Labor Market Concentration and the Gender Wage Gap: Evidence from Mass Layoffs

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Abstract

I investigate the extent to which labor market power in the Brazilian formal labor market contributes to the prevalence of the gender wage gap. First, I show that higher labor market concentration is associated with higher gender gaps, although this association does not explain a large part of the gap. Then, I use quasi-experimental variation from mass layoffs to identify the causal relationship between labor market concentration and the gender wage gap. This analysis is restricted to four sectors and three occupations. The results suggest that if labor markets were perfectly competitive, the residual gender wage gap would be 38% to 73.8% lower, depending on the specification.

Key words: labor, gender, labor market concentration, labor market power

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1 Introduction

Women receive lower wages on average than men. This statement holds true in most countries in the world, and although this gender wage gap has diminished throughout time, it remains relevant to this day (Blau and Kahn, 1996; Weichselbaumer and Winter-Ebmer, 2005; Goldin, 2014; Blau and Kahn, 2017). For example, the gender wage gap in Brazil has remained practically stable over the last 10 years, from 24.7% (Madalozzo and Artes, 2017) in 2000 to 20.1% in 2018 (ILO, 2019). What drives this gap? Part of the gap has been attributed to mechanisms linked to the behavior of individuals and to society's norms, such as occupational choices, differences in risk preferences or human capital accumulation, the responsibilities of having a child, the willingness to bargain over wages, lower requests for initial salaries, the preference for time flexibility, among many others.[1] Another branch of proposed mechanisms relate to the behavior and perceptions of employers, such as statistical discrimination and taste-based discrimination, disparities in promotions, the provision of certain amenities on the job, etc.[2] Regarding employer mechanisms, economic theory predicts that competition in product and labor markets would punish firms that engage in discriminatory behavior (Becker, 1957; Guryan and Charles, 2013; Weber and Zulehner, 2014). Yet, there is a lack of empirical evidence showing whether the level of market competition limits employer discrimination and reduces the gender wage gap.

In this paper, I study the empirical relationship between the gender wage gap and labor market competition. I implement two analyses using labor market data from Brazil. First, I present a gender wage gap decomposition exercise. In this exercise, I show that the residual gender wage gap is associated with labor market concentration (a proxy for labor market competition). I later discuss a few reasons why this association may not represent a causal relation. To estimate the causal relation between the gender gap and labor market concentration, the second analysis explores a quasi-experiment that uses mass layoffs as exogenous shocks to labor market concentration. This analysis focuses on office assistants, janitors, and security guards from the human health, information, textile, and construction sectors.

Both analyses use the Brazilian linked employer-employee dataset (RAIS), from 2010 to 2017. A great advantadge of studying Brazil and using RAIS, relative to other datasets in other countries, is that RAIS has information of workers' wages, gender and occupation, and of firms' industries and locations. Using this information, we construct measures of labor market concentration for each period and labor market, where the later are defined as the intersection between occupations and municipality.

In the gap decomposition exercise, I regress wages on gender while incrementally adding control variables. These controls are commonly identified in the literature as causes of the gender wage gap,

[1] Aguero and Marks (2008); Bertrand et al. (2010); Goldin (2014); Angelov et al. (2016); Blau and Kahn (2017); Adda et al. (2017); Wiswall and Zafar (2017); Grossman et al. (2019); Kleven et al. (2019); Le Barbanchon et al. (2020); Biasi and Sarsons (2021); Exley and Kessler (2022); Roussille (2024)

[2] Barth and Dale-Olsen (2009); Riach and Rich (2002); Weber and Zulehner (2014); Guryan and Charles (2013); Card et al. (2016)

such as schooling, experience, and occupational choices (Goldin, 2014; Blau and Kahn, 2017), and firm-specific premiums (Card et al., 2016; Barth and Dale-Olsen, 2009). In addition, I include the labor market concentration variable in the regressions. The goal is to investigate how the gender wage gap is associated with labor market competitiveness.

The main result is that the gender wage gap narrows after the inclusion of labor market concentration, but persists. Controlling exclusively for schooling, the gender wage gap estimated is at 32%. Including labor market concentration as a control brings the gender gap down to 27%. Even after controlling for all typical controls mentioned the residual estimated gap remains at 6%.

However, the labor market concentration variable might be endogenous in this scenario. Labor market concentration and wages are both equilibrium outcomes. They are jointly determined together with productivity, structure costs, and different demands, among others. Controlling for labor market fixed effects might mitigate this problem, but it is unlikely to resolve it completely.

In the second analysis, I use variation from mass layoffs to estimate the causal effect of labor market concentration on the gender wage gap. Mass layoffs can change labor market concentration by reducing the share of workers employed by a particular employer in the labor market. However, mass layoffs may result from shocks to the product market in the firm's sector meaning that both productivity and concentration effects could play a role. For this reason, the wage analysis in this paper focuses on four industry sectors (human health, information, textile, and construction sectors) while the mass layoff shocks are obtained from all other sectors in the economy. The underlying identification hypothesis is that productivity shocks are contained within the industry, while concentration shocks spread across occupations. Since this may not hold true for all workers, I focus on three occupations (office assistants, janitors, and security guards) that are less likely to be influenced by the shocks through mechanisms other than labor market competition.

Results from the second analysis suggest that labor market concentration could explain a significant part of the gender wage gap. When I pool all the selected occupations from all selected sectors together, a negative significant shock in the labor market concentration could reduce 6.9% to 10.4% the gender wage gap. This shock is of 132 Herfindahl–Hirschman Index (HHI) points, a shock equivalent of the first quartile in shock size distribution. However, the average labor market has 934 HHI points. If the average labor market were brought to perfect competition, the gender wage gap could be reduced from 38.3% to 73.8%. This phenomenon is heterogeneous across occupations and sectors. Most of them are consistent with the theory, though they were relatively small. Of the twelve relative gender gap reductions, five of them were less than 10% and three of them ranged between 19% and 33%. Overall, the effects seem to point in the same direction.

This paper contributes to two literatures. First, it contributes to the growing literature on how labor market power could explain the remaining gender wage gap (Barth and Dale-Olsen, 2009; Hirsch et al., 2010; Vick, 2017; Caldwell and Oehksen, 2023). More closely related to this paper, Sharma (2022) shows how labor market power in Brazil could partially explain the remaining wage gap. She also uses a quasi-experiment, but her empirical strategy limits her to the textile sector. This paper contributes by giving a novel approach to explore variation in labor market concentration, not being tied to a specific sector.

Second, this paper contributes to the growing literature on labor market power's influence on wages. Some studies showed a correlation between market concentration and wages (Azar et al., 2022; Bassanini et al., 2023). Others derived general equilibrium models to more precisely comprehend labor market power and its implications to wages (Berger et al., 2022; Sharma, 2022; Felix, 2022). This paper, however, is more strongly connected with a body of papers that uses events that impact the labor market concentration to quantify the causal effect of labor market power in wages (Prager and Schmitt, 2021; Guanziroli, 2023).

The rest of the paper is organized as follows. Section 2 explores the data, bringing some insights and some descriptive statistics. Section 3 estimates a preliminary empirical strategy. Section 4 presents the final results. Finally, section 5 concludes the paper.

2 Data and Labor Market Definitions

2.1 The Brazilian Linked Employer-Employee Dataset

The dataset used in this paper is the "Relação Anual de Informações Sociais" (RAIS). RAIS is a comprehensive administrative database managed by the Brazilian Ministry of Labor. It annually collects detailed information on Brazil's formal labor market universe. On December 23, 1975, RAIS was established as mandatory by law.[3] Each record in the RAIS database represents an employment relationship between an employer and an employee. The RAIS dataset contained an average of approximately 36.6 million active non-public job contracts per year from 2010 to 2017 in the sample. Failure to report data to the RAIS, or reporting incomplete or incorrect information, subjects employers to fines.[4] The main limitation of RAIS is that it does not cover the informal labor market. This is especially significant in Brazil because the informal labor market is a considerable part of the labor force.

RAIS requires all employers to provide extensive information. It includes company details such as the unique identifier for Brazilian companies, business name, and address, and employee details such as name, individual taxpayer registry, date of birth, gender, education level, date of hire and separation, the December wage, and working hours.[5]

To determine the industry of a specific employer, I utilize the industry code available from

[3] Decret Nº 76.900.

[4] Failure to comply with RAIS regulations can result in significant penalties. According to Law Nº. 7.998/1990 (Art. 25), late submission of the RAIS incurs a base fine of R$ 425.64, with an additional R$ 106.40 for each late bimonth, plus a percentage surcharge based on company size. Omitting information or providing false or inaccurate data also carries a base fine of R$ 425.64, with an additional R$ 26.60 per omitted or misreported employee. These fines double if the delay in submission or correction exceeds the deadline. Payment of the fines does not exempt the employer from fulfilling their obligation to provide the required information to the Ministry of Labor and Employment.

[5] The unique identifier for Brazilian companies is the "Cadastro de Pessoas Juríridicas", akin to a tax identification number. The individual taxpayer registry for Brazilians is the "Cadastro de Pessoas Físicas".

RAIS.[6] This code system categorizes economic activities across various sectors and industries. Additionally, I use the occupation code variable.[7] This variable categorizes occupations hierarchically. I utilize both of these variables to select contracts for specific occupations and sectors. The occupation variable is also utilized in defining labor markets as described in the next subsection 2.2.

2.2 Labor Market Definitions

In this section, I present the definitions of the labor market used in the paper. I define a labor market as an occupation × municipality. Next, I define the HHI of market share of employees. Let the s_{zmt} be the firm's z share of employees in the labor market m in year t, defined as:

$$s_{zmt} \equiv \frac{n_{zmt}}{\sum_{j \in \Theta_m} n_{jmt}}, \tag{1}$$

where n_{zmt} is the number of employees and Θ_m is the set of all firms in labor market m, thus s_{zm} is the fraction of number of employees of that firm z with respect to that labor market in that year. Then the HHI for each labor market m and year t is:

$$HHI_{mt} = \sum_{z \in \Theta_m} s_{zmt}^2. \tag{2}$$

The HHI is a number between 0 and 1, but I re-scale it to be between 0 and 10,000 (as typical analyses do).

