IARIW 2021

Monday 23 – Friday 27 August

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Between Sticky Floors and Glass Ceilings:

The Effect of Trade Liberalization on Double Discrimination in Brazil

Laura Barros

(University of Goettingen)

Manuel Santos Silva

(University of Münster)

Paper prepared for the 36th IARIW Virtual General Conference
August 23-27, 2021
Session 4: Globalization and Inequality I
Time: Tuesday, August 24, 2021 [14:00-16:00 CEST]

Between sticky floors and glass ceilings: the effect of trade liberalization on double discrimination in Brazil

Laura Barros[1] and Manuel Santos Silva[2]

[1] *University of Goettingen*
[2] *University of Münster*

This version: May 2, 2021.

Abstract

This article investigates how trade liberalization affects gender and racial pay inequalities in the short run. Guided by an intersectional perspective, we consider overlapping effects across gender, race, and wage levels. We exploit Brazil's trade liberalization process (1988–95) as a natural experiment. On average, liberalization increased wages of nonwhite women relative to men and white women. However, this average effect masks substantial heterogeneity. When we decompose pay gaps along the wage distribution, we find that liberalization increased racial and gender discrimination at low wages, which reinforced preexisting 'sticky floors' for nonwhite women. In contrast, at the top of the distribution, liberalization reduced racial discrimination, which mitigated existing 'glass ceilings' by race.

JEL-Classification: F13, F14, J15, J71.

Keywords: trade liberalization, wage inequality, intersectionality, gender, race

All correspondence to: Laura Barros, University of Goettingen, Department of Economics, Platz der Göttinger Sieben 5, 37073 Goettingen, Germany, Email: laura.barros@uni-goettingen.de.

We are grateful to Lennart Kaplan, Krisztina Kis-Katos, Stephan Klasen, Friederike Lenel and Samuel Siewers for comments and suggestions.

1 Introduction

In developing countries, where segregated labor markets and diffused gains from trade are widespread, there is a growing interest in the implications of international trade for economic inequality. Whereas most studies have focused on the average effects of trade across countries, sectors, and skill levels,[1] increasing attention has been given to the effects of international trade for gender equality.[2] Yet, little is known about the heterogeneous effects of opening up to international trade along the wage distribution and from an intersectional perspective—that is, one that takes into account how identities of gender, race, class (and others) intersect and overlap to create complex patterns of social advantage and disadvantage (Crenshawt, 1989).

In this article, we investigate the consequences of Brazil's trade liberalization for gender and racial inequalities both on average and along the wage distribution. Between 1988 and 1995, Brazil drastically opened up to international trade. The main policy objective was to reduce and equalize import tariffs across sectors. As a result, cross-sectoral variation in tariff reduction is almost perfectly predicted by initial sectoral tariff levels. In short, conditional on the initial tariff level, tariff reductions between 1988 and 1995 were exogenous to local labor market conditions. Due to this feature, this episode of trade liberalization has been considered a close-to-ideal natural experiment and has been widely studied in the literature.[3] Overall, local labor markets that were more exposed to tariff reductions experienced, in the medium and long run, larger losses in employment and wages (Kovak, 2013; Dix-Carneiro and Kovak, 2017, 2019).[4]

[1]E.g., Wood (1998); Dollar and Kraay (2004); Ferreira *et al.* (2007); Egger and Kreickemeier (2009, 2012); Topalova (2010); Autor *et al.* (2013); Kovak (2013); Helpman *et al.* (2017).

[2]See, among others, Black and Brainerd (2004) and Autor *et al.* (2019) for the US; Berik *et al.* (2004) for Korea and Taiwan; Juhn *et al.* (2014) and Ben Yahmed and Bombarda (2020) for Mexico; Anukriti and Kumler (2019) for India; Kis-Katos *et al.* (2018) for Indonesia; and Gaddis and Pieters (2017) for Brazil.

[3]A non-exhaustive list includes Castilho *et al.* (2012); Kovak (2013); Dix-Carneiro and Kovak (2015, 2017); Gaddis and Pieters (2017); Braga (2018); Costa *et al.* (2018); Dix-Carneiro *et al.* (2018); Hirata and Soares (2020).

[4]Articles studying the adjustment dynamics of formal sector employees (roughly 43% of the workforce as of 1991) find that trade liberalization effects were slow and grew over time after 1995. These dynamics have been explained by slow capital reallocation across local labor markets, on the demand side (Dix-Carneiro and Kovak, 2017), and, on the supply side, by large costs of inter-sectoral and inter-regional mobility of workers (Dix-Carneiro, 2014; Dix-Carneiro and Kovak, 2019).

We focus particularly on the effects for nonwhite women, a group which, so far, has received little attention in the literature. In her seminal article on intersectionality, legal scholar Kimberle Crenshawt posits, for the United States, that "[b]ecause the intersectional experience is greater than the sum of racism and sexism, any analysis that does not take intersectionality into account cannot sufficiently address the particular manner in which Black women are subordinated" (Crenshawt, 1989, p. 140). However, very few papers on applied economics take intersectionality seriously (Lovell, 1994; Brewer *et al.*, 2002; Ruwanpura, 2008; Elu and Loubert, 2013; Weichselbaumer, 2020).[5] Most articles study gender or racial inequalities in isolation. In Brazil, as in other former colonies engaged in the Atlantic slave trade, nonwhite women have been, throughout history, particularly disadvantaged in the labor market. In comparison to other gender-race groups, nonwhite women earn the lowest average wage, are less likely to be formally employed, and are over-represented in jobs with poor working conditions (Lovell, 1994; Soares, 2000; Ipea, 2011).

Theoretically, international trade is expected to affect gender and racial inequalities in the labor market through different channels. First, according to Gary Becker's theory of taste-based discrimination, increased competition forces firms to abandon discriminatory practices, because discriminating individuals of similar productivity is costly (Becker, 1957). Once competition increases, firms reduce discrimination to minimize costs, at the risk of being driven out of the market. On the other hand, access to cheaper intermediate goods reduces production costs and may increase the markups of some firms (De Loecker *et al.*, 2016), thus increasing margins for discrimination. Second, in the framework of the Hecksher-Ohlin model, trade will benefit sectors that employ the country's relatively most abundant factor. In labor markets with high levels of sectoral segregation, trade liberalization will have distributional consequences along gender and racial lines, thus creating winners and losers. These differential impacts of trade liberalization are further mediated by labor market conditions, such as the size of the informal market (Ben Yahmed

[5]We acknowledge that selection bias is an important threat to empirical studies investigating gender and racial gaps in the labor market, which might explain the relatively low number of papers published in the literature.

and Bombarda, 2020), mobility across sectors, and wage rigidity (Pavcnik, 2017). While the competitive channel predicts that exposure to liberalization reduces discrimination, the increase in markups could lead to the opposite effect. The second channel is also ambiguous *a priori*, depending on the patterns of labor market segregation and on which sectors are more exposed to import competition.

The empirical evidence on gendered effects of liberalization is mixed. For the United States, Black and Brainerd (2004) show that exposure to competition in manufacturing industries reduces the gender wage gap. In Indonesia, Kis-Katos *et al.* (2018) find that exposure to tariff reductions on intermediate goods increases female labor force participation and reduces the share of women primarily occupied with domestic tasks. For Mexico, Juhn *et al.* (2014) show that trade integration following the North American Free Trade Agreement (NAFTA) increased female productivity in blue collar jobs, mostly through technology diffusion. On the other hand, Ben Yahmed and Bombarda (2020) document that, following liberalization in Mexico, women became more likely to enter the informal service sector, while men were more likely to work formally in the manufacturing sector. Exploiting China's tariff liberalization, between 1990 and 2005, Wang *et al.* (2020) find that exposure to import competition reduces the gender employment gap.

For Brazil, studies on trade liberalization and gender and racial inequality mostly investigate medium to long-term average effects, exploiting the long difference between the 1991 and 2000 censuses.[6] Gaddis and Pieters (2017) find that exposure to liberalization reduces both male and female average employment rates. Since the negative effects are larger for males, the gender gap in employment reduces in absolute terms. However, because men had higher initial employment rates, there was no reduction in the *relative* gender gap. In one of the few studies on the racial effects of liberalization, Hirata and Soares (2020) test Becker's (1957) model of taste-based discrimination among men. Consistent with Becker's hypothesis, the authors find that in regions more exposed to liberalization there was a reduction in the unexplained wage gap (i.e., discrimination) between white

[6]For a good overview of the literature about liberalization and gender and race inequality, see section 3.3 of Firpo and Portella (2019).

and nonwhite male workers. Their preferred estimate suggests that a tariff cut of 9.7 percentage points (the sample average in 1990–1995) reduces the racial wage gap among men by 18% between 1991 and 2000, with the effect persisting with a similar magnitude until 2010 (the year of the last available census). Whether similar effects occurred in the short run for the pay gap across gender-race groups and throughout the wage distribution remain open questions that we tackle in this article.

We complement the existing literature by focusing on short-term dynamics and by considering heterogeneity for all gender and racial groups, both on average and along the wage distribution. While the majority of the papers in the literature focus on long-run rather than on short-run dynamics, we argue that these transition periods are equally important. For instance, anti-globalization sentiments fueled by negative short-run effects of liberalization can undermine the government's ability to push forward liberalization reforms.[7] Over time, the unequal distribution of adjustment costs across regions can lead to the build-up of political polarization and populism (e.g., Dippel *et al.*, 2015; Colantone and Stanig, 2018; Autor *et al.*, 2020).

For identification, we follow the standard strategy in the literature (e.g., Topalova, 2010; Kovak, 2013; Dix-Carneiro and Kovak, 2017) and construct a regional measure of trade exposure based on pre-liberalization sectoral employment shares and exogenous cuts in sectoral import tariffs over time. By covering the period 1987–2001 and measuring labor market outcomes yearly, we capture the short-term effects of liberalization for men and women of different races. The identification strategy exploiting yearly variation in exposure to liberalization instead of long differences is similar to that of Erten *et al.* (2019), who study the labor market adjustments of liberalization in South Africa. Later on we discuss in detail the limitations of our identification strategy, particularly the threats associated with yearly variation in trade exposure.

A clear limitation of our analysis is selection into employment, a widely discussed issue in labor economics (e.g., Blau and Kahn, 2017; Machado, 2017). We take a closer

[7] In the words of Goldberg and Pavcnik (2004, pp. 10–15): "From a policy perspective, concern about the negative short-run effects of trade liberalization often impedes broad acceptance of free trade by the public and policymakers."

look at employment by gender and race. Although liberalization differentially affects the employment rates of men and women of different races, our results are robust to the inclusion of a fine-grained measure of average employment for different demographic groups. Altogether, the evidence suggests that our results are not entirely driven by selection into employment.[8]

Because gender and racial pay gaps vary along the wage distribution, we decompose the impact of trade liberalization at different wage quantiles, using the method developed in Firpo *et al.* (2009) and Firpo *et al.* (2018). For gender, many studies from different contexts find 'glass ceilings'—larger pay gaps at the top of the distribution than at the median— or 'sticky floors'—larger pay gaps at the bottom of the distribution than at the median (Albrecht *et al.*, 2003; Arulampalam *et al.*, 2007; Chi and Li, 2008; Salardi, 2012; Carrillo *et al.*, 2014; Bertrand, 2018; Deshpande *et al.*, 2018). A major contribution of our paper is to connect the literature on gendered and racial effects of trade liberalization to the literature on pay gaps over the wage distribution.

We find that, at first, trade liberalization had no overall effect on wages for all gender-race groups. For women, however, there is a positive and persistent increase in wages following liberalization. More interestingly, this positive effect is larger for nonwhite women, which contributes to a temporary reduction in average gender and race inequality. Among men, in contrast, the mean racial pay gap remains unaffected by tariff reductions. Overall, with a lag of two years, liberalization contributed to a reduction of 17.5% in the mean racial wage gap among women, a reduction of 6.5% in the gender wage gap between white men and white women, and a reduction of 19.4% in the gap between nonwhite men and women.

We then decompose wage gaps between gender-race groups at several quantiles of the wage distribution. We find that trade liberalization increases racial wage discrimination at the bottom half of the wage distribution, but reduces discrimination at the upper half. These distributional effects suggest that, overall, liberalization mitigated existing 'glass

[8]We acknowledge that selection into employment is an important issue along the gender dimension. However, we expect this concern to be less pronounced for race, as employment gaps are considerably smaller along this dimension.

ceilings' for nonwhite men and women alike. In contrast, trade liberalization reinforced gender wage discrimination among whites and nonwhites alike, but only at low wages. Thus, liberalization reinforced preexisting 'sticky floors' for nonwhite women. In comparison, the contribution of trade liberalization to the explained portion of the wage gap was quantitatively negligible for all gender-race pairs.

To study the short-term effects of trade liberalization by gender and race, we are restricted to the yearly national household survey (PNAD).[9] The smallest geographical units available in the PNAD are the 26 federal states plus the federal district. We define a local labor market as a state-urban or state-rural cell, which leaves us with substantially less spatial variation when compared to the literature using microregions from the decennial censuses. However, the analysis at the state-urban-rural level has the advantage of including a large enough number of observations per gender-race group in each sector and regional cell, which is crucial for the estimation of intersectional effects. The main disadvantage is that state-urban-rural areas are not necessarily geographically contiguous and, thus, should not be interpreted as commuting zones, as microregions usually are. Because our regions are not standard, we discuss this issue at length and provide supportive descriptive evidence from the 1991 census. To be conservative, we also construct a measure of trade protection at the state level and re-run our main analysis, finding very similar results.

We confirm that the results are robust to several sensitivity tests. First, we show that pre-liberalization trends go in the opposite direction of the main findings, as also documented in Dix-Carneiro and Kovak (2017). Before liberalization, wages, employment, and gender gaps were higher in areas that would suffer larger tariff cuts five years in the future. However, during liberalization, tariff cuts are associated with smaller gender gaps. Second, the results are robust to excluding the automotive sector, whose tariff cuts were temporarily reversed in a few years. Third, controlling directly for part-time work, despite

[9]More generally, the literature on the labor market effects of liberalization in Brazil uses a range of different data sources. Bosch *et al.* (2012) use the Monthly Employment Survey (Pesquisa Mensal de Emprego) and the PNAD to assess the effects of liberalization and labor market reforms on informality in Brazil. Krishna *et al.* (2014) exploit administrative linked employer-employee data from the Relação Anual de Informações Sociais (RAIS) to assess the wage-effects of liberalization for formal sector employees.

clear endogeneity problems, does not affect the heterogeneous effects of tariff reductions. Fourth, alternative estimators for standard errors produce similar significance levels for the trade protection coefficients. And, lastly, results are robust to removing potential outliers in the wage distribution by winsorizing and trimming the dependent variable.

The paper is structured as follows. Section 2 introduces the process of liberalization and facts about gender and racial inequality in Brazil. In section 3, we present the data and, in section 4, discuss the identification strategy and empirical specifications. In section 5, we report and discuss the results. Section 6 concludes.

2 Background

Trade liberalization Starting in 1988, Brazil initiated a comprehensive process of trade liberalization involving extensive reductions in import tariffs, elimination of discretionary controls, and overall reduction of non-tariff barriers (Kume *et al.*, 2003; Abreu, 2004). As in many other Latin American countries, Brazil's liberalization agenda occurred in a larger context of economic liberalization in the region, related to the Washington Consensus and the advancements of the negotiations of the Mercosur agreement (Castilho *et al.*, 2012; Gaddis and Pieters, 2017). Between 1988 and 1995, import tariffs decreased substantially across economic sectors, albeit at varying speeds. Online Appendix Figure A1 plots the effective tariff levels over time across sectors.[10] Except for the automotive sector, whose tariffs oscillated throughout the period, the figure shows a general trend of rapidly declining import tariffs.

The main objectives of the liberalization process were to reduce distortions in production and to equalize tariff levels across sectors. Following this logic, sectors that were initially highly protected experienced larger tariff cuts (Kovak, 2013). Figure 1 plots the change in effective tariff between 1987 and 1995 against the pre-liberalization tariff level for each sector at the 2-digit level.[11] The strong negative correlation between the two measures and

[10]We describe the data in detail in the next section.

[11]As discussed in further detail in section 4, to assess short-run effects of liberalization, our identification strategy relies on yearly variation in tariffs, rather than on long differences. Figures A2 and A3 plot the biannual changes in tariffs and the initial tariff levels with and without the automotive sector. Similarly

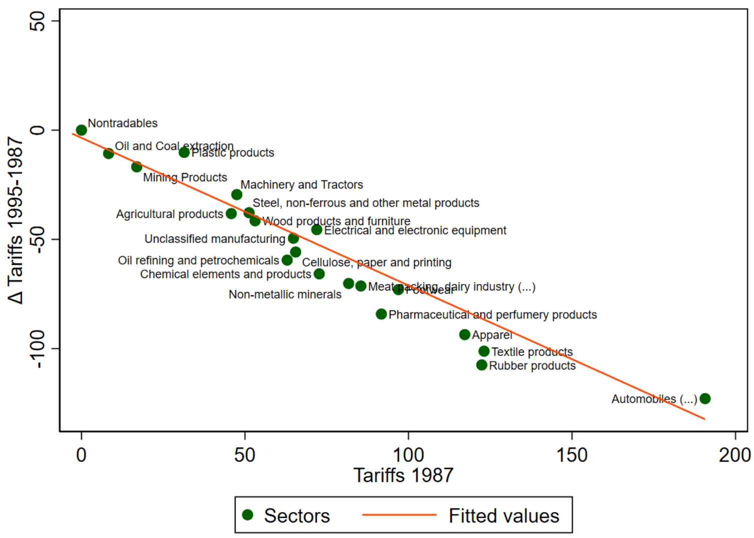


Figure (1) Changes in effective tariffs between 1987 and 1995 and pre-liberalization tariff levels

close to perfect fit confirm that tariff cuts were mostly determined by initial tariff levels. Kovak (2013) and Gaddis and Pieters (2017) emphasize, in addition, that the federal government was able to restrain protectionist interests and to put forward the liberalization process. Overall, the fact that the process of liberalization was mostly determined by policy, rather than by sectoral performance or economic interests, explains its suitability as a natural experiment.

Gender and race inequalities The Brazilian labor market exhibits substantial levels of segmentation and wage inequality by gender and race (Lovell, 1994; Salardi, 2016; Firpo and Portella, 2019). Because historical race and gender inequalities accumulate and reinforce each other, labor market outcomes are particularly disadvantageous for nonwhite women. In addition to being overrepresented in marginalized sectors, nonwhite women work on average longer hours and receive lower wages (Lovell, 1994). Whereas these differences are partially explained by observable characteristics (e.g., education, experience), a substantial residual remains, which is often interpreted in the literature as the effect of discrimination. In our sample from the PNAD, nonwhite women earn

to Figure 1, the plots show that, with the exception of the automotive sector, tariff cuts were larger for sectors that were initially more protected. As the liberalization process advanced, tariff cuts converged to zero.

