firm identifiers.For worker-level outcomes I use linked employer-employee records from Brazil's labor ministry known as *Relaçao Anual de Informacões Sociais* (RAIS), which cover the universe of formal sector workers. For each work spell, RAIS reports a worker's average monthly earnings, (6-digit) occupation, tenure, hours; worker characteristics like gender, age, and education; and establishment characteristics like location (municipality) and industry (6-digit).

I supplement these datasets with two others: O*NET data reveal skills employed in an occupation. These data are based on interviews with thousands of US-based workers and report the skill level (on a 1-8 scale) required to execute each of 35 skills in an 8-digit SOC occupation. Examples of skills include coordination, operation and control, and equipment maintenance, among others. I follow Maciente 2013 in using job titles to map SOC codes to Brazilian occupation codes.

Second, I uncover establishment-level amenities using the text of all collective bargaining agreements registered on the Brazilian Ministry of Labor's Sistema Mediador registry (Lagos, 2019). They report 137 different provisions offered by establishments, including maternity leave, childcare, worker safety, hazard pay, and work hours. I follow (Corradini et al., 2022) to define "female (male)-focused" amenities as those predicting women (men)'s revealed preference value for an employer (Table 2 in their paper).

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[12]These datasets were obtained from Brambilla et al. (2010) and are assembled using "U.S. trading partners' Expired Performance Reports" used by OTEXA to monitor MFA quota compliance.

Treatment definition   I define treatment using quotas imposed by the United States, as these were most binding on China. A textile and clothing product is treated if it was quota-bound in China in 2004 and in the comparison group if not. The sample comprises all HS codes with first two digits 61 (textile) or 62 (garments). MFA quotas were imposed at the subgroup level, comprising on average fifteen 10-digit-HS products. I consider a quota binding if its fill rate exceeds 90%, and assign each product the treatment status of its parent-subgroup. Because Brazilian export data is at the 6-digit level, I assign each 6-digit product the treatment status of its modal 10-digit product. Ultimately, this yields 181 treated and 680 comparison products of a total 861.

I expand this definition of treatment to establishments and their incumbent workers. An establishment is treated if its highest sales value exported product was quota-bound in China and in the comparison-group if quota-free. The definition is nearly unambiguous since over 50% of establishments export a single product and, if exporting multiple products, earn 80% of revenue from a single product. A worker is treated if employed at a treated establishment at baseline and in the comparison group if employed at a comparison establishment.

The treatment definition is robust to reasonable changes along three dimensions, using (i) the share of an establishment's sales under binding quota instead of its highest value export, (ii) an 85% fill rate to define bindingness, and (iii) a higher threshold of treated 10-digit-HS products within a 6-digit product.

1.3   Descriptive statistics

I first show that exposed and unexposed products and workers exhibit balance on baseline characteristics. Next, I show that the MFA shock has a small effect on aggregate employment across local textile and clothing labor markets.

Products: Treated and comparison products were similar in material and good type (Table 1). For example, while "men's shirts of cotton" and "women's skirts of wool" were quota-bound in China, "men's t-shirts of cotton" and "women's trousers of wool" were quota-free.

Workers: Unsurprisingly, then, the workers employed at two sets of establishments exhibit balance on baseline characteristics: wage levels, tenure, education, and age (Table 2). The women earned on average 560 Brazilian real per month, roughly equivalent in PPP terms to USD (879 USD PPP in 2022). They were on average 33 years old and had 4.3 years of tenure. About 75% were high school dropouts, 24% were high school graduates and 1% attended some college. The men earned on average 1096 Brazilian real per month. They were on average 32 years old, with 5.2 years of tenure. The men had obtained more years of education, with 67% being high school dropouts, 31% high school graduates, and 1% with some college. Treated and comparison workers are statistically indistinguishable on these observable margins.

Figure 2 (A) demonstrates overlap in treated and comparison workers' (4-digit) occupations. Over half of all women and 20% of men worked as tailors. The men inhabited a wider range of occupations, as spinning operators (9%), production line feeders (8%), and machine operators

(6%). Figure 2 (B) demonstrates overlap in geography (of 557 microregions).[13] Finally, workers had overlapping occupational transitions (Figure 2 (C)). Of those transitioning jobs, the share transitioning into any 4-digit occupation from treated employers is strongly positively correlated with that from comparison (0.9).

Size of shock: The MFA shock had small effects on aggregate employment in textile and clothing manufacturing. On average, about 2% of establishments and 10% of employment in a geography were exposed (Figure 3). Exposed establishments shed on average 10-20% of their workforce, with a small positive effect among the unexposed (Appendix Figure C2). On average about 0.2% of workers transitioned jobs, with little change in aggregate demand, and the shock was firm-specific.

2 Reduced form effects on wages and employment

I begin by establishing my main reduced form finding: the MFA's end spurs wage declines among both men and women but men are substantially more likely to exit in response such that their wages eventually recover whereas women's remain persistently lower even five years later. I rule out several competing explanations to show that lower separations indicate higher monopsony power over women. I conclude with implications for the gender wage gap.

2.1 Empirical Strategy

The following dynamic difference-in-differences (DiD) specification estimates reduced form effects on wages and employment:

$$Y_{it} = \alpha_i + \gamma_{mt} + \sum_{t=-3}^{5} \beta_t (D_i \times 1_{year=t}) + \lambda X_{it} + v_{it} \tag{1}$$

where i indexes a worker and t a year. The unit of observation is an incumbent worker tracked wherever she or he goes. The outcome Y_{it} is wages or exit. $1_{year=t}$ is an indicator equal to one in periods $t \in \{-3, 5\}$ relative to the MFA's end in 2005, D_i is a treatment indicator equal to one if a worker's baseline employer exports a treated product (quota-bound in China) and zero if a comparison product. Microregion-year fixed effects γ_{mt} control for location-specific shocks to the textile industry. v_{it} is an idiosyncratic error term. I compare treated women (men) with their comparison counterparts. To compare identically skilled workers, later specifications leverage variation in treatment within the same geography and occupation via occupation-geography-year fixed effects (X_{it}). Standard errors are clustered by establishment.[14] Since the MFA shock occurs

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[13]Although textile manufacturing is concentrated in hubs, the MFA shock is not. Appendix Figure **??** shows no correlation between the number of total and share of treated textile workers.

[14]The Bartik analogy for this clustering scheme is "exogenous shares", i.e. that establishments are shocked at random. As discussed, the shock is as-if-randomly assigned across workers. Clustering standard errors by worker leaves conclusions unchanged.

once and involves a binary treatment, the OLS twoway fixed-effects estimator is unbiased for the true ATT (De Chaisemartin and d'Haultfoeuille, 2020).[15]

The identifying variation in this regression occurs within the same worker, comparing outcomes in any year relative to $t = -1$, and within the same time period, comparing treated to comparison workers. The key identifying assumption is a parallel evolution in outcomes absent the MFA shock. While parallel evolution does not require workers to possess similar baseline characteristics, it may be implausible if workers differ in pre-treatment characteristics that predict the *dynamics* of wage growth or labor supply. I therefore both check for parallel trends in the pre-period and show similarity in levels.

The following pooled regression evaluates gender differences in treatment effects:

$$Y_{it} = \alpha_i + \gamma_{mgt} + \sum_{p \in \{1,2\}} \delta_p(D_i \times Post_p) + \sum_{p \in \{1,2\}} \beta_p(D_i \times Post_p \times F_i) + \lambda X_{it} + \epsilon_{it} \qquad (2)$$

With F_i indicating female, $Post_1$ an indicator for the first three post-MFA years (years 0 to 2), and $Post_2$ indicating the subsequent three years (years 3 to 5). γ_{mgt} represent microregion-gender-year fixed effects. β_p estimates gender differences in treatment effects. I pool time into these two periods because the dynamic DiD reveals temporal differences in treatment effects between them.

2.2 Results

Wages Figure 4 plots dynamic treatment effects on incumbent women (Panel A) and men's (Panel B) wages and Table 3 reports gender differences. There are no pre-trends. Immediately following the MFA's conclusion, both men and women's wages decline by 6% points compared to their labor market counterparts at comparison firms. The decline reflects both a decline in treated workers' nominal earnings and slower wage growth relative to the comparison group. The treatment effect of the likelihood of a nominal wage decline relative to $t = -1$ is 5.3% among women and 6% among men (Appendix Table C3).[16] Hours remain unchanged (Appendix Figure C3). Over time, I find that treated men's wages fully recover relative to the comparison group whereas women's wages remain persistently lower (3.6% points by year six).

Retention Figure 4 plots the dynamic treatment effects on incumbent workers' likelihood of retention at their baseline (2004) employer (Panel C for women, and Panel D for men). Treated men are substantially more likely to exit their employer compared to women. In the first three years following the MFA, the treatment effect on exit among men is 3pp compared to no statistical difference among women. By year five, the effect grows to 10pp among men, compared to 5pp

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[15]Formally, each worker receives exactly the same weight and the DiD estimate is a weighted average of these heterogeneous treatment effects.

[16]Brazilian labor law prohibits nominal wage cuts unless authorized by a union. My results show declines in the log of workers' average monthly earnings as opposed to in contracted wages. In addition to wages, earnings include other forms of compensation such as a 13th month salary. At baseline, over 30% of workers in the sample earn 10% or more over their contracted wage. Among all textile workers this fraction is 43%. Workers' December earnings used as the wage measure in Gerard et al. 2021, Felix 2022 also fall (Appendix Table C3).

among women. I find that gender differences in exit entirely account for gender differences in wage recovery: while both male and female stayers' wages remain persistently lower at treated employers, leavers' wages recover (Figure 5).

Ruling out alternatives to monopsony power   At face value, men's substantially higher exit following similar wage declines indicates employers' higher monopsony power over women. However, two potential concerns confound this interpretation.

First, even in a perfectly competitive world, per a standard comparative advantage argument, treated women (men)'s lower (higher) rate of exit following a wage cut may reflect lower (higher) substitutability with comparison women (men). To compare substitutable workers whose wages would not diverge under perfect competition, I first leverage variation in MFA treatment within the same narrow 4-digit-occupation (e.g., tailor, loom operator, supervisor) and geography, via occupation by geography by time fixed effects. I also zoom in on a single large occupation, tailoring, which employs over 50% of women and 20% of men at both treated and comparison employers. Table 3 demonstrates no change in point estimates or conclusions from drawing these narrow comparisons, suggesting that the MFA-induced wage drop reflects imperfect competition rather than imperfect substitutability between workers.

A second concern is that higher male exits indicate larger MFA-induced marginal product declines for men, and, hence, higher layoffs. Two findings counter this claim. First, the entire treatment effect on exit reflects moves to new employers as opposed to unemployment (Figure C4). Second, leavers' wages fully recover (Figure 5). Both findings contrast with a generation of involuntary job loss studies, which find persistent unemployment and earnings losses among laid-off workers (Jacobson et al., 1993), including in Brazil outside of recessions (Hoek (2006), Kaplan et al. (2005)). Higher separations among men are therefore indicative of quits as opposed to layoffs.

In addition to ruling out alternatives to gender differences in monopsony as driving my findings, I identify two patterns consistent with static wage posting models. First, these models predict that a monopsonistic employer that reduces his wage loses marginal workers off his upward-sloping supply curve while retaining inframarginal workers at the lower wage (Manning, 2003). As predicted, retained workers experience persistent wage declines (by $t = 4$) while leavers' wages fully recover (Figure 5). Second, wage posting models predict wage declines among the monopsonist's new hires. As predicted, Appendix Figure C5 shows a 6pp decline in new workers' wages. These low wages may reflect lower productivity among new workers. Indeed, concerns re. changes in worker composition plague early, seminal studies of rent-sharing that use establishment-level data (e.g. Van Reenen (1997), Hildreth (1998)). Without taking a strong stance on the topic, I demonstrate no treatment effect on new worker composition (Appendix Table C4).

2.3   Gender wage gap

In sum, I find that men leave substantially more than women following a wage cut, indicating that employers possess higher monopsony power over women. To estimate the share of the gender

wage gap attributable to monopsony power, I estimate men and women's firm-specific elasticities of labor supply using the MFA shock as an instrument. These elasticities govern markdowns in standard monopsony models where workers earn $w_{gj} = \frac{e_{gj}}{e_{gj+1}} mrpl_{gj}$. Two challenges impede estimation. First, elasticities may be heterogeneous across employers. Second, wage spillovers may violate the exclusion restriction — that the shock only affects labor supply through changes to an establishment's own wage as opposed to changes in competitor wages.[17] Section 4 microfounds the structural elasticity of residual labor supply to an employer that governs markdowns (heterogenous by employer size). Section 5 estimates these elasticities.

Women's average elasticity is 1.23 and men's is 2.70 (Table 7). Per these estimates, the average woman earns 55% the value of her marginal product and the average man earns 73%. Gender differences in monopsony power thus generate an 18pp gender wage gap among equally productive workers, explaining over half the observed (35pp) gender wage gap. This gap is substantially larger than found in developed economies (for example, Webber (2016) estimates a 3.3% gap in the US and Caldwell and Oehlsen (2022) find no gap among US-based Uber drivers).

3 Stylized Facts

Section 4 develops a discrete choice model to probe the source of differential monopsony by gender. Here I present stylized facts that motivate its key ingredients: (a) three-nested structure (location, industry, and employer within industry), (b) horizontal differences across employers by industry, and (c) vertical differences across industries due to industry-specific amenities or productivity.

Fact 1: MFA-treated workers are most likely to switch to a new textile employer, then to switch industries, and finally to switch geography   Per Fact 1, workers are appropriately considered as first choosing locations, then industries, and finally within-industry employers. Table 5 reports treatment effects on workers' likelihood of being employed at a new (non-baseline) textile employer, non-textile employer, and in a new geography, three to five years following the MFA. Examples of two digit industries include the manufacturing of metal products, food and beverages, and leather. Five years following the MFA, treated men are 5.9% points more likely than the comparison group to switch to a new textile employer, 4% points more likely to switch to a non-textile employer, and no more likely to switch geographies. Among women, these rates are 4.8% points, 0.1% points and 0% points respectively. Thus, workers in the MFA's aftermath are most likely to switch to new textile employers, then to non-textile employers, and are geographically immobile.[18]

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[17]The labor supply to a large and oligopsonistic employer depends both on its own and its competitors' wages. A shock to firm A can therefore spur best response wage changes among competitor B, which feeds back into A's labor supply.

[18]Low geographic mobility here mirrors similar findings following large, negative trade-induced shocks, including in Brazil (Topalova 2010, Autor et al. 2013, Dix-Carneiro & Kovak 2015).

Fact 2: Men exit industries substantially more than women Fact 2 shows that women's low responsiveness to wage drops reflects lower cross-industry mobility. While the treatment effect on exit among women is entirely accounted for by within-industry moves, this ratio among men is only 5.9pp of the total 10pp effect (Table 5, Columns 2 and 3). Gender differences in cross-industry switches thus entirely explain gender differences in exit. Pursuant to this fact, the model introduces two forces potentially tethering women to the textile industry: idiosyncratic reasons specific to a worker-industry relationship (horizontal differences), and industry-specific attributes that render the textile industry desirable to all women (vertical differences). The first encompass different proclivities for learning new skills. The second encompass common amenities, such as longer maternity leaves, flexibility, safety, female coworkers, or discrimination. They also encompass gender differences in sectoral comparative advantage.

Fact 3: Industries are large, especially for women Industries therefore likely differ in amenities or productivity for women more than men. Women are disproportionately employed in fewer industries in general and the textile industry in particular (Figure C13).[19] Among high school dropouts, over 11% of women but only 3% of men are employed in textile jobs. More generally, over 40% of women are employed in their two most important industries, 60% in their five most important, and 80% in their ten most important industries. These fractions are invariably lower for men, 20%, 35% and 40%.

Fact 4: Industries differ in amenities Industries differ in the female (male)-focused amenities they offer workers. I employ the method developed in Corradini et al. (2022) to classify female (male)-centric amenities as those positively correlated with women's (men's) revealed preference value for an employer (Appendix Table **??**). Textile contracts offer on average 5.8 female-centric provisions compared to 4.37 in non-textile contracts.

Fact 5: Observed skill differences do not drive gender differences in exit Gender differences in comparative advantage are therefore unlikely to impede women's exit from textile jobs. Following the MFA, women remain as unlikely to (i) exit employers, and (ii) exit industries after controlling for gender differences in skill (Table 6). I use three measures of skill. First, workers' education, split into three categories: high school dropouts, high school graduates, and some college education. Second, workers' 4-digit occupation, which proxies for currently employed skills. Finally, I create an O*NET-based measure of skill transferability by linking workers' current skills to those required in other jobs within their geography (Macaluso, 2022) (Appendix D.2.1). O*NET reports the skill level (from 1-8) on each of 35 skills employed in any occupation. Skill transferability is a weighted average of the skill distance (L1-norm) between a worker's current occupation and other occupations in her geography, with weights equalling the share of local jobs in that occupation. I separate workers into 10 deciles of skill transferability. Controlling for skill transferability through

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[19]Figure C13 plots the share of workers' wage bill in various industries, which is the model-consistent measure of size.

fixed effects interacting skill level with treatment status and indicators for the two post periods (years 0-2 and years 3-5), women are as unlikely to exit MFA-exposed employers and textiles as absent controls.[20] Observed skill differences therefore do not drive differential exit by gender.

Fact 1 motivates the model's three-nested structure with workers first choosing a location, then industry, and finally an employer within the industry. Together facts 2, 3, and 4 motivate differences in horizontal preferences and vertical amenities across industries as sources of differential monopsony by gender. Finally, although fact 5 motivates not modeling gender differences in comparative advantage at baseline, Section 6 revisits it.

4   Model

I develop a nested logit model to probe two sources of higher monopsony power over women: (i) women strongly prefer their specific employer, all else equal (horizontal differences), or (ii) women have fewer good employers than men (vertical differences). Employers face upward-sloping labor supply curves, which I estimate in Section 5. Section 6 derives and estimates a set of sufficient statistics to quantify the contribution of each force to differential monopsony by gender. Section 7 uses the model's structure to study counterfactual scenarios. The model resembles Berger et al. (2022) in featuring nested logit supply and oligopsonistic employers, but departs in featuring three nests and amenities, which emerge as key drivers of gender differences in monopsony power.

4.1   Setup

Market   The economy has a continuum of geographies $r \in [0, 1]$ (microregions). Each geography has a discrete number of industries indexed by $k \in 1, ..., M_r$, and firms within the industry $j \in 1, ..., J_m$. Throughout I refer to a geography as a "local labor market" and all same-gender jobs within an industry as the within-industry market.

Firms   Firms compete in a Cournot oligopsony. Each posts gender-specific wages $\{w_m, w_f\}_j$ and chooses employment to maximize profits given the (inverse) labor supply it faces. A firm's revenue function is differentiable and concave, with men and women as imperfect substitutes $F(f_j, m_j)$. Each firm is endowed with exogenously-given industry-specific amenities (a_{gk}) and the firm's deviation from this industry norm (a_{gj}). I abstract from competition in amenities for simplicity.[21]

Workers   Workers, indexed by group g (men or women), possess heterogeneous preferences over employers. They work at their highest utility employer and exhibit three-nested preferences, first choosing a location, then industry, and finally an employer within the industry. A worker's utility from working at j has a common group-specific component (rising in wages and amenities), and an

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[20]The regression is: $Y_{it} = \alpha_i + \gamma_{mgt} + \sum_{p \in \{1,2\}} \delta_p(D_i \times Post_p \times skill_{level}) + \sum_{p \in \{1,2\}} \beta_p(D_i \times Post_p \times F_i) + \epsilon_{it}$.

[21]Ex post I find that at least half the amenities drawing women to textiles and raising monopsony power are not directly controlled by employers in contracts, thereby being difficult to change. For example, gender norms that classify textile jobs "appropriate" or a majority-female workforce that improves safety.

idiosyncratic preference shock specific to that employment relationship, ϵ_{igjk}. Each worker must earn income $y_i \sim F(y)$ which is a product of wages and hours $y_i = w_{gj}h_{igj}$.

$$u_{igjk} = lnw_{gj} + lna_{gk} + lna_{gj} + \epsilon_{igjk}$$

ϵ_{igjk} has a nested GEV Type I extreme value distribution with variance governed by three dispersion parameters, η_g, θ_g, and λ_g.[22]

$$F(\epsilon_{i1}, ..., \epsilon_{NJ}) = \exp\left[-\sum_r (\sum_{k=1}^{M} (\sum_{j=1}^{J_m} e^{-(1+\eta_g)\epsilon_{igjk}})^{\frac{1+\theta_g}{1+\eta_g}})^{\frac{1+\lambda_g}{1+\theta_g}}\right]$$

Amenities Amenities a_{jg} and a_{kg} represent non-wage attributes that are commonly valued by all members of a group and vertically differentiate employers. They include tangible attributes of a workplace such as flexible hours, maternity leave, female coworkers, or safety.[23] They additionally constitute intangible features such as gender norms that classify certain work as "inappropriate" for women. Amenities in this setup can also represent hiring discrimination.

Wages Wages rise in employer productivity and vertically differentiate employers. While my main conclusions regarding the source of gender differences in monopsony power are agnostic to the functional form of the production function, 7 imposes a functional form to illustrate how gender differences in comparative advantage can, by altering the gender and industry-specific wage index, vertically differentiate industries.

Dispersion parameters Dispersion parameters govern the distribution of idiosyncratic draws. These idiosyncratic preferences horizontally differentiate employers. Within an industry, η_g represents cross-employer mobility costs such as due to commuting or search frictions (Robinson, 1933).[24] The higher the η_g, the lower the variance of idiosyncratic draws across employers within an industry and, thus, the higher workers' cross-employer mobility. θ_g represent cross-industry mobility costs such as an aversion to learning new skills. The higher the θ_g the lower the variance of idiosyncratic draws across industries and, thus, higher workers' cross-industry mobility. Finally, λ_g represent cross-location costs, such as family relocation. A high λ_g lowers the overall variance of draws, raising cross-location mobility. Pursuant to fact 1 (Section 3), workers most easily substitute across

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[22] As shown by Anderson et al. (1992), subject to functional form choices about the terms in the CES function, this discrete choice framework generates the same labor supply to firms as obtained in a nested CES setting with the outermost nest being regions, the middle nest being industries, and the bottom nest being employers within the industry. η_g then corresponds with the within-industry elasticity of substitution, θ_g is the cross-industry elasticity of substitution, and λ_g the cross-region.

[23] Women's preference for female coworkers creates the possibility for multiple equilibria. While a fascinating question, modeling endogenous amenities is beyond the scope of this paper. Section 6 can be thought of as studying the source of monopsony power in the current equilibrium. The counterfactuals in Section 7 could yield different quantitative conclusions under multiple equilibria, and should be interpreted with this caveat.

[24] η_g also roughly represents loyalty, which is a commonly cited female attribute among employers in developing countries. The simple, static formulation of η_g developed here does not fully capture the dynamic nature of loyalty but serves as a rough proxy.

employers within an industry, then across industries, and finally across locations, $\eta_g > \theta_g > \lambda_g$. Although I do not impose this during estimation, I find it is true.

In this setup, η_g parameterizes women's match-specific preference for their specific employer, all else equal. Similarly, the cross-industry (θ_f) and cross-location parameters (λ_f) parameterize their match-specific preference for their industry and location. While a stronger preference for specific employers (lower η_g) confers each employer with higher monopsony power by making it harder for workers to switch to a new employer, a stronger preference for one's industry or location, by trapping workers within that industry or location, exacerbates the monopsony power of good employers within the industry or location as shown below.

Labor supply I obtain labor supply to an employer by aggregating the preferences of individual workers. The probability of choosing employer j is rising in its wage and amenity and is given by the standard nested logit formula (McFadden, 1978):

$$p_{gj} = \underbrace{\frac{(a_{gj}w_{gj})^{1+\eta_g}}{\sum_{j'\in k}(a_{gj}w_{gj'})^{1+\eta_g}}}_{\text{prob of choosing firm } j \text{ in industry } k} \times \underbrace{\frac{a_{kg}^{1+\theta_g}\left(\sum_{j\in k}(a_{gj}w_{gj})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}}{\sum_{k'\in R}a_{k'g}^{1+\theta_g}\left(\sum_{j\in k'}(a_{gj}w_{gj})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}}}_{\text{prob of choosing industry } k} \times \underbrace{\frac{\bar{W}_{gr}^{1+\lambda_g}}{\sum_{R'}\bar{W}_{gr'}^{1+\lambda_g}}}_{\text{prob of choosing region } r}$$

Aggregating these probabilities over workers yields the labor supply to j:

$$n_{gjkr} = \left(\frac{w_{gjkr}}{\bar{W}_{kgr}}\right)^{\eta_g}\left(\frac{\bar{W}_{kgr}}{\bar{W}_{gr}}\right)^{\theta_g}\left(\frac{\bar{W}_{gr}}{\bar{W}_g}\right)^{\lambda_g}a_{gjkr}^{1+\eta_g}a_{gk}^{1+\theta_g}N_g$$

Here $\bar{W}_{kgr} = (\sum_{j\in k}a_{gjkr}w_{gjkr}{}^{1+\eta_g})^{\frac{1}{1+\eta_g}}$ represents the amenity-adjusted group-specific wage index of industry k, $\bar{W}_{gr}$ is the wage index of r, and $\bar{W}_g$ is the aggregate wage index of g. The bars indicate that these expressions also include amenities, for example $(w_{gjkr}^-)^{\eta_g} = (a_{gjkr}w_{gjkr})^{\eta_g}$.