There is a vast literature identifying various ways of defining a labor market. The most common definitions of labor market are geography × occupation (Azar et al., 2022; Felix, 2022; Azar et al., 2018; Schubert et al., 2024), geography × sector boundaries (Urena et al., 2021; Berger et al., 2022), and geography only (Dix-Carneiro and Kovak, 2017; Topalova, 2010). In fact, Felix (2022) shows that, given a person is changing jobs, most people stay inside a labor market when the first definition is used. However, I use a more granular definition of labor markets to generate more dispersion on the market concentration variable. This will allow me to better analyze the labor market concentration relationship with wages. For the same reason, I use the full five-digit occupational code.[8]

[6] "Classificação Nacional de Atividades Econômicas" (CNAE).

[7] "Classificação Brasileira de Ocupações" (CBO)

[8] The CBO is a hierarchical code. The first digit represents the Broad Occupational Group, dividing occupations into 10 categories. The second digit indicates the Primary Occupational Subgroup, dividing occupations into 48 categories. The third and fourth digits identify the Occupational Subgroup, dividing occupations into 192 categories. Finally, the fifth digit denotes the Occupational Family, dividing occupations into 607 categories. This last digit is the one that I use in these analyses.

3 Gap Decomposition

3.1 Empirical Strategy

The goal of this section is to decompose the gender wage gap. I investigate to which extent the gender wage gap is associated with labor market concentration. To do this, I regress wage on the gender variable. Then, I include HHI as a control. Next, I cumulative add other control variables. These controls are commonly identified in the literature as the main causes of the gender wage gap, such as differences in schooling, experience, occupational choices, and firm-specific wage premiums. To perform this exercise, I run the following equation:

$$Y_{imt} = \beta_1 HHI_{mt} + \beta_2 HHI_{mt} \times Male_i + \beta_3 Male_i + \beta_4 \mathbb{X}_{imt} + \delta_t + \delta_m + \delta_{zm} + \delta_i + \epsilon_{imt}, \quad (3)$$

where Y_{imt} is the real December wage[9] for individual i in labor market m in year t, HHI_{mt} is defined as in subsection 2.2, $Male$ is a dummy which is 1 if the individual is male, $\mathbb{X}_{imt}$ is a set of controls, δ_t, δ_m, δ_{zm}, and δ_i are time, labor market, firm-labor market, and individual fixed effects. The controls included in $\mathbb{X}_{imt}$ are age, the square of age, and education.

The core idea is to investigate what happens with the gender wage gap after including all controls. If labor market concentration and all other typical controls fully explain the gender wage gap, then the coefficient associated with $Male_i$ should be statistically zero. However, if the coefficient is still significant, these variables cannot account for the whole gender gap. That is, there is still a residual gap.

It is important to highlight what is expected from the coefficient of $HHI_{mt} \times Male_i$, β_2. This coefficient represents how labor market concentration affects men and women differently. If the initial hypothesis is correct, then this coefficient should be positive. That is, men earn greater wages than women in more concentrated markets.

The reasons for labor market concentration to impact the gender wage gap are twofold. First, there is the traditional taste-based discrimination from Becker (1957). This theory says that if an employer prefers men over women, it should pay lesser wages to this second group. In competitive labor markets, however, these employers would be wiped out from the market. Therefore, it is crucial to investigate what happens in environments with imperfect competition.

However, employers having a preference for one group over another is not a necessary condition to imply a gender wage gap. In the monopsonistic discrimination model, there are two necessary conditions: that the employer is profit maximizing, and that the two groups in question have different supply labor elasticities. If women had a smaller labor supply elasticity than men (in absolute value), then it would be profit-maximizing for the employer to offer smaller wages to women.[10]

[9] Real value from January 2010.

[10] In fact, Robinson (1934) has brought up the model for monopsonistic discrimination a long time. Yet,

Finally, the coefficient of β_1 is expected to be negative. HHI_{mt} should be a proxy for labor market power. Therefore it is expected that the more the labor market power, the lesser the wages for anyone.

The labor market fixed effects are vital to a cleaner identification. As discussed in appendix A, regressions with HHI and wages have a lot of confounders. Different labor market structures should generate different relationships between labor market concentration and wages. That is, the labor market concentration in regression 3 is potentially endogenous.

Nonetheless, the challenge of identification due to confounding should be greater for β_1 than β_2. When comparing different labor markets, it is expected that the relationship between labor concentration and wages will vary. However, the gender wage gap should not exhibit the same variation. Specifically, there is no reason for the gender wage gap to be influenced by differences in labor market concentration driven by productivity motives, distinct cost structures, or other variations in labor market structure. The only plausible explanation for changes in the gender wage gap in response to differences in the HHI is shifts in labor market power.

Another identification challenge is individual productivity. It could be that the differences observed in wages are just differences in individual productivity. In that case, employers are just remunerating individuals accordingly, and not making use of labor market power. If this happens disproportionally in some labor markets, the estimates would be biased. To try to control for individual productivity, I include the individual fixed effects in the last specification. In this specification, the identification would come from workers who move from labor markets.[11]

The main limitations of this approach are twofold: first, about the endogeneity of labor market concentration. In this analysis, I include labor market fixed effects to mitigate the problem. However, it is unlikely the problem will be eliminated. The second problem is the variation in the last specification which identifies the estimates. The typical mover is probably very different from typical workers, and thus, it is still not the ideal scenario to recover the association between labor market concentration and the gender wage gap. Those are the main motivations to explore an exogenous variation in labor market concentration in section 4.

3.2 Sample Selection and Descriptives

To proceed with all analyses, I restrict the sample to all contracts from 2010 to 2017 and from people who were still employed on December 31. I also restrict labor markets to at least 100 people because I want to focus on labor markets with a significant number of people. This also excludes uninteresting cases where the market concentration has great variation due to small employment

the main challenge economists faced to show was, theoretically and empirically, why men and women would have different labor supply elasticities. Only recent work has managed to do this (Barth and Dale-Olsen, 2009; Sharma, 2022; Caldwell and Oehksen, 2023).

[11]It is clear to see why that is the case. If there were no movers, it would not be possible to distinguish the labor market and individual fixed effects.

variations.[12] Finally, I restricted people to people who were at least 25 years old. This sample consists of about 157 million observations.

I show in Table 1 the descriptive statistics of the sample. On average, men work slightly more hours, are slightly older, have more tenure, and are more represented in the sample than women. Interestingly, the men are less educated but earn greater wages than women, with a wage gap of 23.14%. Men are also in more concentrated labor markets. Nonetheless, the sample is, on average, present very competitive markets, 315 HHI points out of 10,000.

Table 1: Descriptive statistics of workers used in gap decomposition analysis

	All	Women	Men
Avg. (monthly) wage	1722.83	1463.96	1904.83
Avg. hours	42.32	41.62	42.80
Avg. tenure (months)	44.22	41.99	45.78
Avg. age	38.06	37.25	38.62
Education			
Less than HS	0.335	0.254	0.392
HS grad	0.487	0.517	0.467
More than HS	0.177	0.229	0.141
Observations	157,286,264	64,928,831	92,357,433
Avg. HHI	315.15	230.34	374.77

Notes: This Table presents descriptive statistics for workers used in the decomposition exercise. The first column displays these statistics for all workers pooled together, while the second and third columns show the same statistics separately for women and men, respectively. Data source: RAIS 2010-2017.

3.3 Results

I show the results of the estimates of Equation 3 in Table 2. I re-scale the HHI variable to be between 0 and 1. Thus, β_1 and β_2 are the effects on the wage from going to a perfect competition (0 HHI points) to monopsony (10,000 HHI points) in percentage points. Each column represents a different specification.

The main result is how the $Male$ dummy behaves between specifications. In the first column, I only include the controls of $\mathbb{X}_{imt}$. This implies a gender wage gap of 32.2%, about 9 pp. higher than the gender gap in Table 1. When we include the HHI variable alone in the second column, the $Male$ estimate drops by little, meaning the selection of men and women into more concentrated labor markets says little about the difference in wages. When I control for the interaction between $Male$ and HHI in the third column, the impact on the gap is more meaningful. It drops by an additional 3 pp. But it maintains higher than the unconditional gender gap observed in Table 1.

[12] An extreme example is a labor market with two firms, each one with one worker. If a firm left the market, the HHI from that market would go from 0.5 to 1. Such big variations that would come from a single worker are not the focus of the analysis.

Table 2: Regression Table of gender gap decomposition

	Log Real Wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.322***	0.315***	0.282***	0.095***	0.063***	
	(0.008)	(0.008)	(0.007)	(0.001)	(0.001)	
HHI		0.093***	0.002	0.007***	-0.012***	-0.002*
		(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
HHI × Male			0.139***	0.001	0.017***	0.000
			(0.005)	(0.001)	(0.001)	(0.001)
Observations	157,286,264	157,286,264	157,286,264	157,286,264	157,286,264	157,286,264
R^2	0.299	0.302	0.304	0.712	0.818	0.930
Labor Market FE				×	×	×
Firm × Labor Market FE					×	×
Worker FE						×

Notes: This Table show the estimates from Equation 3 for the 139 million sample. Each column is a different specification, and the only difference is which variables are included as controls. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

The relevant impact on the gender wage gap comes from controlling occupational choices. When I control for labor market fixed effects in the fourth column, the gender gap is reduced by almost 19 pp. This result is very much in line with Goldin (2014). Finally, when I control for the firm × labor market fixed effect, it is possible to see an additional reduction of 3 pp. in the $Male$ dummy. This result is in line with Card et al. (2016).

The results suggest that labor market concentration might explain the gender gap to a limited extent. Even after controlling for several factors considered important by the literature to explain the gender wage gap and the labor market concentration, there is still a residual gap of 6.3%.

Furthermore, the estimates of HHI × $Male$ indicate that labor market concentration should have a mild direct impact on the gender gap. If we take the estimate of the third column, it means that going from a monopsony to perfect competition would diminish the gap by almost 14 pp, which seems significant at first. However, if we consider that the average worker is in a market with 315 HHI points, then bringing the average labor market to perfect competition would reduce the gender gap by only about 0.44 pp.[13] This represents a gender wage gap reduction of only 1.55%. When we control for firm × labor market fixed effects, we see that this effect is effectively zero.