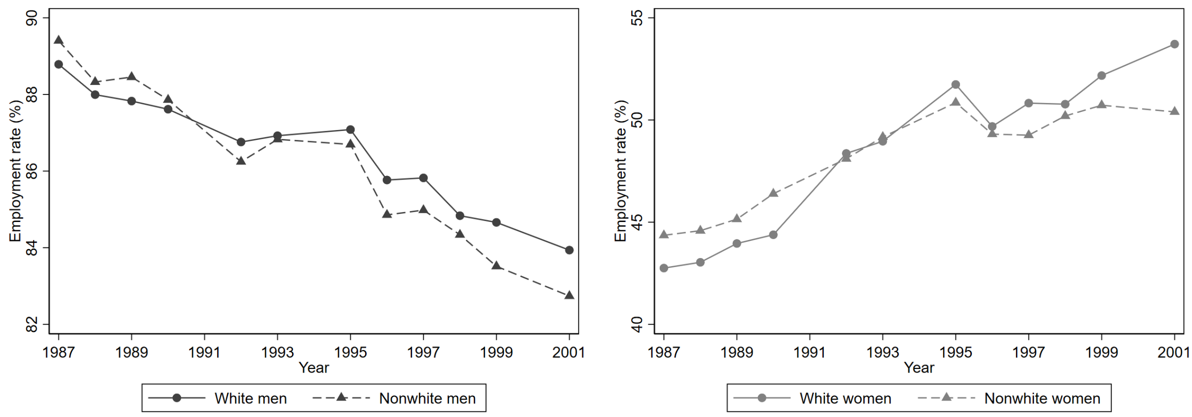
the lowest average log hourly wage and are most likely to be working informally, as compared to all other gender-race groups (see Online Appendix Table A1). Using survey data for 2010, Layton and Smith (2017) show that nonwhite women are more likely to report having suffered gender discrimination than white women of similar socioeconomic backgrounds. Moreover, perceptions of discrimination by class, gender, and race are closely interlinked, with a measure of the respondent's skin color coded by the interviewer being more predictive of perceived discrimination by class than household wealth or educational attainment. As put by the authors, "race underlies discrimination even when respondents fail to perceived it as race-based" (Layton and Smith, 2017, p. 54).

To be sure, productivity differences between groups may not be directly related to labor market discrimination, and may instead be driven by pre-market inequalities in parental investments during childhood, school quality, peer-effects, and so on. Even in the absence of taste-based or statistical discrimination by the employer, pre-market discrimination may generate pay inequality by lowering perceived returns to education or effort among discriminated groups (Bertrand and Duflo, 2017). Because we rely on repeated cross-sections, we cannot purge out time-invariant individual productivity in our analysis.[12] Thus, the term discrimination is used here in a broader sense, as encompassing employer discrimination and pre-market discrimination.

What were the broader trends in labor market outcomes by gender and race during the trade liberalization period considered in this article? The first key trend is that women were rapidly joining the labor market. Between 1987 and 1996, the gender gap in employment rates fell by 10 percentage points (Figure 2), with very similar trends across racial groups. At the same time, however, occupational segregation by gender and race did not fall (Salardi, 2016). Overall, this was a period of rising poverty and inequality (Ferreira *et al.*, 2008). Between 1996 and 2001, the gender gap in employment rates continued to fall, but at a slower pace.

In 1987, the gender wage gap among whites—conditional on age, education, number

[12]Freguglia and Menezes-Filho (2012) show that individual time-invariant heterogeneity explains two-thirds of wage differentials across federal states for formal sector employees, between 1995 and 2002.



(a) Men, by race

(b) Women, by race

Figure (2) Employment trends by gender and race, 1987–2001

Notes: Authors' calculation from PNAD, 1987–2001. Survey weights are used. The figure considers individuals aged 25–64.

of children, state of residence and 2-digit employment sector—was 54%. The conditional racial wage gap among men was 14%. On top of both these effects, nonwhite women suffered an additional pay penalty of 5% relative to other groups. Figure 3 shows how these conditional pay gaps evolved over time. The gender wage gap falls, in absolute terms, to 41% in 1996, and 38% in 2001, whereas the racial wage gap actually increases over time, stabilizing around 17% after 1996. Lastly, the wage penalty for being nonwhite *and* woman shrinks after 1989, and actually turns positive after 1995. In sum, gender pay gaps are much larger than racial pay gaps, but while the former decline over the liberalization period, the latter slightly increase. Nonwhite women's experience is not fully captured by the additive effects of being female and nonwhite; there is an additional intersectional effect, which is negative until 1992 and becomes positive afterwards.

Importantly, the average wage gap by gender or race hides substantial heterogeneity along the wage distribution. Studying the 1987–2006 period, Salardi (2012) finds that gender pay gaps exhibit both sticky floors and glass ceilings, although both phenomena become smaller over the period. Racial wage gaps reveal a persistent glass ceiling for nonwhite workers. By the early 2000s, urban Brazil had the highest gendered glass ceiling, conditional on education and experience, among the urban areas of 12 Latin American countries (Carrillo *et al.*, 2014). Figure 4 shows the unconditional wage gap across the

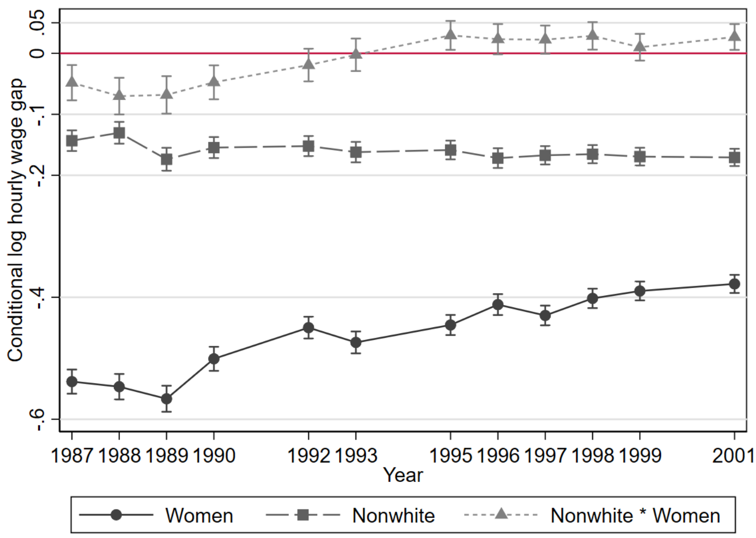


Figure (3) Evolution of conditional pay gaps across gender-race groups. Reference group: white men

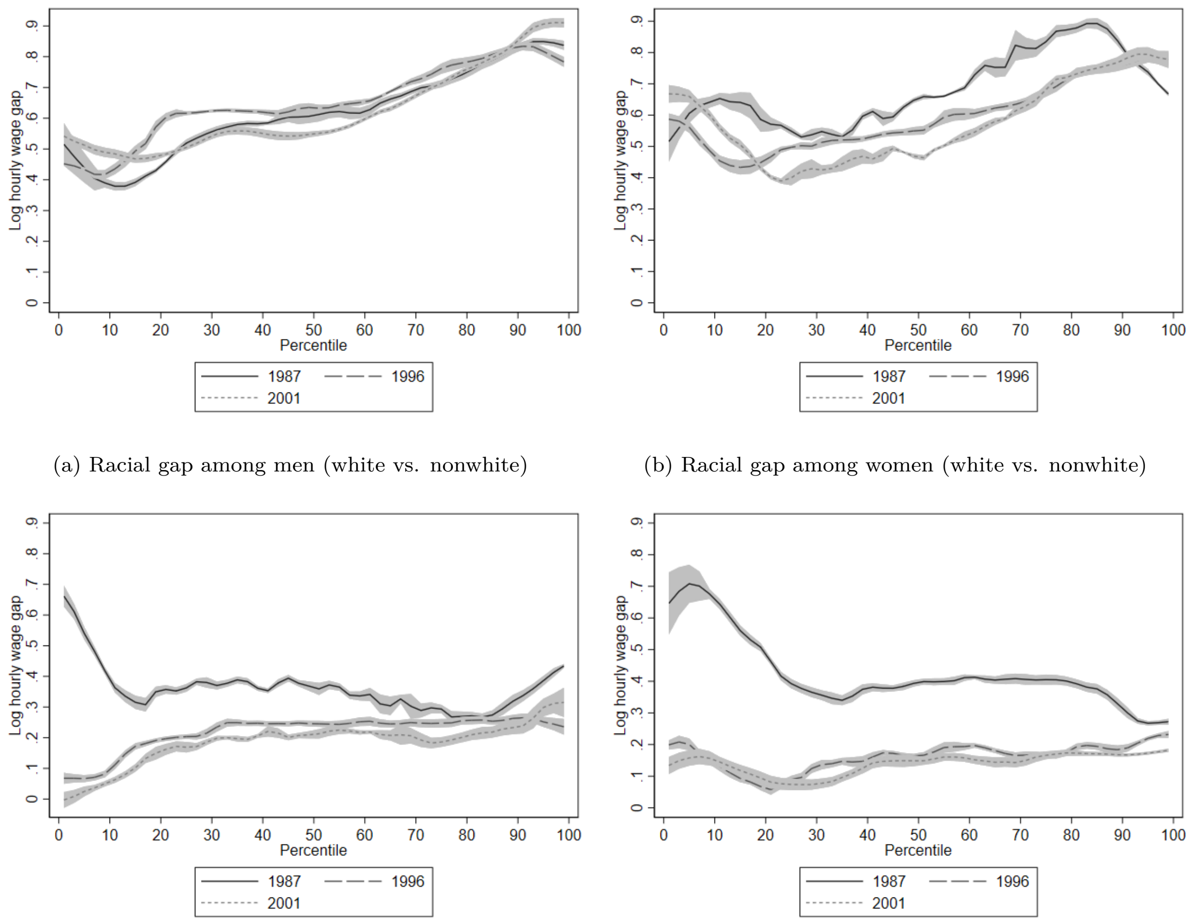
Notes: Authors' calculation from PNAD, 1987–2001. OLS estimates of women, nonwhite, and women × nonwhite dummies with 95% confidence intervals from Mincerian regressions of log hourly wage on age (quadratic), education, number of children, state dummies, and 21 sectoral dummies. Regressions are estimated separately for each year. Survey weights from PNAD are used. Includes all workers aged 25–64 with positive earnings.

distribution for 1987, 1996, and 2001. Overall, the figure reveals clear glass ceilings by race and large sticky floors for nonwhite women. Between 1987 and 1996, sticky floors and glass ceilings by gender became less pronounced; racial glass ceilings, on the other hand, did not improve substantially. Between 1996 and 2001, gender gaps remained fairly constant, whereas racial inequality increased both at the top and at the bottom of the wage distribution.

The remainder of the paper will attempt to rigorously estimate if and how trade liberalization contributed to changing wage differentials across demographic groups over time, both on average and along the wage distribution.

3 Data

We combine two data sources in our empirical analysis. Data on import tariffs by economic sector come originally from Kume *et al.* (2003) and are compiled in Abreu (2004). We have yearly information on import tariffs for 20 2-digit sectors between 1987 and 1996. We make use of the information on the effective tariff rate, which considers both tariffs



(a) Racial gap among men (white vs. nonwhite)

(b) Racial gap among women (white vs. nonwhite)

(c) Gender gap among whites (men vs. women)

(d) Gender gap among nonwhites (men vs. women)

Figure (4) Raw wage gaps: log hourly wage difference between social groups

Notes: Kernel-weighted local polynomial smooth plots with 95% confidence bands. Common Y-axis for all subfigures. Years are 1987, 1996, and 2001. Survey weights from PNAD are used. Includes all workers aged 25–64 with positive earnings.

on final as well as on intermediate goods.[13] All in all, data on import tariffs reflect the exposure of different sectors to import competition.

Individual-level data on labor market outcomes and socio-demographics come from the PNAD, a nationally representative yearly household survey.[14] We use 12 survey rounds, covering the period 1987 to 2001.[15] For our purposes, the PNAD offers three main advantages. First, since it is a household survey, it includes a large sample of individuals irrespective of their employment status, including both formal and informal

[13] For methodological details on how effective tariff rates are calculated, see Kume *et al.* (2003).

[14] Before 2003, the PNAD did not include the rural areas of the Northern states of Acre, Amapá, Amazonas, Pará, Rondônia and Roraima. According to the 1991 census, only 1.95% of the 25–64 population lived in these rural areas, which mostly overlap with the Amazon rainforest.

[15] The PNAD was not conducted in 1991 and 2001, which were census years, and in 1994, due to budgetary reasons.

workers, self-employed, unemployed and inactive individuals. Second, the survey contains a large enough number of observations for each gender-race group by sector and state. This is critical, because our main objective is to estimate the heterogeneous effect of trade opening across gender and race. Third, by being conducted annually, the data allow us to cover the exact years of liberalization and to estimate its short-run effects on labor market outcomes. Despite its comprehensiveness, the PNAD has one main drawback: it is only representative at the state level, which is a relatively large unit of analysis as compared to other administrative units that have been used in the literature, such as microregions or municipalities. We further divide each state into rural and urban cells, as those cells are more homogeneous in terms of sectoral composition and labor market characteristics and increase the spatial variation in our analysis.[16]

Two alternative data sources which have been previously used in the literature are the Demographic Censuses and the administrative records of the Relação Anual de Informações Sociais (RAIS). The main disadvantage of the census is its decennial time span 1991, 2000. Liberalization of import tariffs occurred mainly between 1990 and 1995, with a small reversion of the process after 1995 (see Online Appendix Figure A1). Measuring outcomes only using the 2000 census, therefore, captures the net effect of liberalization and could be potentially confounded by other policy changes happening at the same period. Between 1995 and 1998, the Brazilian government started to register current account imbalances (Kume *et al.*, 2003). This was related to rising imports that resulted from tariff reductions and exchange rate appreciation following the monetary stabilization plan (Plano Real). Additionally, capital flight following the Mexican crisis of 1994 made it more difficult for the government to finance current account deficits. In this context, between 1995 and 1998, the Brazilian government increased import tariff rates in some sectors that were driving the increase in overall imports (Kume *et al.*, 2003, p. 18).

The other alternative data source would be the RAIS, a yearly administrative census, covering all workers employed in the formal sector. Although very comprehensive, the

[16]In the robustness checks section, we discuss in more detail our choice of regional aggregation and provide evidence that our results hold with an alternative specification of labor market.

database excludes self-employed workers, informal workers and unemployed individuals. Additionally, information on employees' race was only introduced in the 2000s, so it is not available for the period analyzed in this paper. For the reasons discussed above, we believe the PNAD is the most suitable source of microdata for our empirical analysis. Next, we discuss our measure of local trade exposure as well as our empirical model.

4 Empirical strategy

Our identification strategy relies on a shift-share design, which is the standard design in the literature for estimating the causal effects of aggregate shocks on local labor markets (e.g., Topalova, 2010; Autor *et al.*, 2013; Kovak, 2013). Our measure of exposure to trade liberalization varies depending on pre-liberalization sectoral composition of employment across state-rural-urban cells and changes in sectoral tariffs over time.[17] Intuitively, although sectoral tariff cuts occur at the national level, their differential impact across regions depends on pre-existing local sectoral shares (Castilho *et al.*, 2012; Gaddis and Pieters, 2017; Dix-Carneiro and Kovak, 2017). To assess the short-run effects of liberalization, we exploit yearly variation in trade exposure—a strategy used, among others, by Erten *et al.* (2019) for South Africa. We measure trade protection as:

$$TP_{dut} = \sum_{s=1}^{20} \frac{L^0_{dus}}{L^0_{du}} \times \pi_{st} \tag{1}$$

where d denotes state, u is a urban/rural indicator, t denotes year, and s denotes sector. L^0_{dus} is the sectoral employment in a state-urban-rural cell in 1987, before liberalization started. L^0_{du} is overall employment in a state urban-rural area, also in 1987. π_{st} is the effective tariff level in sector s and year t. When computing sectoral employment shares, we follow Gaddis and Pieters (2017) and exclude the nontradable sector, because its implicit tariff is always zero. We assume, however, that prices in the tradable sector are transmitted to the nontradable sector (Kovak, 2013; Gaddis and Pieters, 2017). Thus,

[17] For details on the compatibilization between the PNAD industry classification with the sectoral tariff data, see Section A.2 in the Online Appendix.

while excluded from the variable TP, workers in the nontradable sector are included in the regression analysis. The higher the value of TP_{dut}, the higher the level of trade protection in a local labor market. Accordingly, tariff reduction corresponds to a fall of TP_{dut} over time.

The validity of the shift-share strategy for causal identification relies on the assumption that either the shifts—here, changes in sectoral tariffs—or the shares—here, sectoral employment shares—are exogenous (Borusyak *et al.*, forthcoming; Goldsmith-Pinkham *et al.*, 2020). While assuming exogeneity of employment shares is unrealistic, prior literature has convincingly argued that the 1988–1995 cuts in import tariffs in Brazil are exogenous to local labor market conditions.[18]

In the Online Appendix, we plot yearly tariff changes across sectors, with and without the automotive sector (Figures A2 and A3).[19] Initially, tariff cuts were larger for sectors that were heavily protected in 1987, with a stronger negative correlation between 1987 and 1992. Afterwards, yearly tariff changes slowly approached zero, indicating the completion of the process of liberalization. Overall, the figure with yearly variation also corroborates the hypothesis that the main objective of the liberalization process was to equalize tariff levels, without being susceptible to substantial protectionist interests by certain groups. This reduces concerns that the timing of tariff cuts was endogenous, i.e., driven by a particular liberalization agenda or by certain interest groups.[20]

Across regions, tariff cuts were largest in more economically developed areas. Areas whose initial protection levels were above the median have, in 1987, higher hourly wages, more educated workers, lower fertility, and a larger share of whites (Table A2). Online Appendix Figure A4 plots the protection levels for each state-urban-rural cell before

[18] An incomplete list of papers using this identification assumption for Brazil's trade liberalization includes: Castilho *et al.* (2012); Kovak (2013); Dix-Carneiro and Kovak (2017); Gaddis and Pieters (2017); Braga (2018); Costa *et al.* (2018); Dix-Carneiro *et al.* (2018).

[19] We show later that the results are robust to excluding the automotive sector altogether.

[20] As pointed out by Dix-Carneiro and Kovak (2017), there is a concern that the timing of tariff cuts was not exogenous, but driven by policy interests. According to the authors, to support the liberalization plan, tariffs on intermediate inputs were cut before the tariffs on consumer goods. Although we acknowledge that the timing of tariff cuts might not have been entirely random, Online Appendix Figures A2 and A3 reduce concerns that this was systematic, as we see a negative correlation between tariff levels and tariff cuts for most sectors and years.

(1987), during (1991), and after (1996) liberalization. The fact that richer areas suffered the largest reduction in protection against import competition suggests, once again, that powerful interest groups were unable to successfully capture or jeopardize the process of liberalization.

We estimate the reduced-form model:

$$
\begin{aligned}
ln(Y_{idsut}) = & \beta_1 F_{idsut} + \beta_2 N_{idsut} + \beta_3 F_{idsut} \times N_{idsut} + \beta_4 TP_{dut} + \beta_5 TP_{dut} \times F_{idsut} + \\
& \beta_6 TP_{dut} \times N_{idsut} + \beta_7 TP_{dut} \times F_{idsut} \times N_{idsut} + \lambda X_{idut} + \delta_t + \gamma_{du} + \phi_s + \\
& \eta_{dp} + \epsilon_{idsut}
\end{aligned} \tag{2}
$$

where the dependent variable is the logarithm of the deflated hourly wage of individual i living in state d, rural or urban area u, employed in sector s at time t. TP is the trade protection measure for each state-urban-rural area regressed separately with lags up to 5 years. F is a female dummy; N is a nonwhite dummy equal to one if the individual self-declares as black (*preto*) or brown (*pardo*). X is a vector of individual controls: age, age squared, educational attainment and number of children. We also include year fixed effects δ_t, state-urban-rural fixed effects γ_{du}, sector fixed effects ϕ_s, and state-phase fixed effects η_{dp}. We divide the period into three distinct phases, indexed by p: 1987–89, 1990–95, 1996–2001. The first phase, 1987–89, corresponds to the first stage of liberalization, when tariff schedules were simplified, and tariff redundancy eliminated, but non-tariff barriers remained largely unchanged. The second phase, 1990–95, corresponds to the main liberalization period, when effective rates of protection were rapidly and systematically reduced. The third phase, 1996–2001, corresponds to the immediate post-liberalization period. By allowing different state intercepts for each phase, we flexibly control for shocks that vary by phase and state. Taken together, the fixed effects account for yearly shocks that commonly affected the Brazilian labor market, historical factors that are constant over time for each state-urban-rural area or 2-digit sector, and state-specific shocks in each of the three distinct phases of the liberalization process.[21] Standard errors are clustered at

[21]The results are, overall, qualitatively similar if, instead of the state-phase dummies, the model

the state-urban-rural level.