Workers flock to relatively desirable industries that offer relatively higher amenities or wages and, within them, to relatively desirable employers. These industries and employers are therefore larger and comprise a larger share of the wage bill within their nest.

$$s_{gkr} := \frac{\sum_{j'\in k}w_{gj'}n_{gj'}}{\sum_{k'\in R}\sum_{j'\in k'}w_{gj'}n_{gj'}} = \frac{a_{kg}^{1+\theta_g}\left(\sum_{j\in k}(a_{gj}w_{gj})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}}{\sum_{k'\in R}a_{k'g}^{1+\theta_g}\left[\sum_{j'\in k'}(a_{gj}w_{gj'})^{1+\eta_g}\right]^{\frac{1+\theta_g}{1+\eta_g}}}$$

$$s_{gjkr} := \frac{w_{gj}n_{gj}}{\sum_{j'\in k}w_{gj'}n_{gj'}} = \frac{(a_{gj}w_{gj})^{1+\eta_g}}{\sum_{j'\in k}(a_{gj'}w_{gj'})^{1+\eta_g}}$$

Because the solution concept is Cournot, employers optimize taking into account their inverse labor supply curve:

$$w_{gjkr} = \left(\frac{n_{gjkr}}{N_{gkr}}\right)^{\frac{1}{\eta_g}}\left(\frac{N_{gkr}}{N_{gr}}\right)^{\frac{1}{\theta_g}}\left(\frac{N_{gr}}{N_g}\right)^{\frac{1}{\lambda_g}}W_g a_{gk}^{\frac{-(1+\theta_g)}{\theta_g}}a_{gjkr}^{\frac{-(1+\eta_g)}{\eta_g}}$$

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with the elasticity of residual labor supply defined as $e_{gj} := \left[\frac{\partial ln w_{gjkr}}{\partial ln n_{gjkr}}\right]^{-1}$.

Labor demand An employer chooses employment to maximize profits given the inverse labor supply it faces, yielding the following first order condition:

$$\frac{\partial R_j}{\partial n_{gj}} = w_{gj} \underbrace{\left(1 + \frac{1}{e_{gj}}\right)}_{\mu_{gj}^{-1}}$$

where e_{gj} is the elasticity of residual labor supply. Workers are paid a markdown under marginal product whenever labor supply is upward-sloping $e_{gj} < \infty$.

4.2 Monopsony Power

In this model, horizontal differences confer all employers with monopsony power whereas vertical differences confer large (desirable) employers with higher monopsony power. The residual elasticity facing each employer depends on shares and the three dispersion parameters:

$$e_{gj} = \left[\frac{1}{\eta_g} + \left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right) s_{gjkr} + \left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right) s_{gjkr} s_{gkr}\right]^{-1} \tag{3}$$

Atomistic employers ($s_{gjkr} \sim 0$) possess monopsony power due to η_g differences alone and face elasticity η_g. Match-specific preferences are the only force tethering workers to these employers.[25]

Large employers in an industry (high s_{gjkr}) exert greater monopsony power because they compete more intensely with relatively less desirable employers within their industry than with employers in other industries ($\theta_g < \eta_g$). (Their largeness reflects their desirability relative to their within-industry competitors.) The condition $\theta_g < \eta_g$ is key for this conclusion; it captures the fact that workers are relatively trapped in their industry.

Large employers in large industries (high $s_{gjkr} s_{gkr}$) exert even greater monopsony power because they compete intensely with less desirable industries in their geography compared to industries in other geographies ($\lambda_g < \theta_g$). (Their largeness reflects their desirability relative to their within-geography counterparts). As above, the condition $\lambda_g < \theta_g$ is key, and captures workers' relative entrapment in their geography compared to their industry.

4.3 Monopsony over the average worker

A key implication of the model is that market power over the average worker, defined as the markdown on the average worker's wage, is determined by a few sufficient statistics. These sufficient statistics capture two forces: (i) workers may prefer their specific employer due to horizontal preferences, and (ii) workers may have fewer good employers due to vertical differences. The former

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[25]Formally, any change in an atomistic employer's employment does not alter the employment index of its industry or location.

confers each employer with monopsony power. The latter causes workers to cluster at the few employers that are good for them, conferring these employers with higher monopsony power.

Proposition 1 *The inverse markdown for the average worker in group g in industry k in region r is:*

$$\bar{\mu}_{gkr}^{-1} = \frac{\bar{mrpl}_{gkr}}{\bar{w}_{gkr}} = \underbrace{1 + \frac{1}{\eta_g}}_{(i)} + \underbrace{\left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right) HHI_{gkr} + \left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right) s_{gkr} HHI_{gkr}}_{(ii)}$$

Where the inverse average markdown is defined as the ratio of the average worker's marginal product $(\bar{mrpl}_{gkr} = \frac{\sum_{i \in gkr} mrpl_i n_i}{\sum_i n_i})$ and wage $(\bar{w}_{gkr} = \frac{\sum_{i \in gkr} w_i n_i}{\sum_i n_i})$. $HHI_{gkr} = \sum_{j \in k} s_{gjkr}^2$ measures within-industry concentration through the payroll-weighted Herfindahl-Hirschmann Index and $s_{gkr} HHI_{gkr}$ weights this within-industry HHI_{gkr} by the share of the industry's wage bill in region r (s_{gkr}). Term (i) represents monopsony due to match-specific horizontal preferences and term (ii) represents monopsony due to concentration stemming from vertical differences.

Proof. The proof has two parts. First I show that the inverse of a group's average markdown is the share-weighted average of individual employers' inverse markdowns, i.e. $\bar{\mu}_{gkr}^{-1} = \left(\sum_{j \in k,r} s_{gj} \mu_{gj}^{-1}\right)$. To obtain the expression in the proposition, I then calculate this inverse markdown $(\bar{\mu}_{gkr}^{-1})$ through the lens of the model by substituting in model-based inverse elasticities from equation (3). Proof in Appendix A. ∎

Monopsony over the average woman is higher when match-specific reasons limit her mobility even as her local labor market abounds with textile jobs (low η_g). In addition, it is higher when fewer within-industry employers offer relatively desirable jobs, thereby raising concentration (HHI_{gkr}). Concentration contributes more to monopsony when workers find it harder to substitute across industries (higher $\left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right)$). Finally, monopsony over the average woman is higher when the concentrated industry is also large, increasing concentration in the geography $(s_{gkr} HHI_{gkr})$. This contributes to monopsony whenever workers are trapped in their geography (higher $\left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right)$).

Before proceeding to estimation it is worth highlighting that the model distills a number of intuitive sources of differential monopsony over women to two forces: (i) match-specific preferences (η_g), and (ii) concentration. For example, commuting frictions when homes are idiosyncratically distributed lowers η_g. Fewer employers paying high wages w_{gj} or offering desirable amenities a_{gj} raises within-industry concentration (HHI_{gkr}). Hiring discrimination in an industry k' lowers its amenity $a_{k'g}$ and increases the size (s_{kg}) and monopsony power of employers in non-discriminating industry k. Wage discrimination similarly lowers the wage index and size of discriminator k', raising monopsony in non-discriminator k.[26] Higher comparative advantage in k raises its compensation, size, and, consequently, monopsony power.

Section 5 estimates employers' market power over the average man and woman by estimating their firm-specific labor supply elasticities. Section 6 then estimates the sufficient statistics from Proposition 1 to uncover the source of gender differences in monopsony power.

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[26]Discrimination could be a monopsonistic wedge between wages and marginal product or a non-monopsonistic wedge as in Becker (1962), Altonji and Blank (1999), Hsieh et al. (2019).

5 Estimating elasticities

I must address two factors in order to estimate elasticities. First, these elasticities are heterogeneous by employer size. Second, the elasticity in equation (3) is a partial equilibrium concept. It measures how much a firm must increase its wage in order to expand employment by one percent, holding its competitors' responses fixed. This elasticity cannot typically be measured even using wage and employment responses to well identified firm-level shocks if firms behave strategically. Intuitively, because the labor supply curve of an oligopsonistic employer depends on not only its own but also its competitors' wages, a shock to one can spur best response wage changes among competitors, in turn changing labor supply to the originally shocked firm. Firm-specific shocks uncover this composite effect — the total derivative with respect to j's wage — instead of the required partial derivative (Appendix A.1.4). In other words, the exclusion restriction is violated. The elasticity *can*, however, be estimated if spillovers are absent (proof in Appendix A.1.4).

I first establish that the MFA shock does not spur wage spillovers. I subsequently estimate heterogeneous elasticities and aggregate them to an industry level average.

5.1 Ruling out strategic wage responses

I test for wage spillovers via a test from the exchange rate pass-through literature (Amiti et al., 2019). Its key insight is that strategic interaction operates by altering markdowns: as workers exit China-competing employers, non-China-competing employers can pay them a smaller fraction of their marginal product. I show that $\forall$ competition structures (including Bertrand or Cournot oligopsony) and invertible labor supply systems where employers are not perfect substitutes (including nested CES) I can thus estimate wage spillovers by regressing an employer's wage change on a sufficient statistic for competitor wage changes, controlling for changes to its own marginal product (Appendix B). For nested CES supply, the sufficient statistic is a weighted average of changes in competitors' log wages $\Delta lnw_{-jt} = \sum_{j'} s_{j'} \Delta lnw_{j'}$. The estimating equation is:

$$\Delta lnw_{jt} = \delta \Delta lnmrpl_{jt} + \gamma \Delta lnw_{-jt} + \xi_{jt}$$

The coefficient δ estimates pass-through of shock to own marginal product and γ estimates spillovers.[27] The MFA shock provides an employer-level instrument for $\Delta mrpl$ and a market-level instrument for Δlnw_{-jt} (Acemoglu & Angrist 2001). The variation identifying γ compares employers in locations with fewer versus many MFA-competing firms.

Table 4 evidences a strong first stage (F-stat > 60). There are no wage spillovers. Column 1 shows no spillovers on the wages of incumbent workers employed at any exporter in $t = -1$, Column 2 shows no spillovers at unaffected exporters, and Column 3 shows no spillovers among any employer of textile or clothing (including non-exporters), and Column 4 shows no spillovers among new

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[27]Controlling for changes to one's own marginal product is what makes this a test of strategic interaction; even in a competitive market, market-level shocks spur wage spillovers but those operate by changing marginal products as opposed to markdowns.

workers (establishment-level regression, which yields the right structural object). Across samples, $\hat{\gamma}$ is a tightly estimated zero, ruling out changes above 0.01% with a high degree of confidence (95%). In addition, I cannot reject the sharp null of zero spillovers for every employer using randomization inference p-values.[28]

I interpret no spillovers as evidencing the MFA's small size—only 0.6% of textile workers were shed in the most affected geography. Recent work highlights a number of frictions that could prevent employers from best responding to neighbors' wage cuts in this setting, including optimization errors due to the small shock (Dube et al., 2020) or nominal rigidities (Hazell and Taska, 2020). I do not interpret no spillovers as evidence against oligopsony. As predicted under oligopsony, shocks to employers' own marginal product have incomplete pass-through that falls with employer size (Appendix Figure C8).

5.2   Elasticity estimates

I estimate elasticities using the following instrumental variables strategy, in separate regressions for establishments located in regions with a large (over 10% of local wage bill share) and small (less than 10% of local wage bill share) textile industry, $L_{txt,j} \in 0, 1$:

$$\Delta lnn_{jgt} = \alpha_1 D_j + \alpha_2 D_j s_{gj} + \alpha_3 s_{gj} + \gamma_{1mt} + \upsilon_{jgt}$$
$$\Delta lnw_{jgt} = \beta_1 D_j + \beta_2 D_j s_{gj} + \beta_4 s_{gj} + \gamma_{2mt} + \psi_{jgt}$$

where D_j is an indicator equal to 1 for establishments exporting a treated product at baseline (under quota in China) and 0 for those exporting a comparison product, s_{gj} is j's share of its within-industry-geography wage bill, Δlnn_{jg} is the change in employment between $t = -1$ and $t = 5$ and Δlnw_{jg} is the change in the offered wage over the same period. γ_{mt} control for time and region-specific shocks. The coefficients α_1 (β_1), and α_2 (β_2) capture the average effect of treatment and its differential effect by employer share. The elasticity of labor supply to j is:

$$\frac{\Delta lnn_{jgt}(s_{jg}, s_{gk})}{\Delta lnw_{jgt}(s_{jg}, s_{gk})} = \frac{\hat{\alpha}_1 + \hat{\alpha}_2 s_{gj}}{\hat{\beta}_1 + \hat{\beta}_2 s_{gj}}$$

from its respective regression (i.e. using $\hat{\alpha}, \hat{\beta}$ from the regression corresponding with a large or small textile industry depending on its location). Because the correct measure of the offered wage is not obvious, I use two different measures which yield identical estimates. First, I use the average wage of stayers (Kline et al. 2019). Second, I use the average wage of all workers. The first wage measure is preferred and reported as my main estimate as it controls for any potential changes to worker composition.

Having estimated heterogeneous elasticities, I aggregate them to the inverse markdown on the average worker's wage in the industry using the identity $\bar{\mu}_{gk}^{-1} = \sum_r s_{gk}^r \bar{\mu}_{gkr}^{-1} = \sum_r s_{gk}^r \sum_{j \in k,r} s_{gj} \left(1 + \frac{1}{e_{gj}}\right)$

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[28]Appendix B discusses measurement error in $mrpl$ in detail.

(see Step 1 in proof of Proposition 1). The "average elasticity" is such that the average worker earns a fraction $\bar{\mu}_{gk} = \frac{\bar{e}_{gk}}{\bar{e}_{gk}+1}$ of her marginal product.

Table 7 reports results. As predicted, both men and women's labor supply becomes less elastic as employers grow large. Elasticities fall faster when the textile industry is also large, comprising a higher share of the same-gender wage bill in a worker's location. Women's average elasticity is $\bar{e}_{fk} = 1.236$ and men's is $\bar{e}_{mk} = 2.689$. These imply that the average man earns 73% of the value of his marginal product whereas the average woman earns 55% the value of hers. Gender differences in monopsony power thus generate an 18pp gender wage gap among equally productive workers.

6   Sources of Gender Differences in Monopsony Power

Through the lens of the model, higher monopsony power over women has two sources. First, women may strongly prefer their specific employer. Second, women may have fewer good employers than men, leading to higher labor market concentration. I first show that both match-quality and the concentration of women's employment drive gender differences in monopsony power (Decomposition #1). Next, I show that concentration is itself driven by the concentration of women's jobs in the textile industry rather than gender differences in concentration *within* textiles (Decomposition #2). Finally, I show that women's concentration in textiles can be largely attributed to non-wage amenities as opposed to gender gaps in productivity. Therefore, although textile employers draw women through desirable jobs, this in turn confers them with higher monopsony power.[29]

6.1   Theory

Proposition 1 yields two sufficient statistics to decompose the contribution of women's higher match-specific preference and concentration to gender differences in monopsony power. It further yields four sufficient statistics to decompose the relative contribution of within and cross-industry concentration.

Decomposition #1: Match-specific preference versus concentration   Together, the elasticity of labor supply to atomistic employers, η_g, and the elasticity associated with the average inverse markdown, $\bar{e}_g$, quantify the relative contribution of match-specific preferences and concentration to gender differences in monopsony.

Implication 1   Match-specific reasons differentially increase monopsony over women if women's labor supply to atomistic employers is less elastic than men's ($\eta_f < \eta_m$). In other words, $e_{fj} < e_{mj}$ even when $s_{gjkr} \sim 0$. The share of the monopsony-induced gender wage gap attributable to these preferences is $\frac{\eta_m}{\eta_m+1} - \frac{\eta_f}{\eta_f+1}$.
Proof. Implication 1 comes from observing that $e_g = \eta_g$ when $s_{gjkr} = 0$ in Equation (3).   ∎

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[29]This section studies workers without high school degrees, who constitute over 75% of textile workers.

Implication 2 Concentration differentially increases monopsony over women if women's average elasticity (corresponding with the average inverse markdown) is further from η_f relative to this difference among men. In other words, $e_f(\bar{\mu}_f^{-1}) - \eta_f > e_m(\bar{\mu}_m^{-1}) - \eta_m$. The share of the monopsony-induced gender wage gap attributable to gender differences in concentration is $\left(\frac{\bar{e_m}}{\bar{e_m}+1} - \frac{\bar{e_f}}{\bar{e_f}+1}\right) - \left(\frac{\eta_m}{\eta_m+1} - \frac{\eta_f}{\eta_f+1}\right)$.

Proof. Implication 2 comes from observing in Proposition 1 that concentration causes the average markdown to deviate from $1 + \frac{1}{\eta_g}$. Therefore, the average elasticity deviates from η_g. ∎

Decomposition #2: Within versus cross-industry concentration Four sufficient statistics quantify the relative contribution of within-industry concentration and concentration of employment in that industry to the monopsony-induced gender wage gap (Proposition 1). First, HHI_{gkr} is the within-industry concentration of employers. By itself, it raises monopsony power whenever workers substitute more easily within than across industries $\left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right) > 0$. Third, $s_{gkr}HHI_{gkr}$ is the concentration of within-geography employers in industry k. It raises monopsony whenever workers substitute more easily across industries than locations $\left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right) > 0$.

6.2 Estimation

The five objects to estimate are the average elasticity $\bar{e}_g$, parameters governing horizontal preferences η_g, θ_g, λ_g, and concentration HHI_{gkr}, and $s_{gkr}HHI_{gkr}$.

Average elasticity I estimate industry-level average elasticities $\bar{e}_g$ by aggregating heterogeneous elasticities using the identity $\bar{\mu}_{gk}^{-1} = \sum_r s_{rk}^g \sum_{j \in k,r} s_{gj} \mu_{gj}^{-1}$ (Section 5, proof in Appendix A). Here s_{rk}^g is the share of the total gender-specific textile wage bill in region r and s_{gj} is employer j's share in the textile market in r.

Horizontal preferences I estimate η_g as the elasticity to an atomistic employer, θ_g as the elasticity to an atomistic industry (from a large employer in that industry), and λ_g as the elasticity to an atomistic geography (from a large employer in that geography). Intuitively, horizontal preferences are the only force tethering workers to these atomistic employers, industries, and geographies. Formally, the following partial derivatives with respect to the wage at employer j yield the parameters:

$$\frac{\partial lnn_{gjr}}{\partial lnw_{gjr}} = \eta_g \ when \ s_{gj} \sim 0$$

$$\frac{\partial lnn_{gkr,j}}{\partial lnw_{gjr}} = \theta_g(s_{gj})(1 - s_{gk}) + \lambda_g s_{gj} s_{gk} = \theta_g s_{gj} \ when \ s_{gk} \sim 0$$

$$\frac{\partial lnn_{gr,j}}{\partial lnw_{gjr}} = \lambda_g s_{gj} s_{gk}$$

Although these partial derivatives are typically inestimable in the presence of wage spillovers or amenity changes, the MFA provides a credible instrument by being spillover-free and assumed

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orthogonal to amenity changes (proof in Appendix C.1.1). The intercept in equation (**??**) yields $\hat{\eta}_g$. The following establishment-level regressions yield $\hat{\theta}_g$ and $\hat{\lambda}_g$:

$$\Delta lnn_{gtxt,j} = \theta_g s_{gj} \Delta lnw_{gtxt,j} + \upsilon_{gj}$$

$$\Delta lnn_{gr,j} = \lambda_g s_{gj} s_{gk} \Delta lnw_{gtxt,j} + \psi_{gj}$$

Appendix C re-estimates these parameters using an alternate approach that, rather than using subsamples for estimation, successively estimates η_g, θ_g and λ_g using employer, industry, and location-level shocks (developed in Costinot et al. (2016) to estimate nested CES demand). Since the small MFA shock does not provide the requisite variation at the industry and location levels, I employ Brazil's 1990s trade liberalization as in Felix (2022).

Concentration I directly measure concentration (HHI_{gkr}) and industry size (s_{gkr}) in the RAIS data. A weighted sum over regions aggregates each quantity to an industry-level average, i.e. $HHI_{gk} := \sum_r s_{kr}^g HHI_{gkr}$ and $s_{gk} HHI_{gk} := \sum_r s_{kr}^g s_{gkr} HHI_{gkr}$, where s_{kr}^g is the share of g's overall textile wage bill located in region r. In other words, I sum to the inverse markdown for the average g worker in k: $\bar{\mu}_{gk}^{-1} = \sum_r s_{kr}^g \bar{\mu}_{gkr}^{-1}$ (Appendix A).

6.3 Results

6.3.1 Decomposition #1: Match-specific preference versus concentration

Both match-specific reasons and concentration generate gender differences in monopsony power. I estimate $\eta_f = 2.19$, $\eta_m = 3.89$ (p-value ¡ 0.05 for the difference), $\bar{e}_{fk} = 1.236$, and $\bar{e}_{mk} = 2.689$. These estimates imply that the average man earns 73% the value of his marginal product whereas the average woman earns 55%. Were match-specific preferences the only source of monopsony power, the fractions would instead be 79% and 69% ($\frac{\eta_g}{\eta_g+1}$). Thus, match-specific preferences and concentration contribute 10pp and 8pp respectively to the monopsony-induced gender wage gap.

The decomposition would misestimate the relationship between concentration and monopsony if workers sort on elasticities. For example, if elastic women sort to locations abundant in non-textile jobs, their high elasticity would be wrongly attributed to concentration. Two facts mitigate this concern: first, most workers work in their birthplace, with only 6% migrating between 1991 and 2000 (de Lima Amaral, 2013). Second, public sector jobs form a large share of women's non-textile jobs (30%), and its size in a worker's birthplace is strongly predicted by population density (calculated).

6.3.2 Decomposition #2: Within versus cross-industry concentration

Having uncovered that concentration contributes 8pp to the monopsony-induced gender wage gap, Decomposition #2 probes the relative contribution of concentration within and across industries. Figure 8 sets the stage by plotting the female to male ratio of within-industry concentration

(HHI_{gk}) and what I term cross-industry concentration $(s_{gk}HHI_{gk})$ across Brazil's twelve largest industries by wage bill share. Together these account for over 60% of the formal wage bill. Across industries, within-industry HHI_{gk} is typically higher among men or equal across gender. However, consistent with women's disproportionate employment in fewer industries (Fact 3 of Section 3), the industry-weighted term $s_{gk}HHI_{gk}$ is typically higher for women relative to men. Together these suggest that higher concentration in a few industries as opposed to within the industry drives gender differences in monopsony power.

Table 8 reports estimates of θ_g, λ_g and the gap between inverse elasticities $\left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right)$ and $\left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right)$. Men and women are nearly identically mobile across industries (θ_g) and locations (λ_g). I estimate $\hat{\theta}_f = 0.89$, $\hat{\theta}_m = 0.87$, $\hat{\lambda}_f = 0.03$, $\hat{\lambda}_m = 0.05$, and $\left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right) > 0$ (p-val¡0.05), $\left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right) > 0$ (p-val¡0.05) for both genders.[30],[31]

Table 9 (left panel) formally decomposes the contribution of within-industry and cross-industry concentration to the monopsony-induced gender wage gap by progressively adding the contribution of terms $\left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right)HHI_{gk}$ and $\left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right)s_{gk}HHI_{gk}$ to the markdown generated by match-specific preferences alone $\left(1 + \frac{1}{\eta_g}\right)$. The latter is 10pp.

I find that concentration of employment in, but not *within* the textile industry raises monopsony power over women. Gender differences in within-industry concentration *reduce* the monopsony-induced gender wage gap to 8pp. Women's markdown falls to 66% and men's to 74%. The declining gender gap reflects both men's higher within-industry concentration ($HHI_m = 0.11$, $HHI_f = 0.08$), and, for the same HHI_{gk}, their higher captivity within industries: $\left(\frac{1}{\theta_m} - \frac{1}{\eta_m}\right) = 0.89$ vs $\left(\frac{1}{\theta_f} - \frac{1}{\eta_f}\right) = 0.67$.[32] By contrast, women's higher concentration in the textile industry *increases* the monopsony-induced gender wage gap by 10pp. Women's markdown falls to 55% and men's to 73%/. Usefully, I find that the 18pp gender wage gap generated in the model exactly matches the non-targeted gender gap estimated using average elasticities alone (Section 5).

Monopsony in the economy I next study a natural follow-up question: do employers in other industries possess higher monopsony power over men? The answer is no, as portended by Figure 8. I generate economy-wide average markdowns for g workers by combining estimated elasticities with a weighted sum of within-industry concentration $\sum_k s_k^g \sum_r s_{gk}^r HHI_{gkr}$ and its industry-size-weighted counterpart $\sum_k s_k^g \sum_r s_{gk}^r s_{gkr} HHI_{gkr}$ (proof in Appendix A). The outer sum is over industries where s_k^g is g's wage bill share in k. Akin to textiles, gender differences in within-industry concentration reduce the economy-wide gender gap by 3pp. Women's higher concentration in fewer industries adds 12pp.

Through the lens of the model, thus, women's disproportionate employment in fewer industries

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[30] These estimates imply that an industry must raise its wage by 1/0.87=114% to double its workforce and a microregion by 2000%

[31] My estimate of θ_g is nearly identical to Felix (2022), who uses the same data but estimates mobility across occupation-geographies as opposed to across industries. This is reassuring since each textile occupation is nested within the industry and workers are largely immobile across geographies.

[32] Stemming from different η.

generates higher monopsony power over them. This finding highlights the importance of market definition in diagnosing gender differences in monopsony power. It reveals that traditional within-industry or within-occupation measures of concentration (as in Azar et al. (2022), Berger et al. (2022), Felix (2022), Rinz (2022)) can misdiagnose the extent of gender differences in monopsony power by failing to account for women's concentration in fewer industries.

Real-world determinants of η   What governs women's match-specific affinity for their employer in the real world? Appendix Table C8 explores heterogeneity along two dimensions: motherhood and safety. First, one might expect current or soon-to-be mothers to supply labor less elastically to their specific employer. I find no evidence of this when comparing women of childbearing age (20-35 years) with older workers (Columns 1 and 2). Second, given Brazil's highest rate of violent crime in the world (UNODC), one might expect women's labor supply to be less elastic if unsafe commutes make proximate employers appealing. Exploiting municipality-level data on the homicide rate (Dix-Carneiro et al., 2018), I find that low safety (below the 25th percentile between 2000-2004) indeed predicts lower labor supply elasticities among women but not men.[33] Women's elasticity to atomistic employers in safe municipalities is 2.278 compared to 1.727 in unsafe ones (p-val of difference < 0.05). When translated to markdowns, higher monopsony power in unsafe municipalities adds 6pp to the gender wage gap over this gender gap in safer municipalities.