In the last specification, I add the individual fixed effect. As a consequence, I cannot evaluate the $Male$ dummy. When we look at the β_1 estimate, the negative sign is aligned with what is expected from theory. More labor market power implies smaller wages. However, the impact on

[13]To perform this calculation, we need to do $\frac{315}{10{,}000} \times 0.139$

wages is effectively zero.

Half of the estimates of the HHI variable alone are positive. Those are not aligned with the expected from the theory. Nonetheless, it is important to highlight that is very probable that the HHI is endogenous in this regression. Therefore, both β_1 and β_2 coefficients may not reflect the actual relationship between labor market power and the gender wage gap. This is why I use a mass layoff quasi-experiment in the next section.

4 Mass Layoffs Quasi Experiment

4.1 Empirical Strategy

The main goal is to estimate the causal relationship between labor market concentration and the gender wage gap. Several factors from market structure, like productivity, cost structures, and different demands, are jointly determined with HHI_{mt}. Since the labor market concentration variable is endogenous, I need an exogenous variation to estimate the causal effect.

I use mass layoffs as a source of exogenous variation in labor market concentration. Recall that the HHI_{mt} is a function of all shares of employees for each market. Therefore, unanticipated mass layoffs change the share of employees in a market and, in turn, the concentration of the labor market.

Nevertheless, not all mass layoffs are exogenous. A lot of them confound with productivity. Suppose a shock affected an important firm from a labor market, and it chooses to mass layoff. As a result, the labor market power of the other firms also changed. Firms should set wages accordingly. However, the productivity of the sector in question decreased since an important firm was affected. Because wages are the remuneration for productivity, wages are also lower now.

I follow three occupations of four sectors to isolate the productivity channel and keep only the labor market power channel. The occupations are office assistants, janitors, and security guards.[14] The sectors are human health, information, textile, and construction sectors.[15] In addition, I use only mass layoffs that come from sectors other than those four sectors. By doing it, I expect that changes in productivity stay contained in other sectors.

The choice of occupations is intimately tied to the empirical strategy. I needed occupations present in various sectors in order that the mass layoff shocks significantly varied the labor market concentration. Furthermore, choosing some sectors allows me to infer what happens to the gender gap when the labor market power for that particular sector varies.

To address the causal effect of labor market concentration in the gender wage gap, I estimate the following equation:

[14] The occupational codes for office assistant, security guard, and janitor are, respectively, 411005, 517420, and 514320.

[15] I consider the analyses human health sector as the whole Q section from the industry code, the information sector as the whole J section, the textile sector just the divisions between 13 and 15 from transformation industries C section, and construction sector as the whole F section.

$$
\begin{aligned}
Y_{imjt} = \beta_1 HHI_{mt} + \beta_2 \Delta\text{Projected HHI}_{mt} + \beta_3 \Delta\text{Projected HHI}_{mt} \times Male_i + \\
+ \beta_4 Male_i + \beta_5 \mathbb{X}_{imjt} + \delta_t + \delta_m + \delta_{zm} + \epsilon_{imt}. \quad (4)
\end{aligned}
$$

where Y_{imt} is the log of real December wage for individual i in labor market m and sector j in year t, HHI_{mt} is the HHI before the mass layoff, ΔProjected HHI$_{mt}$ is the difference between HHI_{mt} and the Projected HHI$_{mt}$, $Male$ is a dummy which is 1 if the individual is male, $\mathbb{X}_{imt}$ is a set of controls, δ_t, δ_m, and $\delta_z M$ are time, labor market, and firm-labor market fixed effects.

The inclusion of the labor market and firm-labor market fixed effects guarantees better identification. While the shock timing of the shock in ΔProjected HHI$_{mt}$ is plausibly exogenous, it might not be the case for the size of the shock. Labor markets' fixed effects should mitigate the problem. At the same time, it could be the case that mass layoffs affect firms differently. A lot of the mass layoffs could be happening closer to some firms than others. I expect to prevent this possibility by including firm-labor market fixed effects.

Now, I define the projected changes in HHI due to mass layoffs, the Projected HHI$_{mt}$ variable. Let s_{zmjt} be the share of employees defined as before, with the addition of subscript j standing for sector j. Because a labor market m is defined as occupation $\times$ municipality, I can segment this labor market at the sector level without conflicts. That is, the HHI for the janitors' labor market is a function of the share of employees of each firm that hires janitors from the health sector, plus the construction sector, and so forth. For a given occupation m and sector j,

$$
\text{Projected HHI}_{mt} = \sum_{z\in\Theta_{m0t},\tilde{j}\in\Theta_j} s^2_{zm\tilde{j}t} + \sum_{z\in\Theta_{m1t},\tilde{j}=j} s^2_{zm\tilde{j}t} + \sum_{z\in\Theta_{m1t},\tilde{j}\neq j} s^2_{zm\tilde{j}t+1},
$$

where Θ_{m0t} is the set of firms z in labor market m that do not mass layoff in year $t+1$, Θ_{m1t} is the set of firms that mass layoff in year $t+1$, Θ_j is the set of all sectors, and $\Theta_{m0t} \cup \Theta_{m1t} = \Theta_m$. It is important to observe that HHI_{mt} only differs from Projected HHI$_{mt}$ because of the third sum of the right side. I project the HHI change that comes exclusively from mass layoffs and from all sectors that are not j.[16]

Finally, I need a definition of mass layoff. First, I calculate the difference between active contracts within a firm and year. Then, following Britto et al. (2022), I define a mass layoff if a firm has more than 50 workers (of any occupation) and has laid off more than 30% of them.

There are two main identification hypotheses. First, the timing and which firms are doing the mass layoffs are unanticipated from the point of view of other firms. For instance, both hospitals and real estate firms hire janitors. It seems improbable that a particular hospital can foresee which and when real state firms are performing mass layoffs. Therefore, the labor market concentration

[16] This is a common analysis related to market concentration. For example, suppose two big firms were to merge. Projected HHI$_{mt}$ captures how this merge should affect that market, should everything else stay fixed.

variation would be exogenous. In turn, this strategy allows me to see what happens to the gender wage gap for janitors in the health sector when the labor market power of janitors varies.

Second, the selected mass layoffs shock do not confound with the productivity shocks. If the real state firms are doing mass layoffs, I expect productivity shocks for janitors working in the real state sector. However, the productivity of janitors in the health sector should not be affected by those mass layoffs. Therefore, the variation observed in the gender wage gap should be coming from the variation in the labor market power for these janitors. If these two hypotheses hold, then Projected HHI_{mt} should be exogenous in Equation 4.

The coefficient of interest in Equation 4 is β_3. If the gender gap widens with increased labor market power, then β_3 should be positive. On the other hand, β_2 is expected to be negative. Since Projected HHI_{mt} captures the causal effect of labor market power, the greater the labor market power, the lower the wages.

The coefficient of HHI_{mt}, β_1, should not be interpreted causally howbeit. As before, the pre-mass layoff HHI level is endogenous.[17] Nonetheless, its inclusion is crucial as a control. A shock in ΔProjected HHI_{mt} might correlate with the pre-mass layoff HHI level. For instance, a 50-point shock in ΔProjected HHI_{mt} could have different impacts in markets with initial HHI levels of 200 versus 2,000 points. Therefore, conditioning on the initial market HHI is important to account for these variations.

The main limitation of this approach is that the magnitude of the shock might not be exogenous. The magnitude of the shock is probably correlated with the size of the market. For example, in larger metropolitan areas, it should expected that the shocks might be much smaller. This is because mass layoffs are likely to have a minimal impact on labor market concentration in these larger markets. Including labor market fixed effects helps mitigate this issue to a significant extent. However, it is uncertain how fully they resolve the problem.

4.2 Sample Selection and Descriptives

In subsection 4.1, I discussed the motivation to focus on office assistants, janitors, and security guards from the human health, information, textile, and construction sectors. Furthermore, I restrict the analysis to new contracts. It might be difficult to identify wage settings for existing contracts. Firms cannot adjust wages downward. Focusing on new contracts should give a clearer identification of changes in labor market power in the gender wage gap.

As an additional restriction, I remove markets with shocks smaller than 20 points in ΔProjected HHI_{mt}, in absolute value. This is because the majority of shocks are very close to zero. This occurs because mass layoffs are defined at the firm level. This means companies may do a mass layoff but terminate just a few employees of occupations of interest.[18] With a lot of near-zero shocks, the quality of

[17] See the appendix A for a more detailed discussion.

[18] Despite this implication, defining mass layoffs at the firm level is still more appropriate than defining them at the occupation level. For example, requiring a firm to have at least 50 janitors and lay off at least 30% of them would be overly restrictive.

inference might be affected. There is too much variance in this small range.[19]

Moreover, it aligns with the goal of this exercise to focus on shocks larger than 20 points in absolute value. These are the shocks that effectively move market power at some level. According to the Merger Guidelines of the Department of Justice (DOJ) in the United States (U.S. Department of Justice, 2023; LLP, 2023) and a report presented at the OECD (Azar et al., 2019), large shocks can be defined as those exceeding 100 or 200 points, depending on the context.[20] I define a big shock as one that results in a difference of more than 100 HHI points. By excluding shocks smaller than 20 points in absolute value, I still retain smaller shocks for comparison purposes.

The descriptive statistics of the workers used in this section are presented in Table 3. The sample for the mass layoff quasi-experiment is notably different from the sample used in section 3. Both women's and men's average wages are significantly lower. The workers in this sample are slightly younger, have considerably fewer months of tenure, and are generally less educated. Interestingly, women are more represented than men in this sample.

This sample is also more frequently employed in significantly higher concentrated markets when compared with the sample before. In addition, women and men now appear to be working in markets with similar concentration levels, whereas there was a larger disparity previously. The ΔProjected HHI_{mt} shocks are very similar for men and women. These shocks are less than 100 HHI points, that is, they are classified as not big.