We restrict our sample to working individuals aged 25–64, surveyed between 1987 and 2001. The number of observations ranges from 533,478 to 982,193, depending on the lag structure of the trade protection variable as well as on the outcome variable used in the regression models.[22] See Online Appendix A.1 for variable definitions and Table A3 for summary statistics of the estimation sample. The average log hourly wage in our sample is around 1.57 BRL (at 2012 prices); 41.7% of the individuals self-identify as nonwhites, and 37% are women.[23]

The main coefficients of interest are β_4—the effect of trade liberalization on white male wages; β_5—the differential effect of liberalization on female wages; β_6—the differential effect of liberalization on nonwhite wages; and β_7—the additional effect of liberalization on the wages of nonwhite women.

The time lag between a tariff cut, increased market competition, and firm decisions will depend on many unobservable factors, such as labor market rigidities and international trade frictions. Because, beforehand, we are unsure about the most appropriate time lag for the tariff protection variable, we transparently run regressions with up to five lags of TP. Because the lagged variables are highly correlated from one year to the next, we do not include the full lag structure simultaneously as our main specification.[24] Instead, we introduce time lags separately. As such, the lagged coefficients of TP can be understood as cumulative effects over previous periods. Notice that these coefficients reflect relative wage differences between less and more exposed local labor markets and not overall levels. Overall, this model specification allows us to assess the short-term dynamics of liberalization for the gender-race groups.

includes linear wage trends for each state.

[22]Our main outcome of interest is the log hourly wage, but we also estimate auxiliary models of employment participation. Since only employed individuals report wages, the sample for log wages is much smaller than the sample for employment status.

[23]Tables A4-A7 in the Online Appendix show the sectoral occupation for the gender-race groups in our sample.

[24]cor(TP_t,TP_{t-1})=0.8967 and cor(TP_t,TP_{t-2})=0.7785.

5 Results

5.1 Average effects

We start by estimating the average effect of trade protection on individual wages. The dependent variable is the logarithm of deflated hourly wages. By normalizing with respect to hours worked, this variable comes closest to the concept of pay discrimination. We acknowledge, however, that not accounting for individual productivity or ability in the wage regression makes the interpretation of discrimination open to discussion. Since the PNAD is a repeated cross section and not a panel of individuals, we cannot account for unobserved factors affecting wages. The point estimates are presented in Table 1, with column (1) showing the contemporaneous effect of trade protection, and columns (2) to (6) showing the lagged effects up to five years before the wage measurement.

In line with the stylized facts presented in section 2, the estimated conditional wage gaps by gender and race are large. Women earn, on average, 39%–47% less than comparable males in the same sector of employment. Nonwhites earn 15%–18% less than comparable whites. For nonwhite women, the interaction coefficient (Nonwhite × Women) is statistically insignificant in most specifications and much smaller in magnitude. This suggests that the disadvantage of this group, which obtains the lowest hourly wage, arises entirely from the cumulative effect of two identities—being female and being nonwhite—rather than through their interaction. Later on, however, when decomposing pay gaps across the wage distribution, we show that nonwhite women suffer a large unexplained pay loss at the bottom of the distribution, suggesting a negative interaction effect of being nonwhite and women at low-paying jobs. These nuanced findings highlight the importance of understanding gender and race inequalities from an intersectional perspective.

Turning to the effects of trade liberalization, Figure 5 plots the marginal TP coefficients by gender-race groups across different time lags. At first, a decline in trade protection has no overall effect on wages. Nevertheless, we document significant heterogeneous effects by gender and race. For women, tariff cuts increase wages persistently (Figure 5b), while for nonwhite women there is an additional increase in wages that remains significant and sizable up to three years (Figure 5d). The differential coefficients for nonwhite men are always insignificant (Figure 5c). Lastly, with a 5-year lag, liberalization reduces hourly wages of all gender-race groups (Figure 5a). This overall decrease in wages is consistent with the results of Kovak (2013).

As a whole, in the short run, liberalization reduced average gender and racial inequality in Brazil, with gender effects being persistent and gender-race effects temporary. At first, the contemporaneous positive wage effect was the same for white and nonwhite women, and null for males. Afterwards, wage effects become larger for nonwhite women. A one SD decline in trade exposure TP_{t-2} (TP_{t-3}) increases hourly wages of white women by 2.72% (1.27%) and hourly wages of nonwhite women by 5.42% (2.98%) (Table 1, columns (3) and (4)).[25] With a lag of five years, the overall effect of liberalization becomes negative, particularly so for males. A one SD decline in TP_{t-5} (≈ 2.05) reduces male hourly wages by approximately 4.4%, whereas female hourly wages fall by only 2.4% (Table 1, column (6)). All in all, liberalization contributed to a reduction of 17.5% in the mean racial wage gap among women, a reduction of 6.5% in the gender wage gap between white men and white women, and a reduction of 19.4% in the gap between nonwhite men and women with a lag of two years.

5.2 Selection into employment

A well-known issue in the gender wage gap literature is selection into employment (Gronau, 1974; Heckman, 1979). Because wages are only observed for the employed, and women's labor force participation rates are much lower than men's, selection on unobservables in the participation decision will bias the estimated coefficients of wage gap regressions. In our case, the effect of trade liberalization on wage gaps across social groups could be driven (to an unknown extent) by changes in selection into employment over time.

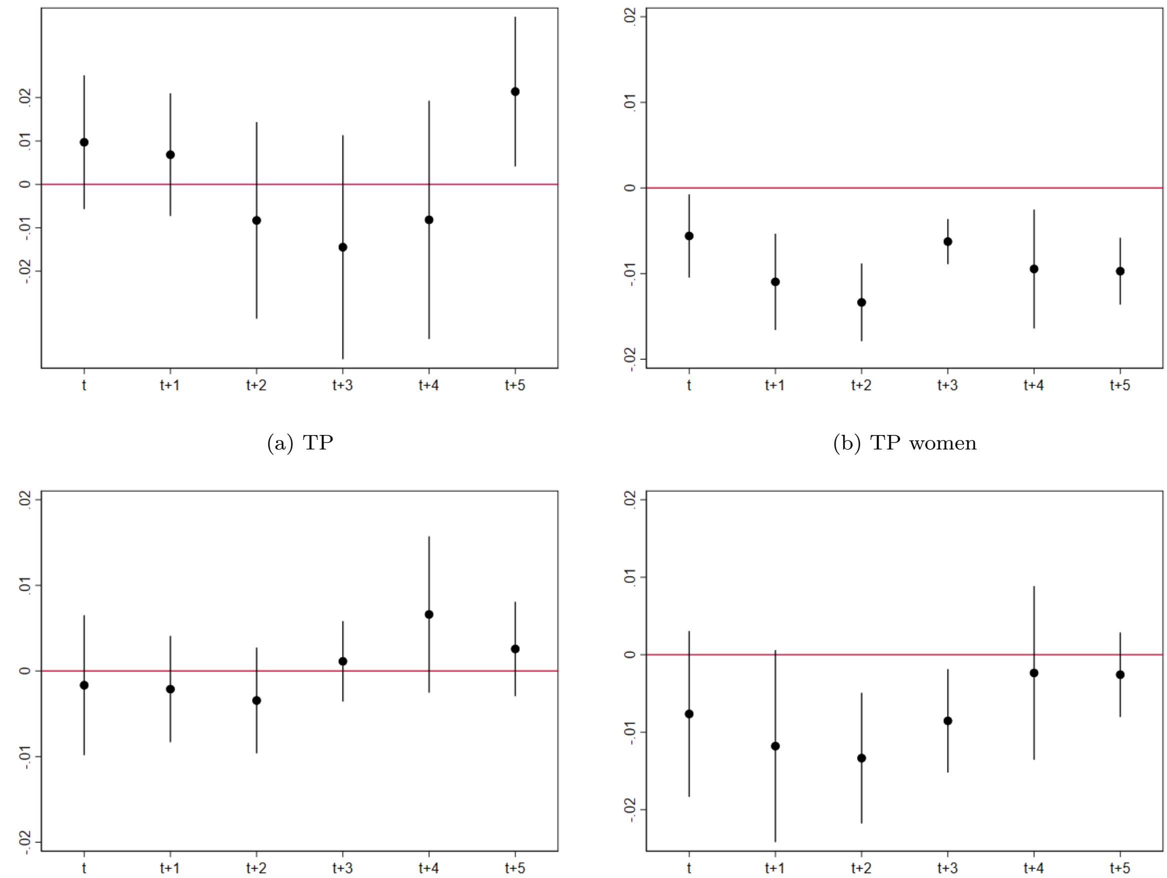
Unfortunately, there is no consensual econometric fix for the selection problem, with different correction methods producing disparate results (e.g., Blau and Kahn, 2017; Machado, 2017). Most of the existing correction methods rely on stringent assumptions on

[25] SD of $TP_{t-2} \approx 2.03$ and $TP_{t-3} \approx 2.01$.

Table (1) Trade protection and hourly wage

	Log(hourly wage)					
	(1) $\ell = t$	(2) $\ell = t-1$	(3) $\ell = t-2$	(4) $\ell = t-3$	(5) $\ell = t-4$	(6) $\ell = t-5$
Women	-0.4706***	-0.4428***	-0.4191***	-0.4198***	-0.4062***	-0.3926***
	(0.0172)	(0.0172)	(0.0126)	(0.0133)	(0.0166)	(0.0137)
Nonwhite	-0.1537***	-0.1545***	-0.1547***	-0.1674***	-0.1793***	-0.1732***
	(0.0125)	(0.0121)	(0.0105)	(0.0098)	(0.0129)	(0.0107)
Nonwhite $\times$ Women	-0.0030	0.0142	0.0292*	0.0273**	0.0180	0.0213
	(0.0197)	(0.0195)	(0.0153)	(0.0132)	(0.0170)	(0.0137)
TP_ℓ	0.0097	0.0068	-0.0083	-0.0145	-0.0082	0.0214**
	(0.0077)	(0.0070)	(0.0113)	(0.0128)	(0.0136)	(0.0086)
$\text{TP}_\ell \times$ Women	-0.0056**	-0.0110***	-0.0134***	-0.0063***	-0.0095***	-0.0097***
	(0.0024)	(0.0028)	(0.0023)	(0.0013)	(0.0034)	(0.0019)
$\text{TP}_\ell \times$ Nonwhite	-0.0017	-0.0021	-0.0034	0.0011	0.0066	0.0026
	(0.0041)	(0.0031)	(0.0031)	(0.0023)	(0.0045)	(0.0027)
$\text{TP}_\ell \times$ Nonwhite $\times$ Women	-0.0076	-0.0118*	-0.0133***	-0.0085**	-0.0024	-0.0026
	(0.0053)	(0.0062)	(0.0042)	(0.0033)	(0.0056)	(0.0027)
N	549716	566938	583082	600334	533478	624293
Year FE	✓	✓	✓	✓	✓	✓
State $\times$ urban FE	✓	✓	✓	✓	✓	✓
State $\times$ phase FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary least squares (OLS) estimates reported with robust standard errors clustered at the state-urban level. Tariff protection measured at time $t-5$, $t-4$, $t-3$, $t-2$, $t-1$, and t. The sample includes individuals aged 25 to 64. Period is 1987–2001. Phase is a categorical variable taking value 1 for the years 1987–89, value 2 for the years 1990–95, and value 3 for the years 1996–2001. Survey weights from PNAD are used. Control variables include age, squared age, educational attainment and number of children.



(a) TP

(b) TP women

(c) TP nonwhite

(d) TP nonwhite women

Figure (5) Trade protection and hourly wage. TP coefficients

Notes: The figure plots the marginal TP coefficients by gender-race group across different time lags. Point estimates shown with 95% confidence intervals.

positive or negative selection patterns, whereas, in reality, the selection process is unknown and may even be heterogeneous across population groups (Neal, 2004).

In the absence of an econometric fix, we gather two pieces of evidence that seem inconsistent with a fully selection-driven story. First, we directly estimate the effects of trade liberalization on employment for the different gender and racial groups. Second, we re-estimate the baseline models, but now controlling for gender-race-cohort employment rates that vary by state-urban-rural area and year.

In Table 2, we estimate the effects of trade liberalization on the employment probability of the different population groups. At first, liberalization decreases employment. After two and three years, however, less tariff protection is associated with higher employment probability for women, and, with a lag of five years, there is a decrease in overall employment. The magnitude of these effects differs between the groups with negative effects of liberalization being strongest for males, followed by nonwhites females and, finally, by white females. From columns (3) and (4), liberalization increases employment of white females by 2.48 pp (2.36 pp) and employment of nonwhite females by 0.89 pp (0.65 pp) with a lag of two and three years. The five-year-lagged effects are consistent with the longer term gender effects of Gaddis and Pieters (2017).[26]

Under the simplifying neoclassical assumption that the first jobs to be cut are those with the lowest marginal productivity, we would expect that more jobs are lost among the lowest paid men than among the lowest paid women. This process would upward bias the gender wage gap estimate. In contrast, we find that trade liberalization reduces the gender wage gap, which is at odds with a purely trade-induced selection effect. Among women, however, if more jobs are lost among the lowest paid nonwhites than among whites, the racial wage gap estimate is downward biased. Indeed, we find that trade liberalization increases nonwhite women wages relative to those of white women. Selection into employment could be driving this effect, although it is unlikely to drive the reduction in average wage gaps between nonwhite women and men.

We then try to explicitly model changing employment rates for the different social groups. We assign to each individual the average employment share of her/his gender, race, and 5 year age cohort, in the state and urban-rural area of residence and survey year. By controlling for this variable, we purge the variation in wages that is systematically related to the evolution of employment rates by different demographic groups over time and across cohorts.[27] As shown in Table 3, the coefficient of the employment share is positive and significant in most specifications: on average, a 10 percentage point increase in the predicted employment rate, is associated with a 1.2 to 3.1 log point increase in hourly wages. Reassuringly, the estimated effects of trade liberalization remain qualitatively

[26]Gaddis and Pieters (2017) estimate that, between 1991 and 2000, one SD decline in TP reduces female employment by 1.03 pp and male employment by 2.92 pp. Our 5-year lagged estimates go in the same direction but are smaller, implying a drop of 1.44 pp in nonwhite female employment, 0.02 in white female employment, and 1.64 pp in male employment (Table 2, column (6)).

[27]In total, there are 15,073 cells defined by gender, race, 5-year age cohort, state-urban-rural area, and year. The employment share across cells has mean 0.741, standard deviation of 0.197, and ranges between the whole unit interval, 0–1.

Table (2) Trade protection and employment

	Worked in the ref week					
	(1) $\ell = t$	(2) $\ell = t-1$	(3) $\ell = t-2$	(4) $\ell = t-3$	(5) $\ell = t-4$	(6) $\ell = t-5$
Women	-0.4102***	-0.3938***	-0.3782***	-0.3674***	-0.3703***	-0.3581***
	(0.0177)	(0.0156)	(0.0143)	(0.0131)	(0.0172)	(0.0132)
Nonwhite	0.0227***	0.0197***	0.0183***	0.0178***	0.0166**	0.0167***
	(0.0065)	(0.0059)	(0.0057)	(0.0054)	(0.0066)	(0.0053)
Nonwhite × Women	-0.0226*	-0.0234*	-0.0253*	-0.0277**	-0.0331**	-0.0292**
	(0.0133)	(0.0128)	(0.0127)	(0.0122)	(0.0153)	(0.0115)
TP_ℓ	0.0179***	0.0139***	0.0036	-0.0009	-0.0049	0.0080*
	(0.0034)	(0.0032)	(0.0026)	(0.0016)	(0.0035)	(0.0041)
TP_ℓ × Women	-0.0102***	-0.0116***	-0.0122***	-0.0117***	-0.0080	-0.0079***
	(0.0034)	(0.0031)	(0.0025)	(0.0023)	(0.0052)	(0.0027)
TP_ℓ × Nonwhite	0.0009	0.0015	0.0017*	0.0008	0.0004	0.0005
	(0.0012)	(0.0010)	(0.0009)	(0.0009)	(0.0016)	(0.0008)
TP_ℓ × Nonwhite × Women	0.0080**	0.0078***	0.0078***	0.0085***	0.0124**	0.0069**
	(0.0031)	(0.0026)	(0.0025)	(0.0027)	(0.0046)	(0.0026)
N	863041	890338	917399	945632	841384	982193
Year FE	✓	✓	✓	✓	✓	✓
State × urban FE	✓	✓	✓	✓	✓	✓
State × phase FE	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary least squares (OLS) estimates reported with robust standard errors clustered at the state-urban level. Tariff protection measured at time $t-5$, $t-4$, $t-3$, $t-2$, $t-1$, and t. Period is 1987–2001. Phase is a categorical variable taking value 1 for the years 1987–89, value 2 for the years 1990–95, and value 3 for the years 1996–2001. Survey weights from PNAD are used. Control variables include age, squared age, educational attainment and number of children.

similar.

In sum, selection into employment is an important caveat of this article, but, from a quantitative perspective, our evidence suggests that it is not a first-order concern. However, we cannot exclude the possibility that part of the wage-effect of trade liberalization is operating via the employment margin.

One question that arises from the results presented so far is whether liberalization had differential effects beyond the mean. In what follows, we decompose the effect of tariff reductions at different points of the wage distribution to investigate if trade liberalization affected inequality and discrimination between gender-race groups.

5.3 Decompositions

So far, we have estimated the average effect of trade liberalization for different gender and racial groups. But how large is this effect when compared to classic Mincerian wage determinants? How did it shape wage inequality among those different groups during the liberalization period? Was the effect heterogeneous across the wage distribution? And, more importantly, how did trade liberalization affect the wage structure between groups—i.e., the unexplained term usually associated with discrimination?

To answer these questions, we decompose the gap in log hourly wages (Y_g) between two mutually exclusive groups, $g = A, B$, at the τth quantile of the unconditional wage distribution ($Q_{g,\tau}$) as[28]

$$\Delta_O^\tau \equiv Q_{B,\tau} - Q_{A,\tau} = \Delta_X^\tau + \Delta_U^\tau \tag{3}$$

where Δ_X^τ is the composition effect (or explained term), which is the part of the gap explained by differences in the distribution of covariates X between the two groups; and Δ_U^τ is the wage structure effect (or unexplained term), which is the part of the gap explained by differences in the returns to covariates and unobservables between the two groups. In our setting, because the features defining group membership—gender, race—are (mostly) fixed

[28]With a few exceptions, we follow the notation in Fortin *et al.* (2011).