6.3.3 What drives concentration in textiles? (non-wage amenities vs comparative advantage)

In the model but also intuitively, the textile industry's prominence in women's labor market reflects either women's relatively higher skills in the industry (comparative advantage) or its provision of desirable non-wage amenities. I estimate both gender-specific schedules of comparative advantage and amenities by industry and use them to evaluate the relative importance of each in driving the industry's high share.

Non-wage amenities   Relatively desirable amenities raise market shares and therefore monopsony power. I estimate gender-specific non-wage amenities across industries by first constructing industry-specific wage indices from observed wages in RAIS and then inferring amenities given this wage index and industry size (the group-specific wage bill share in that industry). I employ the following three-step procedure and highlight objects computed at each stage in red:

Step 1. Estimate the wage index of industry k: $s_{gj} = \frac{(w_{gj})^{1+\eta_g}}{\sum_{j'}(w_{gj'})^{1+\eta_g}} \forall j$; re-arrange, take logs, and sum over all j: $W_{gk} = \tilde{w_{gk}} \tilde{s_{gk}}^{\frac{-1}{1+\eta_g}}$ where the tilde denote a geometric mean. I first calculate industry-region-specific wage indices and aggregate to the industry.[34]

Step 2. Estimate men's amenities in k, normalizing $a_{m,txt} = 1$: $\frac{s_{mk}}{s_{mtxt}} = \frac{a_{mk}^{1+\theta_m} \frac{W_{mk}^{1+\theta_m}}{W_m^{1+\theta_m}}}{\frac{W_{mtxt}^{1+\theta_m}}{W_m^{1+\theta_m}}}$.

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[33] Brazil has 2500 municipalities across 557 microregions. The latter comprise regions r in the model.
[34] Full derivation in Appendix A.

Step 3. Estimate women's amenities in k: $\dfrac{s_{fk}}{s_{mk}} = \dfrac{a_{fk}^{1+\theta_f} \dfrac{W_{fk}^{1+\theta_f}}{W_f^{1+\theta_f}}}{a_{mk}^{1+\theta_m} \dfrac{W_{mk}^{1+\theta_m}}{W_m^{1+\theta_m}}}$.

Figure 9 evidences the prominence of non-wage amenities over wages in drawing women to the textile industry. It plots the female to male ratio of industry-specific wage and amenity indices across Brazil's fifteen large industries by wage bill share (comprising 70% of the total wage bill). While all industries exhibit gender wage gaps, the standard deviation of these gaps (0.18) is substantially lower than that of amenity gaps (0.35). Put another way, while wages alone would predict an identical female share in the textile and auto manufacturing industries, the textiles employ 11% of women but automobiles only 2%.

Comparative advantage Relatively high productivity in textiles also raises compensation, shares, and, consequently, employers' monopsony power. Consider a Cobb-Douglas production function $Y_j = z_j K_j^{\alpha_{k1}} l_j^{\alpha_{k2}}$ with labor a CES aggregation of male and female workers $l_j = [\beta_k f_j^\sigma + m_j^\sigma]^{\frac{1}{\sigma}}$. β_k represents women's relative productivity in k.[35] A high value raises k's wage or amenity index and therefore its share in women's labor market. The marginal revenue product of female labor at j is:

$$mrpl_{jf} = \underbrace{\beta_k}_{common\ to\ industry} \underbrace{\sigma \alpha_{k2} z_j K_j^{\alpha_{k1}} l_j^{\alpha_{k2}-1}[\beta_k f_j^\sigma + m_j^\sigma]^{\frac{1}{\sigma}-1} f_j^{\sigma-1}}_{t_j}$$

β_k therefore aggregates to the industry-wide wage or amenity index, showing wages here:

$$w_{gj} = \beta_k \frac{\epsilon_{gj}}{\epsilon_{gj}+1} t_j$$

$$\sum_j (w_j^{1+\eta_g})^{\frac{1}{1+\eta_g}} = \beta_k [\sum_j \tilde{w}_j^{1+\eta_g}]^{\frac{1}{1+\eta_g}}$$

I estimate $\hat{\beta}_k$ across five key industries: the manufacturing of textile and clothing products, food and beverages, automobiles, machinery, and metal products using standard production function techniques (Ackerberg et al., 2015). I choose these industries because I observe at least 250 establishments in each in a panel between 2000 - 2010, as needed to obtain consistent estimates and tight standard errors (Demirer, 2020). Together they employ 10.4% of formal sector workers. A caveat to my conclusions is that, pending a data application in Brazil, I estimate production functions in two other developing countries: India and Chile. I obtain similar estimates across the two and use the mean value of $\hat{\beta}_k$. Appendix C.3 describes the data and procedure in detail. A second caveat is that the presence of market power potentially biases productivity estimates (see footnote).[36]

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[35] A large literature studying the consequences of changes in the relative supply of high and low skilled labor on wage inequality uses a similar functional form, as illustrated in Katz and Murphy (1992)

[36] Market power in inputs potentially violates the "scalar unobservables" assumption of the proxy variables method of production function estimation and prevents me from inverting input demand to recover productivity shocks (Bond et al. (2021), De Loecker and Syverson (2021)). However, two facts mitigate the concern that bias in $\hat{\beta}_k$ leads to a false conclusion of amenities over productivity drawing women to textiles. First, Yeh et al. (2022) show using

Figure 10 shows that gender productivity gaps predict a much smaller difference in female to male shares across industries than observed. They predict a ratio of 1.24 in textiles, 1.08 in food and beverages, 0.55 in automobiles, 0.58 in machinery, and 0.39 in the manufacturing of metal products. In reality, these shares are respectively 6, 0.76, 0.27, 0.2, and 0.18. Thus, the textile industry attracts a substantially higher share of women than predicted by gender differences in productivity alone, implying a prominent role for non-wage amenities in drawing women to the industry.

Why don't other industries compete away the amenity differences drawing women to the textile industry and conferring its employers with higher monopsony power? Directly examining this question is beyond the scope of the paper, but the evidence suggests two answers. First, at least half the amenities drawing women to textiles are not directly controlled by employers in contracts (seen in Section 7), such as gender norms that classify textile work as more "appropriate" than other jobs, a preference for female co-workers, or, relatedly, workplace safety. Second, Brazilian employers inefficiently underprovide even the female-focused amenities that they *do* control in contracts, suggesting a potential role for mistakes (Corradini et al. (2022)).

6.4 Summary

The findings of this section can be summarized in three takeaways. First, I find that match-specific preferences for specific employers and the concentration of good jobs for women in the textile industry both generate gender differences in monopsony power. Second, I find that the traditional measure of concentration, the within-industry Herfindahl-Hirshmann Index, underdiagnoses gender differences in concentration by failing to account for women's disproportionate employment in fewer industries. Finally, I show that women's concentration in textiles is largely a product of non-wage amenities present in different sectors and not gender differences in productivity. These amenities could be those drawing women to textiles (female-focused contracts, female coworkers, safe work environment), or disamenities that drive them away from non-textile industries (discrimination, low safety, gender norms). Next I examine the counterfactual effect of altering gender gaps in amenities, both in the model and their real-world analog in collective bargaining contracts.

7 Counterfactuals

This section studies how policy may remedy the monopsony-induced gender wage gap via counterfactuals that close gender gaps in amenities, skills, and safety. To benchmark the contribution of sectoral differences in gender-specific amenities and productivity, I first calculate the effect of

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simulations that despite this limitation the method recovers true parameters in its 95% confidence interval and delivers tight standard errors. Second, gender gaps in compensation (wages plus contracted amenities) still predict a much smaller difference in the relative female to male shares across industries than observed — for example, they predict similar ratios in textiles and the manufacturing of metal products. In reality, the ratio is 6 in the former and 0.2 in the latter. Therefore, other non-wage amenities must differentially draw women to textiles.

leveling each on the monopsony-induced gender wage gap. In two subsequent policy-relevant coun-terfactuals, I study the effect of improving female-centric amenities in contracts and safety.

7.1 Preliminaries

The counterfactual exercises require four key ingredients. First, I parameterize the labor supply system with estimates of the three elasticities of substitution η_g, θ_g, λ_g. Second, I assume that employers compete a la Cournot, choosing employment to maximize profits while taking as given the employment at other firms. Third, I assume a Cobb-Douglas production function in labor and capital, with labor a CES aggregation of male and female workers (as above). I assume that capital is rented in a competitive market.[37] I calibrate other necessary parameters (summarized in Appendix Table C10). I calibrate productivity dispersion to match the observed firm size distribution in the textile industry. I calibrate the distribution of firm frequency in each industry and geography to a Pareto distribution with shape, scale, and location parameters set to minimize distance with the first three moments of the economy-wide distribution. Finally, I calibrate the elasticity of substitution between male and female workers (σ) from Gallen (2018).

I also make a few simplifying assumptions. I assume away establishment-specific amenities a_{gj} that deviate from industry norms. I also assume geographic immobility, $\lambda_g = 0$. I restrict counterfactuals to the five major industries in which I estimate gender-specific productivity (β_k above): the manufacturing of textiles and clothing, food and beverage products, metal products, machinery, and automobiles. Together these industries employ over 10.3% of the formal labor force (7.6% of women and 10.4% of men).

For each counterfactual, I quantify its effect on the monopsony-induced gender wage gap. Un-like estimation, counterfactuals require solving the model. I solve for two fixed points among women: an upper-level industry share and lower-level within-industry share. For counterfactu-als that alter amenities or productivity, I start from the industry shares predicted by the new amenity/productivity distribution and old industry-specific wage part of the wage index (equation 5). As women substitute from textiles to amenity/productivity-enhancing industries, the textile industry's share declines. Its employers face more elastic labor supply (equation 6), which causes them to alter wages and workers to reallocate across textile employers (lower-level fixed point). This yields a new wage index for each industry and upper-level industry share; I solve until a fixed point in this upper-level share. The last counterfactual increases mobility (η_f) to its value in the 75th percentile safest municipality, causing workers to reallocate across employers. As wage indices change, so too do industry shares. As before, I solve for the upper and lower level fixed points.

7.2 Results

Level all gender gaps in amenities   I first study the effect of eliminating gender gaps in non-wage amenities by setting the ratio $a_{fk'}^{1+\theta_f}/a_{mk'}^{1+\theta_m} = 1$ across non-textile industries. Figure 11 shows

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[37]The firm's optimization problem can be recast as optimizing over labor alone by substituting in its optimal capital demand (Berger et al., 2022).

a 8pp decline in the monopsony-induced gender wage gap. Women flock to amenity-improving non-textile industries, which lowers the textile share to 3.4% (from 10.5%) and increases the elasticity of labor supply to textile firms that are now smaller in women's labor market. Women's wages increase for two reasons: (i) they earn a higher share of marginal product, and (ii) they reallocate to larger, higher-wage employers whose monopsony wedge disproportionately falls. Simultaneously, men's wages decline as their marginal product at large employers declines and they reallocate to smaller textile firms. The average woman's markdown rises 6.6pp and the average man's declines 1.4pp. In this way, leveling gender gaps in sector-specific amenities fully erodes the 8pp gender wage gap due to concentration.

Women in non-textile industries do not lose from their now-larger size and higher monopsony power. At the outset, each comprises 1-2% of women's labor market and gains 1.4% following amenity improvements. The average woman's markdown in these industries falls 3pp. However, women are better off in utility terms, as evidenced by net movements into these industries. Formally, utility gains are reflected in (1-10%) higher industry-specific wage indices.[38] Just as changes to the price index measure changes to consumer welfare from improving product varieties, changes to the wage index, i.e., how much workers are paid to work one disutility-weighted hour, measures changes to worker welfare from amenity improvements (Corradini et al., 2022).

How costly are amenity improvements? This paper does not speak to direct costs, but evidences offsetting gains. First, I find that greater equity is coupled with higher efficiency. Because large and productive textile employers disproportionately lose monopsony power, women reallocate to them from smaller ones, which raises productive efficiency in textiles. Aggregate productivity, defined as the ratio of realized to potential production $\Omega = Y_{realized}/Y_{potential}$, increases by 1.1pp.[39] Second, recent work by Corradini et al. (2022) suggests that Brazilian employers inefficiently underprovide female-friendly amenities: they find no tradeoffs in employment, wages, or profits when a female-focused union reform institutes large gains (0.13SD) in these amenities among 20% of the formal labor market. Finally, I show below that non-contracted (likely unpaid) amenities importantly drive women to textiles. On the one hand, these amenities may be resilient to change. On the other hand, changing them may not entail expensive investment.

Level gender-specific comparative advantage I next study the effect of leveling gender gaps in productivity by equalizing a β_k fraction of each industry's amenity advantage. I focus on amenity instead of wage gaps because the former explain textile's prominence in women's labor market (Figure 9). While this choice biases against finding an important role for amenities, they remain important.

Figure 11 shows a 4.12pp decline in the monopsony-induced gender wage gap from eliminating gender productivity gaps. The textile industry share falls from 10.5% to 8.7%. Women's wages increase 3.4pp and men's decline 0.72pp. Productive efficiency increases 0.3pp. Leveling productivity

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[38] $\bar{W}_{kg} = a_{kg}(\sum_{j \in k} w_{gjk}^{1+\eta_g})^{\frac{1}{1+\eta_g}}$

[39] $Y_{potential}$ is defined as the output if employers did not exercise their monopsony power and instead paid workers their marginal product.

thus achieves roughly half the effect of leveling gender amenity gaps.

Level gender-specific amenities in contracts Because a policymaker would likely find it difficult to alter amenity "residuals" that she cannot observe, I study a policy-relevant counterfactual leveling female-focused amenities in collective bargaining contracts. I define amenities predicting women's revealed preference value for an employer as female-focused. These include twenty (of 137) provisions governing maternity leave, flexibility, childcare, and overtime, among others (Table 2 in Corradini et al. (2022)). Textile contracts feature 5.8 female-focused amenities on average compared to 4.37 among non-textile employers. For the counterfactual, I let women vote-with-their-feet toward amenity-improving employers and calibrate this rate with Corradini et al.'s quasi-experimental estimate.

Figure 11 shows that equalizing gender gaps in contracted amenities has roughly half the effect of leveling gaps in all amenities (4.54pp). The textile industry's share falls to 8.1%. Women's wages increase 3.69pp and men's decline 0.85pp. Productive efficiency increases 0.25pp. Because Corradini et al's three-year estimate may underestimate the longer-term draw of amenities, I assess robustness to doubling the rate: the gender wage gap falls 5.5pp. Overall, improving observed and actionable contracted amenities substantially, but does not fully, erode the monopsony-induced gender wage gap due to concentration.

Improve neighborhood safety Finally, we could make the streets safer. Figure 11 shows a 3.64pp decline in the monopsony-induced gender wage gap from improving safety across all municipalities to the 75th percentile. Improving safety raises η_g from 2.19 to 2.278, enhancing cross-employer substitution to high-wage/amenity textile employers. Overall, women's wages rise 2.96pp and men's decline 0.68pp.

Summary I have two main conclusions. First, the textile industry attracts a much higher relative share of women than predicted by productivity differences alone and must thus offer women higher non-wage amenities. These amenities are not fully accounted for by contracted amenities, and would instead comprise gender norms, safety in the workplace, or employer discrimination.

Second, improving non-textile jobs to be as desirable for women as textile jobs would substantially erode the monopsony-induced gender wage gap. The largest gains would accrue from eliminating differences in non-wage amenities, with smaller gains from upskilling women. Improving safety on the streets, by enhancing women's mobility, also reduces the gender gap.

8   Conclusion

This paper highlights the role of an understudied market failure in developing countries, differential monopsony by gender, in effecting a potentially large share of the gender wage gap. Using quasi-experimental firm-level variation in wages, I document substantially lower separation elasticities among women than men, with resulting monopsony power generating an 18pp gender wage gap

among equally productive workers. I show that differential monopsony by gender has two intuitive sources: women are tethered to their current employer even when their labor market abounds with opportunity; in addition, they are tethered to relatively good jobs in the textile industry. Combined with a model, I estimate positive spillovers from improving non-traditional work environments for women via a reduction in monopsony in women's current jobs. Whereas leveling sectoral amenity gaps erodes 8pp of the monopsony-induced gender wage gap, upskilling women to level gender productivity gaps achieves only half this gain.

A surprising conclusion of my findings is that greater equity is coupled with efficiency. Reducing monopsony reallocates women from smaller to larger/more productive employers. This suggests that policies improving non-traditional workplaces, such as combating sexual harassment, instituting flexible work, or enhancing maternity protections, can be a key lever to remedy labor market distortions. While some of these policies (combating sexual harassment), are unambiguously good, others (increasing flexibility), entail costs. Weighing these costs against the estimated gains is a fruitful avenue for policy.

My findings also raise several new questions. First, do employers exercise their higher monopsony power over women? In ongoing work I study this question by examining differences in patterns of pass-through to men and women's wages. Second, does concentration in fewer professions also spur differential monopsony by gender in other contexts? Just as in Brazil, women in other parts of the world are employed in fewer industries and occupations: in the United States, for example, 1 in 8 women is a teacher or nurse (Sokolova and Sorensen, 2021). Studying the consequences of such concentration for monopsony is an important area for future research. Finally, my findings raise the puzzle of why exactly such few jobs are "women's jobs" although women are similarly skilled in, and receive similar wages across, industries. Identifying the amenities/disamenities drawing women towards/away from industries (gender norms, a desire to work with other women, discrimination, or valuing other industry-specific amenities), and, to the extent that they misallocate women's talent, identifying remedies, is an exciting area for future work.

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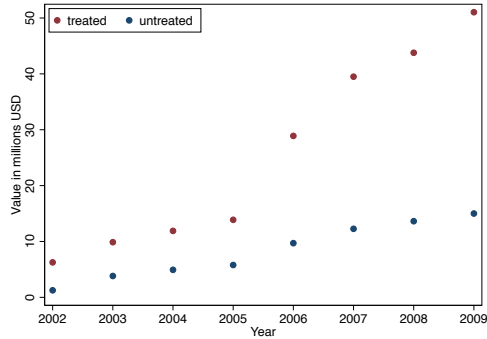
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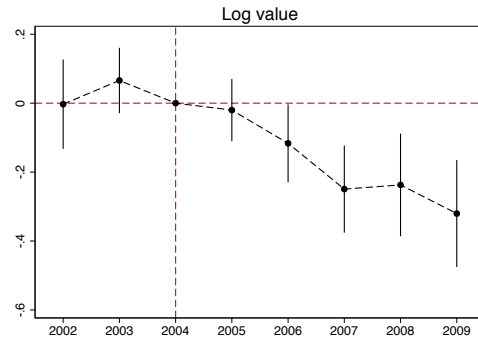
Figures

Figure 1: Effect of MFA's end on Chinese and Brazilian export values
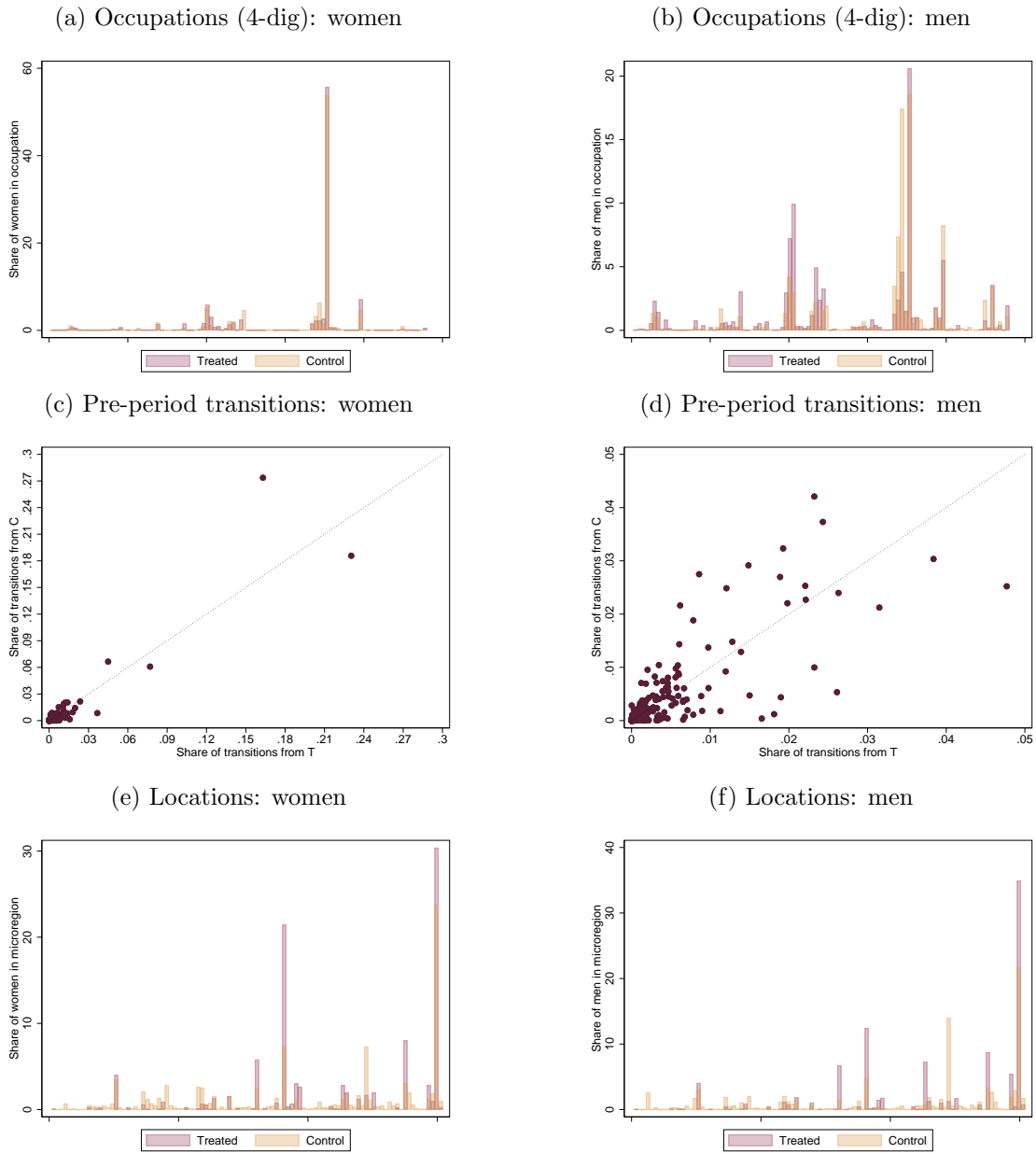
(a) Chinese exports (value in millions USD)   (b) Brazilian exports (firm-level DiD, log value)

Notes: This figure plots the effect of the end of the MFA on Chinese (Panel a) and Brazilian (Panel b) exports of treated and comparison products. Treated products are those whose Chinese exporters faced a binding quota in from the US in 2004. Comparison products comprise all other products in the textile and clothing manufacturing industries. Panel a plots the total value of Chinese exports of the two sets of products between 2001 and 2008 (in millions of USD). Panel b plots an establishment-level DiD event study comparing the log of export value at Brazilian establishments exporting treated versus comparison products. The x-axis plots exports in the preceding year i.e. from year $t-1$ to year t.

Figure 2: Worker characteristics

(a) Occupations (4-dig): women

(b) Occupations (4-dig): men

(c) Pre-period transitions: women

(d) Pre-period transitions: men

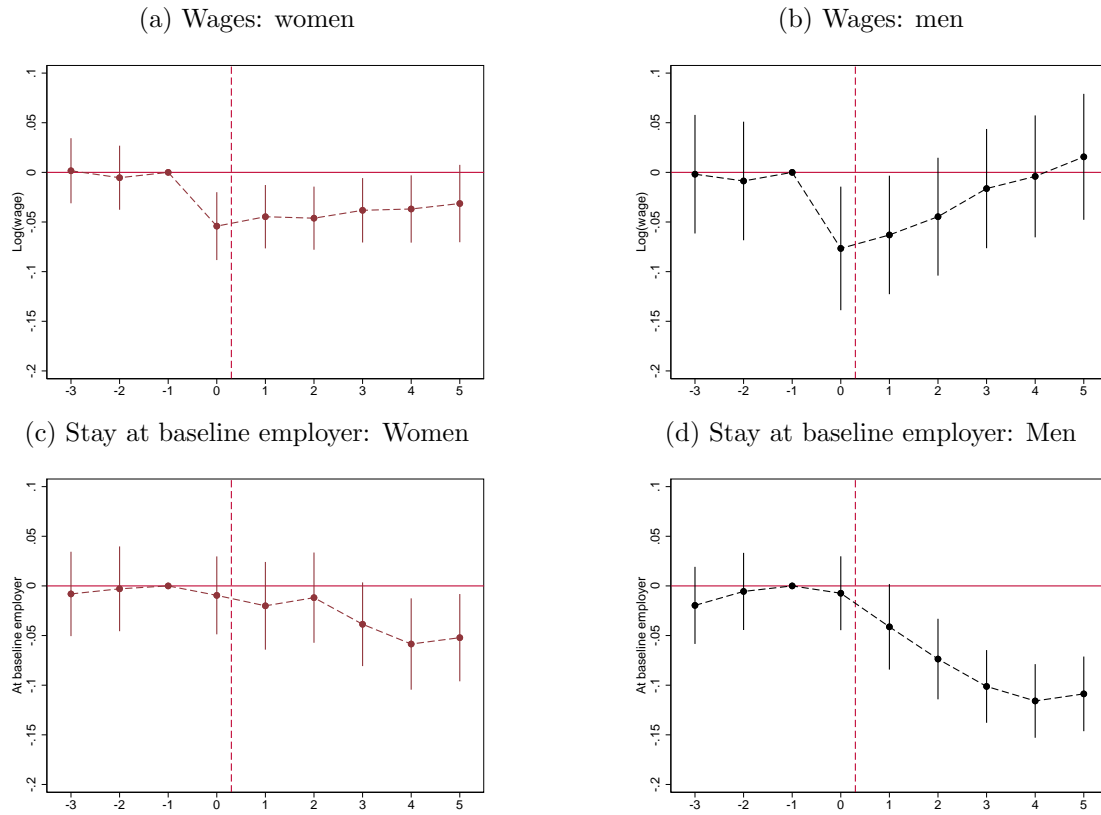(e) Locations: women

(f) Locations: men

Notes: This figure plots baseline (2004) descriptive statistics of treated and comparison establishments. Panels a and b plot the distribution of 4-digit occupations for women and men at treated and comparison establishments. Panels c and d plot the correlation between the share of pre-period transitions to a given 4-digit occupation from treated establishments (x-axis) and comparison establishments (y-axis). Panels e and f plot the distribution of geography (microregions) for women and men at treated and comparison establishments.