When the distribution of mass layoff shocks are analyzed, we see that more than half of the shocks were negative. Figure 1 shows all the shocks used in the analysis in terms of pre-mass layoff HHI, in the horizontal axis, and projected HHI, in the vertical axis. Each point is a shock in a given labor market and year. It is possible to see that the points seem more located below the 45° line. This means that the majority of mass layoff shocks decreased labor market concentration. In appendix B, Table 14 shows that the average shock was of negative 99 HHI points, and the median shock was of negative 35 points. The proportion of big shocks were about 33%. In appendix B, I also show with figures 3 and 4 that even though the majority of shocks were less than 20 points in absolute value, there is a vast variation in shocks to take advantage of.

Table 3 reveals that the relationship between the gender gap and labor market concentration is ambiguous. Although a notable gender gap persists, both men and women are employed in labor markets with similar levels of concentration. Women are slightly more likely to be in higher concentrated labor markets, suggesting a potential weak association between labor market concentration and the gender wage gap. To illustrate this association further, I conducted a

[19] In the appendix, I provide results including all shocks, showing that the estimates do not change significantly, as expected, only the significance is altered. This demonstrates that excluding negligibly small shocks improves the robustness of the results without fundamentally changing the findings.

[20] The DOJ would classify as potentially creating a monopsony a merger that increased the HHI by 100 points and either generated an HHI market level greater than 1800 or a firm with market share greater than 30%. The report by Azar et al. (2019) would classify as sufficient to increase labor market power a change that resulted in 200 HHI points.

Figure 1: HHI projected with mass layoffs variation versus pre-mass layoff HHI

Notes: This figure exhibits all the shocks in labor market concentration analyzed in the mass layoff quasi-experiment. Therefore, it contains only shocks greater than 20 Herfindahl–Hirschman Index (HHI) points in absolute value. The horizontal axis displays the HHI pre-mass layoff in the labor markets of office assistants, security guards, and janitors of the human health, information, textile, and construction sectors. The vertical axis displays the HHI projected with the selected mass layoffs. The shock, ΔProjected HHI$_{mt}$, is defined as the Projected HHI minus the HHI. Following U.S. Department of Justice (2023), a shock is defined as big if it is greater than 100 points in absolute value. Points in dark red represent big shocks and silver points represent small shocks. U.S. Department of Justice (2023) also gives the possibility of defining shocks as a big shock either those that the pre-event HHI level was greater than 1800 points or those markets that turn into greater than 1800. The dashed red lines indicate the 1800 HHI points.

Table 3: Descriptive statistics of workers used in mass layoff exercise

	All	Women	Men
Avg. wage	887.76	847.81	958.63
Avg. hours	40.41	40.32	40.58
Avg. tenure (months)	12.29	13.00	11.03
Avg. age	32.92	33.60	31.70
Education			
Less than HS	0.448	0.436	0.468
HS grad	0.463	0.469	0.453
More than HS	0.089	0.079	0.095
Observations	74,066	47,368	26,698
Avg. HHI	630.83	642.65	609.65
Avg. ΔProjected HHI	-62.25	-62.08	-62.53

Notes: This Table presents descriptive statistics for workers utilized in the mass layoff quasi-experiment. The sample comprises exclusively new contracts and labor markets that experienced shocks greater than 20 points in absolute value. The first column depicts these statistics for all workers pooled together, while the second and third columns delineate the same statistics separately for women and men, respectively. Data source: RAIS 2010-2017.

binscatter regression analysis, following Cattaneo et al. (2024).[21]

The analysis of binscatter regression in figure 2 weakly suggests that the gender wage gap might not widen with greater labor market concentration. As expected, the greater the labor market concentration, the lesser the wages for both men and women. It is also clear that men earn greater wages than women for nearly all labor market concentration levels. However, if the gap widened with labor market concentration, there would be a difference in the lines' inclination. The dark red line is slightly steeper, which would be consistent with the gender gap being higher in more concentrated labor markets. Nonetheless, the difference in inclinations could be driven by the uncertainty from the points in the figure more to the right.

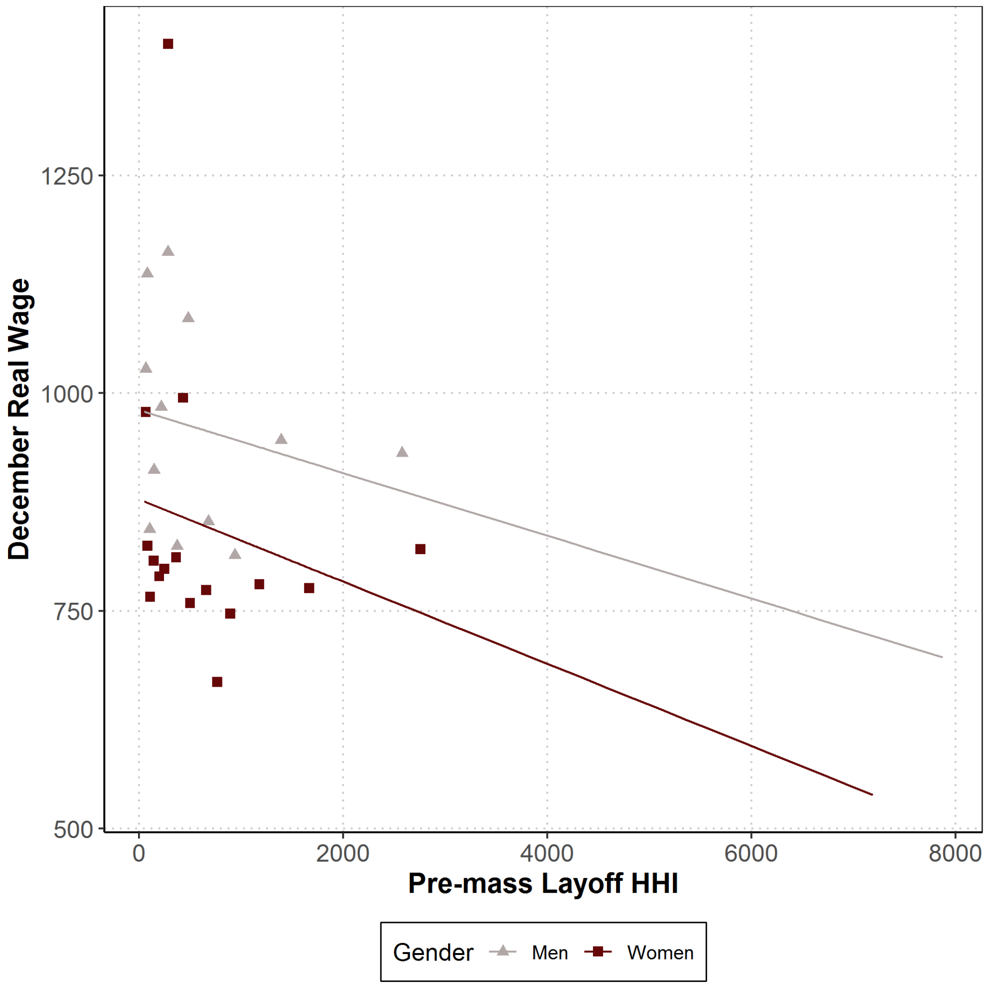
4.3 Main Results

Table 4 shows the results estimated by Equation 4 for all selected occupations and sectors. In the first column, I include only year-fixed effects. In the second column, I include labor market fixed effects. This means that the results of labor market variation are within labor markets. In the third column, I include the firm-labor market fixed effects. Since the ΔProjected HHI_{mt} is at the labor market level, the variation is still within labor markets. For all specifications, errors were clustered at the labor market level.

For all columns, the coefficient of interest, ΔProjected $\text{HHI}_{mt} \times Male_i$, is positive. Qualitatively,

[21] Binscatter is widely used for visualizing bivariate relationships and performing informal specification testing. Cattaneo et al. (2024) improve this method by including optimal binning for estimating conditional means and methods to quantify uncertainty.

Figure 2: Binscatter regression of HHI and wages, by gender



Notes: This figures shows the binscatter regression of HHI and wages, by gender. The horizontal axis is the HHI level of labor markets before the mass layoffs shocks. The vertical axis is the December Real wage, in 2010 values. The data are grouped into bins based on the HHI, the independent variable, in an optimal way following Cattaneo et al. (2024). Then, the conditional mean of the dependent variable, the wage, is calculated for each interval. This is what generates each point in the figure. The line is also fitted optimally following Cattaneo et al. (2024) method. Points and the line in dark red represent data from women and points and the line in silver represents data from men.

Table 4: Regression Table of mass layoff quasi-experiment

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.1425^{***}	0.1109^{***}	0.0645^{***}
	(0.0194)	(0.0134)	(0.0113)
HHI_{mt}	-1.23×10^{-5}	2.34×10^{-5}	2.74×10^{-6}
	(1.81×10^{-5})	(3.2×10^{-5})	(1.66×10^{-5})
$\Delta\text{Projected HHI}_{mt}$	3.4×10^{-5}	3.22×10^{-5}	-3.3×10^{-5}
	(4.08×10^{-5})	(7.5×10^{-5})	(2.12×10^{-5})
$\Delta\text{Projected HHI}_{mt} \times Male$	$7.56 \times 10^{-5**}$	$4.53 \times 10^{-5*}$	$4.84 \times 10^{-5**}$
	(3.7×10^{-5})	(2.44×10^{-5})	(1.96×10^{-5})
Labor Market FE (1,037)		×	×
Firm × Labor Market FE (13,009)			×
No. of Small HHI shocks:	779	779	779
No. of Big HHI shocks:	497	497	497
Observations	74,066	74,066	74,066
R^2	0.28819	0.45757	0.75350
Within R^2	0.26618	0.24274	0.13161

Notes: This Table shows the estimates from Equation 4. The sample consists of office assistants, security guards, and janitors from the human health, information, textile, and construction sectors sample. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. The number in parenthesis after Labor Market FE and Firm × Labor Market FE represents the quantity of fixed effects estimated. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

this means that men have greater wages than women in more concentrated labor markets. This is coherent with the initial hypothesis of labor market power driving the gender wage gap. Since most of the mass layoffs produced negative shocks in labor market concentration, on average, labor markets experienced a reduction in the gender wage gap.