Table (3) Trade protection and hourly wage. Selection into employment

	Log(hourly wage)					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ell = t$	$\ell = t-1$	$\ell = t-2$	$\ell = t-3$	$\ell = t-4$	$\ell = t-5$
Women	-0.3609***	-0.3580***	-0.3602***	-0.3809***	-0.3812***	-0.3771***
	(0.0339)	(0.0313)	(0.0242)	(0.0240)	(0.0261)	(0.0220)
Nonwhite	-0.1516***	-0.1520***	-0.1522***	-0.1655***	-0.1781***	-0.1723***
	(0.0122)	(0.0123)	(0.0107)	(0.0102)	(0.0131)	(0.0110)
Nonwhite × Women	0.0040	0.0191	0.0325**	0.0297**	0.0199	0.0224
	(0.0182)	(0.0184)	(0.0148)	(0.0127)	(0.0163)	(0.0134)
TP_ℓ	0.0074	0.0056	-0.0082	-0.0142	-0.0079	0.0211**
	(0.0073)	(0.0070)	(0.0114)	(0.0129)	(0.0137)	(0.0084)
TP_ℓ × Women	-0.0019	-0.0079***	-0.0111***	-0.0049***	-0.0088***	-0.0093***
	(0.0026)	(0.0024)	(0.0025)	(0.0012)	(0.0031)	(0.0018)
TP_ℓ × Nonwhite	-0.0015	-0.0021	-0.0036	0.0011	0.0067	0.0026
	(0.0040)	(0.0030)	(0.0030)	(0.0023)	(0.0045)	(0.0027)
TP_ℓ × Nonwhite × Women	-0.0108**	-0.0139**	-0.0147***	-0.0095***	-0.0033	-0.0029
	(0.0046)	(0.0056)	(0.0039)	(0.0029)	(0.0051)	(0.0025)
Employment share	0.3129***	0.2507***	0.1806***	0.1227**	0.0783	0.0505
	(0.0812)	(0.0699)	(0.0583)	(0.0539)	(0.0481)	(0.0444)
N	549716	566938	583082	600334	533478	624293
Year FE	✓	✓	✓	✓	✓	✓
State × urban FE	✓	✓	✓	✓	✓	✓
State × phase FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary least squares (OLS) estimates reported with robust standard errors clustered at the state-urban level. Tariff protection measured at time $t-5$, $t-4$, $t-3$, $t-2$, $t-1$, and t. Period is 1987–2001. Phase is a categorical variable taking value 1 for the years 1987–89, value 2 for the years 1990–95, and value 3 for the years 1996–2001. Survey weights from PNAD are used. Control variables include age, squared age, educational attainment, number of children and the average employment share of the individual's gender, race and 5 year age cohort, in the state and urban-rural area of residence and survey year.

from birth, the wage structure effect is usually associated with labor market discrimination, although the term also captures any productivity differences between groups that may not be directly related to discrimination.

Method We use the decomposition method based on recentered influence function (RIF) regressions (Firpo *et al.*, 2009) proposed in Firpo *et al.* (2018). This method has three main advantages. First, it can be used to decompose any general distributional statistic. In our context, the relevant distributional statistics are different quantiles of the wage distribution. Second, the method in Firpo *et al.* (2018) provides a detailed decomposition of each variable's contribution to the composition and wage structure components of the wage gap, allowing us to isolate the contribution of trade liberalization. Third, because the method uses RIF regressions, it follows the same logic and computational attractiveness of other regression-based methods, such as the Oaxaca-Blinder mean-decomposition method (Oaxaca, 1973; Blinder, 1973). In sum, it is a convenient tool to estimate how trade liberalization affected wage gaps between different demographic groups, at different points of the wage distribution.

The RIF is a re-centered version of the influence function (IF)—a function that measures how each data point affects the value of a distributional statistic and is widely used in the literature on robust statistics (Hampel, 1974). For example, the IF of the mean (μ) of the distribution F at point y is simply the point's deviation from the mean, i.e., $IF(y;\mu,F) = y - \mu$. By definition, the expected value of any IF is zero. The re-centered version has an expectation equal to the distributional statistic of interest. For the mean, $RIF(y;\mu,F) = \mu + IF(y;\mu,F) = y$. For a general distribution statistic v, then, $RIF(y;v,F) = v(F) + IF(y;v,F)$. By the law of iterated iterated expectations, v can be expressed as the expectation of conditional RIFs given covariates X.[29]

Firpo *et al.* (2009) show that the average derivative of the conditional RIF expectation, $E[RIF(Y;v,F)|X]$, amounts to the effect on v of a marginal shift in the distribution of

[29]
$$v(F) = \int \mathbb{E}[RIF(Y;v,F)|X = x] \cdot dF_X(x).$$

X. Under the assumption that $E[RIF(Y; v, F)|X]$ is linear, its average derivative can be estimated by a linear regression of $RIF(Y; v, F)$ on X. In the case of the mean ($v = \mu$), the RIF-regression coefficients are simply the OLS coefficients of regressing Y on X.[30]

Intuitively, RIF-regressions are an attractive way to compute linear approximations of the counterfactual quantities of interest when decomposing distributional statistics beyond the mean. We now briefly present the decomposition procedure for the case of quantiles of the unconditional wage distribution.[31] The RIF for quantile τth is given by

$$RIF(y_g; Q_{g,\tau}) = Q_{g,\tau} + \frac{\tau - \mathbb{1}\{y_g \leq Q_{g,\tau}\}}{f_{Y_g}(Q_{g,\tau})}, \qquad g = A, B \tag{4}$$

where $\mathbb{1}\{.\}$ is an indicator function and $f_{Y_g}(.)$ is the density of the marginal distribution of Y for group g. In equation (4), we then plug in the estimated sample quantile, $\widehat{Q}_{g,\tau}$, and the density $\widehat{f}_{Y_g}(\widehat{Q}_{g,\tau})$ and run OLS regressions of $\widehat{RIF}(y_g; \widehat{Q}_{g,\tau})$ on covariates X_g.[32] The OLS coefficients ($\widehat{\gamma}_{g,\tau}$) play a role similar to the coefficients in a Oaxaca-Blinder mean decomposition. The empirical counterpart of equation (3) becomes

$$\begin{aligned} \widehat{\Delta}_O^{\tau} &= \widehat{\Delta}_X^{\tau} + \widehat{\Delta}_U^{\tau} \\ &= (\overline{X}_B - \overline{X}_A)\widehat{\gamma}_{A,\tau} + \overline{X}_B(\widehat{\gamma}_{B,\tau} - \widehat{\gamma}_{A,\tau}) \end{aligned} \tag{5}$$

The individual contribution of a covariate k, X_k, to the composition effect is $(\overline{X}_{Bk} - \overline{X}_{Ak})\widehat{\gamma}_{Ak,\tau}$. Its contribution to the wage structure is $\overline{X}_{Bk}(\widehat{\gamma}_{Bk,\tau} - \widehat{\gamma}_{Ak,\tau})$.

We decompose wage gaps for each 5th percentile of the wage distribution between the 5th and the 95th percentiles. The dependent variable is, as before, the log hourly wage. The covariates mimic the model in column 3 of Table 3, which uses tariff protection with a two-year lag, sector fixed effects, and controls for the group's employment share. For ease of computation, state time trends are used instead of state × phase dummies. As a

[30] Likewise, assuming linearity, the RIF-decomposition of the mean is equivalent to the classic Oaxaca-Blinder mean decomposition.

[31] For more details, see Firpo *et al.* (2009); Fortin *et al.* (2011); Firpo *et al.* (2018). For a related application of RIF-decompositions to Brazilian survey data, see Ferreira *et al.* (forthcoming), who decompose changes in the PNAD's earnings inequality between 1995 and 2012.

[32] $\widehat{f}_{Y_g}(\widehat{Q}_{g,\tau})$ is estimated with a kernel density estimator.

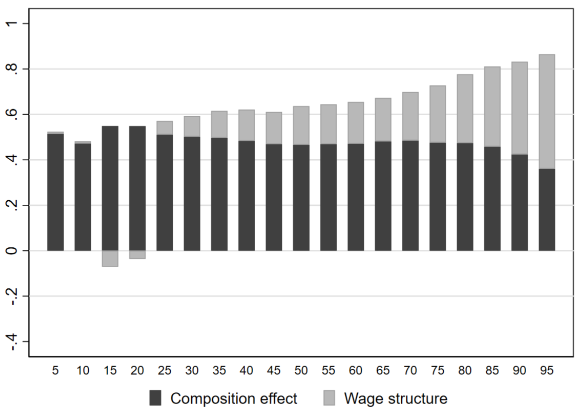
result, we are decomposing wage differentials between two groups *within* sector, year, and state-urban/rural cells, holding their employment propensities constant.

We decompose racial gaps for each gender (male, female), and gender gaps for each racial group (white, nonwhite). For each decomposition, the reference group—i.e., group A in equation (5), whose coefficients, $\widehat{\gamma}_{A,\tau}$, weigh the composition effect—is the group with highest hourly wage: white in the racial gap decompositions, and men in the gender gap decompositions. As suggested in Fortin *et al.* (2011), standard errors are obtained by bootstrapping the whole procedure (500 replications); although, due to high computation costs, bootstrap standard errors are only estimated for selected quantiles (10th, 25th, 50th, 75th, 90th).

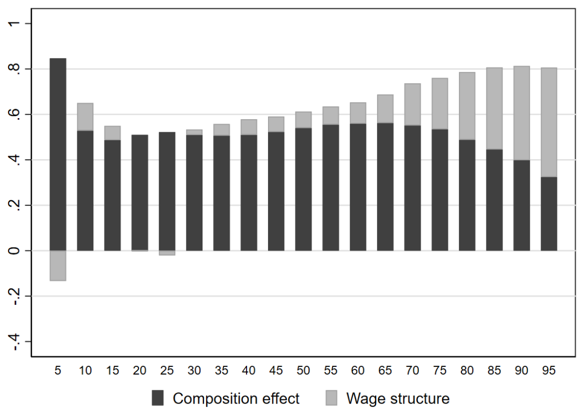
Findings Before considering the impact of trade liberalization, it is worth noting a few interesting decomposition patterns. Figure 6 plots the composition and wage structure effects across the wage distribution for gender-race pairs. The two terms sum up to the observed wage gap. Overall, wage gaps by race are much larger across all quantiles than wage gaps by gender. However, wage structure matters much more by gender than by race.

Racial wage gaps increase over the wage distribution, with the gradient being steeper for men than women (Figure 6). Among men, the racial wage gap at the 90th percentile is 1.7 times higher than the gap at the 10th percentile. Among women, the racial gap at the top is 1.3 times higher than at the bottom. Moreover, discrimination by race matters more at higher quantiles of the wage distribution. This pattern is particularly strong among men: at the 10th percentile, discrimination accounts for 2% of the wage differential; at the 90th percentile, it accounts for 49%. These patterns suggest strong glass ceiling effects by race, both for nonwhite men and nonwhite women. Among women, Figure 6 reveals a racial sticky floor, which is almost entirely explained by differences in observable characteristics.

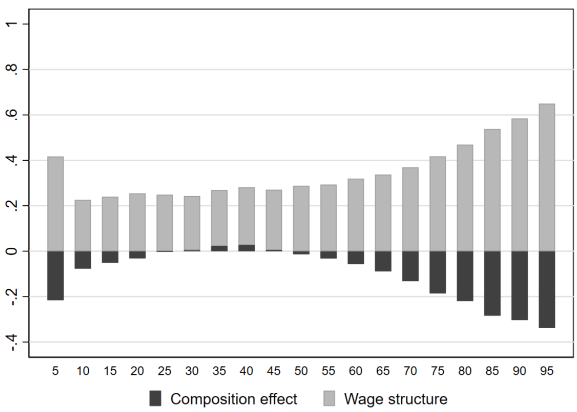
The gender gaps within racial groups exhibit different patterns. Among whites, gender gaps increase from 15 log points, at the 10th percentile, up to 28 log points, at the 90th



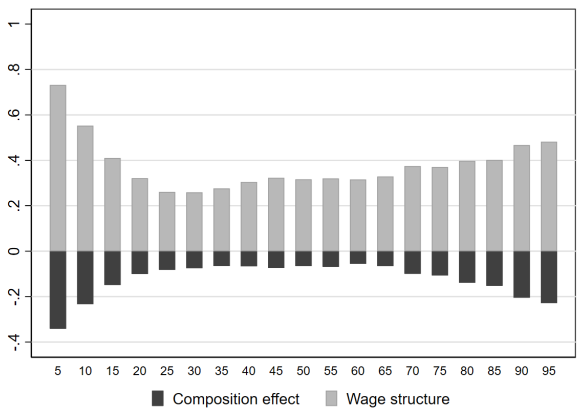
(a) Racial gap among men (white vs. nonwhite)



(b) Racial gap among women (white vs. nonwhite)



(c) Gender gap among whites (men vs. women)



(d) Gender gap among nonwhites (men vs. women)

Figure (6) RIF-decompositions: composition effect and wage structure over quantiles of the wage distribution

Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. 19 quantiles shown: τ = 0.05, 0.10, 0.15, ..., 0.95. Period is 1987–2001. Survey weights from PNAD are used. The reference groups are whites for racial gaps and men for gender gaps.

percentile. Among nonwhites, however, the gender wage gap is largest at the 5th percentile: 39 log points, revealing a large sticky floor for nonwhite women. As one moves up the wage distribution, the magnitude of the gender wage gap becomes similar among whites and nonwhites. With respect to composition vs. discrimination effects, the gender gap is entirely due to discrimination. Composition effects alone would predict a reversal of the gender gap across the whole distribution for nonwhites. For whites, composition effects are also negative at the bottom and top of the distribution, and approximately zero or slightly positive between the 25th and 50th percentiles. Discrimination effects are particularly large at the top of the wage distribution and, among nonwhites, at the bottom as well. Absent discrimination, white women would out-earn white men by 30 log points at the

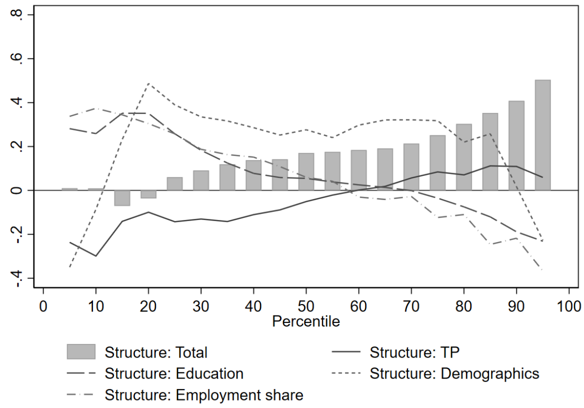
90th percentile; nonwhite women would out-earn nonwhite men by 23 log points at the 10th percentile and by 20 log points at the 90th (Figure 6).

We now turn to the contribution of trade liberalization. Figure 7 plots the contribution of trade liberalization to the wage structure for each gender-race pair. For comparison, the contributions of key Mincerian factors, such as education, demographics (age and number of children), and the employment share are also shown. For racial wage gaps, trade liberalization increases discrimination at the bottom of the wage distribution, between the 5th and 50th percentiles, as shown by the negative and large contributions of tariff protection to the unexplained term among men and among women. However, between the 50th and 90th percentiles, tariff protection contributes positively to the wage structure—that is, tariff reductions decrease discrimination at the top.

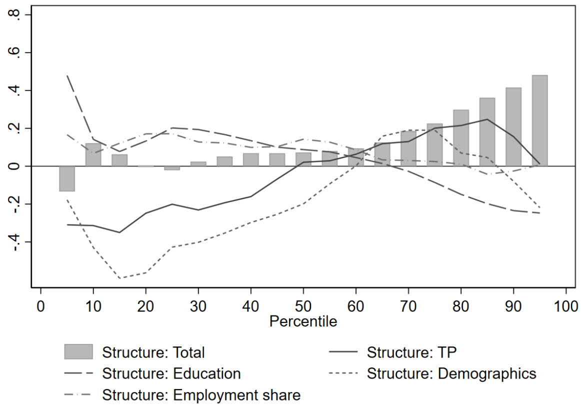
For gender wage gaps, trade liberalization increases the unexplained term at the 5th percentile among whites, but has no sizable effect for higher quantiles. Among nonwhites, tariff reduction increased discrimination below the 30th percentile, but reduced it at the top, between the 70th and 90th percentiles.

For all decompositions, the contribution of trade liberalization to the wage structure is larger (in absolute terms) than its contribution to the composition effect (see Figure A5). Therefore, while gender-race groups were differentially exposed to tariff reduction, the contribution of this differential exposure was small, when compared to the difference in the *impact* of tariff reduction experienced by each group. This is particularly true at the tails of the distribution. For example, the estimates suggest that, in the absence of trade liberalization, racial pay discrimination among men would be 30 log points smaller at the 10th percentile and 11 larger at the 90th percentile. Among women, no liberalization would imply a 31 log point smaller unexplained racial gap at the bottom and a 16 log point larger gap at the top of the wage distribution.

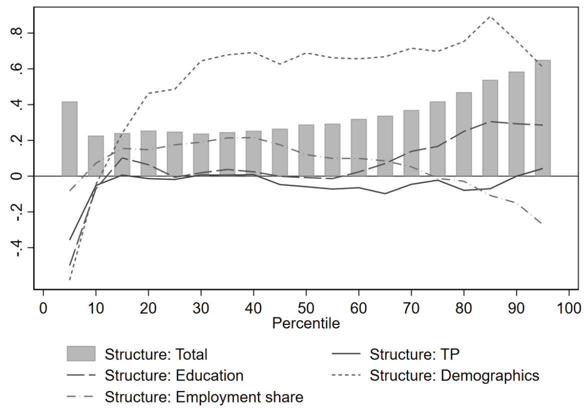
Overall, in the short term, trade liberalization increased existing sticky floors for nonwhite women, but reduced racial glass ceilings in the Brazilian labor market.



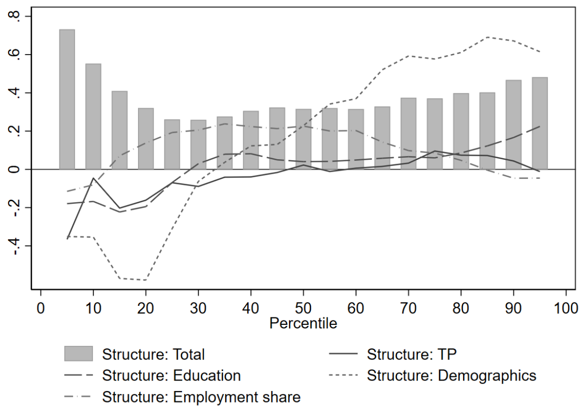
(a) Racial gap among men (white vs. nonwhite)



(b) Racial gap among women (white vs. nonwhite)



(c) Gender gap among whites (men vs. women)



(d) Gender gap among nonwhites (men vs. women)

Figure (7) Contribution of selected covariates to wage structure over quantiles of the wage distribution

Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. 19 quantiles shown: τ = 0.05, 0.10, 0.15, ..., 0.95. Period is 1987–2001. Survey weights from PNAD are used. Common Y-axis for all subfigures. Each plot line shows the contribution of a (group of) covariate to the wage structure. Total wage structure is shown by the vertical bars. Similar covariates are sorted into variable groups: education dummies are grouped as 'Education', age (quadratic) and number of children are grouped as 'Demographics'. TP is tariff protection measured in $t-2$. The model also includes sector of employment fixed effects, state × urban and year fixed effects, and linear state trends. The reference groups are whites for racial gaps and men for gender gaps.

5.4 Robustness Checks

In what follows, we briefly report on several robustness checks.

Pre-liberalization trends The results would be spurious if regions' future exposure to tariff cuts predict similar wage and employment trends before trade liberalization started. For example, if tariff cuts were larger in industries where gender gaps were already declining relatively faster, we would mistakenly attribute this effect to liberalization rather than to industry-specific pre-trends.

To address this concern, we regress future values of exposure to tariff protection during liberalization (TP) on pre-liberalization wages and employment probability. We extend our PNAD data to cover the period between 1982 and 1986 and, to maximize the number of observations, we concentrate on TP_{t+5}, i.e., the level of tariff protection 5 years in the future. Unfortunately, the race variable is missing in most years of the pre-liberalization period, which prevents us from systematically testing if wages of nonwhite women living in states that were subsequently more affected by liberalization were already higher. Nevertheless, we can test for pre-trends in the overall trade protection measure and its gender interaction.