Figure 3: Firm-specific shock in textile and clothing labor market

(a) Share of affected establishments

(b) Share of affected employment
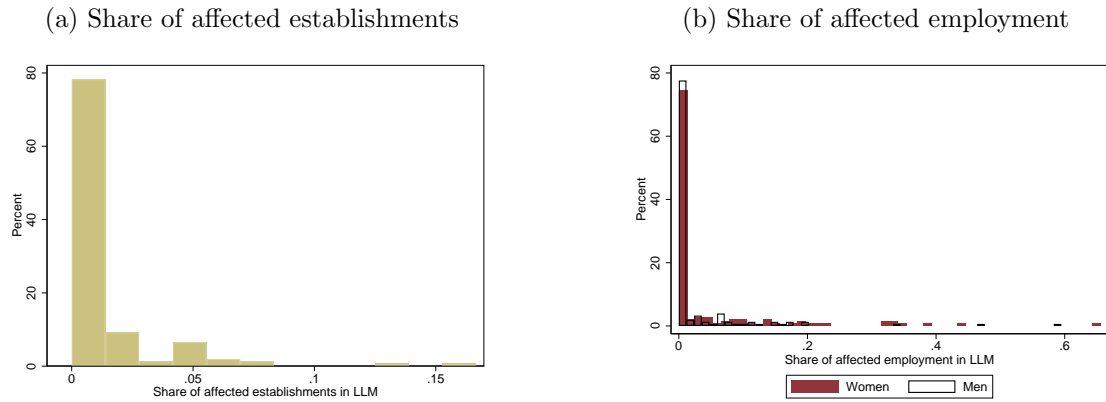
Notes: This figure shows that the MFA shock affected a small share of employment and establishments in the textile and clothing manufacturing industries. Panel a plots the share of treated establishments in a given geography (microregion). Panel b plots the share of treated male and female employment in a geography. The mean share of establishments is 2% and of employment is 10%.

Figure 4: Effect of the MFA's end on wages and employment

(a) Wages: women

(b) Wages: men

(c) Stay at baseline employer: Women

(d) Stay at baseline employer: Men

Notes: These figures plot estimates of the δ_t coefficients for $t \in [-3, 5]$ (with $t = -1$ omitted) from a DiD specification comparing treated men and women with their comparison counterparts. The outcome in Panels a and b is log wages and in Panels c and d is retention at one's baseline employer. $t = 0$ corresponds with 2005. MFA quotas were lifted in January 2005. Confidence intervals at a 95% level are reported. Standard errors are clustered at the establishment level.

Figure 5: Wages of stayers and leavers

(a) Leavers: women

(b) Leavers: men

(c) Stayers: Women
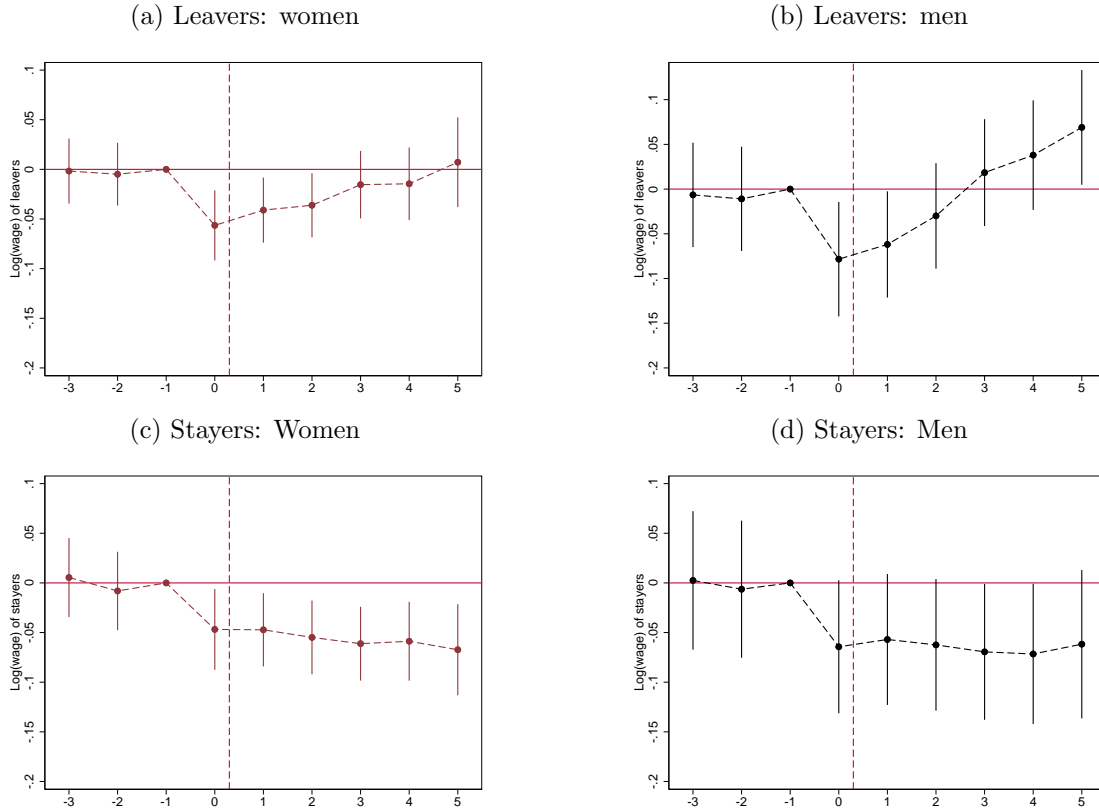
(d) Stayers: Men

Notes: These figures plot estimates of the δ_t coefficients for $t \in [-3, 5]$ (with $t = -1$ omitted) from the DiD specification on the log wages of leavers (Panels a and b) and stayers (Panels c and d), comparing them with all same-gender workers in the comparison group. $t = 0$ corresponds with 2005. MFA quotas were lifted in January 2005. Stayers are defined as those who remain at their baseline employer four years following the MFA's end. Standard errors are clustered at the establishment level.

Figure 6: Men and women's skill transferability and occupations

Skill distance from jobs in geography

Occupations
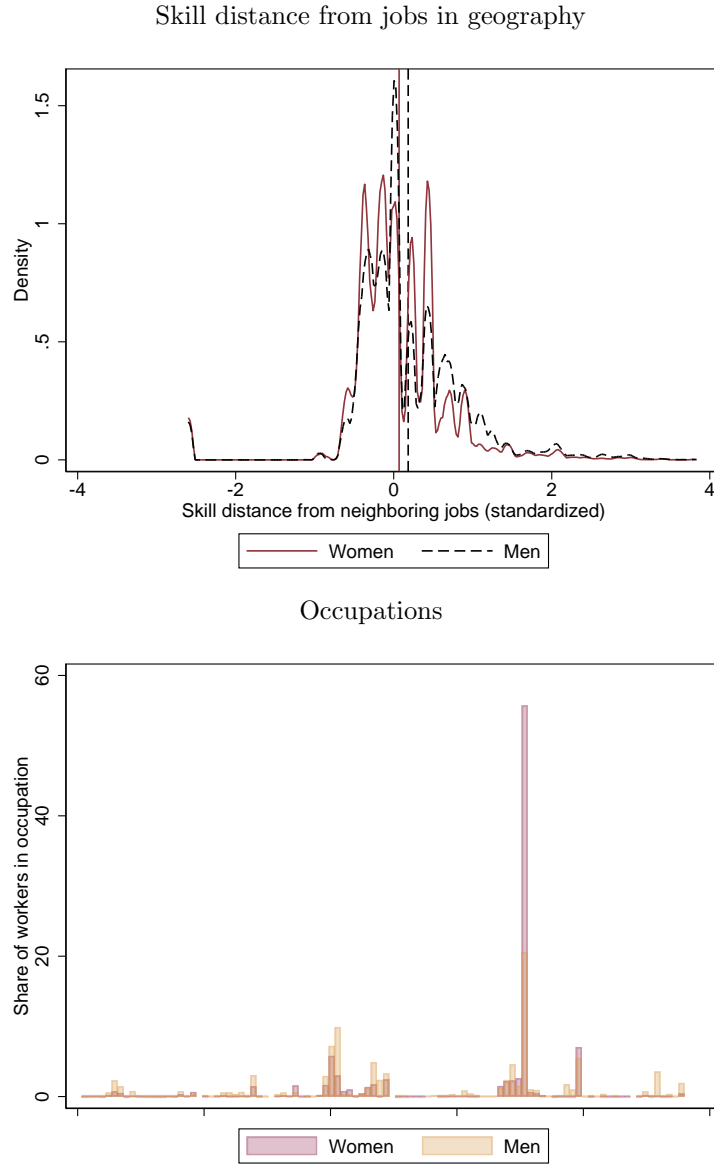
Notes: The top panel plots kernel density estimates of the distribution of skill distance from other jobs in a worker's geography, separately for women (maroon, solid line) and men (black, dashed line) at treated employers. Vertical lines indicate the mean distance respectively for male and female. The skill level (1-8) on each of 35 skills required to do an occupation comes from O*NET. Skill distance is the weighted average of the distance (L1-norm) between a worker's current occupation and all other occupations in her geography, with weights being that occupation's share among jobs in the geography. I standardize this remoteness measure among all workers to have mean 0 and standard deviation 1. The bottom panel plots the distribution of occupations among male and female workers at treated employers. Occupations are 4-digit occupations.

Figure 7: Share of women's and men's wage bill in top industries
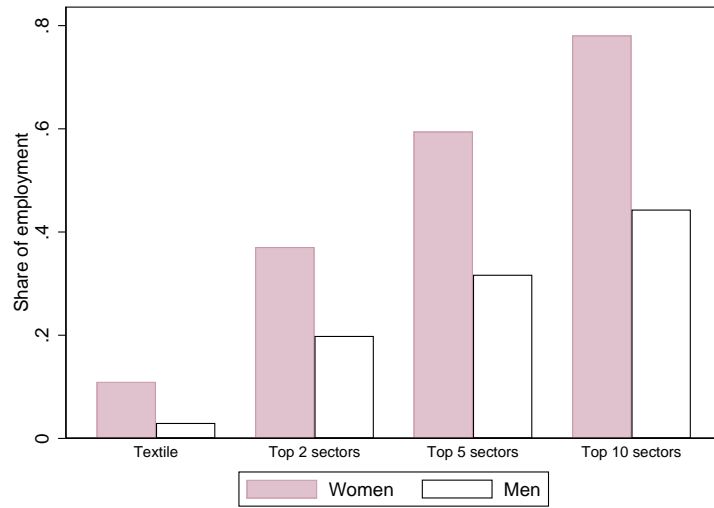
Notes: This figure plots the share of women and men's overall wage bill in the textile industry as well as their two, five, and ten most important industries.

Figure 8: Within-industry HHI and industry-share-weighted HHI
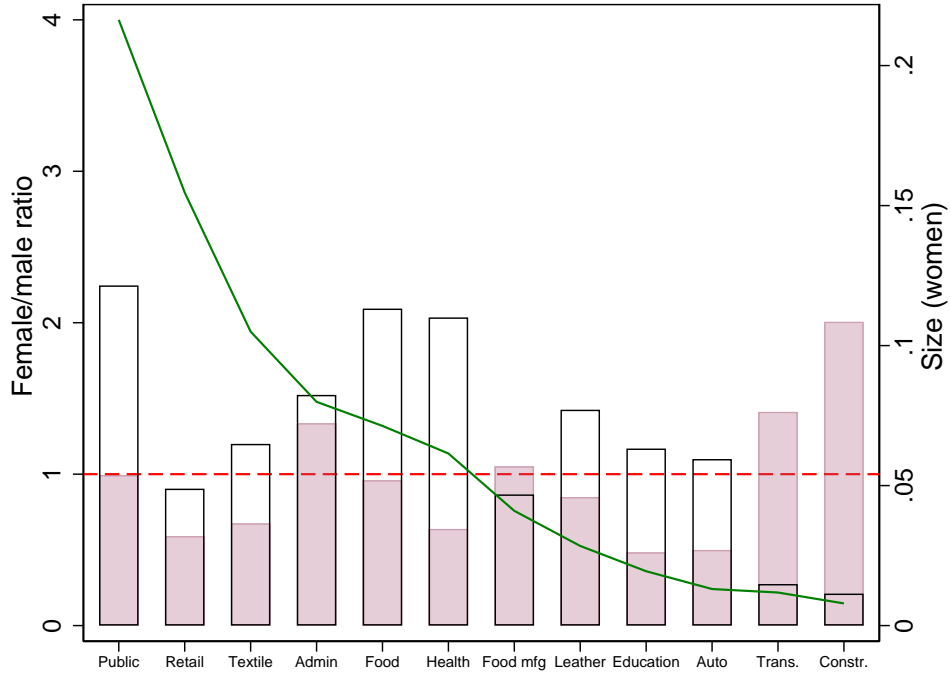
Notes: This figure plots the ratio of female/male within-industry HHIs (term a) and concentration in industry (term b) in Proposition 1 for the twelve largest employers of workers who are high school dropouts. The line plots the share of women's wage bill in a given industry. The main message is that women's within-industry concentration resembles men's, but that women are disproportionately employed in a small number of industries raising overall concentration.
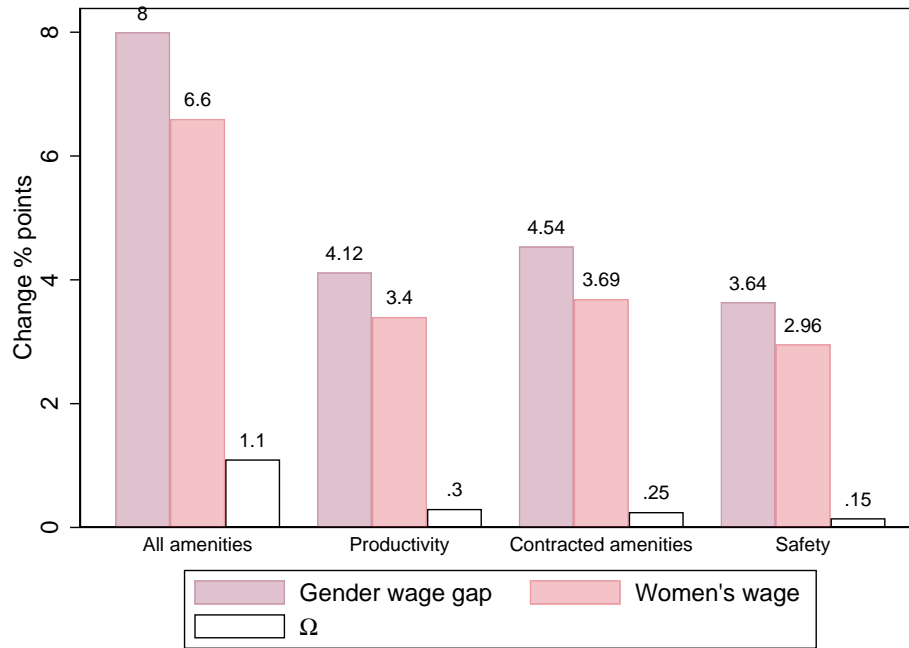
Figure 9: Amenities and wages across industries
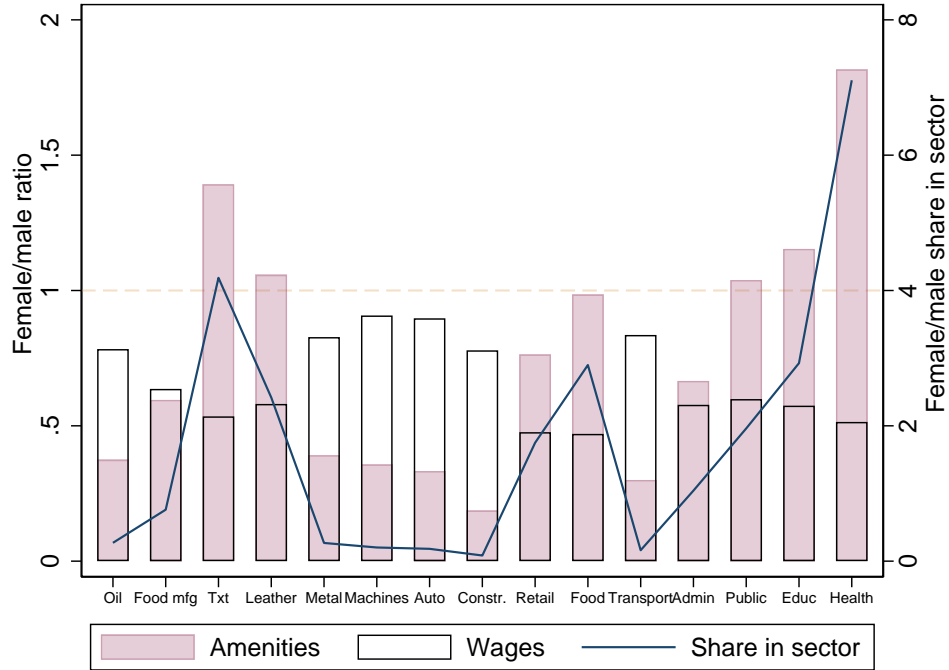
Notes: This figure plots the ratio of female/male amenity and wage indices across the fifteen largest 2-digit industries (sectors) by share of wage bill in Brazil. Together, these industries employ over 70% of workers. I observe wages across all formal sector employers in the RAIS data and aggregate them to a wage index at the sector level for men and women. I then use the discrete choice assumption of the model to infer amenities. Intuitively, a sector attracts many workers if it offers either high wages or high amenities. Appendix C.2 provides detail on constructing wage indices and inferring amenities.

Figure 10: Actual and predicted ratio of women to men across industries
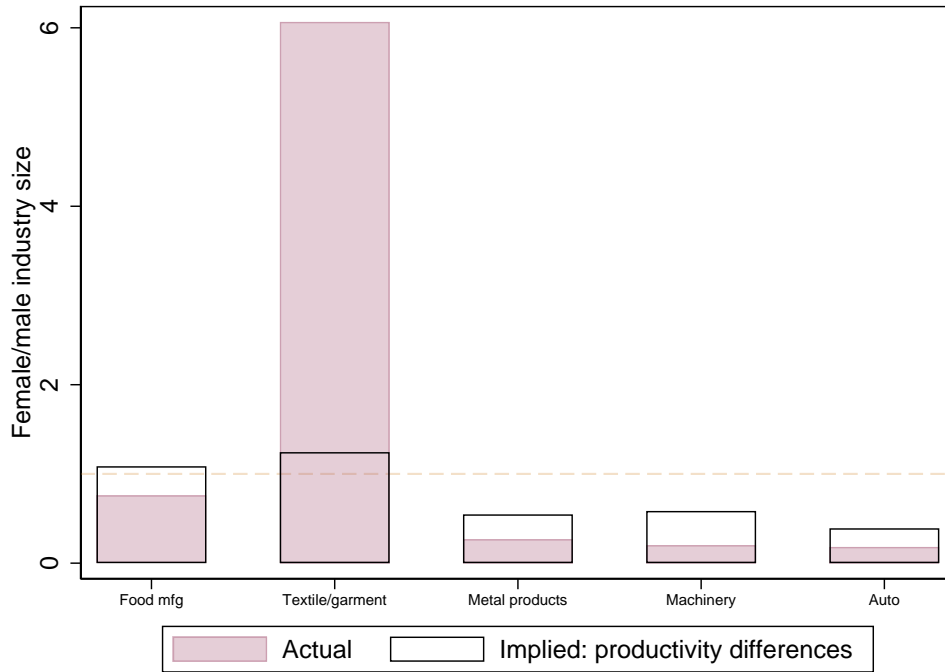
Notes: The pink bars plot the actual ratio of the wage bill share of women's labor market and men's labor market in an industry. The black bars plot the implied ratio based on gender diffrences in productivity alone. I assume productivity differences are entirely compensated through non-wage amenities (using wages instead predicts an even smaller share of women in textiles). Appendix C.3 describes the procedure for estimating men and women's relative productivity across industries.

Figure 11: Counterfactual exercises to alleviate gender differences in monopsony power

Notes: This figure plots the change in the gender wage gap, the average woman's wage, and productive efficiency (Ω) in the textile industry from various policies. The first equalizes all non-wage amenities across industries; the second equalizes gender productivity gaps across industries; the third equalizes non-wage amenities included in collective bargaining agreements; the final improves safety to the level of the 75th percentile municipality, thereby making it easier for women to substitute across employers within the industry η_g. Section 6 describes details.

Table 1: Examples of treated and comparison HS codes

Comparison		Treated	
Code	Product name	Code	Product name
620341	Men's or boys' trousers, bib and brace overalls, breeches and shorts of wool or fine animal hair	620461	Women's or girls' trousers, bib and brace overalls of wool or fine animal hair
620510	Men's or boys' shirts of cotton	610910	Men's or boys' t-shirts of cotton
620449	Women's or girls' dresses of other txt materials	620463	Women's or girls' trousers, bib and brace overalls of synthetic fibers
620451	Women's or girls' skirts of wool or fine animal hair	611011	Sweaters, pullovers, sweatshirts, waistcoats of wool or fine animal hair
610839	Women's or girls' nightdresses and pajamas of other textile materials	620811	Women's or girls' slips and petticoats of man-made fibers
621132	Men's or boys' track suits of cotton	620520	Men's or boys' dress shirts of cotton
621142	Women's or girls' track suits of cotton	620821	Women's or girls' nightdresses and pajamas of cotton
621050	Women's or girls' other garments of man-made fibers	620530	Men's or boys' shirts of man-made fibers
610729	Men's or boys' nightshirts and pajamas of other txt materials	610329	Men's or boys' ensembles of other txt materials
620332	Men's or boys' suit type jackets and blazers of cotton	620412	Women's or girls' suit type jackets and blazers of cotton
620333	Men's or boys' suit type jackets and blazers of synthetic fibers	620433	Women's or girls' suit-type jackets and blazers of synthetic fibers
620339	Men's or boys' suit type jackets and blazers of other txt materials	620419	Women's or girls' suits or other txt materials
610791	Men's or boys' nightshirts of cotton	620711	Men's or boys' underpants and briefs of cotton
621710	Other made-up clothing parts/accessories	621790	Other made-up clothing parts/accessories
620891	Women's or girls singlets, slips, petticoats of cotton	620322	Men's or boys' ensembles of cotton
621210	Women or girls' brassieres of man-made fibers	620530	Men's or boys' shirts of man-made fibers
620341	Men's or boys' trousers, bib and brace overalls, breeches and shorts of wool or fine animal hair	620342	Men's or boys trousers, bib and brace overalls, breeches and shorts of cotton

Notes: This table depicts example 6-digit HS codes for products whose exports from China to the US did not face a binding quota under the MFA's phase IV (comparison) and whose exports from China to the US did face a binding quota under the MFA's phase IV (treated). A binding quota is defined as one whose fill rate at baseline (2004) is over 85%.

Table 2: Descriptive statistics

	Full sector			Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Estab characteristics						
				All	Treated	Control
Avg. employment	29.855			152.070	150.675	152.914
Avg. # products exported	X	X	X	1.720	1.681	1.743
No. of estabs	15971			751	283	468

	Women			Men		
	All	Treated	Control	All	Treated	Control
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Worker characteristics (Sample)						
Avg. wage (per month)	559.769	550.856	567.697	1096.006	1050.331	1114.961
Avg. hours (per week)	43.885	43.961	43.737	43.731	43.647	43.745
Avg. tenure (years)	4.316	4.105	4.504	5.243	4.661	5.243
Age (years)	33.542	33.182	34.251	32.898	31.223	33.188
Education						
Less than HS	0.749	0.758	0.732	0.677	0.666	0.679
HS grad	0.242	0.232	0.262	0.315	0.319	0.315
More than HS	0.009	0.010	0.006	0.008	0.015	0.006
No. of workers	51533	24260	27273	62672	18381	44291

Notes: This table presents descriptive statistics for the sample of treated and comparison establishments and workers at baseline ($t = -1$). Treated establishments are those that were exporting treated products at baseline, i.e. those under binding quota in China under the MFA. Comparison establishments are those exporting other textile and clothing products. Panel A describes establishments. Panel B describes incumbent workers, i.e. those employed at treated or comparison establishments in ($t = -1$).

Table 3: Effects on wages and employment

	All workers						Tailors	
	Log earn (1)	Retention (2)	Log earn (3)	Retention (4)	Log earn (5)	Retention (6)	Log earn (7)	Retention (8)
D_i*Post$_1$	-0.059***	-0.032***	-0.058***	-0.018	x	x	-0.054***	-0.043*
	(0.013)	(0.011)	(0.013)	(0.012)	x	x	(0.014)	(0.024)
D_i*Post$_1$*F	0.012	0.022*	0.011	0.015	0.003	0.019*	-0.004	0.049*
	(0.010)	(0.012)	(0.009)	(0.014)	(0.006)	(0.010)	(0.014)	(0.026)
D_i*Post$_2$	0.001	-0.100***	-0.002	-0.099***	x	x	0.005	-0.178***
	(0.014)	(0.010)	(0.013)	(0.011)	x	x	(0.016)	(0.022)
D_i*Post$_2$*F	-0.036***	0.054***	-0.029***	0.052***	-0.022***	0.045***	-0.057***	0.161***
	(0.011)	(0.012)	(0.011)	(0.013)	(0.008)	(0.010)	(0.016)	(0.024)
Loc-gender-year FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Loc-occ-gender-year FE	No	No	Yes	Yes	No	No	No	No
Est-year FE	No	No	No	No	Yes	Yes	No	No
N	765486	850646	765486	850646	765486	850646	236722	266139

Notes: This table estimates the MFA's treatment effects and gender differences in these effects. $Post_1$ is an indicator equal to one in years $t = 0$ to $t = 2$ and $Post_2$ equals one in years $t = 3$ to $t = 5$. F is a dummy variable indicating a female worker. The sample comprises all incumbent workers. These workers are tracked wherever they go. A worker is treated $D_i = 1$ if employed at an establishment exporting MFA-affected products at baseline and in the control group if exporting a different textile and clothing product. All specifications include worker fixed effects. Columns (1) and (2) are the baseline specification, including microregion x gender x year fixed effects. Columns (3) and (4) instead include 4 digit occupation x microregion x gender x year fixed effects. Columns (5) and (6) include establishment-year fixed effects, which absorb the main effect of treatment. Columns (7) and (8) present results narrowing in on workers in a specific but large 4-digit occupation, tailors, which employs 50% of women and 20% of men. Standard errors are clustered by establishment.