To properly quantify the impact of the mass layoff shocks, a translation of the coefficient of interest in terms of the wage gap is needed. To do this, I multiply the coefficient by a shock of HHI of relevant size. I choose the first quartile shock, a negative shock of 132 HHI points.

The results are summarized in Counterfactual A of Table 5. Notably, the negative shock in labor market concentration had little impact on the gender wage gap. At most, the gender wage gap was reduced by 1 p.p. In relative terms, the reduction is somewhat significant. The reduction could be up to 10.4%.

An important exercise is to investigate what would happen if we were to bring the labor market concentration to zero. The average labor market concentration is 934 HHI points. Thus I remake the exercise above, using 934 as the relevant shock. The results are summarized in Counterfactual B of Table 5. The relative reduction of the gender wage gap would range from 38% to 73%. This means that improving competition could significantly diminish the gender wage gap. But even in perfect competition labor markets, there would still be a remaining gender wage gap.

Table 5: Counterfactuals - Measuring the importance of labor market concentration on the gender wage gap

	Specification		
	(1)	(2)	(3)
Gender gap at baseline	14.25 pp.	11.09 pp.	6.04 pp.
Counterfactual A: Effects from reducing HHI by 132 points			
Effect of decreasing HHI on the gender gap	−0.99 pp.	−0.60 pp.	−0.63 pp.
Relative reduction in gender gap	6.95%	5.41%	10.43%
Counterfactual B: Perfect competition			
Effect of decreasing HHI on the gender gap	−7.00 pp.	−4.24 pp.	−4.45 pp.
Relative reduction in the gender gap	49.18%	38.28%	73.80%
Labor Market FE		×	×
Firm × Municipality			×

Notes: This Table presents the quantified impact of labor market concentration shocks in the gender wage gap. In the first row, I show the gender wage gap at baseline, which is the coefficient associated with the $Male$ dummy estimated in Equation 4. In the second row of each Counterfactual, I multiply the coefficient ΔProjected $\text{HHI}_{mt} \times Male$ by a quantity of HHI points. In the third row of each Counterfactual, I calculate by how much the shock in labor market concentration has reduced the gender wage gap, relative to the gap at baseline. That is, the third row is just the second row divided by the first one, in absolute value. The columns represent each specification estimated in 4. In Counterfactual A, the quantity of HHI used in the analysis is 132, which represents the first quartile of the shock size distribution in HHI points. In Counterfactual B, the quantity of HHI used in the analysis is 934, which is the average labor market concentration.

As a robustness check, I estimate the Equation 4 for all mass layoff shocks, including those smaller than 20 HHI points. The results are presented in Table 16. The estimates for the coefficient of interest, ΔProjected $\text{HHI}_{mt} \times Male_i$, are not significant. However, they are very similar in magnitude to the estimates in 4. As discussed, it was expected that a massive quantity of observations near zero should make inference harder. The fact that the estimates were similar suggests that they point in the same direction.

The main limitation of these results is their external validity. The sample consists of workers present in labor markets that the labor market concentration had meaningful variation. Labor markets with a persistent labor market concentration might be out of the sample. These labor markets might be inherently concentrated, and no policy could change that. Also, the sample consists of occupations that are widely presented in all sectors. It could be that these results do not apply to occupations intimately tied to the sector, like physicians and the health sector, or engineers and the construction sector, for example.

4.4 Heterogeneity by Occupations and Sectors

In this section, I present the results separately for each selected occupation and sector. I estimate the Equation 4 for each combination of occupation and sector. The regression tables are available in the appendix D. To perform the same exercise of the impact of labor market concentration on the gender wage gap from subsection 4.3, I use the coefficients estimated for the second specification. This is the one that includes year and labor market fixed effects only.[22]

Looking at the first panel from Table 6, it is possible to see that all occupations had a positive gender wage gap. Looking at the second panel of Counterfactual A, is notable that most of the labor market concentration changes diminished the gender wage gap. Almost of all these reductions seem small at first, except for security guards in the information sector. When we look at the third panel, we see that many of the relative changes in the gender wage gap were also relatively small. Five of them were less than 10%. Three of them were plausibly significant, ranging between 19% and 33%.

Four results are outside of the expected: office assistants in the construction sector, security guards in the human health sector, janitors in the textile sector, and security guards in the information sector. It was not expected the first three would be negative. It was also not expected the magnitude of the fourth result.

Looking at Table 22 in appendix C, it shows that security guards in the information sector were a very small sample. None of the estimates were significant. Looking at the Table 21, we see that the sample of security guards in the human health sector had substantial observations. But when we look at the proportion of female security guards in the health sector versus male security guards

[22] Within an occupation and sector, the coefficient of ΔProjected HHI_{mt} are of similar magnitude between specifications. The statistical significance of each specification may vary, but is difficult to say if this comes from the fact the statistical power is much lower for each occupation $\times$ sector sub-sample. It could be that not always the labor market concentration is relevant to explain the gender wage gap. In any case, it would not make much difference to choose a coefficient of a different specification to perform this analysis.

Table 6: Counterfactuals - Measuring the importance of labor market concentration on the gender wage gap, by industry and occupation

	Occupation		
	Office Assistant	Security Guard	Janitor
Industry:	(1)	(2)	(3)
	Gender gap at baseline		
Human Health	4.73 pp.	7.20 pp.	2.91 pp.
Information	6.73 pp.	26.09 pp.	6.91 pp.
Textile	7.37 pp.	16.39 pp.	8.57 pp.
Construction	15.63 pp.	8.87 pp.	12.13 pp.
	Counterfactual A: Effects from reducing HHI by 132 points		
Human Health	-1.65 pp.	0.56 pp.	-0.06 pp.
Information	-0.287 pp.	-145.24 pp.	-1.36 pp.
Textile	-0.20 pp.	-3.95 pp.	0.13 pp.
Construction	0.83 pp.	-0.77 pp.	-1.20 pp.
	Relative reduction on gender wage gap		
Human Health	32.89%	-7.78%	2.07%
Information	4.26%	558.61%	19.51%
Textile	2.74%	24.1%	-1.5%
Construction	-5.31%	8.68%	9.89%

Notes: This Table presents the quantified impact of labor market concentration shocks in the gender wage gap, by occupation and sector. In the first panel, I show the unconditional gender wage gap, which is the $Male$ dummy estimated in Equation 4 for each combination of sector and occupation. In the Counterfactual A panel, I multiply the coefficient ΔProjected $\text{HHI}_{mt} \times Male$ by 132, which represents the first quartile of the shock size distribution in HHI points. Negative numbers mean that the estimated coefficient was negative. In the third panel, I calculate how much the shock in labor market concentration has reduced the gender wage gap, relative to the unconditional wage gap. That is, each number in the third panel is just the equivalent number in the second divided by the equivalent number in the first panel. A negative number in the relative reduction of the gender wage gap means that the gender wage gap in that combination of occupation and sector widened.

in tables 12 and 13, we see that the sample had more than 5 times more males than females. These facts should point to why the results of these two occupations $\times$ sector alone should not be trusted.

However, the same cannot be said of office assistants in the construction sector and janitors in the textile sector. Both of them are composed of a substantial sample size and similar proportions of men versus women. The estimates of both of them were not statistically significant nonetheless.

Overall, the results of the heterogeneity analysis and the results from section 4.3 seem to agree. Eight out of the twelve estimates are within the expected. Out of the four that were not expected, two of them can be explained why they behaved oddly. That is, the majority of the results seem to indicate that the gender wage gap could be reduced with a negative labor market concentration shock.

5 Conclusion

This paper investigates the relationship between the gender wage gap and labor market competition in Brazil. In the decomposition exercise, I show that labor market concentration explains the gender gap to a limited extent, at first. Even after including all the typical controls identified in the literature as the main causes of the gender wage gap, there is a residual gap that remains. Nonetheless, labor market concentration is likely endogenous in this analysis. To address this issue, I use quasi-experimental variation in labor market concentration due to mass layoffs. The main result of this paper is that if it were possible to bring labor markets to perfect competition conditions, the gender wage gap might be reduced up to 73.8%. This result is heterogeneous across occupations and sectors. The main limitation of this result is external validity. It is crucial to the empirical strategy proposed to look at specific occupations, those that are widely present among various sectors. It could be that this result does not hold to other occupations.

This study demonstrates that the implications of the findings are significant for policy formulation. Addressing labor market concentration not only directly tackles this specific issue but also substantially contributes to reducing the gender wage gap. Thus, by focusing on labor market concentration, it is possible to mitigate two crucial problems simultaneously.

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A About Regressions with HHI and Wages

In all analyses of this paper, I use regressions of wages against HHI labor markets to infer the relationship between the gender wage gap and labor market power. One might be concerned that labor market concentration is endogenous in this regression. While this may hold for a lot of cases, in this section I lay out why the setup of the gender wage gap poses a different setup.

The main problem with using HHI and wages in regressions is discussed in Miller et al. (2022), which is summarized here. Suppose two symmetrical firms compete a la Cournot in three markets. Now, suppose that the first firm has increased its productivity in the second labor market and has its productivity decreased in the third market relative to the first market. Suppose the initial wage level was w in the first market. The resulting wage levels at the second and third markets were w' and w", respectively. The Cournot competition setting implies that $w' > w > w$". Because in the first market, firms were symmetric, the resulting HHI is 5,000. Suppose that productivity has adjusted in the other markets such that, in the second market, the first firm has 62% share of the labor market and the second firm 38%, while in the third market, the first firm has 38% share of the labor market and the second firm 62%. [23] The resulting HHI in both markets is 5,288. Table 7 summarizes this situation.