Results are presented in Table A8. The outcome in the first two columns is the log of hourly wages; in the last two columns, the outcome is an employment dummy. For comparison, we report, in columns 2 and 4, the 'usual' liberalization results, i.e., with a 5-year *lag* of tariff protection, TP_{t-5}, covering the years 1992–2001. The estimates for the pre-liberalization period suggest the existence of a pre-trend, but one that goes in the opposite direction of the main findings. Between 1982 and 1986, exposure to (future) tariff reductions predicts higher salaries and lower employment rates for men. For women, the increase in wages and the reduction in employment's propensity are smaller, in absolute terms, than for men. During the actual liberalization period, tariff reductions reduce wages and employment, but more so for men than for women. To summarize, we find pre-existing trends, but these run counter our main findings. Before 1987, gender pay and employment gaps were *higher* in the regions that would later experience large tariff reductions; whereas, during liberalization itself, gender gaps *decrease* as a response to tariff reductions. These patterns are similar to those documented for formal sector employment by Dix-Carneiro and Kovak (2017), who find a positive pre-trend of (future) regional tariff reductions on formal sector wages and the number of formal firms.

Definition of regional labor markets By defining the regional labor markets at the federal state by urban/rural area, we are exploiting to the fullest the regional disaggregation of the PNAD. However, the typical local labor in Brazil is defined at the microregional level, a level below the federal state, and available in the decennial censuses. Because our labor market units are not standard, it is important to systematically show that the results are not spuriously driven by the choice of regional aggregation.

We first estimate Mincer-regressions using microdata from the 1991 census and show that gender and racial gaps are very similar within differently defined labor markets. We use all regional levels available in the census: from 27 federal states down to the 4491 municipalities (Table A9). After controlling for industry-of-employment fixed effects, there is actually very little variation in wages that is explained by regional labor markets, irrespective of their size. These results suggest that (conditional) gender and racial wage gaps do not depend on residential sorting or commuting behavior across different regional levels.

The split of rural and urban areas within states is justified by the widely different industrial structures of these areas (Table A10). In the 1991 census, even within the smallest unit (the municipality), we find a substantial urban wage premium of 13%, suggesting that urban and rural areas are not fully integrated labor markets (Table A11). This interpretation is consistent with the very high costs of inter-sectoral mobility in Brazil (e.g., Dix-Carneiro, 2014).

A remaining concern is that rural and urban areas within a state are not geographically contiguous. The natural geographically contiguous alternative available in the PNAD is a federal state. We thus construct an alternative measure of trade protection at the state level and re-run our main estimation models. Despite having less variation with this alternative exposure measure, our results are very similar to the ones using the trade protection variable at the state-urban-rural cell, both in magnitude and statistical significance (Figure A6).

Inter-regional mobility Could the heterogeneous effects of trade liberalization be explained by differences in inter-regional mobility of population groups? Previous studies document low mobility in the medium and long-term (Dix-Carneiro, 2014; Dix-Carneiro and Kovak, 2017, 2019), but short-run estimates by gender and race are not available. Unfortunately, we cannot estimate mobility-responses directly, due to data constraints. To get a sense of the magnitude of mobility differentials by gender and race, we use microdata from the 1991 census. Mobility is very low: in the 5 years before the census interview, only 3.7% of adults (25–64) lived in another federal state, and only 7.5% lived in another microregion. Adjusting for age and education, we find that women are slightly less mobile than men, and, among women, nonwhites are less likely to migrate than whites. But the magnitudes are relatively low: white (nonwhite) women are 0.39 (0.49) percentage points less likely to migrate between states than white men and 0.58 (1.30) percentage points less likely to migrate between microregions than white men. The lower mobility of women is consistent with the persistence of the female effects, although the even lower mobility of nonwhite women seems at odds with the temporary effect of the nonwhite women interaction. While being only a descriptive snapshot, we believe these differences are too small to be first-order mechanisms.

Alternative specifications The results are robust to several additional sensitivity tests. First, as discussed in section 4, there is a concern that tariff cuts were smaller in the automotive sector due to protectionist interests. We show that our findings are not driven by individuals employed in this sector (see Figure A7). Second, we control for part-time workers, by adding a dummy variable for whether an individual reports working less than 40 hours in the survey's reference week. Although part-time status is highly endogenous to individual unobservables, we find it reassuring that, overall, trade protection coefficients remain similar (Figure A7). Finally, we explore alternative estimators for standard errors (see Table A12) and remove potential outliers in the wage distribution by winsorizing (Figure A8) and trimming (Figure A9) the dependent variable. The results are robust throughout.

In addition, we performed all decompositions, for the 2 year lag specification, without sampling weights and with bootstrap standard errors (500 replications) for 5 selected quantiles: 10th, 25th, 50th, 75th, and 90th. In the Online Appendix, we provide the detailed contributions of variable (groups) to the composition and wage structure effects for each population pair: racial gap among men (Table A13), racial gap among women (Table A14), gender gap among whites (Table A15), and gender gap among nonwhites (Table A16). Overall, the magnitude of the effects without sampling weights, and the significance levels implied by the bootstrap standard errors are consistent with the visual inspection of Figure 7. Lastly, to assess effects in the medium run, we re-estimate all decompositions with tariff protection lagged by five years (Figure A10). For most pairs, the contribution of tariff cuts to the wage structure weakens in the medium term. The reduction of racial glass ceilings and the increase in racial gaps at low wages mostly disappear in the medium run. Instead, the effects are concentrated in the gender gaps, which is consistent with the persistence of the average effect of liberalization for women in the baseline regressions. Liberalization decreases the wage structure effect by gender among whites above the 70th percentile, but increases it below the 40th.

6 Conclusion

This article revisits Brazil's trade liberalization process (1987–1995), a natural experiment that has been widely studied in the literature. By combining a local labor market approach with decomposition methods, we paint a rich picture of the short-run effect of trade liberalization for gender and racial inequality, both at the mean and along the wage distribution. After an initial adjustment period, trade liberalization caused an increase of approximately 1.27%–2.72% in hourly wages of white women and 2.98%–5.42% in hourly wages of nonwhite women, which contributed to a reduction both in *average* gender wage inequality and *average* racial wage inequality among women. However, trade liberalization had heterogeneous consequences along the wage distribution. Liberalization increased racial and gender discrimination at low wages, reinforcing preexisting 'sticky floors' for nonwhite women, but mitigated existing 'glass ceilings' by race.

Although in decline, those sticky floors and glass ceilings reflect the persistence of discrimination in the Brazilian labor market. In terms of public policy, it is important to understand how economic shocks and policies shape those patterns of labor market inequality, even if unintentionally. Our results show that even though liberalization contributed to a reduction in *average* gender and racial wage inequality and discrimination at the *top* of the distribution—consistent with Becker (1957)— it contributed to an increase in racial discrimination in the bottom part of the wage distribution. As discussed by Borrowman and Klasen (2020), there is a great amount of persistence in labor market inequalities. Breaking these patterns requires concatenated efforts. In particular, the double burden of discrimination experienced by nonwhite women, which is often invisible to society, should be given more focus in future research and policy agendas.

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Online Appendix

Between sticky floors and glass ceilings: the effect of trade liberalization on double discrimination in Brazil

A.1 Variable definition

Variable	**Description**
Ln(Hourly wage)	Logarithm of deflated hourly wages from main occupation (BRL).
Worked in the ref week	Worked in the reference week
Nonwhite	Individual self-declared as black (*preto*) or brown (*pardo*)
Women	Female respondent
Age	Age in completed years
Squared Age	Squared age
Education 1	Respondent completed no years of education
Education 2	Respondent completed between 1 and 3 years of education
Education 3	Respondent completed between 4 and 7 years of education
Education 4	Respondent completed between 8 and 10 years of education
Education 5	Respondent completed between 11 and 14 years of education
Education 6	Respondent completed more than 14 years of education
Number of Children	Number of children in the household
TP_t	Trade exposure at the state-rural/urban cell
TP_{t-1}	One year lagged trade exposure at the state-rural/urban cell
TP_{t-2}	Two-years lagged trade exposure at the state-rural/urban cell
TP_{t-3}	Three-years lagged trade exposure at the state-rural/urban cell
TP_{t-4}	Four-years lagged trade exposure at the state-rural/urban cell
TP_{t-5}	Five-years lagged trade exposure at the state-rural/urban cell
Part time	Worked less than 40 hours per week
Employment share	Average employment share of respondent's gender, race and 5 year age cohort in the state and urban-rural area of residence

A.2 Industry concordance

The construction of our trade protection measure, specified in equation 1, requires the concordance between the PNAD industry classification—which we use to construct our employment shares—with the sectoral tariff data by Kume *et al.* (2003)—which we use as our shifter. We follow the concordance methodology in Ferreira *et al.* (2007) with three alterations proposed by Gaddis and Pieters (2017): combining sectors 'processing of vegetal products' with 'meat packing, dairy industry, vegetal and other food products'; 'leather and skins' with 'footwear'; and 'manufacturing of synthetic materials' with 'unclassified manufacturing'.

A.3 Additional Figures and Tables

Table (A1) Group differences

Panel A: Women	White women		Nonwhite women		Difference	
	mean	sd	mean	sd	b	t
Ln(Hourly wage)	1.68	1.05	1.02	0.98	0.61***	164.27
Worked in the ref week	0.98	0.14	0.98	0.14	-0.00	-1.40
Age	39.79	9.39	40.21	9.58	-0.28***	-8.77
Squared Age	1671.10	794.41	1708.71	816.06	-25.01***	-9.23
Education 1	0.09	0.28	0.24	0.43	-0.14***	-118.31
Education 2	0.14	0.34	0.20	0.40	-0.07***	-53.81
Education 3	0.30	0.46	0.28	0.45	0.01***	3.54
Education 4	0.12	0.32	0.10	0.30	0.02***	14.16
Education 5	0.22	0.42	0.14	0.35	0.08***	57.49
Education 6	0.14	0.34	0.03	0.18	0.11***	104.57
Number of Children	1.87	1.43	2.46	1.88	-0.56***	-101.41
Observations	195878		154821		350699	

Panel B: Women and men	Men		Women		Difference	
	mean	sd	mean	sd	b	t
Ln(Hourly wage)	1.66	1.08	1.41	1.07	0.24***	100.05
Worked in the ref week	0.99	0.12	0.98	0.14	0.01***	20.21
Nonwhite	0.42	0.49	0.41	0.49	0.02***	16.56
Nonwhite × Women	0.00	0.00	0.41	0.49	-0.44***	-679.58
Age	40.87	10.09	39.96	9.47	0.86***	40.95
Squared Age	1772.41	872.42	1686.46	803.53	81.49***	45.35
Education 1	0.18	0.38	0.15	0.36	0.03***	39.07
Education 2	0.18	0.39	0.16	0.37	0.02***	27.41
Education 3	0.31	0.46	0.29	0.46	0.02***	20.87
Education 4	0.12	0.32	0.11	0.31	0.01***	10.26
Education 5	0.14	0.34	0.19	0.39	-0.05***	-66.34
Education 6	0.07	0.25	0.09	0.29	-0.03***	-46.56
Number of Children	2.15	1.70	2.11	1.66	0.04***	11.37
Observations	584298		350699		934997	

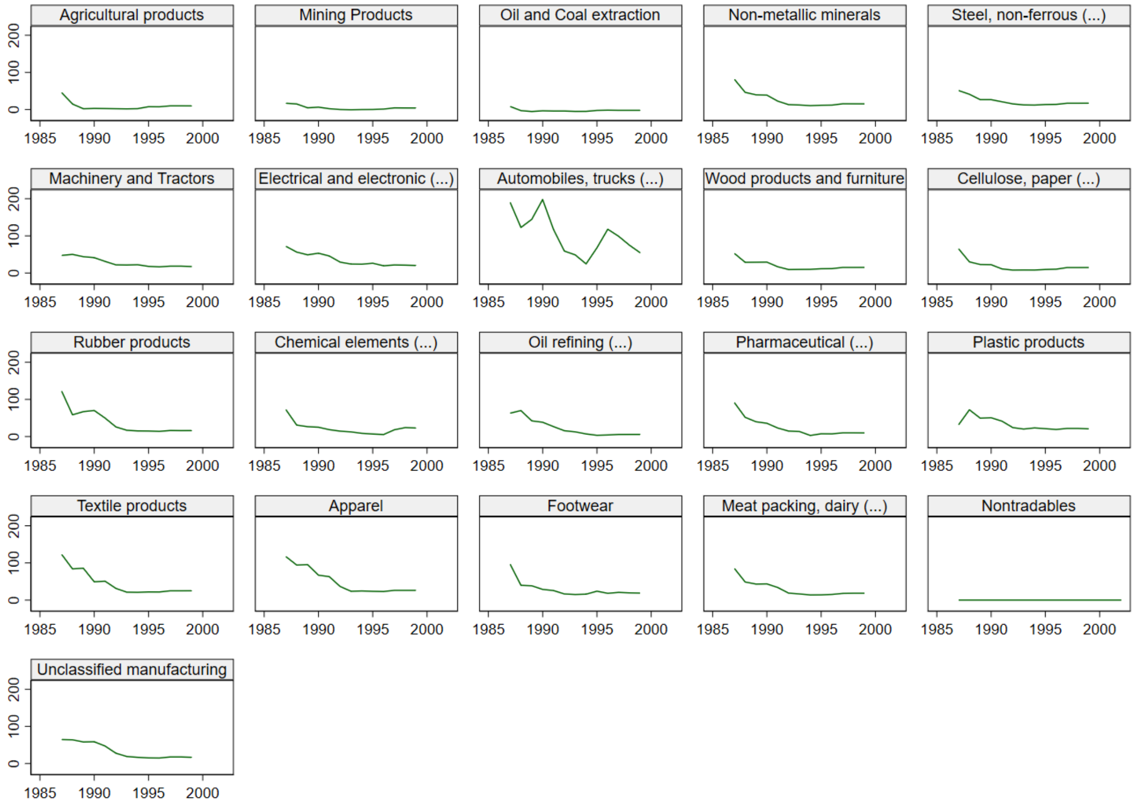
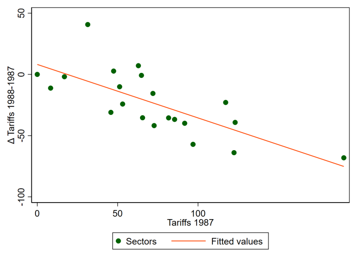


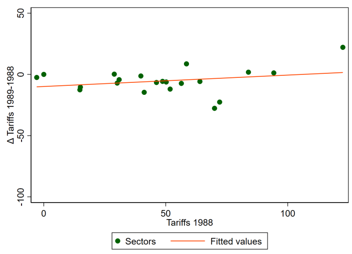
Figure (A1) Tariffs across sectors and over time

Table (A2) Descriptives statistics above and below TP, 1987

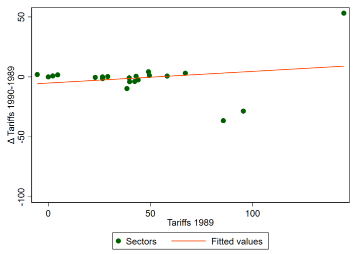
	Above median TP		Below median TP		Difference	
	mean	sd	mean	sd	b	t
Nonwhite	0.29	0.46	0.55	0.50	0.26***	68.56
Women	0.33	0.47	0.26	0.44	-0.06***	-16.78
Nonwhite × Women	0.10	0.30	0.15	0.36	0.05***	19.50
Age	39.73	9.80	40.66	10.33	0.62***	7.82
Squared Age	1674.36	834.37	1760.00	890.41	58.97***	8.65
Education 1	0.11	0.32	0.32	0.47	0.17***	53.78
Education 2	0.18	0.38	0.25	0.44	0.07***	20.46
Education 3	0.35	0.48	0.24	0.43	-0.09***	-23.57
Education 4	0.11	0.32	0.06	0.24	-0.04***	-15.68
Education 5	0.15	0.36	0.09	0.28	-0.05***	-17.37
Education 6	0.10	0.30	0.03	0.18	-0.06***	-28.11
Number of Children	2.13	1.65	2.92	2.22	0.71***	45.76
Ln(Hourly wage)	1.89	1.03	1.22	1.08	-0.48***	-56.08
Worked in the ref week	0.98	0.15	0.98	0.12	0.01***	7.19
Observations	32914		29464		62378	