Table 4: Testing exclusion: pass-through estimates

(test of strategic wage spillovers)

Panel A: Pass-through estimates

	Exporters (1)	Untreated exporters (2)	All unaffected employers (3)	Establishments (4)
Δw_{-jt}	-0.003	0.000	0.005	0.034
	(0.003)	(0.002)	(0.005)	(0.036)
$\Delta mrpl_{jt}$	0.145***			
	(0.052)			

Panel B: First stage on Δw_{-jt}

	Exporters (1)	Untreated exporters (2)	All unaffected employers (3)	Establishments (4)
Per 100 treated workers, excluding j	-0.100***	-0.099***	-0.089***	-0.036***
	(0.013)	(0.014)	(0.021)	(0.003)
First stage F-stat	60.830	47.366	17.258	60.813
Avg. no. of treated workers, excluding j (hundreds)	25.833	20.018	30.239	38.284
Observations	147883	110595	426111	37674

Notes: This table estimates pass-through of own and competitor wage shocks. The outcome Δw_{jt} is the change in log wage at establishment j between $t = -1$ and $t \in 3, 5$. $\Delta mrpl_{jt}$ measures change in the log of own marginal product. Δw_{-jt} is the weighted sum of log wage changes at other textile and clothing establishments in j's geography, excluding j, between $t = -1$ and $t = 1$, with weights equal to an establishment's baseline wage bill share in the labor market (textile and clothing industry x microregion). The coefficient on Δw_{-jt} estimates wage spillovers. The outcome in Columns (1)-(3) is the wages of incumbent workers whereas in Column (4) is the average wage of new workers. Own MFA status is the employer-level instrument for change in own marginal product. The share of treated employment in one's geography excluding one's own employer is the market-level instrument for competitor wage changes. Column (1) reports results for all establishments exporting textile or clothing products at baseline, column (2) for untreated exporters, column (3) for all textile and clothing establishments including non-exporters, and column (4) for textile and clothing exporters. Panel A reports pass-through estimates. Panel B reports the first stage on Δw_{jt} and the Kleibergen-Paap first stage F-stat. Standard errors are clustered at the establishment level.

Table 5: Gender differences in destination

	New txt. employer	New sector	New geography
	(1)	(2)	(3)
D_i*Post$_1$	-0.004	0.026***	0.010**
	(0.008)	(0.007)	(0.005)
D_i*Post$_1$*F	0.008	0.000	-0.006
	(0.008)	(0.008)	(0.005)
D_i*Post$_2$	0.059**	0.040***	0.006
	(0.008)	(0.008)	(0.005)
D_i*Post$_2$*F	-0.011**	-0.043***	-0.008
	(0.009)	(0.009)	(0.006)
Observations	765486	765486	765486

Notes: This table estimates treatment effects and gender differences on worker destinations. $Post_1$ is an indicator equal to one in years $t = 0$ to $t = 2$ and $Post_2$ equals one in years $t = 3$ to $t = 5$. F is a dummy variable indicating female. The sample is all incumbent workers. They are tracked wherever they go. A worker is treated $D_i = 1$ if she worked at an establishment exporting MFA-treated products at baseline and in the control group if at a different textile exporter. All specifications include worker fixed effects. New is defined relative to baseline ($t = -1$). The outcome in Column (1) is a binary variable equal to one if a worker is employed at a new textile or garment industry employer. The textile and garment industries correspond with 2-digit 1995 CNAE industry codes 17 and 18. The outcome in column (2) is a binary variable equal to one if a worker is employed at a new non-textile employer. The outcome in column (3) equals one if the worker is employed in a new geography (microregion). Standard errors are clustered at the establishment level.

Table 6: Role of skills and occupations in explaining gender differences

	Role of skills			Role of occupations		
	Retention	New sector	New occupation	Retention	New sector	New occupation
	(1)	(2)	(3)	(4)	(5)	(6)
D_i*Post_1*F	0.025**	-0.009	-0.017*	0.018	-0.001	-0.017*
	(0.012)	(0.008)	(0.009)	(0.012)	(0.008)	(0.009)
D_i*Post_2*F	0.057***	-0.051***	-0.062***	0.055***	-0.057***	-0.070***
	(0.012)	(0.009)	(0.010)	(0.011)	(0.009)	(0.010)
Skill decile-treat-post FE	Yes	Yes	Yes	No	No	No
Occ-treat-post FE	No	No	No	Yes	Yes	Yes
Observations	850646	850646	850646	850646	850646	850646

Notes: This table explores the role of gender differences in skill and occupation in explaining gender differences in leaving after a wage drop. $Post_1$ is an indicator equal to one in years $t = 0$ to $t = 2$ and $Post_2$ equals one in years $t = 3$ to $t = 5$. F is a dummy for female. The skill level (1-8) on each of 35 skills required to do an occupation comes from O*NET. Skill distance is the weighted average of the distance (L1-norm) between a worker's current occupation and all other occupations in her geography, with weights being that occupation's share among jobs in the geography. Columns (1)-(3) control for a fixed effect for the post period x decile of skill distance from other jobs in one's geography, and treatment. This regression thus answers the question: controlling for some common rate of retention, switching industries, or switching to a new occupation among treated workers in the same skill decile in the post period, do women still leave less than men? Columns (4)-(6) do the analog, but with 4-digit occupation instead of the decile of skill transferability. The sample is all incumbent workers, tracked wherever they go. A worker is treated $D_i = 1$ if she worked at an establishment exporting MFA-affected products at baseline and in the comparison group if the establishment exported other textile and clothing products. All specifications include worker fixed effects. Standard errors are clustered by establishment.

Table 7: Elasticities fall as employers and industry grows larger

Panel A: Elasticities by industry and employer size

Firm share	Large txt sector		Small txt sector	
	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$s = 0.01$	2.113	x	2.294	3.597
	(0.333)	x	(0.373)	(0.51)
$s = 0.05$	1.377	x	2.068	2.766
	(0.192)	x	(0.287)	(0.380)
$s = 0.1$	0.767	x	1.8	2.105
	(0.097)	x	(0.248)	(0.305)

Panel B: Average

	Women	Men
	(1)	(2)
e_g	1.236	2.689
μ_g	0.553	0.729

Notes: This table plots heterogeneity in labor supply elasticities by employer size (share of wage bill) and the size of the textile sector. The textile sector is considered large when its share is over 10% or more of a worker's labor market (geography x education group). To estimate heterogeneous effects on the change in log wage and change in labor supply by share I interact a dummy for treatment with the share. I separately estimate this regression in locations with a large (>10% wage bill at baseline) and small (<10% wage bill at baseline) textile industry. Labor supply and wage variables are defined in Section 5. I use the delta method to create standard errors around elasticity estimates, since they are a ratio $\Delta lnn/\Delta lnw$.

Table 8: Estimates of η, θ, λ

Parameter	Women (1)	Men (2)
η_g	2.19	3.89
	(0.402)	(0.890)
θ_g	0.89	0.87
	(0.355)	(0.421)
λ_g	0.03	0.05
	(0.097)	(0.010)

Notes: This table reports estimates of η_g, θ_g, and λ_g. I estimate η_g as the elasticity facing atomistic employers in the textile and garment manufacturing industry, θ_g as the change in the rate at which workers exit an industry from a large versus small employer in the industry when the industry is small, and λ_g as the change in the rate at which workers exit a location from a large versus small employer in the location. Each estimate employs moments derived from the labor supply system, described in Section 6. All specifications include microregion x year fixed effects.

Table 9: Sources: gender differences in monopsony power

| | Textile | | Economy-wide | |
	(1)	(2)	(3)	(4)
	Women	Men	Women	Men
Match-specific preference				
$(1 + 1/\eta)$	69%	79%	69%	79%
Concentration				
Within-industry - $(1/\theta - 1/\eta) * HHI_{gk}$	66%	74%	66%	75%
Industry - $(1/\lambda - 1/\theta) * s_{gk} * HHI_{gk}$	55%	73%	45%	66%
ΔGWG				
Match-specific preference	10%		10%	
Within-industry concentration	-2%		-2%	
Concentration in industry	10%		12%	
Total monopsony-induced GWG	18%		20%	
p-val test: $1/\eta - 1/\theta < 0$	0.006	0.104	0.006	0.104
p-val test: $1/\lambda - 1/\theta < 0$	0.013	0.134	0.013	0.134

Notes: This table combines estimates of η_g, θ_g, and λ_g for each gender with measures of concentration and industry sizes in the RAIS data to calculate the gender wage gap from match-specific preferences, within-industry concentration, and concentration in some industries. As in Proposition 1.

C Appendix Tables

Table C1: Bindingness of MFA quota regime

	China	Brazil
6-digit products under quota	62%	14%
Fill rate (fr), conditional on quota	81%	13%
Binding (fr > 90%), conditional on quota	55%	5%

Notes: This table describes the share of 6-digit products facing quotas in China and Brazil at the MFA's end on January 1, 2005.

Table C2: MFA schedule of integration

Phase	Start date	No. of (10 digit) HS products integrated	Share of export volume
I	Jan 1, 1995	318	16%
II	Jan 1, 1998	744	17%
III	Jan 1, 2002	745	18%
IV	Jan 1, 2005	2978	49%

Notes: This table describes the schedule of quota removal on 10-digit HS products under the MFA, as implemented by the United States. It is from Brambilla et al. 2010.

Table C3: Nominal wage declines

	(1)	(2)	(3)	(4)
	Avg. monthly wage		December wage	
	Women	Men	Women	Men
D_i	0.053***	0.060**	0.075**	0.057**
	(0.012)	(0.029)	(0.033)	(0.027)
Constant	0.058***	0.072***	0.226***	0.225***
	(0.003)	(0.003)	(0.013)	(0.013)
Observations	51533	62672	51533	62672

Notes: This table reports the MFA's effect on a dummy variable equal to one if a worker's nominal earnings fell between $t = -1$ and $t = 1$. The sample is incumbent workers. A worker is treated if s/he worked at an MFA-product-exporting establishment at baseline and comparison if at an exporter of a different textile and clothing product. Columns (1) and (2) report effects on monthly nominal earnings and Columns (3) and (4) on December earnings.

Table C4: New worker characteristics

| | Women | | | Men | | |
| | Age | No high school degree | Poached | Age | No high school degree | Poached |
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*post	-0.060	-0.010	-0.001	-0.540	-0.032	-0.004
	(0.294)	(0.015)	(0.011)	(0.349)	(0.020)	(0.012)
Baseline mean	29.515	0.605	0.558	26.667	0.577	0.586
Observations	6759	6759	6759	6759	6759	6759

Notes: This table reports treatment effects on new worker characteristics before versus after the MFA. Each regression is at the establishment level. The outcome is the average characteristic of new workers in any given year. Each regression includes establishment and year fixed effects and clusters standard errors by establishment. Post is an indicator equal to one in and after 2005. Columns (1)-(3) report results for new female hires while Columns (4)-(6) report results for new male hires. Age is measured in years. High school dropout is the share of new workers without high school degrees. Poached is the share of workers poached in from another employer in the formal sector.

Table C5: Female and male-focused amenities in contracts

Top 20 female clauses	Top 20 male clauses	Rank
Childcare assistance	On-call pay	1
Absences	Life insurance	2
Adoption leave	Strike procedures	3
Other: holidays and leaves	Other: protections for injured workers	4
Seniority pay	Profit sharing	5
Maternity protections	Salary deductions	6
Abortion protections	Work constraints	7
Paid leave	Transfers	8
Night pay	Machine and equipment maintenance	9
Nonwork-related injury protections	Duration and schedule	10
Abortion leave	Working environment conditions	11
Policy for dependents	Salary payment - means and timeframes	12
Extension/reduction of workday	Hazard pay (danger risk)	13
Guarantees to union officers	Safety equipment	14
Renewal/termination of the CBA	CIPA: accident prevention committee	15
Medical exams	Other assistances	16
Unionization campaigns	Death/funeral assistance	17
Health education campaigns	Workday compensation	18
Waiving union fees	Collective vacations	19
Salary adjustments/corrections	Tools and equipment	20

Notes: This table replicates Table 2 in Corradini et al. (2022) and reports amenities uncovered as female and male-centric using the revealed preference approach described in their paper.

Table C6: Skills predictive of leaving for men

	Retention	New sector	New occupation
	(1)	(2)	(3)
D_i*Post$_1$	-0.027*	0.020**	0.015
	(0.016)	(0.008)	(0.010)
D_i*Post$_2$	-0.069***	0.040***	0.045***
	(0.014)	(0.009)	(0.010)
D_i*Post$_1$*Transferable	-0.013	0.015	0.019
	(0.019)	(0.011)	(0.012)
D_i*Post$_2$*Transferable	-0.067***	0.039***	0.054***
	(0.017)	(0.013)	(0.014)
Observations	397188	397188	397188

Notes: This table shows that skill transferability is predictive of leaving one's baseline employer, switching to a new sector, and switching to a new occupation for men. Skill transferability is defined as having above median transferable skills on the (negative) of the skill remoteness measure described in Appendix D.2. Post$_1$ is a dummy equal to 1 in years 0-2 after the MFA and Post$_2$ in years 3-5. The sample for these regressions is men. All specifications include geography x year fixed effects. Standard errors are clustered by establishment.

Table C7: Role of education and tenure

	Role of education			Role of tenure		
	Retention	New sector	New occupation	Retention	New sector	New occupation
	(1)	(2)	(3)	(4)	(5)	(6)
Treat*Post*F	0.023*	0.000	-0.017*	0.002	0.028***	-0.018*
	(0.012)	(0.008)	(0.009)	(0.013)	(0.010)	(0.011)
Treat*Post*F	0.054***	-0.042***	-0.059***	0.049***	-0.029**	-0.063***
	(0.012)	(0.009)	(0.010)	(0.015)	(0.011)	(0.012)
Education-treat-post FE	Yes	Yes	Yes	No	No	No
Tenure-treat-post FE	No	No	No	Yes	Yes	Yes
Observations	850646	850646	850646	850646	850646	850646

Notes: This table explores the role of gender differences in education and baseline tenure in explaining gender differences in leaving after a wage drop. $Post_1$ is an indicator equal to one in years $t = 0$ to $t = 2$ and $Post_2$ equals one in years $t = 3$ to $t = 5$. F is a dummy for female. Education is divided into three categories: high school dropouts, high school graduates, and those with some college education. Tenure is divided into ten deciles on baseline value. Columns (1)-(3) include controls for education level x treatment x post period and Columns (4)-(6) include controls for decile of tenure x treatment x post period. The sample is all incumbent workers, tracked wherever they go. A worker is treated $D_i = 1$ if she worked at an establishment exporting MFA-affected products at baseline and in the comparison group if the establishment exported other textile and clothing products. All specifications include worker fixed effects. Standard errors are clustered by establishment.

Table C8: Idiosyncratic constraints

	Women		Men	
	Childbearing	Unsafe municipality	Childbearing	Unsafe municipality
	(1)	(3)	(4)	(6)
Δlnw_i	2.110***	2.278***	4.997***	3.104***
	(0.474)	(0.486)	(0.976)	(0.925)
$\Delta lnw_i \times X_i$	-0.542***	-0.551*	-1.898***	-1.239
	(0.070)	(0.166)	(0.332)	(1.381)
Observations	65913	65913	49482	49482

Notes: This table plots heterogeneous elasticities along two dimensions: being of childbearing age, defined as between 20 and 35 years; and employer location in an unsafe municipality. A municipality is designated unsafe if, in the four years between 2000 and 2004, its homicide rate was above the 75th percentile.

Table C9: Summary, sources of disproportionate monopsony

	Name	Women	Men	Source	Specification
Panel A: Horizontal differentiation					
η_g	Idiosyncratic ability to switch employers	2.19	3.89	Elasticity at atomistic employers ($s \sim 0$)	Section 5
θ_g	Idiosyncratic ability to switch employers across sectors	0.89	0.87	Change in elasticity of leaving sector with employer size	Section 5
λ_g	Idiosyncratic ability to switch employers across regions	0.03	0.05	Change in elasticity of leaving region with employer size	Section 5
Panel B: Concentration within sector					
HHI	Payroll weighted Herfindahl	0.08	0.112	Calculated in RAIS	x
Panel C: Share of textiles					
s_{txt}	Share of T&C in labor market	0.105	0.035	Calculated in RAIS	x

Notes: This table summarizes the sources of disproportionate monopsony. η_g, θ_g, λ_g are as estimated in Section 5. The payroll-weighted Herfindahl is calculated in RAIS as is the share of the textile and clothing industry in the labor market. The share of textiles is the weighed average over microregions, where each microregion is weighted by the share of the total textile wage bill in that microregion.

Table C10: Model parameters for counterfactuals

Parameter	Name	Value	Source	Component
Estimated				
η_g	Cross-employer	2.19 (w), 3.89 (m)	Elasticity estimate	LS
θ_g	Cross-industry elasticity of substitution	0.89 (w), 0.87 (m)	Elasticity estimate	LS
λ_g	Cross-location elasticity of substitution	0.03 (w), 0.05 (m)	Elasticity estimate	LS
s_{gk}	Share of industries	Varies	Data	Eqbm
a_{gk}	Industry-specific amenities	Varies	Match s_{gk} in data	Eqbm
W_{gk}	Industry-specific wages	Varies	Match s_{gk} in data	Eqbm
β_k	Women's productivity shifter in textiles	1.286	Estimated (Ackerberg et al. 2015)	Prod
β_k	Food mfg	1.1	Estimated (Ackerberg et al. 2015)	Prod
β_k	Metal	0.5	Estimated (Ackerberg et al. 2015)	Prod
β_k	Machinery	0.54	Estimated (Ackerberg et al. 2015)	Prod
β_k	Auto	0.34	Estimated (Ackerberg et al. 2015)	Prod
ζ	Productivity dispersion	0.7	Firm size distribution in textiles	Prod
Calibrated				
σ	Elasticity of substitution between men and women	5.94	Gallen 2022	Prod

Notes: This table notes parameters needed to simulate the model, their source, and which feature of the environment they correspond with (LS = labor supply, Prod = production function, Eqbm = equilibrium object, LD = labor demand is determined under a Cournot oligopsony).

Table C11: Non-targeted moments

	Name	Model	Data
μ_f	Women's markdown	0.552	0.553
μ_m	Men's markdown	0.727	0.729
$ln(\mu_m) - ln(\mu_f)$	Monopsony-induced GWG	0.119	0.120

*Notes:* This table describes the average markdown and GWG simulated in the model using the baseline parameter values.

C   Appendix Figures

Figure C1: Share of affected jobs over total number of textile jobs
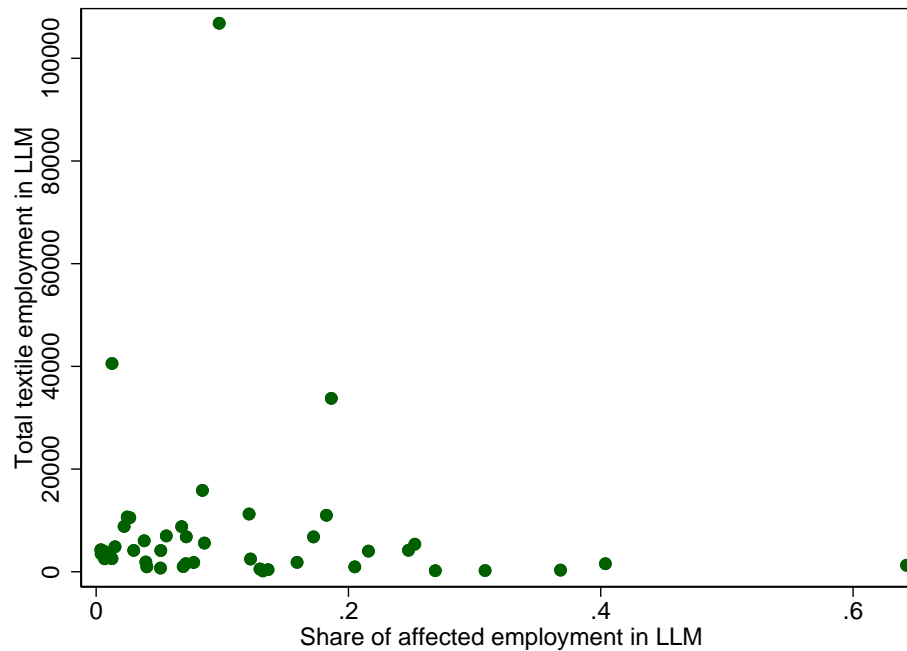
Notes: This figure shows that the MFA shock was small in all geographies, i.e. that, while textile and clothing industry may be clustered in some locations, treated employment still comprises a small share of total employment in these locations. In other words, the number of baseline T&C jobs in a microregion (y-axis) is uncorrelated with the share of treated T&C jobs in that microregion (x-axis).

Figure C2: Effect on aggregate employment

Log workers
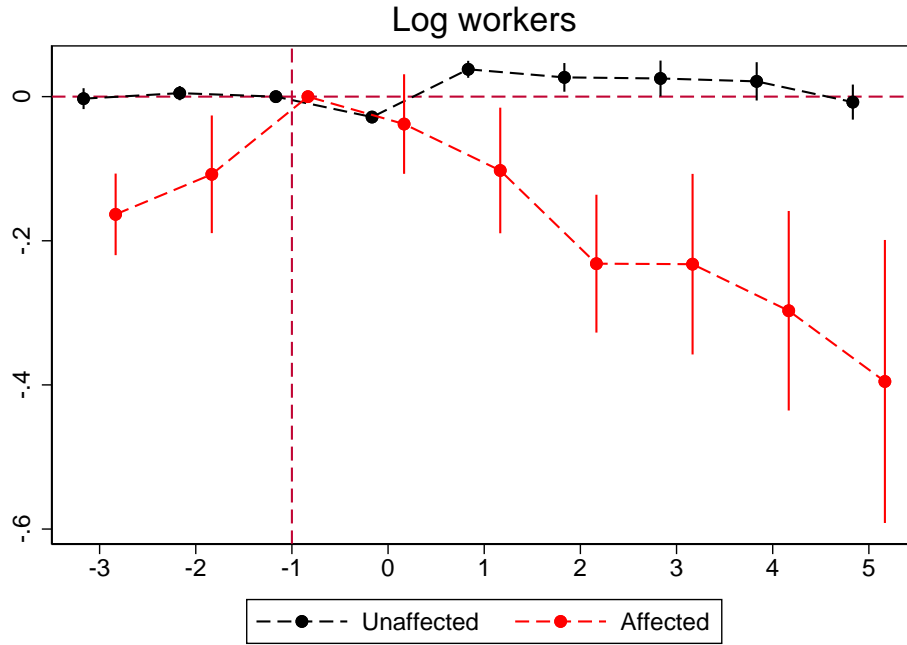
Notes: This figure plots the treatment effect on the log of employment at treated establishments and all other textile and clothing manufacturing establishments (including non-exporters). Standard errors are clustered by microregion

Figure C3: Effect on hours

(a) Contracted hours: women   (b) Contracted hours: men
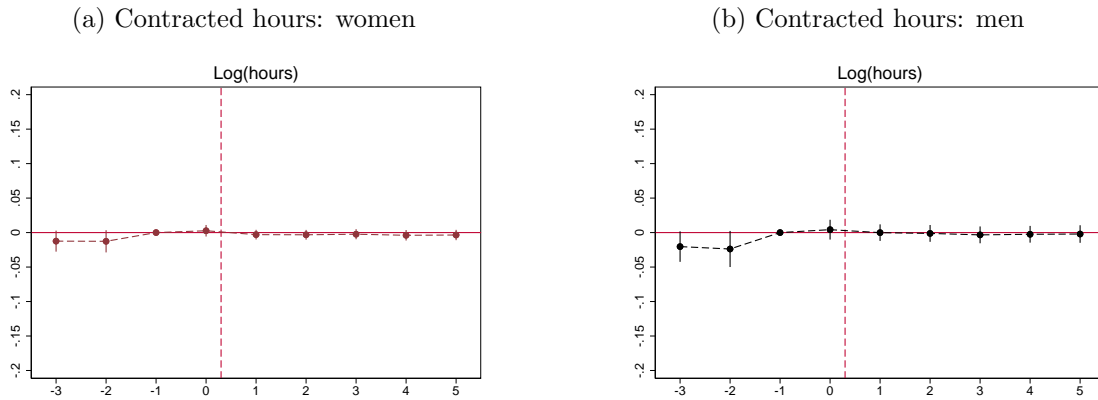
Notes: This figure plots treatment effects on men and women's contracted hours.

Figure C4: Effect on employer-to-employer transitions

(a) Switching to a new employer: women
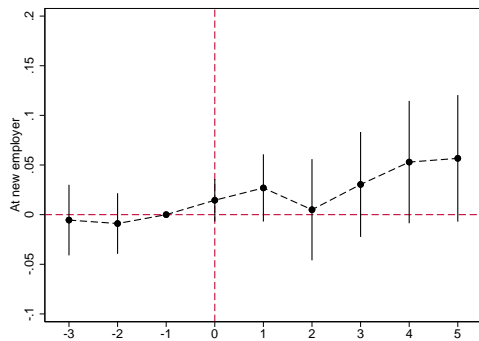
(b) Switching to a new employer: men
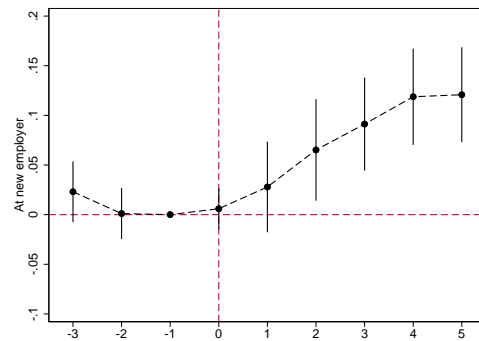
Notes: This figure plots treatment effects on employer-to-employer transitions, showing that the entire leaving response among men and women is driven by transitions to new employers as opposed to transitions into unemployment.