Table 7: Example of three hypothetical situations of two firms competing in three labor markets

Markets	1	2	3
Market Structure	Symmetric Firms	Firm 1's productiveness ↑	Firm 1's productiveness ↓
Wage	w	w'	w''
HHI	5,000	5,288	5,288

Note: This Table illustrates how the correlation between HHI and wages could be misleading. It summarizes two firms competing in three different labor markets. Each column represents a hypothetical labor market. In the first line, it shows the labor market structure regarding firms' productivity. In the first labor market, they are symmetric. In the second labor market, the firm's 1 productiveness has increased relatively to the first column. In the third labor market, the firm's 1 productiveness has decreased relatively to the first column. Equilibrium wages are w, w', and w'', respectively. Cournot competition setup implies that $w' > w > w$". In this example, firms' shares of each market are such that the resulting HHI, summarized in the third line, is 5,000, 5,288, and 5,288, respectively.

Suppose economists were to analyze the markets of the first two columns of Table 7. They would find a positive correlation between HHI and wages. However, if they were to analyze the first and third markets, they would find the opposite result. Finally, if they were to analyze the last two columns, they would infer that HHI and wages do not correlate.

This example illustrates the problem's nature: the relation between wages and wage indexes is not causal, at least without any additional setup. This setup would be a comprehensive model where the HHI should have a consistent causal relation with wages. HHI and wage are equilibrium outcome variables, both intrinsically tied and generated by different market structures. These market structures could be cost structures, different demands, different productiveness, as in the example above, and so forth. Without controlling for all these factors, the relationship captured is biased.

This issue is dealt with both by the natural setup of the problem I propose to study and by the inclusion of labor market fixed effects in the regressions. The traditional critique is concerned with the biased relationship between wages and HHI. Nonetheless, I am interested in the relationship between the gender wage gap and HHI. Given a fixed market structure, there is no reason to believe that men's wages should vary differently than women's wages, according to HHI variation.

[23]These numbers are purely illustrative, and the exact ones picked by Miller et al. (2022).

This comparison is outside of the traditional critique's scope, and thus, is valid. In addition, this comparison is even more refined after controlling for labor market fixed effects. Including this control means investigating the relationship between labor market concentration and the gender wage gap within labor markets. In turn, this makes it possible to better fix the market structure, therefore producing more robust estimates. Nonetheless, the analysis in section 3 should be seen more as a decomposition exercise. Conversely, it is the analysis in section 4 that attempts to recover a causal estimation by using plausibly exogenous variation in labor market concentration.

To further illustrate the core idea, I extend the example of the three labor markets discussed above. The actual comparison that is made is summarized in tables 8 and 9. The first analysis investigates the relationship between the difference in wage levels w_M and w_W, and w'_M and w'_W, with labor market concentrations of 5,000 and 5,288, respectively. Similarly, the second analysis examines the relationship between the difference in wage levels w_M and w_W, and w''_M and w''_W, with labor market concentrations of 5,000 and 5,050, respectively.

Table 8: Example of two hypothetical situations of comparing men and women in two different labor markets

Markets	1: Men	1: Women	2: Men	2: Women
Firms Productiveness	Symmetric Firms	Symmetric Firms	Firm 1's productiveness ↑	Firm 1's productiveness ↑
Wage	w_M	w_W	w'_M	w'_W
HHI	5,000	5,000	5,288	5,288

Notes: This Table illustrates the difference between analyzing the HHI and wages, and HHI and the gender wage gap. It summarizes two firms competing in two different labor markets. The first two columns exhibit the first labor market. The last two columns exhibit the second labor. The first and third columns exhibit average men in each market, and the second and fourth columns represent average women in the second labor market. In the first line, it shows the labor market structure regarding firms' productivity. In the first labor market, they are symmetric. In the second labor market, the firm's 1 productiveness has increased relatively to the first column. Equilibrium wages are w_M, w_W, w'_M, and w'_W, respectively. The competition structure should not be related relationship between HHI and the potential gender wage gap in these labor markets. In this example, firms' shares of each market are such that the resulting HHI, summarized in the third line, is 5,000 and 5,288, respectively.

Table 9: Example of two hypothetical situations of comparing men and women in two different labor markets, within a labor market structure

Markets	1: Men	1: Women	1: Men	1: Women
Firms Productiveness	Symmetric Firms	Symmetric Firms	Symmetric Firms	Symmetric Firms
Wage	w_M	w_W	w''_M	w''_W
HHI	5,000	5,000	5,050	5,050

Notes: This Table illustrates the difference between analyzing the HHI and wages, and HHI and the gender wage gap. In addition, it refines the analysis by fixing the labor market structure. It summarizes two firms competing in two different labor markets. The first two columns exhibit the first labor market. The last two columns exhibit the second labor. The first and third columns exhibit average men in each market, and the second and fourth columns represent average women in the second labor market. In the first line, it shows the labor market structure regarding firms' productivity. In both labor markets, firms are symmetric. Equilibrium wages are w_M, w_W, w''_M, and w''_W, respectively. The competition structure should not be related relationship between HHI and the potential gender wage gap in these labor markets. Moreover, variation within a labor market structure should generate a cleaner analysis. In this example, firms' shares of each market are such that the resulting HHI, summarized in the third line, is 5,000 and 5,050, respectively.

B Descriptives of Mass Layoff Quasi-Experiment

Table 10: Marginal Table of the sample used in the mass layoff quasi-experiment, as a proportion of the whole sample of gender gap decomposition sample, in percentage points

	Human Health Sector	Information Sector	Textile Sector	Construction Sector	Other	Total
Office Assistant	0.30	0.10	0.10	0.20	4.00	4.80
Security Guard	0.00	0.00	0.00	0.10	0.50	0.60
Janitor	0.20	0.00	0.00	0.10	2.50	2.90
Other	4.40	2.20	3.60	6.70	74.80	91.70
Total	5.00	2.30	3.70	7.10	81.90	100.00

Notes: This Table shows how much each occupation × sector represents of the total sample of 157 million observations. For example, office assistants in the human health sector represents 0.3% of the 157 million observation. Data source: RAIS 2010-2017.

Table 11: Marginal Table of the sample used in the mass layoff quasi-experiment, in percentage points

	Construction Sector	Human Health Sector	Information Sector	Textile Sector	Total
Office Assistant	13.40	15.60	9.90	4.30	43.10
Janitor	16.60	25.60	3.10	3.30	48.60
Security Guard	5.80	1.60	0.30	0.50	8.30
Total	35.70	42.80	13.40	8.10	100.00

Notes: This Table shows how much each occupation × sector represents of the sample used in the mass layoff quasi-experiment. For example, office assistants in the human health sector represents 16.6% of the 74,066 observations. Data source: RAIS 2010-2017.

Table 12: Marginal Table of the female sample used in the mass layoff quasi-experiment, in percentage points

	Construction Sector	Human Health Sector	Information Sector	Textile Sector	Total
Office Assistant	7.30	10.80	6.40	2.70	27.10
Janitor	11.60	21.20	2.30	2.00	37.10
Security Guard	0.10	0.20	0.00	0.10	0.40
Total	19.00	32.10	8.70	4.80	64.60

Notes: This Table shows how much each occupation × sector represents of the female sample used, as a proportion of the mass layoff quasi-experiment sample. For example, female office assistants in the human health sector represent 16.6% of the 74,066 observations. Data source: RAIS 2010-2017.

Table 13: Marginal Table of the male sample used in the mass layoff quasi-experiment, in percentage points

	Construction Sector	Human Health Sector	Information Sector	Textile Sector	Total
Janitor	5.00	4.40	0.80	1.30	11.50
Office Assistant	6.10	4.80	3.50	1.60	16.00
Security Guard	5.70	1.50	0.30	0.40	7.90
Total	16.70	10.70	4.70	3.30	35.40

Notes: This Table shows how much each occupation × sector represents of the male sample used, as a proportion of the mass layoff quasi-experiment sample. For example, male office assistants in the human health sector represent 4.8% of the 74,066 observations. Data source: RAIS 2010-2017.

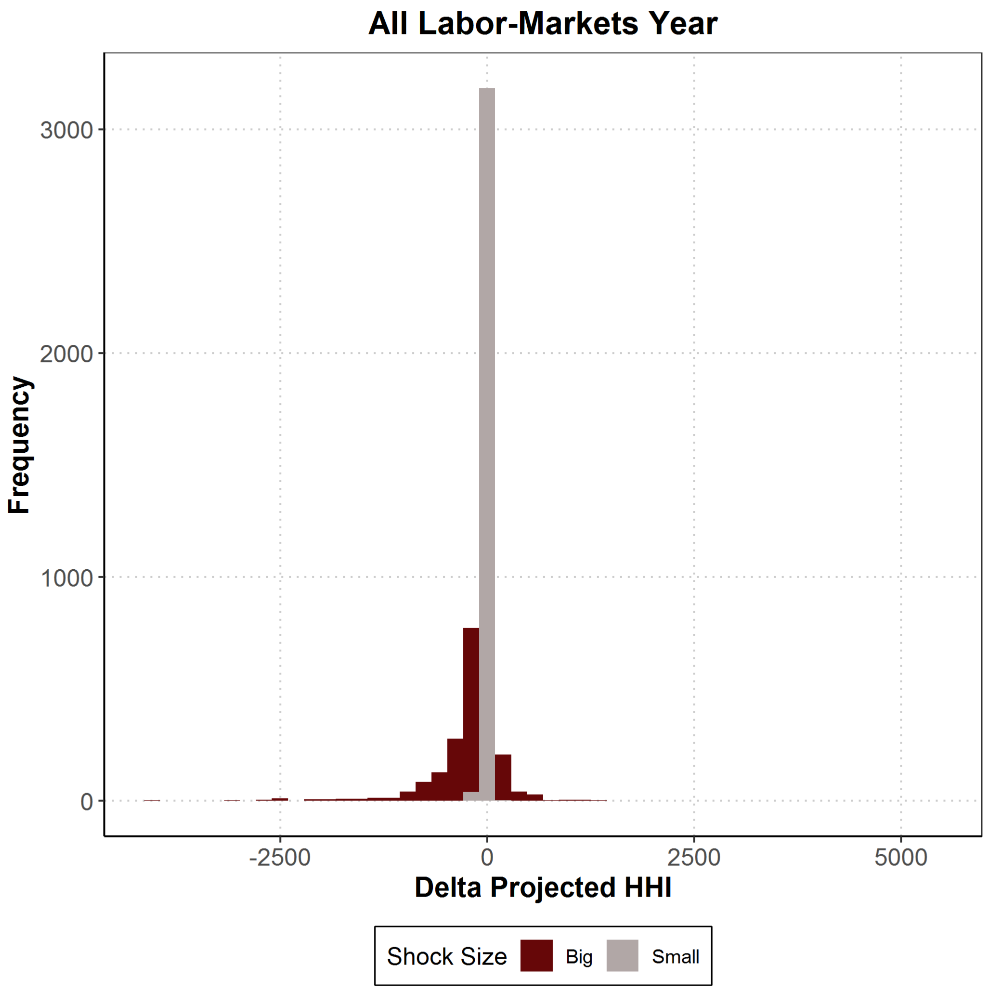

Figure 3: Histogram of ΔProjected HHI with mass layoffs variation, by size of shock

Notes: This figure exhibits the frequency of all the shocks in labor market concentration analyzed in the mass layoff quasi-experiment. Therefore, it contains only shocks greater than 20 Herfindahl–Hirschman Index (HHI) points in absolute value. The horizontal axis displays the value of ΔProjected HHI$_{mt}$ in the labor markets of office assistants, security guards, and janitors of the human health, information, textile, and construction sectors. Following U.S. Department of Justice (2023), a shock is defined as big if it is greater than 100 points in absolute value. Bars in dark red represent big shocks and silver bars represent small shocks.