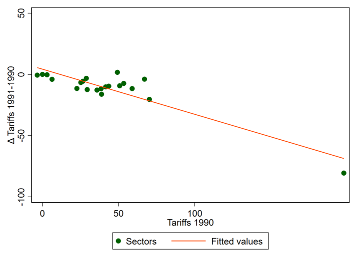
(a) Δ 1988–1987



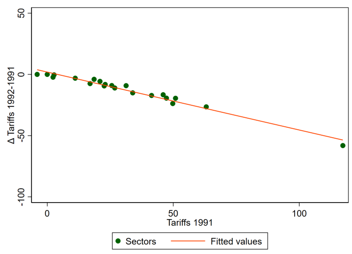
(b) Δ 1989–1988



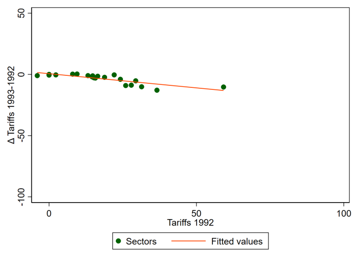
(c) Δ 1990–1989



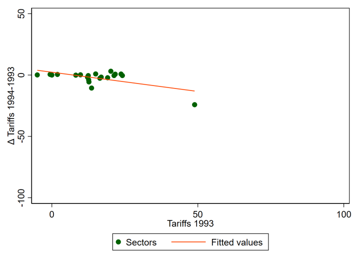
(d) Δ 1991–1990



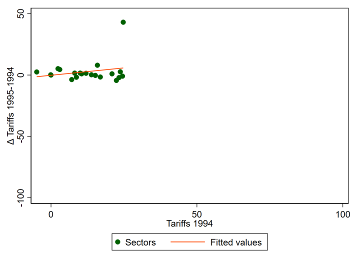
(e) Δ 1992–1991



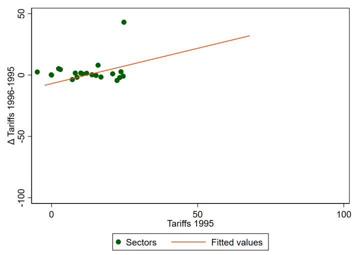
(f) Δ 1993–1992



(g) Δ 1994–1993

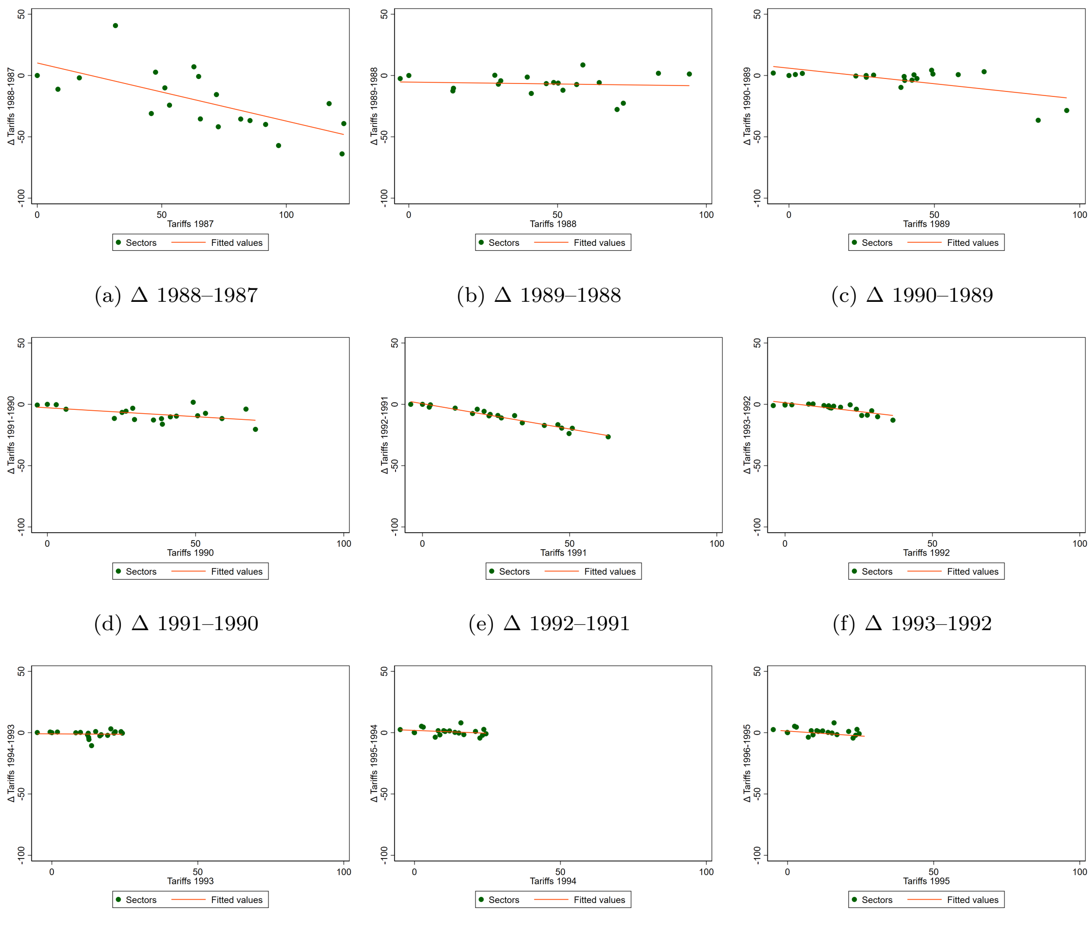


(h) Δ 1995–1994



(i) Δ 1996–1995

Figure (A2) Changes in tariffs and initial tariff level across sectors

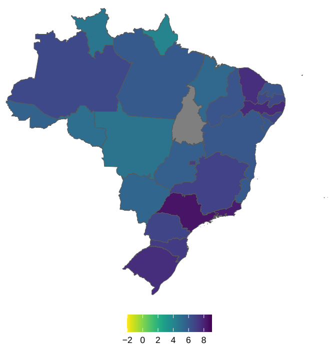


(a) Δ 1988–1987 (b) Δ 1989–1988 (c) Δ 1990–1989

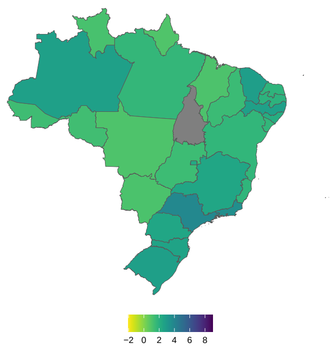
(d) Δ 1991–1990 (e) Δ 1992–1991 (f) Δ 1993–1992

(g) Δ 1994–1993 (h) Δ 1995–1994 (i) Δ 1996–1995

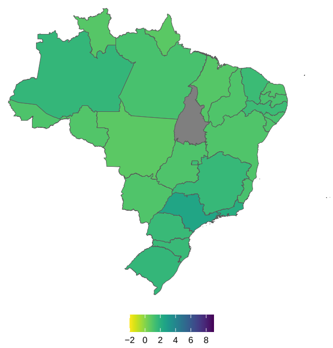
Figure (A3) Changes in tariffs and initial tariff level across sectors; excluding automotive sector



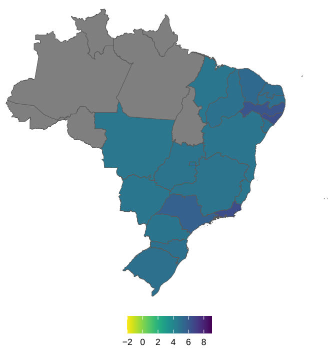
(a) TP urban 1987



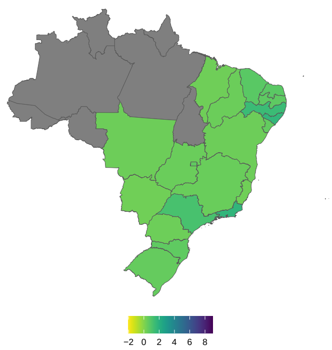
(b) TP urban 1991



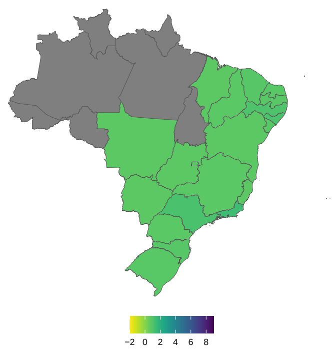
(c) TP urban 1996



(d) TP rural 1987



(e) TP rural 1991



(f) TP rural 1996

Figure (A4) TP 1987–1996

Notes: Trade protection before (1987), during (1991) and after (1996) liberalization for urban and rural areas. Missing data in grey. Before 2003, the PNAD did not include the rural areas of the Northern states of Acre, Amapá, Amazonas, Pará, Rondônia and Roraima. According to the 1991 census, only 1.95% of the 25–64 population lived in these rural areas, which mostly overlap with the Amazon rainforest.

Table (A3) Summary statistics

	mean	sd	min	max
Ln(Hourly wage)	1.572	1.081	-9	8
Worked in the ref week	0.983	0.128	0	1
Nonwhite	0.417	0.493	0	1
Women	0.370	0.483	0	1
Nonwhite $\times$ Women	0.151	0.358	0	1
Age	40.535	9.876	25	64
Squared Age	1740.626	848.613	625	4096
Education 1	0.168	0.374	0	1
Education 2	0.177	0.381	0	1
Education 3	0.305	0.460	0	1
Education 4	0.115	0.319	0	1
Education 5	0.156	0.363	0	1
Education 6	0.079	0.270	0	1
Number of Children	2.138	1.685	0	17
TP_t	2.692	2.058	0	8
$\text{TP}_t \times$ Women	0.937	1.741	0	8
$\text{TP}_t \times$ Nonwhite	0.985	1.715	0	8
$\text{TP}_t \times$ Nonwhite $\times$ Women	0.343	1.108	0	8
TP_{t-1}	2.595	2.039	0	8
$\text{TP}_{t-1} \times$ Women	0.920	1.710	0	8
$\text{TP}_{t-1} \times$ Nonwhite	0.963	1.691	0	8
$\text{TP}_{t-1} \times$ Nonwhite $\times$ Women	0.340	1.098	0	8
TP_{t-2}	2.551	2.030	0	8
$\text{TP}_{t-2} \times$ Women	0.921	1.703	0	8
$\text{TP}_{t-2} \times$ Nonwhite	0.954	1.679	0	8
$\text{TP}_{t-2} \times$ Nonwhite $\times$ Women	0.340	1.094	0	8
TP_{t-3}	2.370	2.016	0	8
$\text{TP}_{t-3} \times$ Women	0.874	1.646	0	8
$\text{TP}_{t-3} \times$ Nonwhite	0.887	1.624	0	8
$\text{TP}_{t-3} \times$ Nonwhite $\times$ Women	0.323	1.060	0	8
TP_{t-4}	2.038	1.423	0	6
$\text{TP}_{t-4} \times$ Women	0.774	1.312	0	6
$\text{TP}_{t-4} \times$ Nonwhite	0.754	1.238	0	6
$\text{TP}_{t-4} \times$ Nonwhite $\times$ Women	0.279	0.833	0	6
TP_{t-5}	2.594	2.055	0	8
$\text{TP}_{t-5} \times$ Women	0.987	1.769	0	8
$\text{TP}_{t-5} \times$ Nonwhite	0.979	1.719	0	8
$\text{TP}_{t-5} \times$ Nonwhite $\times$ Women	0.363	1.140	0	8
Observations	934997			

Table (A4) Sectoral occupation: Nonwhite women

	b	pct	cumpct
Agricultural products	27905.10	18.02	18
Mining Products	169.44	0.11	18
Oil and Coal extraction	15.20	0.01	18
Non-metallic minerals	369.31	0.24	18
Steel, non-ferrous and other metal products	256.07	0.17	19
Machinery and Tractors	230.40	0.15	19
Electrical and electronic equipment	334.00	0.22	19
Automobiles, trucks and buses; parts, comp. and other vehicles	167.44	0.11	19
Wood products and furniture	798.38	0.52	20
Cellulose, paper and printing	355.60	0.23	20
Rubber products	44.33	0.03	20
Chemical elements and products	192.12	0.12	20
Oil refining and petrochemicals	30.71	0.02	20
Pharmaceutical and perfumery products	197.99	0.13	20
Plastic products	255.63	0.17	20
Textile products	1380.07	0.89	21
Apparel	2279.27	1.47	23
Footwear	486.85	0.31	23
Meat packing, dairy industry, vegetable and other food products	3914.34	2.53	25
Nontradables	114815.42	74.16	100
Unclassified manufacturing	623.33	0.40	100
Total	154821.00	100.00	
Observations	154821		

Table (A5) Sectoral occupation: White women

	b	pct	cumpct
Agricultural products	22972.03	11.73	12
Mining Products	92.99	0.05	12
Oil and Coal extraction	43.79	0.02	12
Non-metallic minerals	494.55	0.25	12
Steel, non-ferrous and other metal products	860.72	0.44	12
Machinery and Tractors	552.07	0.28	13
Electrical and electronic equipment	630.26	0.32	13
Automobiles, trucks and buses; parts, comp. and other vehicles	520.43	0.27	13
Wood products and furniture	868.06	0.44	14
Cellulose, paper and printing	926.42	0.47	14
Rubber products	99.83	0.05	14
Chemical elements and products	459.41	0.23	15
Oil refining and petrochemicals	96.25	0.05	15
Pharmaceutical and perfumery products	405.50	0.21	15
Plastic products	466.47	0.24	15
Textile products	1776.74	0.91	16
Apparel	3990.15	2.04	18
Footwear	1896.73	0.97	19
Meat packing, dairy industry, vegetable and other food products	5025.61	2.57	22
Nontradables	152597.50	77.90	99
Unclassified manufacturing	1102.47	0.56	100
Total	195878.00	100.00	
Observations	195878		

Table (A6) Sectoral occupation: Nonwhite men

	b	pct	cumpct
Agricultural products	74509.99	27.78	28
Mining Products	2296.52	0.86	29
Oil and Coal extraction	338.48	0.13	29
Non-metallic minerals	3575.36	1.33	30
Steel, non-ferrous and other metal products	5173.88	1.93	32
Machinery and Tractors	1681.15	0.63	33
Electrical and electronic equipment	1017.33	0.38	33
Automobiles, trucks and buses; parts, comp. and other vehicles	2154.39	0.80	34
Wood products and furniture	5679.33	2.12	36
Cellulose, paper and printing	1727.18	0.64	37
Rubber products	388.05	0.14	37
Chemical elements and products	1486.49	0.55	37
Oil refining and petrochemicals	363.43	0.14	37
Pharmaceutical and perfumery products	411.62	0.15	38
Plastic products	595.81	0.22	38
Textile products	1211.95	0.45	38
Apparel	539.88	0.20	38
Footwear	807.94	0.30	39
Meat packing, dairy industry, vegetable and other food products	11474.95	4.28	43
Nontradables	152082.96	56.70	100
Unclassified manufacturing	716.30	0.27	100
Total	268233.00	100.00	
Observations	268233		

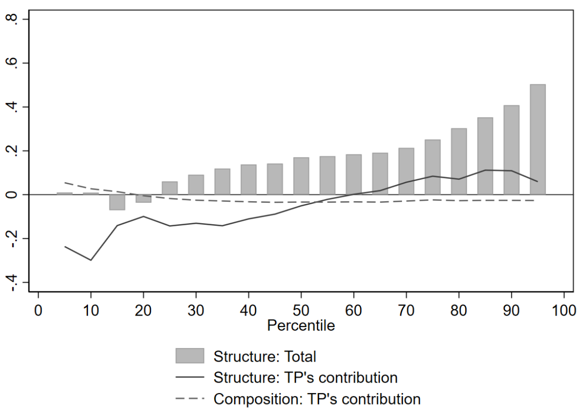
Table (A7) Sectoral occupation: White men

	b	pct	cumpct
Agricultural products	25809.00	16.98	17
Mining Products	881.00	0.58	18
Oil and Coal extraction	244.00	0.16	18
Non-metallic minerals	1755.00	1.15	19
Steel, non-ferrous and other metal products	4042.00	2.66	22
Machinery and Tractors	1692.00	1.11	23
Electrical and electronic equipment	1086.00	0.71	23
Automobiles, trucks and buses; parts, comp. and other vehicles	1830.00	1.20	25
Wood products and furniture	3484.00	2.29	27
Cellulose, paper and printing	1645.00	1.08	28
Rubber products	343.00	0.23	28
Chemical elements and products	1184.00	0.78	29
Oil refining and petrochemicals	363.00	0.24	29
Pharmaceutical and perfumery products	389.00	0.26	29
Plastic products	559.00	0.37	30
Textile products	1015.00	0.67	30
Apparel	529.00	0.35	31
Footwear	1338.00	0.88	32
Meat packing, dairy industry, vegetable and other food products	5600.00	3.68	35
Nontradables	97629.00	64.22	100
Unclassified manufacturing	597.00	0.39	100
Total	152014.00	100.00	
Observations	152014		

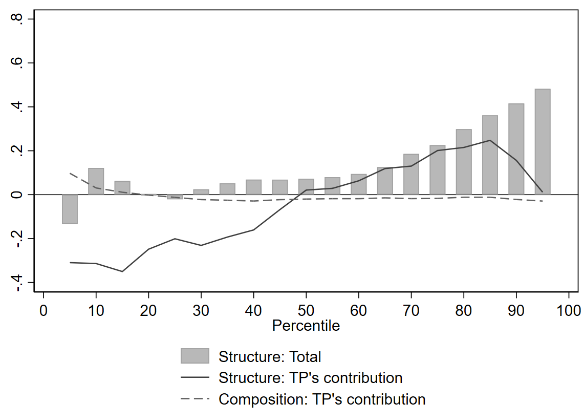
Table (A8) Trade protection and pre-liberalization outcomes

	Log(hourly wage)		Worked in the ref week	
	Pre: 1982–1986	Post: 1992–2001	Pre: 1982–1986	Post: 1992–2001
	$\ell = t+5$	$\ell = t-5$	$\ell = t+5$	$\ell = t-5$
	(1)	(2)	(3)	(4)
Women	-0.5077***	-0.3066***	-0.5737***	-0.3712***
	(0.0374)	(0.0282)	(0.0245)	(0.0120)
TP_ℓ	-0.0327*	0.0217**	-0.0238***	0.0077*
	(0.0178)	(0.0091)	(0.0050)	(0.0039)
$TP_\ell \times$ Women	0.0121**	-0.0098***	0.0130***	-0.0050**
	(0.0050)	(0.0022)	(0.0047)	(0.0024)
N	467375	627853	759512	987796
Year FE	✓	✓	✓	✓
State × urban FE	✓	✓	✓	✓
State trends	✓		✓	
State × phase FE		✓		✓
Individual controls	✓	✓	✓	✓

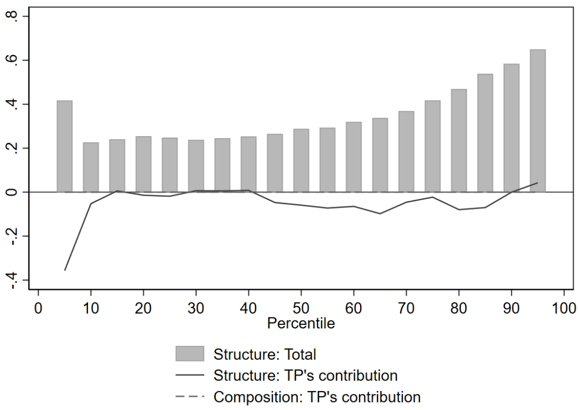
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary least squares (OLS) estimates reported with robust standard errors clustered at the state-urban level. Tariff protection measured at time $t+5$ in columns (1) and (3) and at time $t-5$ in columns (2) and (4). The sample includes individuals aged 25 to 64. Survey weights from PNAD are used. Control variables include age, squared age, educational attainment and number of children. In columns (1) and (2), employment share and industry-of-employment dummies are also included.



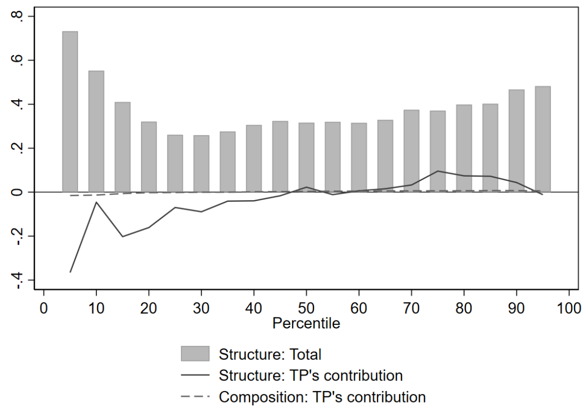
(a) Racial gap among men (white vs. nonwhite)



(b) Racial gap among women (white vs. nonwhite)



(c) Gender gap among whites (men vs. women)



(d) Gender gap among nonwhites (men vs. women)

Figure (A5) Contribution of trade liberalization to composition and wage structure over quantiles of the wage distribution

Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. 19 quantiles shown: τ = 0.05, 0.10, 0.15, ..., 0.95. Period is 1987–2001. Survey weights from PNAD are used. Common Y-axis for all subfigures. The solid line shows the contribution of TP_{t-2} to the wage structure. The dashed line shows the contribution of TP_{t-2} to the composition effect. Total wage structure is shown by the vertical bars. TP is tariff protection measured in $t-2$. The model also includes individual controls (age, age squared, education dummies, number of children, employment share), sector of employment fixed effects, state $\times$ urban and year fixed effects and linear state trends. The reference groups are whites for racial gaps and men for gender gaps.

Table (A9) Conditional gender and racial wage gaps within different local labor markets

	Log(hourly wage)				
	(1) State	(2) State-urban	(3) Mesoregion	(4) Microregion	(5) Municipality
Women	-0.3662***	-0.3712***	-0.3677***	-0.3682***	-0.3712***
	(0.0131)	(0.0189)	(0.0100)	(0.0087)	(0.0067)
Nonwhite	-0.1796***	-0.1854***	-0.1961***	-0.1981***	-0.1984***
	(0.0090)	(0.0081)	(0.0068)	(0.0070)	(0.0064)
Nonwhite × Women	-0.0223*	-0.0127	-0.0175**	-0.0152**	-0.0108*
	(0.0125)	(0.0177)	(0.0086)	(0.0063)	(0.0058)
Observations	3449586	3449586	3449586	3449586	3449586
Local labor markets	27	54	137	558	4491
Within-R^2	.232	.227	.227	.222	.213
R^2	.352	.356	.364	.37	.383

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary least squares (OLS) estimates reported with robust standard errors clustered at the local labor market level. Local labor market fixed effects included in all regressions. Local labor markets are: 27 federal states (column 1), 54 state-urban/rural areas (column 2), 137 mesoregions (column 3), 558 microregions (column 4), and 4491 municipalities (column 5). The sample includes individuals aged 25 to 64 from the 1991 census. Survey weights are used. Control variables include age, squared age, educational attainment, number of children, and 21 sector of employment dummies.