Figure C5: Effect on new worker log wages

(a) New workers: women
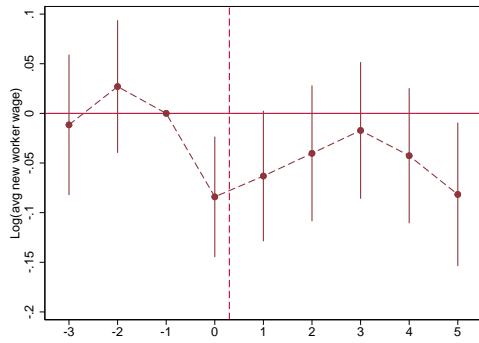
(b) New workers: men
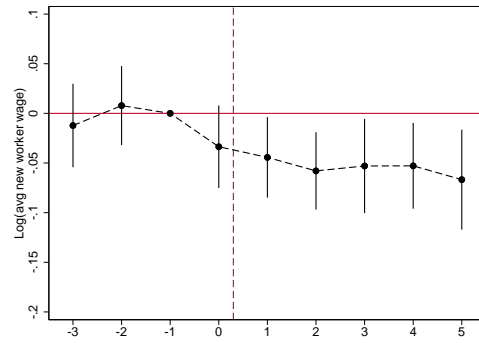
Notes: This figure plots DiD treatment effects on the log of the average wage paid to new workers hired by an establishment in the past year. Each regression is at the establishment-level. Standard errors are clustered by establishment.

Figure C6: Testing exclusion: variation in instrument

(a) Share of treated wage bill in region, excluding self
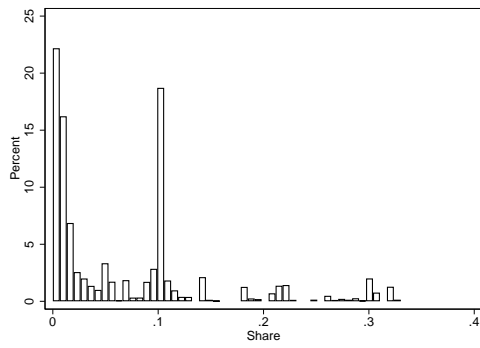
(b) By gender
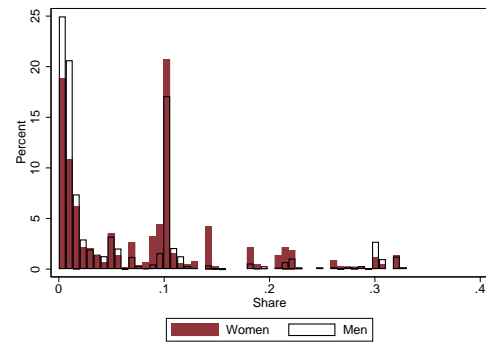
Notes: This figure plots the share of the baseline wage bill in a worker's microregion, excluding his or her own employer, that is treated by the MFA shock. The left panel plots this for all workers and the right separately by gender. This is the instrument that provides variation in how much share-weighted wages at other employers in the labor market change to test for wage spillovers.

Figure C7: Testing exclusion: pass-through of others' wage shocks

(a) First stage
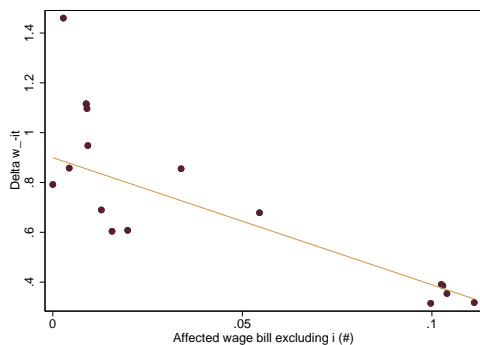
(b) Visual IV
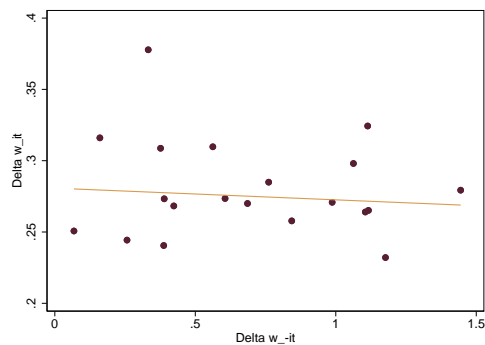
Notes: This figure plots the visual IV version of Table 4. Here the treatment variable, instead of being the number of treated workers in one's industry and geography, is the share of treated wage bill in one's industry and geography (still excluding one's own employer).

Figure C8: Variation in own-mrpl pass-through by employer size
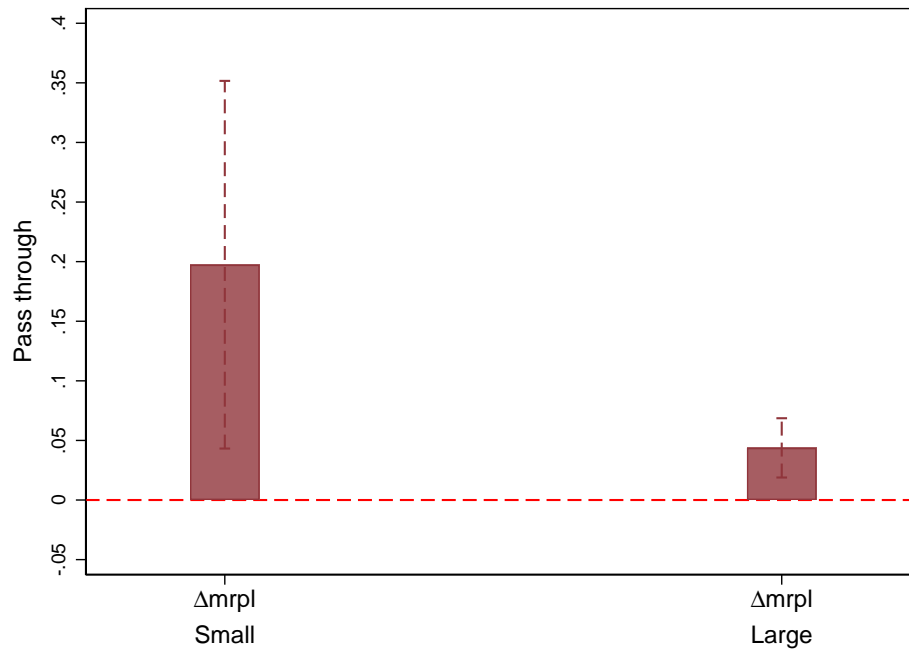
Notes: This figure plots the pass through of shocks to own mrpl on stayers' wages. Small employers are those with wage bill less than 1% of the local textile market whereas large employers are those with wage bill over 10%. The figure plots 95% confidence intervals.

Figure C9: Staying rates for childbearing and non-childbearing workers
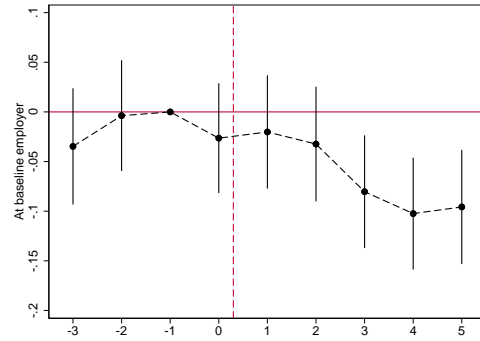
(a) Childbearing: women
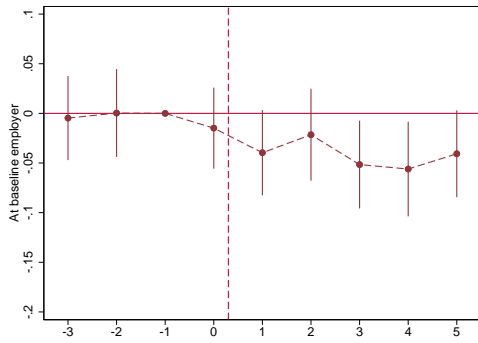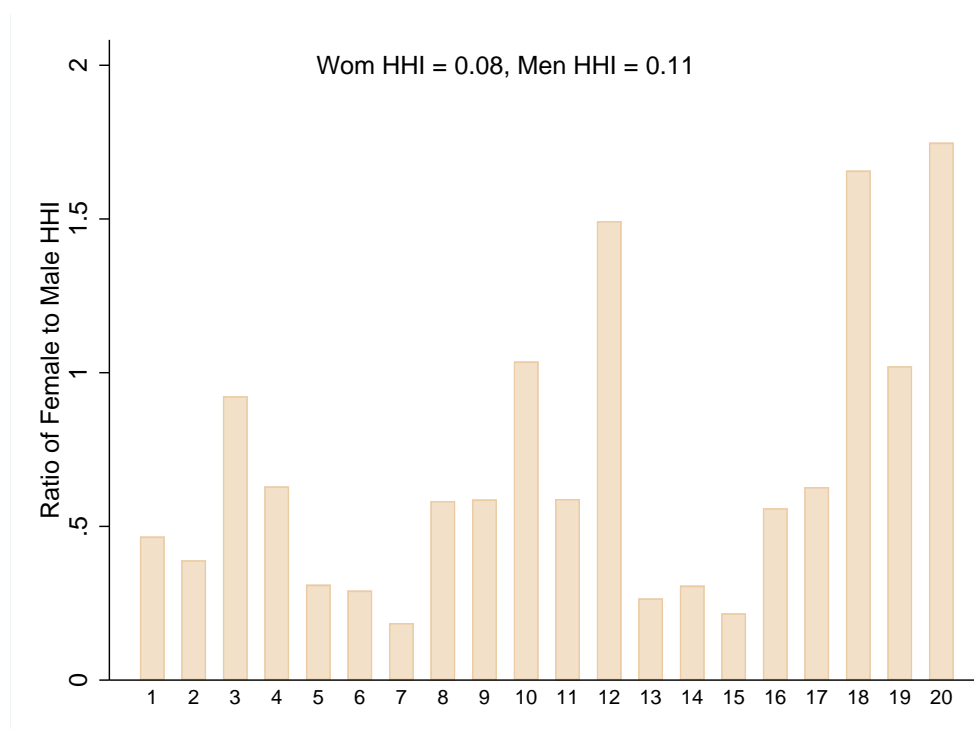

(b) Childbearing: men
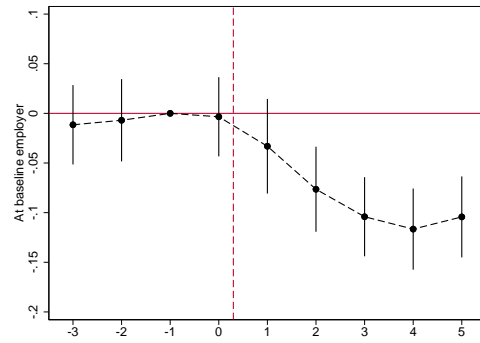
(c) Non-childbearing: women
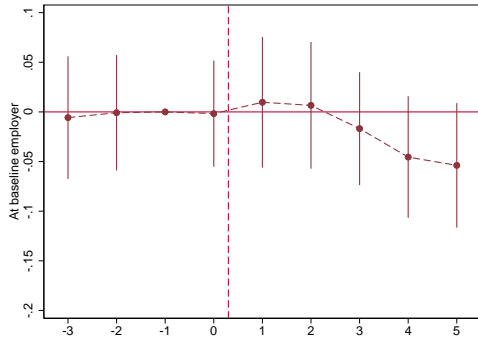
(d) Childbearing: men

Notes: This figure plots treatment effects on retention for women and men of childbearing ages (20-35 years) and other ages. The figure plots 95% confidence intervals

Figure C10: Within-industry concentration in textiles

Wom HHI = 0.08, Men HHI = 0.11

Notes: This figure plots the ratio of female to male payroll-weighted HHIs in the 20 microregions with the highest share of women's total textile wage bill. About 60% of both men and women's textile wage bill is in these microregions. Microregions are sorted from largest to smallest share, with 1 being the largest and 20 being the smallest. The text on top reports women and men's aggregated payroll-weighted HHI, i.e., summing over microregions, where each microregion is weighted by the gender-specific share of the wage bill in that microregion. This is the right notion of an aggregate, as shown in Appendix A.2, where by "right" we mean the HHI facing the average women or the average man in the sector.

Figure C11: Correlation between inferred amenities and observed amenities, women's share in industry

Observed amenities

Share of women
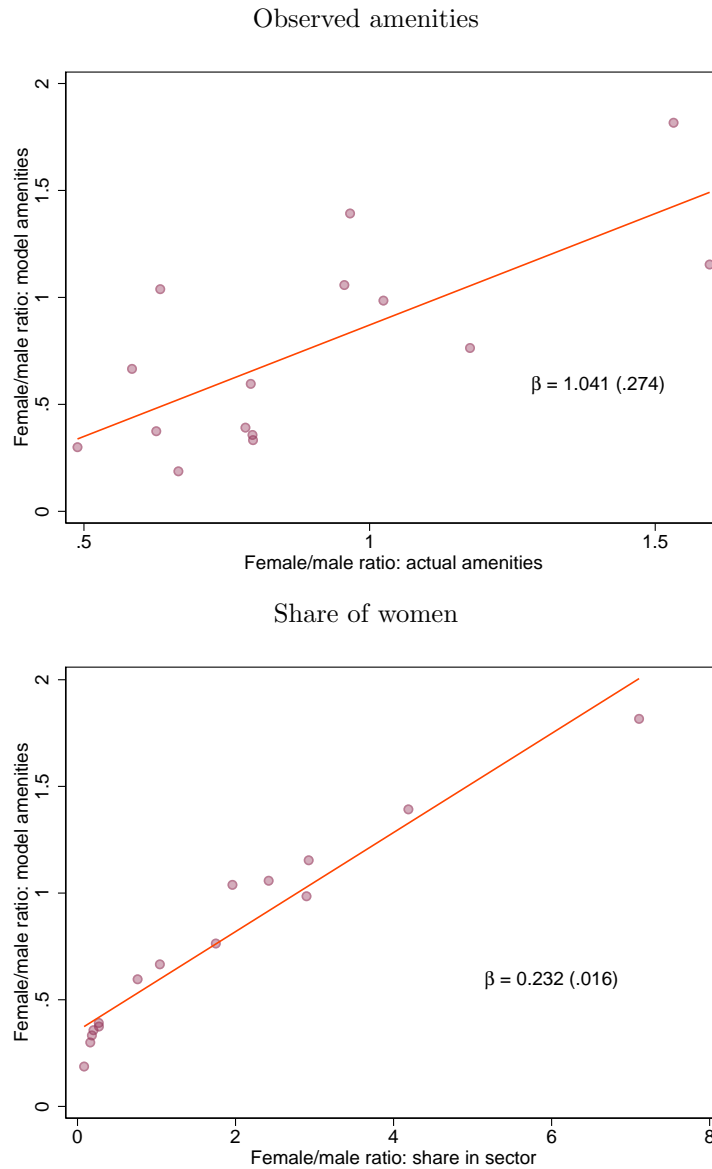
Notes: This figure plots, for each sector, observed and inferred female/male amenities. Observed amenities come from the text of all collective bargaining contracts, where we observe 137 different types of amenities at the establishment level, including maternity leave, childcare, and flexibility in work hours. I use the revealed preference approach developed in Corradini, Lagos & Sharma 2022 to define female and male-centric amenities: correlating correlating gender-specific job ladders inferred from employer-to-employer moves with contracted amenities to infer which are valued. In each sector, average observed amenities are a weighted-average of female and male-centric amenities across all establishments, with the weights being that establishment's share of the sector's wage bill.

Figure C12: GWG increasing with firm size
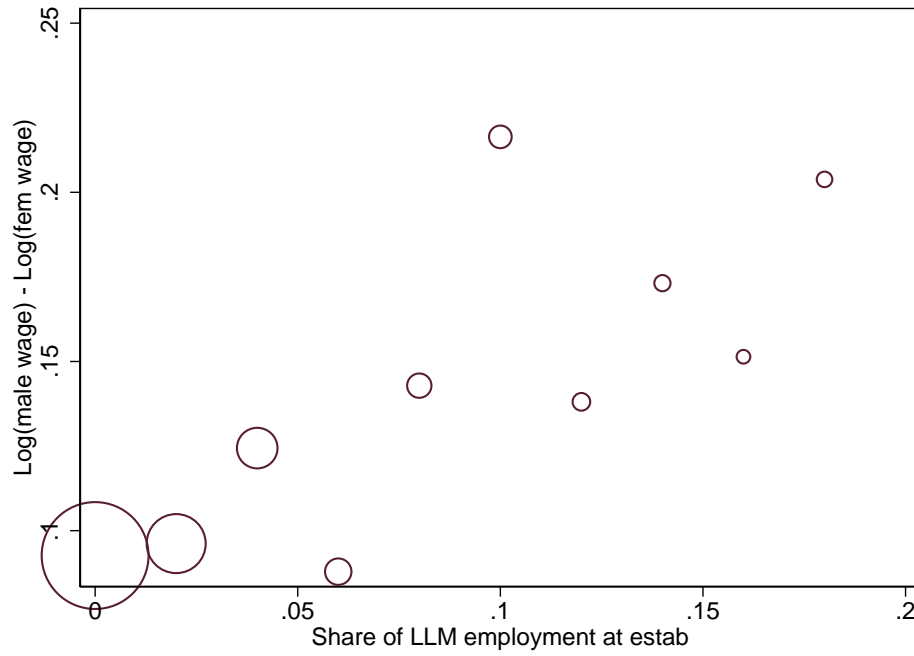
Notes: This figure plots the gender wage gap at an establishment, i.e. the difference in the log of men and log of women's wages (y-axis) against the share of the T&C wage bill in that establishment's microregion at that establishment (x-axis). The size of bins corresponds with the size of employment in that bin. It shows that the gender wage gap rises with establishment size.

Figure C13: Share of women at treated firms
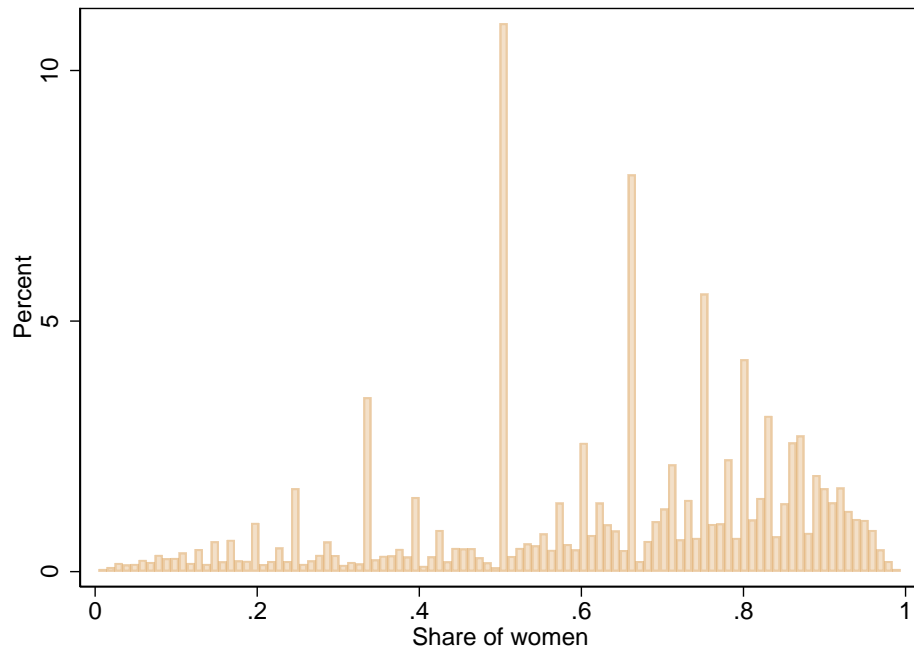
Notes: This figure plots the baseline distribution of the share of women in the workforce of treated establishments.

A Proofs and Derivations

A.1 Model Derivations

A.1.1 Setup

Markets The economy features a continuum of geographies $r \in [0,1]$ (microregions). Each geography features a discrete number of industries indexed by $k \in 1, ..., M_r$, and firms within the industry $j \in 1, ..., J_m$. Throughout I describe a geography as a "local labor market" and all same-gender jobs within an industry as the within-industry market.

Firms Firms compete in a Cournot oligopsony. Each posts gender-specific wages $\{w_m, w_f\}_j$ and chooses employment to maximize profits given the (inverse) labor supply it faces. The production function of each firm is differentiable and concave, with imperfect substitutability between male and female workers $F(f_j, m_j)$. Each firm is associated with exogenously-given industry-specific amenities (a_{gk}) and the firm's deviation from this industry norm (a_{gj}). I abstract from competition in amenities for simplicity.

Workers Workers, indexed by group g (men or women), possess heterogeneous preferences over employers. They choose to work at their higher utility employer, and exhibit three-nested preferences, choosing first a location, then an industry, and finally an employer within the industry. Their utility from working at employer j has a common group-specific component (rising in wages and amenities), and an idiosyncratic preference shock specific to each employment relationship ϵ_{igjk}. Each worker must earn $y_i \sim F(y)$, where earnings equal her wage multiplied by hours of supplied work $y_i = w_{gj} h_{igj}$.

$$u_{igjk} = ln w_{gj} + ln a_{gk} + ln a_{gj} + \epsilon_{igjk}$$

ϵ_{igjk} has a nested GEV Type I extreme value distribution. Its variance depends on three dispersion parameters η_g, θ_g, and λ_g.[40]

$$F(\epsilon_{i1}, ..., \epsilon_{NJ}) = \exp \left[-\sum_r (\sum_{k=1}^{M} (\sum_{j=1}^{J_m} e^{-(1+\eta_g)\epsilon_{igjk}})^{\frac{1+\theta_g}{1+\eta_g}})^{\frac{1+\lambda_g}{1+\theta_g}} \right]$$

A.1.2 Labor supply

The probability of choosing an employer is given by the standard nested logit (McFadden, 1978):

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[40] As shown by Anderson et al. (1992) this discrete choice framework generates the same labor supply to firms as obtained in a nested CES setting with the outermost nest being regions, the middle nest being industries, and the bottom nest being employers within the industry. η_g then corresponds with the within-industry elasticity of substitution, θ_g is the cross-industry elasticity of substitution, and λ_g the cross-region.

$$p_{gjkr} = \underbrace{\frac{(a_{gj}w_{gj})^{1+\eta_g}}{\sum_{j'\in k}(a_{gj'}w_{gj'})^{1+\eta_g}}}_{prob\ of\ choosing\ firm\ j\ in\ industry\ k} \times \underbrace{\frac{a_{kg}^{1+\theta_g}\left(\sum_{j'\in k}(a_{gj'}w_{gj'})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}}{\sum_{k'\in r}a_{k'g}^{1+\theta_g}\left(\sum_{j''\in k'}(a_{gj''}w_{gj''})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}}}_{prob\ of\ choosing\ industry\ k} \times \underbrace{\frac{\bar{W}_{gr}^{1+\lambda_g}}{\sum_{r'}\bar{W}_{gr'}^{1+\lambda_g}}}_{prob\ of\ choosing\ region\ r}$$

I aggregate these probabilities over workers to obtain the labor supply to an employer j in industry k in region r:

$$n_{gjkr} = \int p_{gjkr}h_{igjkr}dF(y_i), \ \ h_{igjkr} = \frac{y_i}{w_{gjkr}}$$

$$n_{gjkr} = \frac{(w_{gjkr})^{\eta_g}}{\sum_{j'\in k}(a_{gj'}w_{gj'})^{1+\eta_g}} \frac{\left(\left(\sum_{j'\in k}(a_{gj'}w_{gj'})^{1+\eta_g}\right)\right)^{\frac{1+\theta_g}{1+\eta_g}}}{\sum_{k'\in r}a_{gk'}^{1+\theta_g}\left(\sum_{j''\in k'}(a_{gj''}w_{gj''})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}} \times$$

$$\frac{\left(\sum_{k'\in r}a_{gk'}^{1+\theta_g}\left(\sum_{j''\in k'}(a_{gj''}w_{gj''})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}\right)^{\frac{1+\lambda_g}{1+\theta_g}}}{\sum_r\left(\sum_{k''\in r}a_{gk''}^{1+\theta_g}\left(\sum_{j'''\in k''}(a_{gj'''}w_{gj''})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}\right)^{\frac{1+\lambda_g}{1+\theta_g}}}(a_{gjkr})^{1+\eta_g}a_{gk}^{1+\theta_g}Y_g$$

where $Y_g = \sum_n w_{gn}n_{gn}$ denotes the total labor income of the group summed over all employers in the economy. I define the following wage indices at the industry-region, region, and group levels:

$$\bar{W}_{gkr} = \left(\sum_{j'\in k,r}(a_{gj'}w_{gj'})^{1+\eta_g}\right)^{\frac{1}{1+\eta_g}}$$

$$\bar{W}_{gr} = \left(\sum_{k'\in r}a_{gk}^{1+\theta_g}\left(\sum_{j'\in k}(a_{gj'}w_{gj'})^{1+\eta_g}\right)^{\frac{1+\theta_g}{1+\eta_g}}\right)^{\frac{1}{1+\theta_g}}$$

$$\bar{W}_g = \left(\sum_r\bar{W}_{gr}^{1+\lambda_g}\right)^{\frac{1}{1+\lambda_g}}$$

And the following employment indices:

$$N_{gkr} = \left(\sum_{j'\in k,r}(a_{gj'}^{-1}n_{gj'})^{\frac{1+\eta_g}{\eta_g}}\right)^{\frac{\eta_g}{1+\eta_g}}$$

$$N_{gr} = \left(\sum_{k\in r}(a_{gk}^{-1}N_{gkr})^{\frac{1+\theta_g}{\theta_g}}\right)^{\frac{\theta_g}{1+\theta_g}}$$

$$N_g = \left(\sum_r N_{gr}^{\frac{1+\lambda_g}{\lambda_g}}\right)^{\frac{\lambda_g}{1+\lambda_g}}$$

Along with (1), these indices imply $W_g N_g = Y_g$. To obtain the labor supply to an employer I plug these expressions back into (1), yielding the nested CES supply curve to j:

$$n_{gjkr} = \left(\frac{w_{gjkr}}{\bar{W}_{kgr}}\right)^{\eta_g} \left(\frac{\bar{W}_{kgr}}{\bar{W}_{gr}}\right)^{\theta_g} \left(\frac{\bar{W}_{gr}}{\bar{W}_g}\right)^{\lambda_g} a_{gjkr}^{1+\eta_g} a_{gk}^{1+\theta_g} N_g$$

I invert the labor supply curve in three steps:

$$N_{gr} = \left(\frac{\bar{W}_{gr}}{\bar{W}_g}\right)^{\lambda_g} N_g$$

$$\bar{W}_{gr} = \left(\frac{N_{gr}}{N_g}\right)^{\frac{1}{\lambda_g}} W_g$$

Next:

$$N_{gkr} = \left(\frac{\bar{W}_{kgr}}{\bar{W}_{gr}}\right)^{\theta_g} \left(\frac{\bar{W}_{gr}}{\bar{W}_g}\right)^{\lambda_g} a_{gk}^{1+\theta_g} N_g$$

$$\bar{W}_{kgr} = \left(\frac{N_{gkr}}{N_{gr}}\right)^{\frac{1}{\theta_g}} a_{gk}^{-\left(\frac{1+\theta_g}{\theta_g}\right)} \bar{W}_{gr}$$

Finally:

$$n_{gjkr} = \left(\frac{w_{gjkr}}{\bar{W}_{kgr}}\right)^{\eta_g} n_{gkr} a_{gjkr}^{1+\eta_g}$$

$$w_{gjkr} = \left(\frac{n_{gjkr}}{n_{gkr}}\right) a_{gjkr}^{-\left(\frac{1+\eta_g}{\eta_g}\right)} \bar{W}_{kgr}$$

Together, these yield the inverse labor supply curve:

$$w_{gjkr} = \left(\frac{n_{gjkr}}{N_{gkr}}\right)^{\frac{1}{\eta_g}} \left(\frac{N_{gkr}}{N_{gr}}\right)^{\frac{1}{\theta_g}} \left(\frac{N_{gr}}{N_g}\right)^{\frac{1}{\lambda_g}} W_g a_{gk}^{\frac{-(1+\theta_g)}{\theta_g}} a_{gjkr}^{\frac{-(1+\eta_g)}{\eta_g}}$$

Labor supply elasticity I obtain the inverse elasticity of residual labor supply to a single employer j by taking the derivative of its log wage wrt log employment:

$$lnw_{gjkr} = \frac{1}{\eta_g} lnn_{gjkr} + \left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right) lnN_{gkr} + \left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right) lnN_{gr} + Aggregates + Amenities$$

Before doing so, I prove a useful lemma.