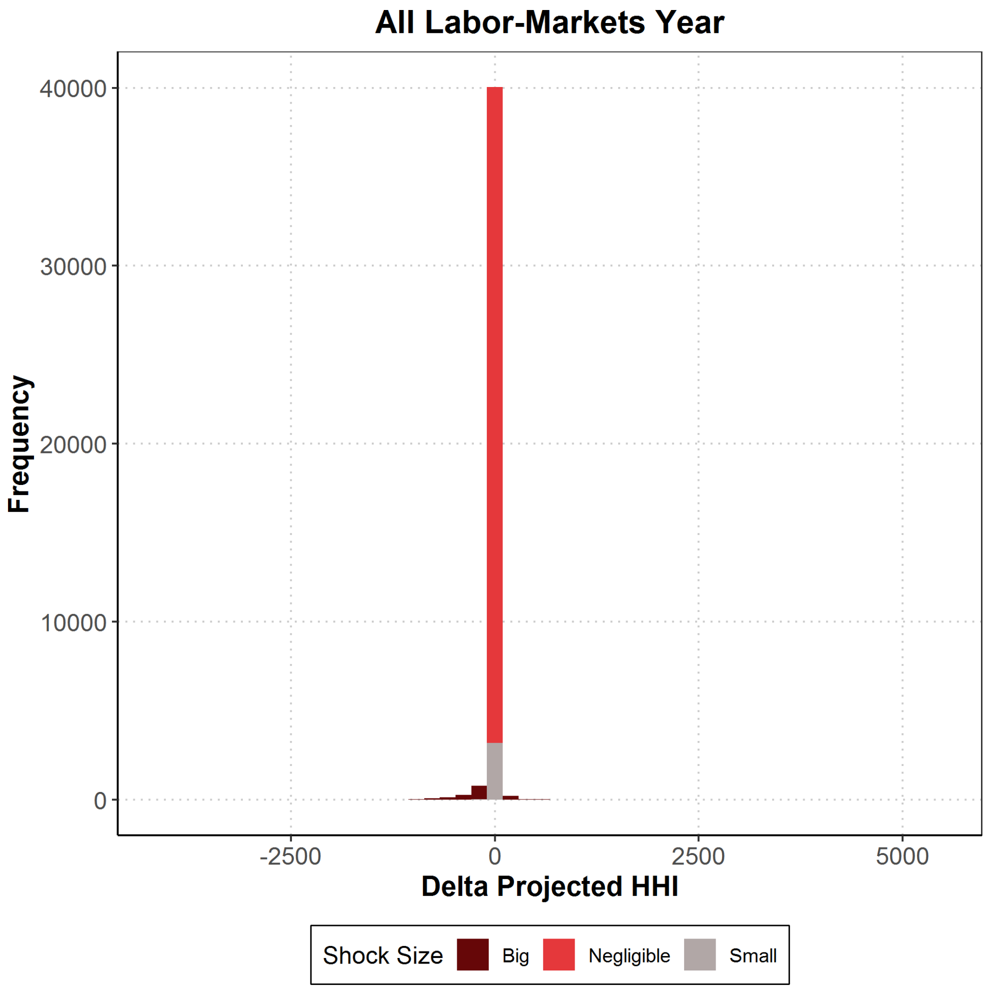

Figure 4: Histogram of ΔProjected HHI with mass layoffs variation, by size of shock

Notes: This figure exhibits the frequency of all the shocks in labor market concentration due to mass layoffs. The horizontal axis displays the value of ΔProjected HHI_{mt} in the labor markets of office assistants, security guards, and janitors of the human health, information, textile, and construction sectors. Following U.S. Department of Justice (2023), a shock is defined as big if it is greater than 100 points in absolute value. A shock is defined as negligible if is smaller than 20 points in absolute value. Bars in dark red represent big shocks, silver bars represent small shocks and red bars represent negligible shocks.

Table 14: Summary Table of labor markets analyzed in the mass layoff quasi-experiment

	Supply Shock	Pre-mass Layoff HHI	Projected HHI	ΔProjected HHI	Big HHI shocks
Min	-3291	53	23	-4084	
1st Quartile	-71	254	177	-132	
Median	-11	544	453	-35	
Mean	-117	844	746	-99	0.3355
3rd Quartile	0	1126	993	29	
Max	2428	8180	7423	5358	

Notes: This Table exhibits moments of the distribution of some variables at the labor market level for the sample analyzed in section 4. In the first column, the variable is the number of variation of contracts in a specific labor market. In the second column, the variable is the pre-mass layoff Herfindahl–Hirschman Index (HHI) level. In the third column, the variable is the Project HHI. In the fourth column, is the ΔProjected HHI, defined as the Projected HHI minus the HHI. In the fifth column, is the proportion of big shocks, defined as a shock of greater than 100 HHI points in absolute value. The lines exhibit the minimum value observed, the first quartile, the median, the mean, the third quartile, and the maximum value observed. It is important to highlight that the fourth column should not be equal to the third column minus the second column. The labor market that exhibited a Projected HHI of 23, for instance, should not be necessarily the labor market that had a pre-mass layoff HHI of 52 points.

Table 15: Summary Table of all labor markets

	Supply Shock	Pre-mass Layoff HHI	Projected HHI	ΔProjected HHI	Big HHI Shocks
Min	-20102	6	5	-4084	
1st Quartile	-198	56	54	-0.387	
Median	-56	116	113	0.201	
Mean	-324	281	270	-10	0.03904
3rd Quartile	-5	282	269	1.354	
Max	2428	8180	7423	5358	

Notes: This Table exhibits moments of the distribution of some variables at the labor market level for all shocks due to all mass layoffs. In the first column, the variable is the number of variation of contracts in a specific labor market. In the second column, the variable is the pre-mass layoff Herfindahl–Hirschman Index (HHI) level. In the third column, the variable is the Project HHI. In the fourth column, is the ΔProjected HHI, defined as the Projected HHI minus the HHI. In the fifth column, is the proportion of big shocks, defined as a shock of greater than 100 HHI points in absolute value. The lines exhibit the minimum value observed, the first quartile, the median, the mean, the third quartile, and the maximum value observed. It is important to highlight that the fourth column should not be equal to the third column minus the second column. The labor market that exhibited a Projected HHI of the minimum value, for instance, should not be necessarily the labor market that had a pre-mass layoff HHI of the minimum value.

C Complementary Results from Main Results in Mass Layoff Quasi-Experiment

Table 16: Regression Table of mass layoff quasi-experiment using all mass layoffs shocks

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.0990***	0.0978***	0.0572***
	(0.0067)	(0.0032)	(0.0034)
HHI_{mt}	-3.42×10^{-5}	-2.09×10^{-5}	-4.65×10^{-5}**
	(3.6×10^{-5})	(2.74×10^{-5})	(2.06×10^{-5})
ΔProjected HHI_{mt}	7.55×10^{-6}	1.35×10^{-5}	-5.17×10^{-5}*
	(5.16×10^{-5})	(5.39×10^{-5})	(2.86×10^{-5})
ΔProjected $\text{HHI}_{mt} \times Male_i$	5.44×10^{-5}	1.99×10^{-5}	3.25×10^{-5}
	(4.48×10^{-5})	(2.73×10^{-5})	(2.21×10^{-5})
Labor Market FE (2,313)		×	×
Firm × Labor Market FE (150,747)			×
No. of Negligible HHI Shocks:	3200	3200	3200
No. of Small HHI shocks:	779	779	779
No. of Big HHI shocks:	497	497	497
Observations	1,731,208	1,731,208	1,731,208
R^2	0.37669	0.45839	0.65615
Within R^2	0.35359	0.37658	0.27647

Notes: This Table shows the estimates from Equation 4. The sample consists of office assistants, security guards, and janitors from the human health, information, textile, and construction sectors sample. The sample contains all mass layoff shocks, including those smaller than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. The number in parenthesis after Labor Market FE and Firm × Labor Market FE represents the quantity of fixed effects estimated. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value ≤ 0.01, **: p_value ≤0.05, *: p_value ≤ 0.1).