Table (A10) Employment distribution by industry in 1991: rural vs. urban areas

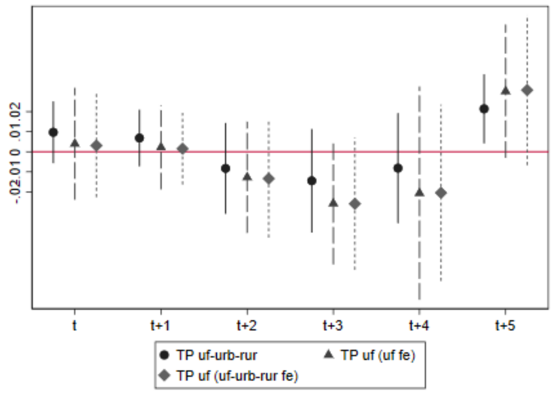
% of employment	Rural	Urban	Total
Agricultural products	72.39	6.32	19.86
Mining Products	1.28	0.67	0.79
Oil and Coal extraction	0.04	0.14	0.12
Non-metallic minerals	0.76	0.90	0.87
Steel, non-ferrous and other metal products	0.39	3.40	2.78
Machinery and Tractors	0.07	0.61	0.50
Electrical and electronic equipment	0.05	0.61	0.50
Automobiles, trucks and buses; parts, comp. and other vehicles	0.12	0.74	0.62
Wood products and furniture	1.06	1.74	1.60
Cellulose, paper and printing	0.17	1.00	0.83
Rubber products	0.02	0.19	0.15
Chemical elements and products	0.33	0.84	0.73
Oil refining and petrochemicals	0.02	0.20	0.17
Pharmaceutical and perfumery products	0.02	0.25	0.20
Plastic products	0.04	0.38	0.31
Textile products	0.38	1.13	0.98
Apparel	0.14	1.20	0.98
Footwear	0.18	0.75	0.63
Meat packing, dairy industry, vegetable and other food products	3.40	3.06	3.13
Nontradables	19.06	75.51	63.94
Unclassified manufacturing	0.07	0.37	0.31
Total	100.00	100.00	100.00

Notes: The sample includes individuals aged 25 to 64 from the 1991 census. Survey weights are used.

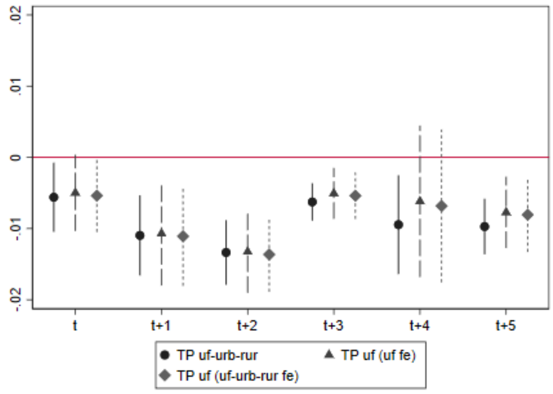
Table (A11) Conditional urban wage premium within different local labor markets

	Log(hourly wage)			
	(1) State	(2) Mesoregion	(3) Microregion	(4) Municipality
Urban	0.1756***	0.1477***	0.1361***	0.1266***
	(0.0238)	(0.0131)	(0.0070)	(0.0055)
Women	-0.3671***	-0.3686***	-0.3689***	-0.3718***
	(0.0131)	(0.0100)	(0.0087)	(0.0067)
Nonwhite	-0.1817***	-0.1976***	-0.1993***	-0.1993***
	(0.0091)	(0.0066)	(0.0068)	(0.0062)
Nonwhite × Women	-0.0214*	-0.0166**	-0.0145**	-0.0101*
	(0.0115)	(0.0083)	(0.0062)	(0.0058)
Observations	3449586	3449586	3449586	3449586
Local labor markets	27	137	558	4491
Within-R^2	.234	.228	.223	.214
R^2	.354	.366	.371	.384

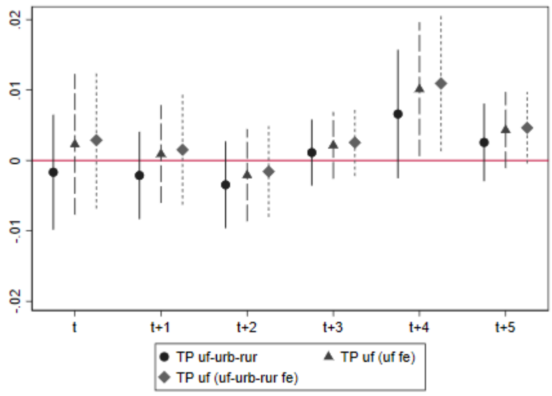
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary least squares (OLS) estimates reported with robust standard errors clustered at the local labor market level. Local labor market fixed effects included in all regressions. Local labor markets are: 27 federal states (column 1), 137 mesoregions (column 2), 558 microregions (column 3), and 4491 municipalities (column 4). The sample includes individuals aged 25 to 64 from the 1991 census. Survey weights are used. Control variables include age, squared age, educational attainment, number of children, and 21 sector of employment dummies.



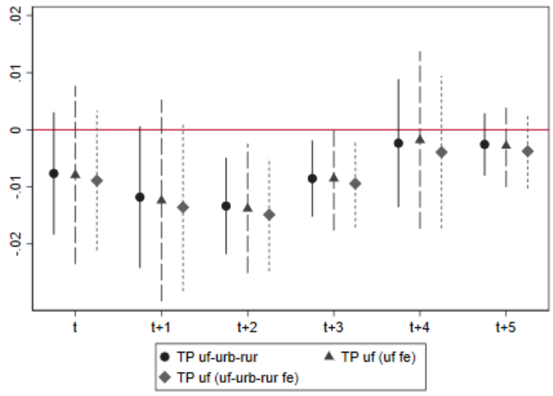
(a) TP



(b) TP women



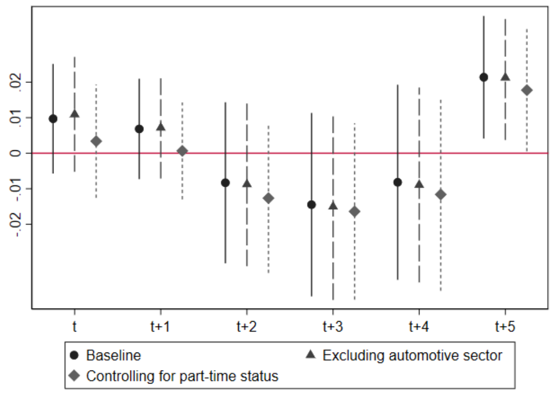
(c) TP nonwhite



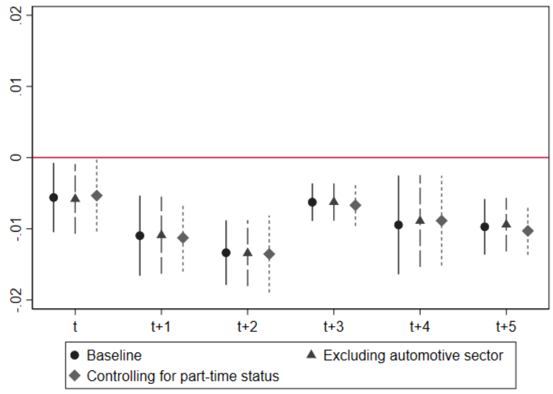
(d) TP nonwhite women

Figure (A6) Trade protection and hourly wage: TP coefficients. TP at state vs state-urban-rural level

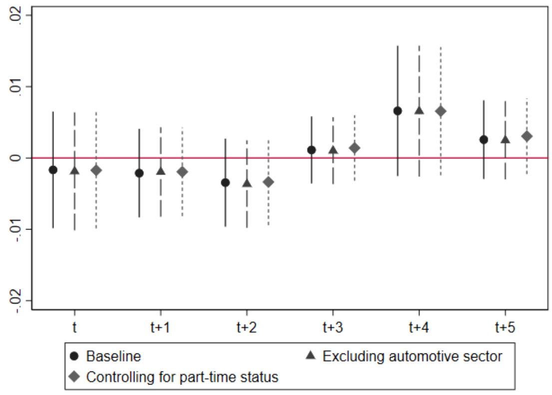
Notes: The figure plots the marginal TP ($TP\ uf$) coefficients by gender-race group across different time lags. Point estimates shown with 95% confidence intervals. Period is 1987-2001.



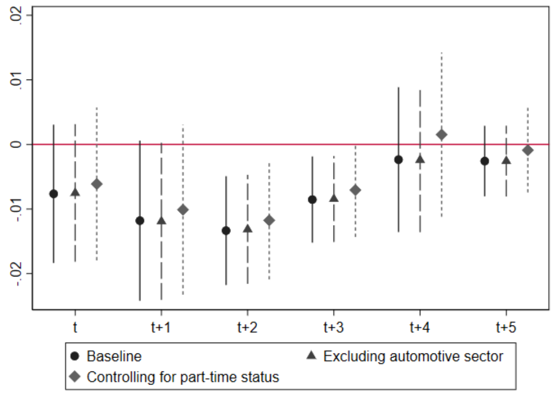
(a) TP



(b) TP women



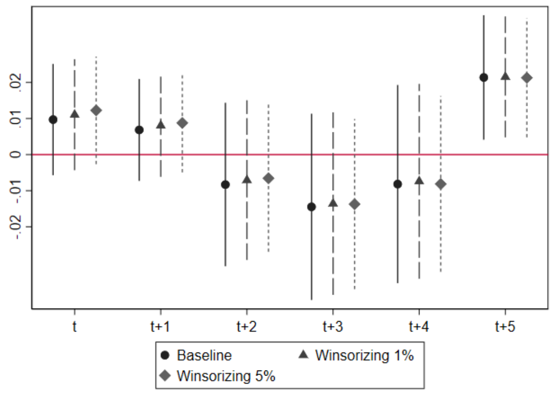
(c) TP nonwhite



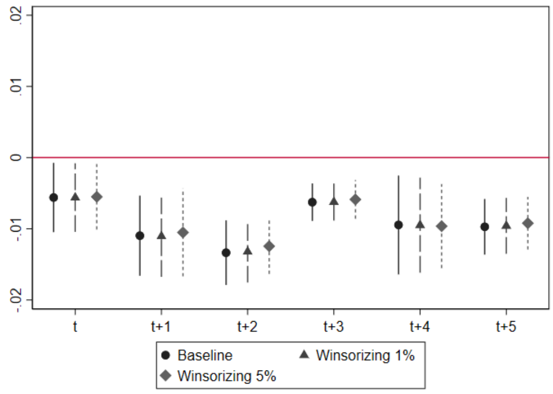
(d) TP nonwhite women

Figure (A7) Robustness checks: Trade protection and hourly wage; TP coefficients; excluding automotive sector or controlling for part-time status

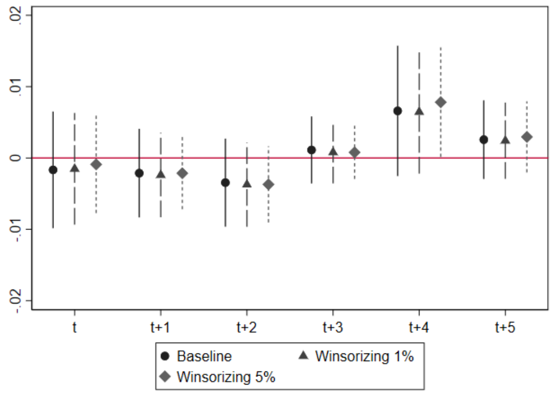
Notes: The figure plots the marginal TP coefficients by gender-race group across different time lags. Point estimates shown with 95% confidence intervals.



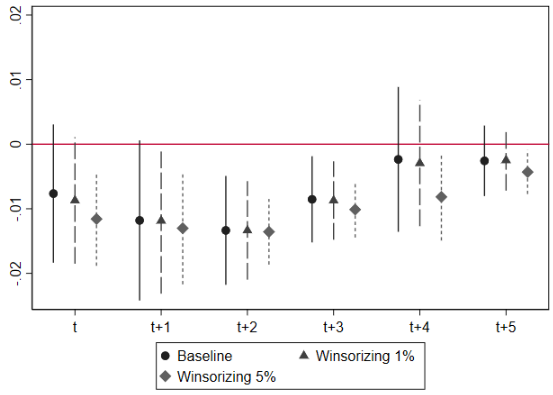
(a) TP



(b) TP women



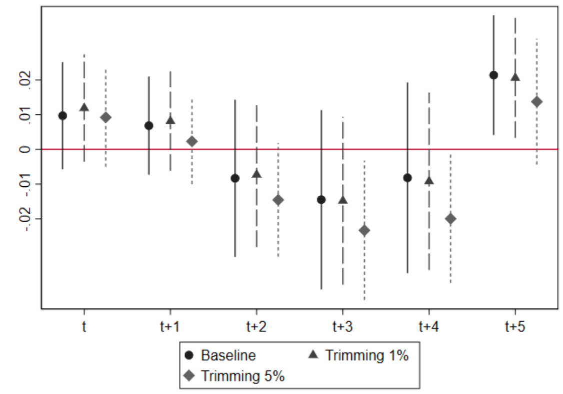
(c) TP nonwhite



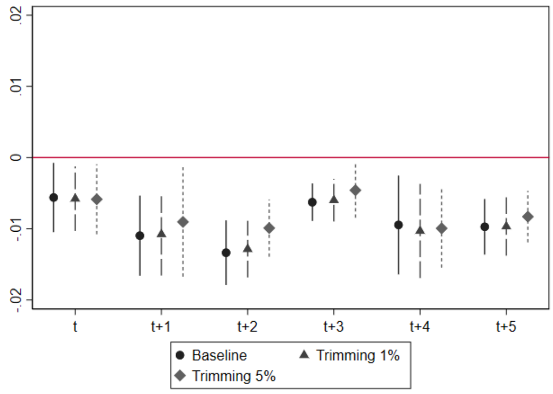
(d) TP nonwhite women

Figure (A8) Robustness checks: Trade protection and hourly wage; TP coefficients; winsorizing wages

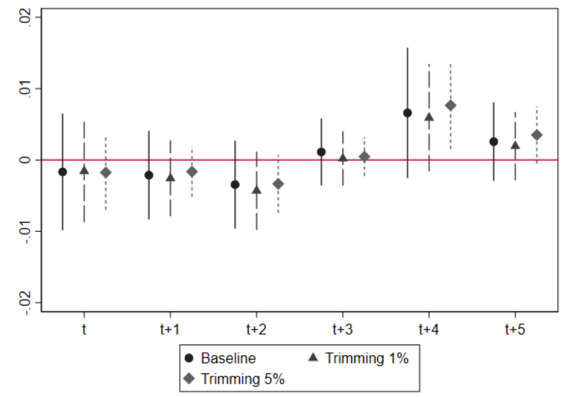
Notes: The figure plots the marginal TP coefficients by gender-race group across different time lags. Point estimates shown with 95% confidence intervals.



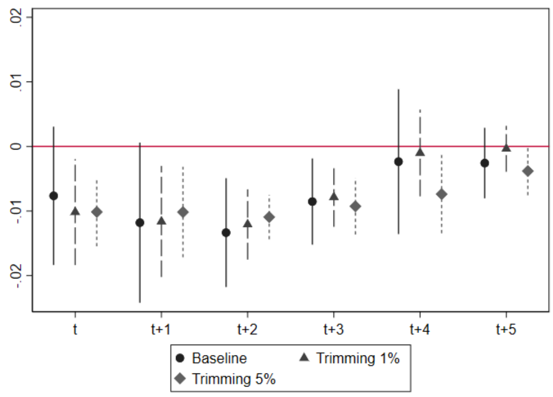
(a) TP



(b) TP women



(c) TP nonwhite



(d) TP nonwhite women

Figure (A9) Robustness checks: Trade protection and hourly wage; TP coefficients; trimming wages

Notes: The figure plots the marginal TP coefficients by gender-race group across different time lags. Point estimates shown with 95% confidence intervals.

Table (A12) Trade protection and hourly wage. Changing standard errors

	Log(hourly wage)					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ell = t$	$\ell = t-1$	$\ell = t-2$	$\ell = t-3$	$\ell = t-4$	$\ell = t-5$
Women	-0.4706	-0.4428	-0.4191	-0.4198	-0.4062	-0.3926
	(0.0192)***	(0.0189)***	(0.0138)***	(0.0144)***	(0.0180)***	(0.0150)***
	[0.0146]***	[0.0127]***	[0.0115]***	[0.0129]***	[0.0224]***	[0.0178]***
Nonwhite	-0.1537	-0.1545	-0.1547	-0.1674	-0.1793	-0.1732
	(0.0117)***	(0.0130)***	(0.0116)***	(0.0105)***	(0.0128)***	(0.0114)***
	[0.0159]***	[0.0181]***	[0.0164]***	[0.0160]***	[0.0129]***	[0.0087]***
Nonwhite × Women	-0.0030	0.0142	0.0292	0.0273	0.0180	0.0213
	(0.0223)	(0.0223)	(0.0180)	(0.0160)	(0.0194)	(0.0171)
	[0.0198]	[0.0195]	[0.0156]*	[0.0149]*	[0.0152]	[0.0112]*
TP_ℓ	0.0097	0.0068	-0.0083	-0.0145	-0.0082	0.0214
	(0.0072)	(0.0072)	(0.0132)	(0.0137)	(0.0150)	(0.0079)**
	[0.0072]	[0.0073]	[0.0039]**	[0.0075]*	[0.0188]	[0.0094]**
TP_ℓ × Women	-0.0056	-0.0110	-0.0134	-0.0063	-0.0095	-0.0097
	(0.0023)**	(0.0029)***	(0.0023)***	(0.0013)***	(0.0036)**	(0.0019)***
	[0.0020]**	[0.0015]***	[0.0024]***	[0.0025]**	[0.0064]	[0.0038]**
TP_ℓ × Nonwhite	-0.0017	-0.0021	-0.0034	0.0011	0.0066	0.0026
	(0.0037)	(0.0028)	(0.0030)	(0.0021)	(0.0038)*	(0.0025)
	[0.0026]	[0.0026]	[0.0020]	[0.0020]	[0.0030]**	[0.0022]
TP_ℓ × Nonwhite × Women	-0.0076	-0.0118	-0.0133	-0.0085	-0.0024	-0.0026
	(0.0053)	(0.0061)*	(0.0042)***	(0.0033)**	(0.0050)	(0.0026)
	[0.0044]*	[0.0047]**	[0.0030]***	[0.0031]**	[0.0052]	[0.0040]
N	549716	566938	583082	600334	533478	624293
Year FE	✓	✓	✓	✓	✓	✓
State × urban FE	✓	✓	✓	✓	✓	✓
State × phase FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary least squares (OLS) estimates reported with robust standard errors clustered at the state level in parentheses and state-urban-rural sector level in brackets. Tariff protection measured at time $t-5$, $t-4$, $t-3$, $t-2$, $t-1$, and t. Period is 1987–2001. Phase is a categorical variable taking value 1 for the years 1987–89, value 2 for the years 1990–95, and value 3 for the years 1996–2001. Survey weights from PNAD are used. Control variables include age, squared age, educational attainment and number of children.