Lemma 1 $\frac{\partial lnN_{gkr}}{\partial lnn_{gjkr}} = s_{gj}$

Proof. By definition, $N_{gkr} = (\sum_{j' \in k,r} a_{gj'}^{-1} n_{gj'}^{\frac{1+\eta_g}{\eta_g}})^{\frac{\eta_g}{1+\eta_g}}$. Thus:

$$\frac{\partial ln N_{gkr}}{\partial ln n_{gjkr}} = \frac{\eta_g}{1+\eta_g} \frac{\partial ln(\sum_{j' \in k,r}(a_{gj'}^{-1} n_{gj'})^{\frac{1+\eta_g}{\eta_g}})}{\partial n_{gj}} n_{gj}$$

$$\frac{\partial ln N_{gkr}}{\partial ln n_{gjkr}} = \frac{(a_{gj'}^{-1} n_{gjkr})^{\frac{1+\eta_g}{\eta_g}}}{\sum_{j' \in k,r}(a_{gj'}^{-1} n_{gj'})^{\frac{1+\eta_g}{\eta_g}}}$$

By definition, $s_{gjkr} := \frac{w_{gjkr} n_{gjkr}}{\sum_{j' \in k,r} w_{j'} n_{j'}} = \frac{(a_{gj'}^{-1} n_{gjkr})^{\frac{1+\eta_g}{\eta_g}}}{\sum_{j' \in k,r}(a_{gj'}^{-1} n_{gj'})^{\frac{1+\eta_g}{\eta_g}}}$ (plugging in the inverse labor supply to j and $j' \in k,r$), thus proving the lemma. ∎

By a similar argument, $\frac{\partial ln N_{gr}}{\partial ln n_{gjkr}} = \frac{\partial ln N_{gr}}{\partial ln N_{gkr}} \frac{\partial ln N_{gkr}}{\partial ln n_{gjkr}} = s_{gk} s_{gj}$. Therefore, the elasticity of residual labor supply to employer j in industry k in region r is:

$$e_{gj} = \left(\frac{\partial ln w_{gj}}{\partial ln n_{gj}}\right)^{-1} = \left[\frac{1}{\eta_g} + (\frac{1}{\theta_g} - \frac{1}{\eta_g})s_{gj} + (\frac{1}{\lambda_g} - \frac{1}{\theta_g})s_{gj}s_{gk}\right]^{-1} \tag{4}$$

A.1.3 Firm optimization: elasticities govern markdowns

Workers are paid only a fraction of their marginal product and markdowns are governed by employer-specific elasticities. Each employer chooses labor f_j and m_j to maximize profits, given the inverse labor supply it faces.

$$\max_{f_j, m_j} F(f_j, m_j) - w_{fj} f_j - w_{mj} m_j$$

with the FOC determining demand for each group:

$$MRPL_{gj} = \left(1 + \frac{1}{e_{gj}}\right) w_{gj}$$

$$MRPL_{gj} = \mu_{gj}^{-1} w_{gj}$$

When $e_{gj} = \infty$, in a competitive market, workers are paid exactly their marginal product. However, because firms have market power, workers are paid below their marginal product of labor with markdown μ_{gj}:

$$\mu_{gj} = \frac{e_{gj}}{1 + e_{gj}}$$

Workers with more elastic supply have higher markdowns, i.e. are paid closer to their marginal product.

A.1.4 Condition for estimated reduced form elasticity to equal structural elasticity

This section demonstrates why the elasticity of residual labor supply governing markdowns is typically inestimable with a firm specific shock. Intuitively, this is because such shocks typically uncover the total derivative with respect to j's wage whereas the structural elasticity that governs markdowns as shown above is a partial derivative. It also yields the conditions under which this structural elasticity *is* estimable with firm-specific shocks. Starting from the labor supply system, where I omit time subscripts t for visual benefit but the changes are one period following time t:

$$lnn_{gjkr} = \eta_g lnw_{gjkr}^- + (\theta_g - \eta_g)lnW_{kgr}^- + (\lambda_g - \theta_g)lnW_{gr}^- + Aggregates$$

Consider a first-order approximation around the Nash equilibrium, following any change to firms in the region:

$$\Delta lnn_{gjkr} = \eta_g \Delta lnw_{gjkr} + (\theta_g - \eta_g) \sum_{j' \in k,r} \frac{\partial lnW_{kgr}^-}{\partial lnw_{gj'}}|_{w*_{j!=j}} \Delta lnw_{j'} + (\lambda_g - \theta_g) \sum_{j'' \in r} \frac{\partial lnW_{gr}^-}{\partial lnW_{kgr}^-}\frac{\partial lnW_{kgr}^-}{\partial lnw_{gj''}}|_{w*_{j!=j''}} \Delta lnw_{j''}$$

$$\frac{\Delta lnn_{gjkr}}{\Delta lnw_{gjkr}} = (\eta_g + (\theta_g - \eta_g)s_{gj} + (\lambda_g - \theta_g)s_{gj}s_{gk}) + \frac{(\theta_g - \eta_g)}{\Delta lnw_{gjkr}} \sum_{j' \in k,r} s_{gj'} \Delta lnw_{j'} + (\lambda_g - \theta_g) \sum_{j'' \in r} s_{gj''} s_{gk} \Delta lnw_{j''}$$

The estimated reduced form elasticity is:

$$\epsilon_{gjkr} = \frac{\Delta lnn_{gjkr}}{\Delta lnw_{gjkr}}$$

$$\epsilon_{gjkr} = e_{gjkr} + \frac{1}{\Delta lnw_{gjkr}}((\theta_g - \eta_g) \sum_{j' \in k,r} s_{gj'} \Delta lnw_{j'} + (\lambda_g - \theta_g) \sum_{j'' \in r} s_{gj''} s_{gk} \Delta lnw_{j''})$$

The test of strategic interaction I perform below argues that $\Delta lnw_{j'} = 0 \forall j' \in k, r$. While I report results only for employers in the textile industry, I can also show that $\Delta lnw_{j''} = 0 \forall j'' \in r \notin k$. This is intuitive, since employers in the textile industry compete most tightly with others that are also in the industry. Therefore, I estimate $\epsilon_{gjkr} = e_{gjkr}$.

A.2 Proofs of in-text propositions

Proposition 1 *Through the lens of the model, monopsony over the average worker in a group g in industry k is given by the following (inverse) average markdown:*

$$\bar{\mu}_{gkr}^{-1} = \frac{mr\bar{p}l_{gkr}}{w_{gkr}^-} = 1 + \frac{1}{\eta_g} + \left(\frac{1}{\theta_g} - \frac{1}{\eta_g}\right) HHI_{gkr} + \left(\frac{1}{\lambda_g} - \frac{1}{\theta_g}\right) HHI_{gkr} s_{gkr}$$

Proof. The proof has two steps. First I show that inverse of the average markdown for the average worker of group g in industry k in region r is just the share-weighted average of the inverse of individual employer markdowns: $\bar{\mu}_{gkr}^{-1} = (\sum_{j \in k,r} s_{gj}\mu_{gj}^{-1})$.

$$\sum_{j \in k,r} s_{gj} \mu_{gj}^{-1} = \sum_{j \in k,r} s_{gj} \left(1 + \frac{1}{e_{gj}} \right)$$

$$= \sum_{j \in k,r} s_{gj} \left(\frac{mrpl_{gj}}{w_{gj}} \right)$$

$$= \sum_{j \in k,r} \frac{n_{gj}}{\sum_{j' \in k,r} w_{gj'} n_{gj'}} \frac{mrpl_{gj}}{1}$$

$$= \frac{\sum_{j \in k,r} mrpl_{gj} n_{gj}}{\sum_{j' \in k,r} w_{gj'} n_{gj'}} \times \frac{\sum_{j' \in k,r} n_{gj}}{\sum_{j' \in k,r} n_{gj}}$$

$$= \frac{\overline{mrpl}_{gkr}}{\overline{w}_{gkr}}$$

$$= \overline{\mu}_{gkr}^{-1}$$

Next, I calculate the average group-specific markdown through the lens of the model:

$$\sum_{j \in k,r} s_{gj} \mu_{gj}^{-1} = \sum_{j \in k,r} s_{gj} \left(1 + \frac{1}{e_{gj}} \right)$$

$$\sum_{j \in k,r} s_{gj} \mu_{gj}^{-1} = \sum_{j \in k,r} s_{gj} \left(1 + \frac{1}{\eta_g}(1 - s_{gj}) + \frac{1}{\theta_g}(s_{gj}(1 - s_{kr})) + \frac{1}{\lambda_g}(s_{gj} s_{kr}) \right)$$

$$\sum_{j \in k,r} s_{gj} \mu_{gj}^{-1} = 1 + \frac{1}{\eta_g} + \left(\frac{1}{\theta_g} - \frac{1}{\eta_g} \right) HHI_{gk} + \left(\frac{1}{\lambda_g} - \frac{1}{\theta_g} \right) \sum_{r} s_{gr} HHI_{gkr} s_{gkr}]$$

■

To obtain the average inverse markdown for a worker of group g in k I aggregate to the industry-level over regions r:

$$\overline{\mu}_{gk}^{-1} = \sum_{r} s_{rk}^{g} \sum_{j \in k,r} s_{gj} \mu_{gj}^{-1}$$

$$= \sum_{r} s_{rk}^{g} \left[1 + \left(\frac{1}{\eta_g} \right)(1 - HHI_{gkr}) + \left(\frac{1}{\theta_g} \right) HHI_{gkr}(1 - s_{gkr}) + \frac{1}{\lambda_g} HHI_{gkr} s_{gkr} \right]$$

$$= 1 + \frac{1}{\eta_g} + \left(\frac{1}{\theta_g} - \frac{1}{\eta_g} \right) HHI_{gk} + \left(\frac{1}{\lambda_g} - \frac{1}{\theta_g} \right) \sum_{r} s_{rk}^{g} HHI_{gkr} s_{gkr}$$

where s_{rk}^{g} is the share of the group's overall wage bill in industry k that is in microregion r. It is straightforward to see that this measures the average inverse markdown of a worker in industry k by closely paralleling Step 1 of the proof of the above proposition.

Proposition 2 *The share of the gender wage gap explained by monopsony over the average worker is.*

$$\frac{ln(\overline{\mu}_m) - ln(\overline{\mu}_f)}{ln(\overline{w}_m) - ln(\overline{w}_f)}$$

where $\bar{w}_m$ is the average man's wage and $\bar{w}_f$ is the average woman's wage and $\bar{\mu}_g = (\sum_j s_{gj}\mu_{gj}^{-1})^{-1}$ is the average markdown, i.e. how much the average worker is paid below marginal product with s_{gj} being the employer's share of the wage bill in textiles.

Proof. Start from the accounting identity $\bar{w}_g = \bar{mrpl}_g\bar{\mu}_g$ Taking logs and re-arranging yields the result:

$$ln(\bar{w_m}) - ln(\bar{w_f}) = ln(\bar{\mu}_m) - ln(\bar{\mu}_f) + ln(\bar{mrpl}_m) - ln(\bar{mrpl}_f)$$

Thus, the share potentially due to monopsony is $\frac{ln(\bar{\mu}_m) - ln(\bar{\mu}_f)}{ln(\bar{w_m}) - ln(\bar{w_f})}$. ∎

B Strategic Wage Setting

B.1 Test and Results

To test for spillover effects, I implement a test from the exchange rate pass-through literature (Amiti et al. 2019) in the labor setting. Its key insight is that strategic motives for wage setting operate by changing an employer's markdown: in other words, as workers flock from a China-competing employer that lowers their wage to a non-China-competing employer, the second can now pay them a smaller fraction of marginal product. I show that, for any structure of competition among employers (including Cournot and Bertrand oligopsony), and invertible labor supply system (where employers are not perfect substitutes), I can estimate wage spillovers by regressing an employer's wage change on a weighted average of wage changes at its competitors, controlling for changes to its own marginal product, without having to account for what spurred the change or who it comes from. While one main motivation for this spillover test is to assess the plausibility of the exclusion restriction, it also offers a general test of oligopsonistic wage setting that can be applied to other settings.

Estimating equation I start with an accounting identity that links an employer j's log wage to the log of its marginal product and markdown:

$$lnw_{jt} = lnmrpl_{jt} + ln\mu_{jt}$$

Proposition 3 *For any competition structure among employers and any invertible labor supply system where firms are not perfect substitutes, ∃ a log markdown function $\Lambda_j(w_{jt}, \mathbf{w_{-jt}}; a_{jt}, a_{-jt})$, such that the firm's profit-max wage $\tilde{w}_{jt}$ is the solution to the following fixed point, for any given wage vector among its competitors $\mathbf{w_{-jt}}$:*

$$ln\tilde{w}_{jt} = lnmrpl_{jt} + \Lambda_j(\tilde{w}_{jt}, \mathbf{w_{-jt}}, a_{jt}, \mathbf{a_{-jt}}) \tag{5}$$

Proof. See below. ■ That j's optimal markdown Λ_j can depend on other employer $-\mathbf{j}$'s wages reflects the potential for wage spillovers. To derive the estimating equation, I totally differentiate and re-arrange equation (7):

$$dlnw_{jt} = \frac{1}{1 + \Gamma_{jt}} dlnmrpl_{jt} + \frac{\Gamma_{-jt}}{1 + \Gamma_{jt}} dlnw_{-jt} + \xi_{jt}$$

where $\Gamma_{jt} := -\frac{\partial \Lambda_i(w_t,;a_t)}{\partial w_{jt}}$ captures how the optimal markdown changes with j's own wage, $\Gamma_{-jt} :=$ $\sum_{j'!=j} \frac{\partial \Lambda_j(w_t,;a_t)}{\partial w_{j't}}$ captures how the optimal markdown changes with other employers' wages, $\xi_{jt} :=$ $\frac{1}{1+\Gamma_{jt}} \sum_{j=1}^{N} \frac{\partial \Lambda_j(w_t,;a_t)}{\partial a_{jt}} da_{jt}$ captures changes in employer-specific preferences or amenities, and $dlnw_{-jt} =$ $\sum_{j'!=j} \omega_{-j't} dlnw_{j't}$, is a weighted sum of wage changes at other employers $-\mathbf{j}$, with weights equal to $\omega_{jj't} = \frac{\partial \Lambda_j(w_t,;a_t)/\partial w_{j't}}{\sum_{k!=j} \frac{\partial \Lambda_j(w_t,;a_t)}{\partial w_{kt}}}$. I term $dlnw_{-jt}$ the competitor wage index. I show below that these weights $(\omega_{jj'})$ are proportional to competitor j' shares when the log expenditure function z_t is a sufficient statistic for competitor wages, i.e. labor supply to j can be denoted as $n_j(w_j, z_t; a_t)$ (this is true, for example, of nested CES). The empirical equation for estimating spillovers is:

$$\Delta lnw_{jt} = \delta \Delta lnmrpl_{jt} + \gamma \Delta lnw_{-jt} + \xi_{jt} \tag{6}$$

Therefore, under price or quantity competition when the expenditure function is a sufficient statistic for competitor wages (including Cournot or Bertrand oligopsony and nested CES supply), δ measures the pass-through of an employer's own marginal product shock, holding competitor wages constant, and γ measures the strength of strategic complementarities in wage setting. In typical monopsony models, where an atomistic monopsonist faces constantly elastic labor supply (e.g. Card et al. 2018), shocks to a firm's marginal product always exhibit complete pass-through since the wage is always proportional to marginal product ($\delta = 1$). However, when employers are large as opposed to atomistic, large employers face less elastic labor supply and need not pass-through all productivity gains to workers ($\delta < 1$). Typical models also abstract away from wage spillovers, $\gamma = 0$; however, if large employers alter markdowns in the face of competitor wage changes that alter worker flows to them, $\gamma > 0$.

Identification To isolate the causal effect of changes in an employer's own productivity (δ) and of competitor wages (γ) on its own wage, I need two demand-side instruments orthogonal to changes in its labor supply from changing preferences (ξ_{jt}). I use an employer's own MFA treatment status to provide variation in its marginal product ($\Delta lnmrpl_{jt}$) and the number of treated workers at other employers in its geography to provide variation in competitor wages (Δlnw_{-jt}). The identifying variation to estimate γ compares employers in places where the MFA shock spurs a large change in competitor wages to those in places where it spurs a small change. Appendix Figure 4 plots variation in the instrument, showing that for most workers less than 10% of their labor market is treated by the MFA shock, but for about 20% of workers this fraction is over 10%. Table 4, Panel B shows a strong first stage (F-stat 47): for every additional one hundred MFA-affected workers in

one's labor market, competitor wages fall by 0.02%. Appendix Figure 5 shows the first stage instead using the share of the MFA-affected wage bill (F-stat 50): as it grows from 0 to 10%, competitor wages fall by 1%.

Measurement As when estimating elasticities, Δlnw_{-jt} and $\Delta lnmrpl_{jt}$ measure the change in wages and marginal products between $t = -1$ and $t = 1$, and Δlnw_{jt} measures wage changes between $t = -1$ and $t \in \{3, 5\}$. I use $t \in \{3, 5\}$ to account for spillovers over time as workers flock to other employers, as opposed to immediately, and because the labor supply response I am trying to transform into an own-wage elasticity occurs in years three to five. I assume that marginal product is proportional to average product, with the same change in log terms. This choice is consistent with a Cobb-Douglas production function, as commonly used to model production in textile and garment manufacturing industry (Cajal, Macchiavelo, & Rossi 2019 for Bangladeshi garment manufacturing, Atkin et al. 2019 for Egyptian carpet making), but also accommodates non-constant returns to scale.[41]

Results Table 4 reports results. To gauge how the average worker's wage responds to competitors' wage changes, Columns (1) - (3) report results for incumbent workers employed in year t=-1. The MFA shock has no wage spillovers among exporters (Column 1), among MFA-unaffected exporters (Column 2) or among all unaffected employers in the textile and clothing manufacturing industry including non-exporters (Column 3). Across samples, $\hat{\gamma}$ is a tightly estimated zero, ruling out changes over 0.01% with a high degree of confidence (95%). In addition to the average zero effect, randomization inference p-values for the sharp null show that we cannot reject the null of zero effect for every employer.

Because new worker wages may more accurately capture the wage workers would receive when choosing a China-competing or non-China-competing employer, column (4) reports spillover effects on the wages of new hires. Again, I reject changes higher than 0.01% with a high degree of confidence.

A key concern is measurement error, which may attenuate estimates of γ and lead to a false conclusion of no strategic responses when in fact they exist ($\gamma > 0$). Measurement error comes from two possible sources. First, I may mismeasure marginal products because I have misspecified the production function and marginal product is not proportional to average product. Second, even if the production function is correctly specified, I may mismeasure marginal products because I only observe exports and not also revenues. To mitigate this concern, I omit $\Delta lnmrpl_{jt}$ from the regression in equation 6 (Columns 2 and 3). Under strategic wage responses, the true $\Delta lnmrpl_{jt}$ and Δlnw_{-jt} are positively related: as j's competitors lower their wage, workers flock to j, who can hire more workers at lower wages, lowering marginal product. Eliminating $\Delta lnmrpl_{jt}$ from the regression should yield upward biased estimates of γ. Here, too, I cannot reject either the null of

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[41]Specifically, I assume a production function of the form $PF = \frac{PL^{1+\lambda}}{1+\lambda}$ with returns to scale parameter $\frac{1}{1+\lambda}$ such that $\Delta logAPL = \Delta logMPL$.

no average effect or the sharp null of no effect on any employer with a high degree of confidence (95%).

Discussion   The small estimates of γ suggest that the exclusion restriction in my setting is satisfied, namely, that labor supply to MFA-affected employers does not change because of wage spillovers to other employers. I view this result as signifying that the shock was too small to compel a competitor response. No spillovers following a small shock might reflect optimization frictions (Dube et al., 2020), nominal rigidities (Hazell and Taska, 2020), or other institutional constraints that prevent employers from changing their wage when a small number of other employers do so. Nonetheless, the result is exciting because it offers the first test of oligopsonistic wage setting in labor markets, and provides a general rubric for such tests in future work.

While I interpret no spillovers as suggesting a small shock as opposed to a verdict that large employers do not fully exercise their market power, the latter is a possibility. My evidence points against it for two reasons: first, employers' own productivity shocks do not change workers' wages one-for-one, and, second, this pass-through falls as they become larger (Appendix Figure C8). Both findings are consistent with oligopsony.

B.2   Proofs

Proposition 3 *For any competition structure among employers and any invertible labor supply system where firms are not perfect substitutes, $\exists$ a log markdown function $\Lambda_j(w_{jt}, \mathbf{w_{-jt}}; a_{jt}, a_{-jt})$, such that the firm's profit-max wage $\tilde{w}_{jt}$ is the solution to the following fixed point, for any given wage vector among its competitors $\mathbf{w_{-jt}}$:*

$$ln\tilde{w}_{jt} = lnmrpl_{jt} + \Lambda_j(\tilde{w}_{jt}, \mathbf{w_{-jt}}, a_{jt}, \mathbf{a_{-jt}}) \tag{7}$$

Proof. This proof closely derives from Amiti et al. (2019). I omit subscripts t for brevity. Writing the profit maximization problem of a firm in conjectural variation form:

$$\max_{w_j, \mathbf{w_{-j}}} \{R_j(\exp(n_j(w_j, \mathbf{w_{-j}}; \mathbf{a}))) - \exp\{w_j + n_j(w_j, \mathbf{w_{-j}}; \mathbf{a})\}| \ s.t. \ h_{-j}(w_j, \mathbf{w_{-j}}; \mathbf{a}) = 0\} \tag{8}$$

where R_j is the revenue function[42], n_j is the **log** labor supply and w_j is the **log** wage in firm j[43], and h_{-j} is the conjectural variation vector function with elements h_{jk} for $k! = j$. For monopolistic and Bertrand competition, this vector takes the form:

$$h_{-j}(w_j, \mathbf{w_{-j}}; \mathbf{a}) = w_{-j} - w^*_{-j}$$

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[42]I assume firms are price-takers in the product market, which is reasonable for textile and clothing products.
[43]Also for brevity, but different from the derivations above where they are levels.

and for Cournot competition it takes the form:

$$h_{-j}(w_j, \mathbf{w_{-j}}; \mathbf{a}) = -(n_{-j}(w_j, \mathbf{w_{-j}}; \mathbf{a}) - n^*_{-j})$$

A conditional profit maximization with respect to wages therefore captures firm behavior under competition in prices and quantities. Introducing four pieces of notation:

1. $e^{w_j + n_j} \lambda_{jk}$ for $k! = j$ represents the set of Lagrange multiplies for the constraints in (8).[44]

2. $\zeta_{jkl}(\mathbf{w}, \mathbf{a}) := \frac{\partial h_{jk}(\mathbf{w}, \mathbf{a})}{\partial w_l}$, which is the elasticity of the conjectural variation function with respect to l's wage (supply invertibility ensures invertibility of the matrix $\zeta_{jkl}(.)\}_{k,j! = l}$)

3. $\epsilon_j(\mathbf{w}, \mathbf{a}) := \frac{\partial n_j(\mathbf{w}, \mathbf{a})}{\partial w_j}$ and $\delta_{jk} := \frac{\partial n_j(\mathbf{w}, \mathbf{a})}{\partial w_k}$ are the own and cross-price elasticities of supply.