D Complementary Results from Heterogeneity in Mass Layoff Quasi-Experiment

D.1 Office Assistants

Table 17: Regressions of office assistants in the human health sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-8.84e-5	0.0001	0.0002
	(5.37e-5)	(0.0001)	(0.0002)
ΔProjected HHI_{mt}	-0.0002	2.63e-5	9.92e-5
	(0.0001)	(0.0001)	(0.0001)
$Male$	0.0471***	0.0473***	0.0307***
	(0.0156)	(0.0126)	(0.0106)
ΔProjected $\text{HHI}_{mt} \times Male_i$	0.0003**	0.0001	0.0002**
	(0.0001)	(7.8e-5)	(9.02e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	128	128	128
Total No. of Municipalities:	1010	1010	1010
Observations	11,266	11,266	11,266
R^2	0.50358	0.59222	0.75404
Within R^2	0.47835	0.46124	0.26322

Notes: This table shows the estimates from Equation 4 for office assistants in the human health sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 18: Regressions of office assistants in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	0.0004*	0.0005***	0.0003
	(0.0002)	(0.0002)	(0.0004)
ΔProjected HHI_{mt}	0.0010***	0.0006***	0.0003
	(0.0004)	(0.0002)	(0.0004)
Male	0.0597***	0.0673***	0.0513**
	(0.0179)	(0.0143)	(0.0225)
ΔProjected $\text{HHI}_{mt} \times Male_i$	-0.0002***	2.58e-5	2.32e-5
	(8.16e-5)	(4.46e-5)	(5.88e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	96	96	96
Total No. of Municipalities:	927	927	927
Observations	7,049	7,049	7,049
R^2	0.57291	0.69066	0.80602
Within R^2	0.32860	0.23232	0.14893

Notes: This Table shows the estimates from Equation 4 for office assistants in the information sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 19: Regressions of office assistants in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-6.58e-5	-0.0002*	-0.0003***
	(6.45e-5)	(0.0001)	(0.0001)
ΔProjected HHI_{mt}	1.68e-5	-0.0002	-0.0003**
	(0.0001)	(0.0001)	(0.0001)
$Male$	0.0600*	0.0737***	0.0608**
	(0.0348)	(0.0227)	(0.0268)
ΔProjected $\text{HHI}_{mt} \times Male_i$	-4.81e-5	1.25e-5	5.12e-5
	(4.96e-5)	(4.73e-5)	(4.51e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	144	144	144
Total No. of Municipalities:	951	951	951
Observations	4,192	4,192	4,192
R^2	0.39222	0.61380	0.79037
Within R^2	0.32779	0.29759	0.29476

Notes: This Table shows the estimates from Equation 4 for office assistants in the textile sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 20: Regressions of office assistants in the construction sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	7.05e-6	0.0002	0.0002
	(7.13e-5)	(0.0003)	(0.0002)
ΔProjected HHI_{mt}	8.1e-5	0.0001	0.0003
	(7.2e-5)	(0.0003)	(0.0002)
$Male$	0.1779***	0.1563***	0.1124***
	(0.0308)	(0.0300)	(0.0210)
ΔProjected $\text{HHI}_{mt} \times Male_i$	2.53e-5	-5.45e-5	-6.74e-5
	(6.26e-5)	(4.31e-5)	(0.0001)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	142	142	142
Total No. of Municipalities:	1,025	1,025	1,025
Observations	9,539	9,539	9,539
R^2	0.42375	0.52471	0.76338
Within R^2	0.38292	0.36827	0.31814

Notes: This Table shows the estimates from Equation 4 for office assistants in the construction sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

D.2 Security Guards

Table 21: Regressions of security guards in the human health sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	0.0001*	5.1e-5	-5.53e-5
	(5.18e-5)	(7.95e-5)	(7.12e-5)
ΔProjected HHI_{mt}	0.0002**	4.86e-5	1.64e-5
	(7.25e-5)	(4.49e-5)	(4.72e-5)
$Male$	0.0285	0.0720***	0.0790***
	(0.0321)	(0.0269)	(0.0268)
ΔProjected $\text{HHI}_{mt} \times Male_i$	-3.16e-5	-5.76e-5**	-5.23e-5**
	(4.66e-5)	(2.74e-5)	(2.28e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	84	84	84
Total No. of Municipalities:	324	324	324
Observations	1,187	1,187	1,187
R^2	0.22890	0.54619	0.77070
Within R^2	0.18130	0.05016	0.08013

Notes: This Table shows the estimates from Equation 4 for security guards in the human health sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 22: Regressions of security guards in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-2.39e-5	-0.0006**	
	(4.64e-5)	(0.0002)	
ΔProjected HHI_{mt}	-0.0017	-0.0074	0.2906
	(0.0031)	(0.0049)	(0.3353)
$Male$	0.1013	0.2608*	0.0128
	(0.0626)	(0.1383)	(0.1959)
ΔProjected $\text{HHI}_{mt} \times Male_i$	0.0017	0.0069	0.0006
	(0.0031)	(0.0048)	(0.0043)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	60	60	60
Total No. of Municipalities:	206	206	206
Observations	249	249	249
R^2	0.39073	0.57520	0.89295
Within R^2	0.10588	0.19085	0.27335

Notes: This Table shows the estimates from Equation 4 for security guards in the information sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 23: Regressions of security guards in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-1.92e-5	-1.19e-5	-0.0002
	(2.95e-5)	(0.0002)	(0.0001)
ΔProjected HHI_{mt}	0.0001	-0.0002	3.09e-5
	(0.0001)	(0.0002)	(0.0002)
$Male$	0.0270	0.1639***	0.0814**
	(0.0452)	(0.0600)	(0.0348)
ΔProjected $\text{HHI}_{mt} \times Male_i$	-7.98e-5	0.0002	0.0001
	(0.0001)	(0.0001)	(0.0001)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	104	104	104
Total No. of Municipalities:	332	332	332
Observations	652	652	652
R^2	0.14309	0.59561	0.72842
Within R^2	0.04499	0.08337	0.07530

Notes: This Table shows the estimates from Equation 4 for security guards in the textile sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 24: Regressions of security guards in the construction sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-4.28e-5**	-4.93e-5	8.03e-5**
	(2.09e-5)	(3.18e-5)	(3.48e-5)
ΔProjected HHI_{mt}	-0.0003	-0.0002	3.9e-5
	(0.0004)	(0.0003)	(0.0004)
$Male$	0.1129**	0.0887**	0.1096***
	(0.0474)	(0.0404)	(0.0360)
ΔProjected $\text{HHI}_{mt} \times Male_i$	0.0002	7.57e-5	-6.47e-5
	(0.0003)	(0.0003)	(0.0004)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	88	88	88
Total No. of Municipalities:	397	397	397
Observations	4,117	4,117	4,117
R^2	0.17925	0.41608	0.76782
Within R^2	0.04126	0.01131	0.02140

Notes: This Table shows the estimates from Equation 4 for security guards in the construction sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

D.3 Janitors

Table 25: Regressions of janitors in the human health sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	2.66e-5**	-2.54e-5	1.84e-5
	(1.27e-5)	(2.75e-5)	(1.49e-5)
$\Delta\text{Projected HHI}_{mt}$	3.23e-5	-9.33e-5	1.43e-6
	(2.36e-5)	(6e-5)	(2.07e-5)
$Male$	0.0108	0.0291***	0.0186**
	(0.0107)	(0.0068)	(0.0073)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	3.53e-5	4.39e-6	2.86e-5
	(5.46e-5)	(2.94e-5)	(2.57e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	179	179	179
Total No. of Municipalities:	669	669	669
Observations	18,386	18,386	18,386
R^2	0.09703	0.29068	0.69087
Within R^2	0.04746	0.05789	0.03680

Notes: This Table shows the estimates from Equation 4 for janitors in the human health sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 26: Regressions of janitors in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	1.01e-5	1.92e-5	8.58e-5*
	(2.14e-5)	(3.32e-5)	(4.44e-5)
$\Delta\text{Projected HHI}_{mt}$	9.81e-5*	2.9e-5	0.0002**
	(5.52e-5)	(9.42e-5)	(6.74e-5)
$Male$	0.0521***	0.0696***	0.0570***
	(0.0173)	(0.0161)	(0.0213)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	2.55e-5	0.0001**	3.21e-5
	(5.33e-5)	(5.14e-5)	(5.03e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	112	112	112
Total No. of Municipalities:	492	492	492
Observations	2,285	2,285	2,285
R^2	0.05523	0.30072	0.79424
Within R^2	0.02457	0.02918	0.06649

Notes: This Table shows the estimates from Equation 4 for janitors in the information sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 27: Regressions of janitors in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	0.0001***	1.52e-5	-1.32e-5
	(2.51e-5)	(4.81e-5)	(3.13e-5)
ΔProjected HHI_{mt}	3.09e-5	-8.02e-5*	-8.57e-5
	(4.17e-5)	(4.73e-5)	(6.01e-5)
$Male$	0.0701**	0.0857***	0.0572***
	(0.0349)	(0.0157)	(0.0191)
ΔProjected $\text{HHI}_{mt} \times Male_i$	1.02e-5	-9.81e-6	-2.69e-6
	(7.67e-5)	(4.87e-5)	(4.93e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	136	136	136
Total No. of Municipalities:	527	527	527
Observations	3,289	3,289	3,289
R^2	0.18535	0.55411	0.76317
Within R^2	0.12571	0.04983	0.05204

Notes: This Table shows the estimates from Equation 4 for janitors in the textile sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table 28: Regressions of janitors in the construction sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	1.89e-5	-6.88e-6	-0.0002*
	(2.29e-5)	(2.24e-5)	(0.0001)
ΔProjected HHI_{mt}	-3.52e-5	5.81e-6	-0.0003**
	(6.32e-5)	(3.92e-5)	(0.0001)
$Male$	0.1472***	0.1213***	0.0825*
	(0.0349)	(0.0356)	(0.0441)
ΔProjected $\text{HHI}_{mt} \times Male_i$	6.97e-5	8.15e-5	7.66e-5
	(7.05e-5)	(6.73e-5)	(8.5e-5)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
No. of Big HHI shocks:	127	127	127
Total No. of Municipalities:	526	526	526
Observations	11,855	11,855	11,855
R^2	0.18166	0.39661	0.65932
Within R^2	0.07970	0.05882	0.03730

Notes: This Table shows the estimates from Equation 4 for janitors in the construction sector. The sample contains exclusively observations in which the labor market received a shock due to mass layoffs greater than 20 HHI points in absolute value. Each column is a different specification, and the only difference is which variables are included as a control. All specifications include year-fixed effects and $\mathbb{X}_{imt}$, which are age, the square of age, and education. It is important to highlight that since a single occupation is being analyzed here, the labor market fixed effect is equal to a municipality fixed effect. Standard errors are clustered at the labor market level and are presented in the parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).