Table (A13) RIF-decompositions: racial gap among men

	Log wage at percentile:				
	(1)	(2)	(3)	(4)	(5)
	10th	25th	50th	75th	90th
Overall					
Log wage white men	0.6316***	1.1980***	1.8597***	2.6321***	3.4111***
	(0.0018)	(0.0034)	(0.0039)	(0.0064)	(0.0038)
Log wage nonwhite men	0.2361***	0.6781***	1.2792***	1.9125***	2.5985***
	(0.0021)	(0.0041)	(0.0035)	(0.0035)	(0.0048)
Difference	0.3955***	0.5199***	0.5805***	0.7196***	0.8127***
	(0.0028)	(0.0053)	(0.0052)	(0.0073)	(0.0060)
Composition	0.3955***	0.4430***	0.4294***	0.4532***	0.3865***
	(0.0058)	(0.0050)	(0.0045)	(0.0054)	(0.0059)
Wage structure	0.0000	0.0770***	0.1511***	0.2665***	0.4262***
	(0.0058)	(0.0069)	(0.0055)	(0.0074)	(0.0077)
Composition					
Tariff protection	0.0209***	-0.0120***	-0.0219***	-0.0182***	-0.0135***
	(0.0039)	(0.0026)	(0.0024)	(0.0026)	(0.0035)
Demographic	-0.0024*	0.0023**	0.0058***	0.0072***	0.0039**
	(0.0014)	(0.0010)	(0.0010)	(0.0012)	(0.0015)
Education	0.1750***	0.2409***	0.3025***	0.4001***	0.3888***
	(0.0030)	(0.0029)	(0.0032)	(0.0045)	(0.0044)
Employment share	0.0021***	0.0040***	0.0036***	0.0006	-0.0016**
	(0.0006)	(0.0005)	(0.0004)	(0.0005)	(0.0006)
Sector	0.0545***	0.0471***	0.0248***	0.0079***	0.0004
	(0.0015)	(0.0012)	(0.0008)	(0.0008)	(0.0009)
Region and Time	0.1454***	0.1607***	0.1146***	0.0556***	0.0084
	(0.0059)	(0.0044)	(0.0037)	(0.0043)	(0.0056)
Wage structure					
Tariff protection	-0.2295***	-0.0873***	-0.0264	0.0248	0.0755**
	(0.0398)	(0.0254)	(0.0224)	(0.0256)	(0.0350)
Demographic	0.0073	0.4018***	0.2638***	0.2532***	-0.0916
	(0.0915)	(0.0686)	(0.0629)	(0.0783)	(0.1034)
Education	0.2770***	0.2464***	0.0697***	-0.0265***	-0.2100***
	(0.0144)	(0.0104)	(0.0084)	(0.0084)	(0.0106)
Employment share	0.2358***	0.1664***	0.0935	-0.0897	-0.1596
	(0.0877)	(0.0642)	(0.0582)	(0.0711)	(0.1001)
Sector	0.0519***	0.0150	-0.1539***	-0.1463***	-0.0947***
	(0.0166)	(0.0122)	(0.0089)	(0.0093)	(0.0122)
Region and Time	-0.3065***	-0.2084***	-0.2023***	-0.1436	0.0971
	(0.0789)	(0.0688)	(0.0754)	(0.1077)	(0.1585)
Constant	-0.0359	-0.4569***	0.1065	0.3946***	0.8094***
	(0.1448)	(0.1070)	(0.1154)	(0.1422)	(0.2085)
N	379678	379678	379678	379678	379678
N White men	206655	206655	206655	206655	206655
N Nonwhite men	173023	173023	173023	173023	173023

Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. Bootstrap standard errors in parentheses (500 replications). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Tariff protection measured at time $t-2$. Period is 1987–2001. Similar covariates are sorted into variable groups: education dummies are grouped as 'Education', age (quadratic); number of children are grouped as 'Demographics'; sector of employment dummies are grouped as 'Sector'; and state × urban fixed effects, year fixed effects and linear state trends are grouped as 'Region and Time'.

Table (A14) RIF-decompositions: racial gap among women

	Log wage at percentile:				
	(1)	(2)	(3)	(4)	(5)
	10th	25th	50th	75th	90th
Overall					
Log wage white women	0.4818***	0.9478***	1.6102***	2.4184***	3.1256***
	(0.0037)	(0.0035)	(0.0061)	(0.0049)	(0.0041)
Log wage nonwhite women	-0.0858***	0.5122***	1.0170***	1.6658***	2.3579***
	(0.0042)	(0.0070)	(0.0058)	(0.0066)	(0.0082)
Difference	0.5676***	0.4356***	0.5932***	0.7525***	0.7677***
	(0.0059)	(0.0082)	(0.0085)	(0.0082)	(0.0095)
Composition	0.4510***	0.4706***	0.5156***	0.4924***	0.3569***
	(0.0076)	(0.0065)	(0.0065)	(0.0065)	(0.0076)
Wage structure	0.1166***	-0.0349***	0.0776***	0.2602***	0.4107***
	(0.0104)	(0.0097)	(0.0088)	(0.0093)	(0.0110)
Composition					
Tariff protection	0.0262***	-0.0066*	-0.0121***	-0.0093**	-0.0121***
	(0.0052)	(0.0039)	(0.0035)	(0.0038)	(0.0047)
Demographic	0.0114***	0.0100***	0.0065***	0.0007	-0.0023
	(0.0019)	(0.0015)	(0.0015)	(0.0017)	(0.0021)
Education	0.2147***	0.2875***	0.3926***	0.4320***	0.3531***
	(0.0043)	(0.0042)	(0.0052)	(0.0051)	(0.0050)
Employment share	0.0018	0.0026***	0.0033***	0.0012	-0.0003
	(0.0011)	(0.0009)	(0.0008)	(0.0010)	(0.0012)
Sector	0.0297***	0.0180***	0.0015*	-0.0041***	-0.0037***
	(0.0016)	(0.0010)	(0.0008)	(0.0008)	(0.0011)
Region and Time	0.1672***	0.1591***	0.1239***	0.0720***	0.0222***
	(0.0066)	(0.0055)	(0.0050)	(0.0057)	(0.0072)
Wage structure					
Tariff protection	-0.4130***	-0.1780***	0.0299	0.1775***	0.1035*
	(0.0818)	(0.0420)	(0.0374)	(0.0431)	(0.0580)
Demographic	-0.4899***	-0.3105***	-0.0801	0.3029**	0.1048
	(0.1599)	(0.0943)	(0.0997)	(0.1238)	(0.1609)
Education	0.1022***	0.2512***	0.1127***	-0.1167***	-0.2656***
	(0.0262)	(0.0176)	(0.0139)	(0.0122)	(0.0127)
Employment share	0.0801	0.1320***	0.1426***	0.0050	-0.0673
	(0.0682)	(0.0408)	(0.0391)	(0.0486)	(0.0668)
Sector	-0.0679	0.0070	-0.1258***	-0.1602***	-0.0810***
	(0.0562)	(0.0290)	(0.0206)	(0.0210)	(0.0271)
Region and Time	-0.5475***	-0.1687*	0.0494	0.4421***	0.2549
	(0.1452)	(0.0948)	(0.1091)	(0.1455)	(0.1933)
Constant	1.4525***	0.2321	-0.0511	-0.3905*	0.3614
	(0.2521)	(0.1476)	(0.1527)	(0.2076)	(0.2679)
N	203404	203404	203404	203404	203404
N White women	113873	113873	113873	113873	113873
N Nonwhite women	89531	89531	89531	89531	89531

Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. Bootstrap standard errors in parentheses (500 replications). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Tariff protection measured at time $t-2$. Period is 1987–2001. Similar covariates are sorted into variable groups: education dummies are grouped as 'Education', age (quadratic); number of children are grouped as 'Demographics'; sector of employment dummies are grouped as 'Sector'; and state × urban fixed effects, year fixed effects and linear state trends are grouped as 'Region and Time'.

Table (A15) RIF-decompositions: gender gap among whites

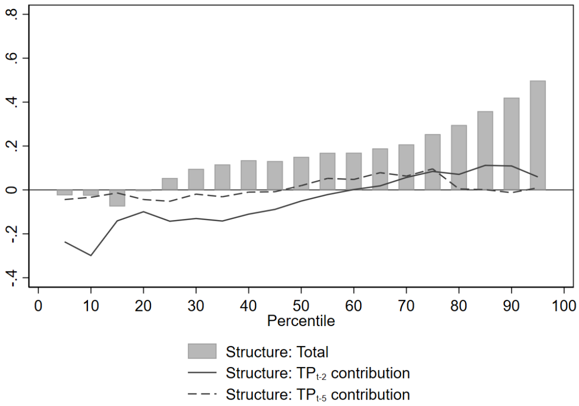
	Log wage at percentile:				
	(1) 10th	(2) 25th	(3) 50th	(4) 75th	(5) 90th
Overall					
Log wage white men	0.6316***	1.1980***	1.8597***	2.6321***	3.4111***
	(0.0018)	(0.0032)	(0.0039)	(0.0067)	(0.0039)
Log wage white women	0.4818***	0.9478***	1.6102***	2.4184***	3.1256***
	(0.0040)	(0.0036)	(0.0056)	(0.0048)	(0.0043)
Difference	0.1498***	0.2502***	0.2495***	0.2138***	0.2855***
	(0.0045)	(0.0048)	(0.0069)	(0.0083)	(0.0058)
Composition	-0.0919***	-0.0208	-0.0365**	-0.2124***	-0.2933***
	(0.0270)	(0.0204)	(0.0173)	(0.0209)	(0.0284)
Wage structure	0.2417***	0.2710***	0.2859***	0.4262***	0.5788***
	(0.0273)	(0.0210)	(0.0180)	(0.0217)	(0.0288)
Composition					
Tariff protection	-0.0002	0.0001	0.0002	0.0002	0.0001
	(0.0004)	(0.0003)	(0.0005)	(0.0004)	(0.0003)
Demographic	0.0038***	0.0085***	0.0126***	0.0150***	0.0177***
	(0.0012)	(0.0009)	(0.0009)	(0.0010)	(0.0012)
Education	-0.0598***	-0.1035***	-0.1653***	-0.2505***	-0.2470***
	(0.0012)	(0.0017)	(0.0025)	(0.0040)	(0.0054)
Employment share	0.0915***	0.1749***	0.1553***	0.0248	-0.0680**
	(0.0266)	(0.0202)	(0.0170)	(0.0203)	(0.0276)
Sector	-0.1009***	-0.0756***	-0.0217***	0.0092***	0.0119***
	(0.0023)	(0.0020)	(0.0017)	(0.0021)	(0.0026)
Region and Time	-0.0262***	-0.0253***	-0.0176***	-0.0110***	-0.0081***
	(0.0018)	(0.0015)	(0.0014)	(0.0015)	(0.0016)
Wage structure					
Tariff protection	-0.0768	-0.0320	-0.0573	-0.0553	0.0062
	(0.0514)	(0.0400)	(0.0356)	(0.0403)	(0.0473)
Demographic	-0.0170	0.5557***	0.7312***	0.6602***	0.5458***
	(0.1120)	(0.0859)	(0.0882)	(0.1004)	(0.1254)
Education	-0.0807***	-0.0086	-0.0231	0.2198***	0.3119***
	(0.0295)	(0.0213)	(0.0161)	(0.0167)	(0.0173)
Employment share	0.0697	0.1626***	0.1081***	-0.0071	-0.0904
	(0.0579)	(0.0436)	(0.0390)	(0.0465)	(0.0633)
Sector	0.0630	0.2027***	0.1627***	0.1277***	0.1059***
	(0.0439)	(0.0273)	(0.0199)	(0.0204)	(0.0258)
Region and Time	-0.1172	-0.1463	-0.1498	-0.3026**	-0.3994**
	(0.1075)	(0.0894)	(0.0928)	(0.1244)	(0.1608)
Constant	0.4006**	-0.4631***	-0.4859***	-0.2165	0.0988
	(0.1628)	(0.1403)	(0.1415)	(0.1736)	(0.2118)
N	320528	320528	320528	320528	320528
N White men	206655	206655	206655	206655	206655
N White women	113873	113873	113873	113873	113873

Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. Bootstrap standard errors in parentheses (500 replications). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Tariff protection measured at time $t-2$. Period is 1987–2001. Similar covariates are sorted into variable groups: education dummies are grouped as 'Education', age (quadratic); number of children are grouped as 'Demographics'; sector of employment dummies are grouped as 'Sector'; and state × urban fixed effects, year fixed effects and linear state trends are grouped as 'Region and Time'.

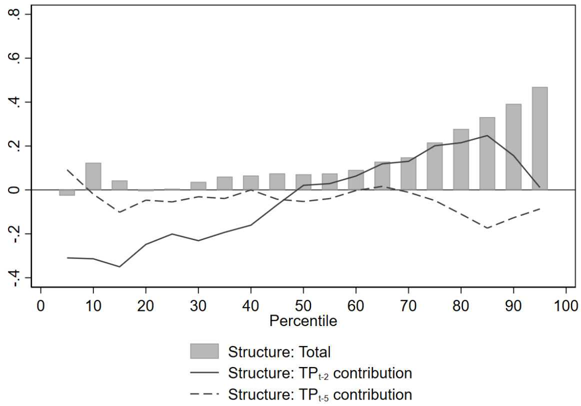
Table (A16) RIF-decompositions: gender gap among nonwhites

	Log wage at percentile:				
	(1)	(2)	(3)	(4)	(5)
	10th	25th	50th	75th	90th
Overall					
Log wage nonwhite men	0.2361***	0.6781***	1.2792***	1.9125***	2.5985***
	(0.0020)	(0.0039)	(0.0036)	(0.0036)	(0.0052)
Log wage nonwhite women	-0.0858***	0.5122***	1.0170***	1.6658***	2.3579***
	(0.0044)	(0.0070)	(0.0057)	(0.0072)	(0.0087)
Difference	0.3219***	0.1659***	0.2622***	0.2467***	0.2406***
	(0.0049)	(0.0079)	(0.0068)	(0.0081)	(0.0103)
Composition	-0.1815***	-0.0662***	-0.0712***	-0.1206***	-0.2214***
	(0.0254)	(0.0173)	(0.0172)	(0.0193)	(0.0305)
Wage structure	0.5034***	0.2321***	0.3334***	0.3673***	0.4620***
	(0.0260)	(0.0193)	(0.0180)	(0.0201)	(0.0306)
Composition					
Tariff protection	-0.0093***	-0.0002	0.0030***	0.0036***	0.0041***
	(0.0015)	(0.0005)	(0.0006)	(0.0007)	(0.0009)
Demographic	-0.0050***	-0.0004	0.0007	0.0013*	0.0025**
	(0.0009)	(0.0005)	(0.0006)	(0.0008)	(0.0010)
Education	-0.0365***	-0.0538***	-0.0942***	-0.1436***	-0.2118***
	(0.0009)	(0.0011)	(0.0018)	(0.0029)	(0.0053)
Employment share	-0.0037	0.1092***	0.1192***	0.0619***	-0.0037
	(0.0255)	(0.0178)	(0.0171)	(0.0192)	(0.0298)
Sector	-0.1169***	-0.0999***	-0.0750***	-0.0240***	-0.0005
	(0.0027)	(0.0020)	(0.0019)	(0.0022)	(0.0030)
Region and Time	-0.0101***	-0.0211***	-0.0249***	-0.0198***	-0.0121***
	(0.0024)	(0.0015)	(0.0016)	(0.0017)	(0.0022)
Wage structure					
Tariff protection	-0.2409***	-0.1150***	0.0058	0.1041***	0.0317
	(0.0780)	(0.0312)	(0.0316)	(0.0389)	(0.0488)
Demographic	-0.4836***	-0.1297	0.4002***	0.7111***	0.7504***
	(0.1493)	(0.0795)	(0.0798)	(0.1041)	(0.1520)
Education	-0.2350***	-0.0009	0.0398***	0.0519***	0.1852***
	(0.0204)	(0.0120)	(0.0102)	(0.0123)	(0.0162)
Employment share	0.0088	0.1912***	0.1924***	0.0508	-0.0613
	(0.0730)	(0.0361)	(0.0346)	(0.0417)	(0.0657)
Sector	-0.0590	0.1949***	0.2207***	0.1344***	0.1278***
	(0.0453)	(0.0185)	(0.0146)	(0.0149)	(0.0189)
Region and Time	-0.3484***	-0.1130	0.1177	0.3116**	-0.2233
	(0.1285)	(0.0737)	(0.0917)	(0.1286)	(0.1850)
Constant	1.8615***	0.2046	-0.6432***	-0.9966***	-0.3485
	(0.2297)	(0.1270)	(0.1395)	(0.1826)	(0.2634)
N	262554	262554	262554	262554	262554
N Nonwhite men	173023	173023	173023	173023	173023
N Nonwhite women	89531	89531	89531	89531	89531

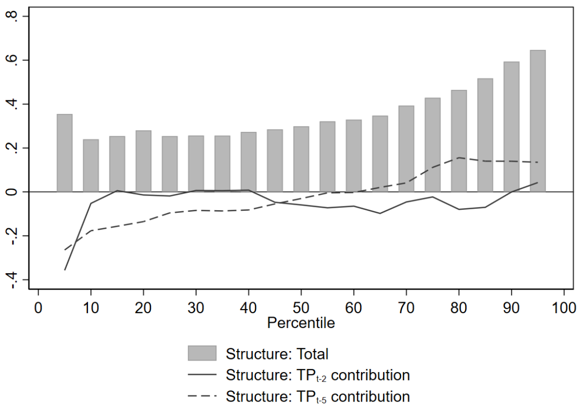
Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. Bootstrap standard errors in parentheses (500 replications). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Tariff protection measured at time $t - 2$. Period is 1987–2001. Similar covariates are sorted into variable groups: education dummies are grouped as 'Education', age (quadratic); number of children are grouped as 'Demographics'; sector of employment dummies are grouped as 'Sector'; and state × urban fixed effects, year fixed effects and linear state trends are grouped as 'Region and Time'.



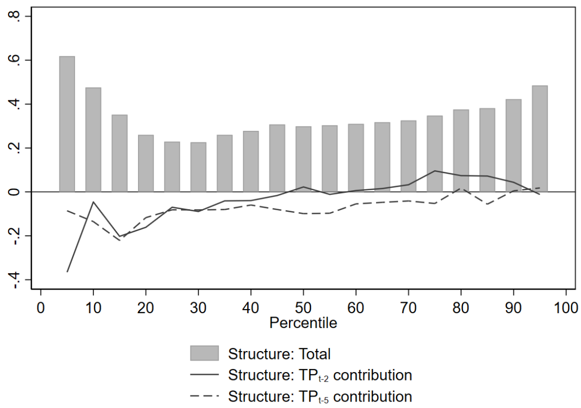
(a) Racial gap among men (white vs. nonwhite)



(b) Racial gap among women (white vs. nonwhite)



(c) Gender gap among whites (men vs. women)



(d) Gender gap among nonwhites (men vs. women)

Figure (A10) Contribution of trade liberalization with a 2- or 5-year lag to wage structure over quantiles of the wage distribution

Notes: RIF-decomposition (Firpo *et al.*, 2018) estimates. 19 quantiles shown: $\tau = 0.05, 0.10, 0.15, ..., 0.95$. Period is 1987–2001. Survey weights from PNAD are used. Common Y-axis for all subfigures. Tariff protection measured at time $t-2$ (solid line) or at time $t-5$ (dashed line). Both lines show the contribution of TP to the wage structure. Total wage structure is shown by the vertical bars. The model also includes individual controls (age, age squared, education dummies, number of children, employment share), sector of employment fixed effects, state × urban and year fixed effects and linear state trends. The reference groups are whites for racial gaps and men for gender gaps.