The FOCs of firm j's profit maximization problem are then given by:

$$-1 - \epsilon_j + \epsilon_j e^{\mu_j} + \sum_{k! = j} \lambda_{jk} \zeta_{jkj} = 0$$

$$-\delta_{jl} + \delta_{jl} e^{\mu_j} + \sum_{k! = j} \lambda_{jk} \zeta_{jkl} = 0 \ \forall \ l! = j$$

where $\mu_j = mrpl_j - w_j$ is the log markdown. Solving out the Lagrange multipliers yields j's optimal markdown:

$$\mu_j = log \frac{\sigma_j}{\sigma_j + 1}$$

where σ_j is the perceived elasticity of labor supply and is given by:

$$\sigma_j := \epsilon_j - \zeta'_{\mathbf{j}} \mathbf{Z_j^{-1}} \delta_{\mathbf{j}}$$

where $\zeta_{\mathbf{j}} := \{\zeta_{jkj}\}_{k! = j}$, $\delta_{\mathbf{j}} := \{\delta_{jk}\}_{k! = j}$, and $\mathbf{Z_j} := \{\zeta_{jkl}\}_{k! = j, \ l! = j}$ is an $(N-1) \times (N-1)$ matrix of cross-price elasticities (which has full rank because the labor supply system is invertible). Because all three are only functions of the wages and amenities at employers, it therefore follows that the optimal markdown is as well:

$$\Lambda_j(w_j, \mathbf{w_{-j}}, a_j, \mathbf{a_{-j}}) := log \frac{\sigma_j(w_j, \mathbf{w_{-j}}, a_j, \mathbf{a_{-j}})}{\sigma_j(w_j, \mathbf{w_{-j}}, a_j, \mathbf{a_{-j}}) + 1}$$

and the firm's profit-maximizing wage solves the fixed point (adding back t subscripts):

$$ln\tilde{w}_{jt} = lnmrpl_{jt} + \Lambda_j(\tilde{w}_{jt}, \mathbf{w_{-jt}}, a_{jt}, \mathbf{a_{-jt}})$$

This proves the proposition. ∎

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[44]This definition allows cancelling out the $e^{w_j + n_j}$ term from both sides of the FOC below.

Proposition 4 *If the log expenditure function z_t is a sufficient statistic for competitor wages, i.e. supply can be written as $n_{jt} = n_j(w_{jt}, z_t,; \mathbf{a_t})$ then the weights in the competitor wage index ($dlnw_{-jt} = \sum_{j'!=j} \omega_{-j't} dlnw_{j't}$) are proportional to the competitor revenue market shares $S_{j't}$ for $j'! = j$ and given by $\omega_{jj't} = \frac{S_{j't}}{1-S_{jt}}$. Thus, the competitor wage index simplifies to:*

$$\sum_{j'!=j} \frac{S_{j't}}{1 - S_{jt}} dw_{j't}$$

Proof. Following the steps from before, the optimal markdown is given by:

$$\Lambda_j(w_{jt}, z_t; \mathbf{a_t}) := log \frac{\sigma_j(w_{jt}, z_t; \mathbf{a_t})}{\sigma_j(w_{jt}, z_t; \mathbf{a_t}) + 1}$$

The weights in the competitor price index are therefore:

$$\omega_{jj't} = \frac{\partial \Lambda_j(w_{jt}, z_t; \mathbf{a_t})/\partial w_{j't}}{\sum_{k!=j} \frac{\partial \Lambda_j(w_{jt}, z_t; \mathbf{a_t})}{\partial w_{kt}}}$$
$$= \frac{\partial \Lambda_j(w_{jt}, z_t; \mathbf{a_t})/\partial z \frac{\partial z}{\partial w_{j't}}}{\partial \Lambda_j(w_{jt}, z_t; \mathbf{a_t})/\partial z \sum_{k!=j} \frac{\partial z}{\partial w_{kt}}}$$
$$= \frac{S_{j't}}{\sum_{k!=j} S_{kt}} = \frac{S_{j't}}{1 - S_{jt}}$$

This relies on the fact that $\frac{\partial z_t}{\partial w_{jt}} = S_{jt} \forall j$ (Shepard's lemma). With (two nested) CES supply, for example, the log expenditure function is just the log wage index of the market, and $\frac{\partial log W_{kt}}{\partial w_{jt}} = S_{jt}$ (where note that w_{jt} is still the log wage). ∎

C   Estimation

C.1   Parameters

C.1.1   Method 1

To estimate θ_g I take the partial derivative of labor supply to an industry with respect to an employer j's wage:

$$n_{gkr} = \left(\frac{W_{gkr}}{W_{gr}}\right)^{\theta_g} \left(\frac{W_{gr}}{W_g}\right)^{\lambda_g} N_g$$

$$\frac{\partial lnn_{gkr,j}}{\partial lnw_{gj}} = \theta_g s_{gj} + (\lambda_g - \theta_g)s_{gj}s_{gk} = \theta_g s_{gj} \text{ when } s_{gk} \sim 0$$

Intuitively, η_g is the elasticity of labor supply to an atomistic employer, θ_g the elasticity of labor supply to an atomistic industry (from a large employer in that industry), and λ_g the elasticity of labor supply to an atomistic geography (from a large employer in that geography). Heterogeneous

preferences are the only force tethering workers to these atomistic employers, industries, and geographies. These partial derivatives are not typically estimable in the presence of wage spillovers or amenity changes. However, as above, this partial equilibrium elasticity is typically inestimable with a reduced form regression in the presence of spillovers. To derive the reduced form elasticity I start from the labor supply system in a geography where the industry is small:

$$lnn_{gkr} = \theta_g lnW_{kgr} + Aggregates$$

Consider a first-order approximation around the Nash equilibrium, following any change to firms in the industry:

$$\sum_{j' \in k,r} \frac{\partial lnn_{gkr}}{\partial lnn_{gkr,j'}}|_{n^*_{j!=j'}} \Delta lnn_{gkr,j'} = (\theta_g) \sum_{j' \in k,r} \frac{\partial lnW_{kgr}}{\partial lnw_{gj'}}|_{w^*_{j!=j'}} \Delta lnw_{j'} + \Delta Amenities$$

$$\Delta lnn_{gkr,j} + \sum_{j'!=j \in k,r} \Delta ln(n_{gkr,j'}) = \theta_g s_{gj} \Delta lnw_j + \theta_g \sum_{j'!=j \in k,r} s_{gj'} \Delta lnw_{j'} + \Delta Amenities$$

I argue in the test of strategic interaction that $\Delta lnw_{j'} = 0 \forall j'! = j \in k, r$ and assume $\Delta Amenities = 0$. Similarly, Appendix Figure C2 shows roughly that $\sum_{j'!=j \in k,r} \Delta lnn_{gkr,j'} \sim 0$. Under both conditions, I can estimate the partial equilibrium elasticity through the reduced form $\epsilon_{gkr,j} = \frac{\Delta lnn_{gkr,j}}{\Delta lnw_{gj}} = \frac{\partial lnn_{gkr,j}}{\partial lnw_{gj}}$. The exclusion restriction may still be violated if there are multiple MFA employers in a geography. However, in half of all geographies there is only one MFA-treated employer and estimates closely resemble those in geographies with many.

Similarly, to derive the moment condition for λ_g I take the partial derivative of labor supply to a geography with respect to employer j's wage:

$$n_{gr} = \left(\frac{\bar{W}_{gr}}{W_g} \right)^{\lambda_g} N_g$$

$$\frac{\partial lnn_{gr}}{\partial lnw_{gj}} = \lambda_g s_{gj} s_{gk}$$

The rate of change of exiting a geography with employer size (in the geography) therefore estimates λ_g. Just as above, this can typically not be estimated under wage spillovers. Following the same steps as above:

$$lnn_{gr} = \lambda_g lnW_{gr} + Aggregates$$

$$\Delta lnn_{gr,j} + \sum_{j'!=j \in r} \Delta lnn_{gr,j'} = \lambda_g s_{gj} s_{gk} \Delta lnw_j + \lambda_g \sum_{j'!=j \in r} s_{gj'} s_{gk} \Delta lnw_{j'} + \Delta Amenities$$

The partial equilibrium elasticity is identified when $\sum_{j'!=j \in r} s_{gj'} s_{gk} \Delta lnw_{j'} \sim 0$ (no spillovers), $\Delta Amenities = 0$ (by assumption) and $\sum_{j'!=j \in r} \Delta lnn_{gr,j'}$ (small shock).

C.1.2 Method 2

I also adopt an alternate estimation strategy from Costinot, Donaldson, and Smith (2016) that requires shocks at the employer, industry and location levels. Because the MFA doesn't provide the requisite variation at industry and location levels, I instead use the shock from the Brazilian trade liberalization of the 1990s. Thanks to the lucid exposition of Felix (2022), who I follow almost exactly in this estimation, varying only the nesting structure, the estimating equations can be obtained by taking logs of the labor supply condition:

$$logn_{gj} = \eta_g logw_{gj} + \underbrace{(\theta_g - \eta_g)logW_{gk,r}}_{Industry \ x Microregion \ xYear \ FE} + \underbrace{(\lambda_g - \theta_g)logW_{gr}}_{Microregion \ xYear \ FE} + \eta loga_{gj}$$

Taking long differences and using an employer-level instrument yields an estimate of η_g. In other words:

$$\Delta logn_{gj} = \eta_g \Delta logw_{gj} + \Delta\delta_{im} + \Delta\delta_m + \epsilon_j$$

where a firm-level instrument can provide requisite variation in $\Delta logw_{gj}$. To obtain an estimate of θ_g, observe:

$$\Delta\delta_{im} = \alpha + (\theta_g - \eta_g)\Delta logW_{gk,r} + \epsilon_{gk,r}$$

an industry-level instrument provides the requisite variation in $\Delta logW_{gk,r}$ to estimate θ_g. Similarly, to obtain an estimate of λ_g observe:

$$\Delta\delta_m = \alpha + (\lambda_g - \theta_g)\Delta logW_{gr} + \epsilon_{gr}$$

a location-level instrument provides the requisite variation in $\Delta logW_{gr}$.

I create instruments using the change in tariff exposure across industries, all of which were liberalized between 1991 and 1994. I instrument for $\Delta logw_{gj}$ using $\Delta ICE_{j,k,r}$, instrument $\Delta logW_{gk,r}$ using $\Delta ICE_{k,r}$, and $\Delta logW_{gr}$ using ΔICE_r to obtain λ_g. The definitions are as follows, j is a firm, k is an industry, r is a region:

$$\Delta ICE_{j,k,r} = ln\left(\frac{1 + \tau_{j(k)1994}}{1 + \tau_{j(k)1991}}\right)$$

$$\Delta ICE_{k,r} = \sum_{j\in k,r} \frac{s_{j,1991}^2}{\sum_j s_{j,1991}^2} ln\left(\frac{1 + \tau_{j(k)1994}}{1 + \tau_{j(k)1991}}\right)$$

$$\Delta ICE_r = \sum_{k\in r} \frac{s_{k,1991}^2}{\sum_{k\in r} s_{k,1991}^2} \sum_{j\in k,r} \frac{s_{j,1991}^2}{\sum_j s_{j,1991}^2} ln\left(\frac{1 + \tau_{j(i)1994}}{1 + \tau_{j(i)1991}}\right)$$

C.2 Estimating wage indices and amenities

I follow the following three steps to measure the industry-level wage index and infer amenity values in an industry for men and women. For this exercise I assume away establishment-specific amenities that deviate from industry norms.

Step 1. Estimating the wage index of an industry Re-arranging the expression for the wage bill share of a firm j in sector k:

$$s_{gj} = \frac{(w_{gj})^{1+\eta_g}}{\sum_{j'}(w_{gj'})^{1+\eta_g}}$$

$$[\sum_{j'}(w_{gj'})^{1+\eta_g}]^{\frac{1}{1+\eta_g}} = w_{gj}(s_{gj})^{\frac{-1}{1+\eta_g}} \forall j$$

Taking the log of both sides and summing over all j, the wage index of a industry k is:

$$W_{gk} = \tilde{w}_{gk}\tilde{s}_{gk}^{\frac{-1}{1+\eta_g}}$$

where $\tilde{w}_{gk}$ is the geometric mean of wages and $\tilde{s}_{gk}$ is the geometric mean of the share of the wage bill within textiles (i.e., exp of the mean of logs). The wage index is higher the higher the geometric mean of wages and the higher the dispersion in shares (the lower the geometric mean of shares).

Lemma 2

$$W_{gk} = \tilde{w}_{gk}\tilde{s}_{gk}^{\frac{-1}{1+\eta_g}}$$

where $\tilde{w}_{gk}$ is the geometric average of wages for group g in sector k and $\tilde{s}_{gk}$ is the geometric average of wage bill shares.

Proof. We know that:

$$s_{gj} = \frac{w_j n_j}{\sum_{j'\in k,r} w_{j'} n_{j'}} = \frac{(w_{gj})^{1+\eta_g}}{\sum_{j'\in k,r}(w_{gj'})^{1+\eta_g}}$$

Thus:

$$[\sum_{j'\in k}(w_{gj'})^{1+\eta_g}]^{\frac{1}{1+\eta_g}} = w_{gj}(s_{gj})^{\frac{-1}{1+\eta_g}} \forall j$$

Taking the log of both sides and summing over $j' \in k$:

$$lnW_{gk} = \frac{1}{N}\sum_{j'\in k} ln(w_{gj'}) + \frac{1}{N}\sum_{j'\in k} ln(s_{gj'})^{\frac{-1}{1+\eta_g}} lnW_{gk} = ln((\Pi w_{gj'})^{\frac{1}{N}}) + \frac{-1}{1+\eta_g} ln((\Pi s_{gj'})^{\frac{1}{N}})$$

Note that the geometric mean is defined:

$$(\Pi w_{gj'})^{\frac{1}{N}} = exp(\frac{1}{N}\sum lnw_{gj'})$$

Therefore:

$$lnW_{gk} = ln(\tilde{w_{gk}}) - \frac{1}{1+\eta_g}ln(\tilde{s_{gk}})$$

Exponentiating both sides gives the result:

$$W_{gk} = \tilde{w_{gk}}\tilde{s_{gk}}^{\frac{-1}{1+\eta_g}}$$

∎

Step 2. Estimating industry-specific amenity values for men   Given estimates of the wage index by industry and geography and θ_m, the amenity values for men can be inferred from the share of men in each sector, normalizing the amenity value for men to 1 in textiles.

$$\frac{s_{mk}}{s_{mtxt}} = \frac{a_{mk}^{1+\theta_m}\frac{W_{mk}^{1+\theta_m}}{W_m^{1+\theta_m}}}{\frac{W_{mtxt}^{1+\theta_m}}{W_m^{1+\theta_m}}}$$

Step 3. Estimating women's amenities relative to men   Given estimates of the wage index by industry for each gender, (θ_m, θ_w), and observed shares, the amenity values for women relative to men can then be inferred from the share of women in each industry relative to the share of men:

$$\frac{s_{wk}}{s_{mk}} = \frac{a_{wk}^{1+\theta_w}\frac{W_{wk}^{1+\theta_w}}{W_w^{1+\theta_w}}}{a_{mk}^{1+\theta_m}\frac{W_{mk}^{1+\theta_m}}{W_m^{1+\theta_m}}}$$

C.3   Estimating industry-specific productivity

I start with the following value added production function that is Cobb-Douglas in labor and capital with labor a CES aggregation of male and female workers: $Y_{jt} = z_{jt}K_{jt}^{\alpha_{k1}}l_{jt}^{\alpha_{k2}}$ with $l_{jt} = [\beta_k f_{jt}^{\sigma} + m_{jt}^{\sigma}]^{\frac{1}{\sigma}}$.[45] I estimate the industry-specific parameters $\{\alpha_{k1}, \alpha_{k2}, \beta_k\}$ by employing standard production function techniques due to Ackerberg et al. (2015) and calibrating σ to Gallen (2018). I describe my assumptions and procedure here.

A firm j picks capital for the subsequent period $(k_{j,t+1})$, labor in the current period (l_{jt}), and materials in the current period (x_{jt}) to maximize profits after observing its productivity shock $(\omega_{jt} := log(z_{jt}))$ that is unobservable to the econometrician. In other words, capital is a state variable (investment i_{jt-1} that determines k_{jt} is picked in $t-1$) and supplied competitively in a rental market. Labor and material inputs are flexible (l_{jt} and m_{jt} are picked in period t). There is monopsony in the labor market but none in the market for materials. I make the following standard assumptions:

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[45]One interpretation of this value-added production function is that gross output is Leontief in materials (Ackerberg et al., 2015).

Assumption 1 Productivity evolves according to a first-order Markov process.

$$\omega_{jt} = f(\omega_{jt-1}) + \zeta_{jt}$$

which I take to be a polynomial of degree three in ω_{jt-1}.

Assumption 2 Scalar unobservable. For at least one flexible input, materials, the only unobservable factor in a firm's input demand function is productivity ω_{jt}.

Assumption 3 Strict monotonicity. A firm's input demand function for materials is strictly monotone in ω_{jt}.

Together, Assumption 2 and 3 imply that material input demand can be inverted to obtain ω_{jt}, which is necessary for Step 1 below. The estimation then proceeds in three steps:

Step 1 Purge output of measurement error, relying on the invertibility of input demand to obtain productivity. Let the log of output be observed with some measurement error τ_{jt}:

$$y_{it} = f(v_{jt}; \beta) + \omega_{jt} + \tau_{jt}$$

where $v_{jt} := \{f_{jt}, m_{jt}, k_{jt}\}$ and $\beta := \{\alpha_{k1}, \alpha_{k2}, \beta_k\}$. By assumption 2:

$$x_{jt} = x_t(\omega_{jt}, k_{jt}, l_{jt})$$

By assumption 3:

$$\omega_{jt} = h_t(x_{jt}, k_{jt}, c_{jt})$$

where c_{jt} are controls that can influence input decisions[46]. Thus we have:

$$y_{jt} = f(v_{jt}; \beta) + h_t(x_{jt}, k_{jt}, c_{jt}) + \tau_{jt}$$

And I can obtain estimates for output net of measurement error by running a non-parametric regression (e.g., a high-order polynomial, in my case approximated by one of degree four) in only observables $\{k_{jt}, l_{jt}, x_{jt}\}$. Let this output be denoted $\phi_{jt}(v_{jt}, x_{jt}; \beta)$.

Step 2 Construct estimates of productivity, relying on timing assumption 1 and some guess of β (simultaneously determined in step 3):

$$\omega_{jt}(\tilde{\beta}) = \phi_{jt} - f(v_{jt}; \tilde{\beta})$$

---

[46]In practice, I only use year fixed effects.

Step 3 Use GMM to recover the β parameters, relying on the timing of input choice to construct instruments:

$$E\left(\zeta_{jt}(\beta)\begin{pmatrix} f_{jt-1} \\ m_{jt-1} \\ k_t \end{pmatrix}\right) = 0$$

This yields three moments to estimate three parameters $\beta := \{\alpha_{k1}, \alpha_{k2}, \beta_k\}$.

Because the CES labor aggregation can be approximated by a translog function, we have for the functional form of f:

$$lnY_{jt} = lnz_{jt} + \alpha_{k1}lnK_{jt} + \alpha_{k2}(\beta_k lnf_{jt} + lnm_{jt} + \sigma\beta_k(lnf_{jt} + lnm_{jt} - lnf_{jt}lnm_{jt}))$$
$$lnY_{jt} = lnz_{jt} + \alpha_{k1}lnK_{jt} + (\alpha_{k2}\beta_k + \alpha_{k2}\sigma\beta_k)lnf_{jt} + (\alpha_{k2} + \alpha_{k2}\sigma\beta_k)lnm_{jt} - (\alpha_{k2}\sigma\beta_k)lnf_{jt}lnm_{jt}$$

A caveat to the proxy variable method for estimating production functions is a potential violation of the "scalar unobservables" assumption under market power, preventing me from inverting input demand to recover productivity shocks (Bond et al. (2021), De Loecker and Syverson (2021)). Intuitively, this is because input demand cannot be inverted in Step 1 without additional controls since materials demand x_{jt} depends on establishment-specific input prices and shares (in c_{jt}). However, two facts mitigate the concern that bias in $\hat{\beta}_k$ leads me to falsely conclude that amenities and not productivity drive women to textiles. First, Yeh et al. (2022) show using simulations that this method recovers the true parameters in its 95% confidence interval and delivers tight standard errors. Second, gender gaps in wages plus contracted amenities predict a much smaller difference in the relative female/male share in industries than observed — for example, they predict similar ratios in textiles and the manufacturing of metal products. In reality, the female share/male share in the former is 6 and in the latter is 0.2.

I suffer an important data limitation because I do not observe workers separately by gender in the Brazilian production data. I thus estimate production functions in two other developing countries: India and Chile. For India, I use the Annual Survey of Industries between 2000 and 2010. The ASI is a manufacturing survey collected for a panel of large manufacturing establishments with over 100 workers. For Chile, I use the census of manufacturing plants covering all plants with over 10 employees between 1979 and 1996. The number of establishments used in estimation range between 295 and 2331. These are above the 250 threshold used in Demirer (2020) to obtain consistent estimates and tight standard errors.

D   Data appendix

D.1   Sample construction

Establishment sample: MFA analysis   To analyze the effect of the Multi-Fiber Arrangement on workers' wage and employment outcomes I construct a sample of all establishments that exported

textile and clothing products in 2004 – with the first two digits 61 or 62. There are 751 such establishments in total, employing 114205 workers as of 2004.

Incumbent worker sample: MFA analysis Incumbent workers defined as those employed at a treated or comparison establishment as of 2004 (based on the establishment sample). Their treatment status depends on the treatment status of their baseline (2004) employer, as described above. Leveraging the linked employer-employee feature of RAIS, incumbent workers are tracked across jobs from 2000 to 2009 —- that is, I do not restrict the sample to job spells at employers in the establishment sample. In constructing this sample, I only consider the "main job spell" for each worker in each year. I define the "main job spell" as a worker's longest spell during the year. In case all job spells have the same duration, I break ties by keeping only one spell at random.

Sample for wage and amenity indices I use the full sample of workers without high school degrees in 2004 to calculate wage indices, shares, and infer amenity indices.

D.2   Outcomes

I briefly discuss how I define the outcomes used for analyses at the establishment-level and incumbent worker-level. While I use a worker's main job spell for all worker-level outcomes, some establishment-level outcomes are constructed using all job spells. I first describe establishment-level outcomes derived from all job spells and then those derived using main job spells. Finally, I describe worker-level outcomes.

Establishment level outcomes - all job spells:

- Total employment: The total number of workers employed at an establishment in a given year.

- New hires: Number of workers recently hired by the establishment, defined as the number of workers employed in a given establishment-year with less than 12 months of tenure.

- Education of new hires: Average years of schooling of workers newly hired at an establishment in a given year, separately by gender.

- Share of female new hires: Share of new hires that are female in any given year.

Establishment level outcomes - main job spell:

- Mean log wage. For any given worker subgroup, we take the mean of the wage outcome (defined below) in logs across all workers in the subgroup employed at the establishment in that year. This variable is defined for the following worker subgroups: women and men.

- Wage bill share in industry. I divide an establishment's wage bill by the overall textile wage bill in the geography in 2004. I do this separately by gender and only among workers without high school degrees.

Worker level outcomes - main job spell:

- <u>Wages</u> The average monthly earnings that a worker makes during a job spell in a given year. We always use earnings in real terms by using the December CPI (i.e., the Indice Nacional de Pre cos ao Consumidor reported by IBGE) with 2015 as the base year.

- <u>Retention</u> A dummy that indicates whether the worker is observed working at the baseline employer in any given year, where the baseline employer is defined as the (main) establishment of employment in 2004.

- <u>Employed in formal sector</u> A dummy that indicates whether the worker is observed working in the formal sector in that year, i.e., they have a job spell registered in RAIS in that year.

- <u>Employed at new textile employer</u> A dummy that indicates whether the worker is observed working at a non-baseline employer in the textile industry in any given year, where the baseline employer is defined as the (main) establishment of employment in 2004.

- <u>Employed at new non-textile employer</u> A dummy that indicates whether the worker is observed working at a non-baseline non-textile employer in the textile industry in any given year, where the baseline employer is defined as the (main) establishment of employment in 2004.

- <u>Employed in new geography</u> A dummy that indicates whether the worker is observed working at a new employer in a different microregion in any given year, where the baseline employer is defined as the (main) establishment of employment in 2004.

D.2.1 Constructing O*NET-based skill transferability

I follow Macaluso (2022) to define O*NET-based measures of skill transferability for men and women. O*NET reports the skill level (from 1-8) on each of 35 skills required to do any job. These data are based on interviews with thousands of US-based workers and include a range of skills including coordination, operation and control, equipment maintenance, and materials management. O*NET data have been heavily employed to build indices of skill relatedness (Gathmann et al. 2010, Neffke et al. 2013). Most pertinently, Macaluso (2022) demonstrates that O*NET-based skill transferability predicts US workers' wage recovery following job loss. The measure of skill transferability from occupation o in geography m is:

$$st_{om} = -\sum_{k \in O} \omega_{km} d_{ok}$$

where O is the set of all occupations, ω_{km} is the share of jobs in geography m in occupation k and d_{ok} is the "skill-distance" (L1 norm taken over 35 tasks) between o and k.

Figure 6, Panel A shows that treated men and women have overlapping distributions of skill transferability. This provides prima facie evidence that gender differences in skills do not explain gender differences in exit.

Appendix Table 4 shows that skill transferability is strongly predictive of switching industries among treated men: those in the bottom eight deciles exit their employer 4% points more compared to those in the comparison group. This rate, however, rises to 7.9% points among treated men with skills in the top two deciles of skill transferability.

Table 4 shows, however, that controlling for gender differences in skill transferability does not meaningfully change the gender difference in treatment effects on exiting one's employer or industry.