Pontifícia Universidade Católica do Rio de Janeiro

Pedro D'Angelo Santos de Moraes

Labor market concentration and the gender wage gap: evidence from mass layoffs

Dissertação de Mestrado

Master's dissertation presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor: Prof. Tomás Guanziroli

Rio de Janeiro
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Abstract

Moraes, Pedro D'Angelo Santos de; Guanziroli, Tomás (Advisor). **Labor market concentration and the gender wage gap: evidence from mass layoffs**. Rio de Janeiro, 2024. 78p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

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.

Keywords

Labor; Gender; Labor Market Concentration; Labor Market Power.

Resumo

Moraes, Pedro D'Angelo Santos de; Guanziroli, Tomás. **Concentração no mercado de trabalho e a disparidade salarial entre homem e mulher: evidência de demissões em massa**. Rio de Janeiro, 2024. 78p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Eu investigo a extensão em que o poder de mercado de trabalho no mercado de trabalho formal brasileiro contribui para a prevalência da disparidade salarial entre homem e mulher. Primeiro, eu mostro que maior concentração no mercado de trabalho é associada a maiores disparidades salariais entre homem e mulher, embora essa associação nao explique grande parte da disparidade. Em seguida, eu uso variação quasi-experimental de demissões em massa para identificar a relação causal entre concentração no mercado de trabalho e a disparidade salarial entre homem e mulher. Essa análise é restrita a quatro setores e três ocupações. Os resultados sugerem que se mercados de trabalho fossem perfeitamente competitivo, a disparidade salarial entre homem e mulher residual seria de 38% a 73.8% menor, dependendo da especificação.

Palavras-chave

Economia do Trabalho; Gênero; Concentração no Mercado de Trabalho; Poder de Mercado de Trabalho.

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CBO – *Classificação Brasileira de Ocupações*

CNAE – *Comissão Nacional de Atividades Espaciais*

DOJ – Department of Justice

HHI – Herfindahl–Hirschman Index

OECD – Organization for Economic Cooperation and Development

RAIS – *Relação Anual de Informações Sociais*

Injustice anywhere is a threat to justice everywhere.

Martin Luther King Jr., *Letter to Birmingham Jail - April 16, 1963.*

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 e Kahn, 1996; Weichselbaumer e Winter-Ebmer, 2005; Goldin, 2014; Blau e Kahn, 2017). For example, the gender wage gap in Brazil has remained practically stable over the last 10 years, from 24.7% (Madalozzo e 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 e Charles, 2013; Weber e 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.

[1]Aguero e Marks (2008), Bertrand, Goldin e Katz (2010), Goldin (2014), Angelov, Johansson e Lindahl (2016), Blau e Kahn (2017), Adda, Dustmann e Stevens (2017), Wiswall e Zafar (2017), Grossman et al. (2019), Kleven, Landais e Søgaard (2019), Barbanchon, Rathelot e Roulet (2020), Biasi e Sarsons (2021), Exley e Kessler (2022), Roussille (2024)

[2]Barth e Dale-Olsen (2009), Riach e Rich (2002), Weber e Zulehner (2014), Guryan e Charles (2013), Card, Cardoso e Kline (2016)

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, such as schooling, experience, and occupational choices (Goldin, 2014; Blau e Kahn, 2017), and firm-specific premiums (Card, Cardoso e Kline, 2016; Barth e 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 e Dale-Olsen, 2009; Hirsch, Schank e Schnabel, 2010; Vick, 2017; Caldwell e 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, Marinescu e Steinbaum, 2022; Bassanini, Batut e Caroli, 2023). Others derived general equilibrium models to more precisely comprehend labor market power and its implications to wages (Berger, Herkenhoff e Mongey, 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 e Schmitt, 2021; Guanziroli, 2023).

This paper relates to several models explaining the relationship between imperfect competition and discrimination. The first is Becker (1957) taste-based discrimination, which suggests that employers preferring men would offer lower wages to women. However, in competitive markets, such employers would disappear, and the gender wage gap would not persist. Since we do observe this gap, economists explored alternative explanations. Some monopsony models, for example, argue that jobs are differentiated due to heterogeneous preferences, leading to upward-sloping labor supply curves for firms (Burdett e Mortensen, 1998; Manning, 2013). In monopsonistic discrimination, the gender gap arises if women's labor supply elasticity is lower than men's (Barth e Dale-Olsen, 2009; Sharma, 2022).

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.[1] 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.[2] 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.[3]

To determine the industry of a specific employer, I utilize the industry code available from RAIS.[4] This code system categorizes economic activities across various sectors and industries. Additionally, I use the occupation code variable.[5] This variable categorizes occupations hierarchically. I utilize both of these variables to select contracts for specific occupations and sectors. The

[1] Decret Nº 76.900.

[2] 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.

[3] 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”.

[4] “Classificação Nacional de Atividades Econômicas” (CNAE).

[5] “Classificação Brasileira de Ocupações” (CBO)

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:

$$s_{zmt} \equiv \frac{n_{zmt}}{\sum_{j \in \Theta_m} n_{jmt}}, \tag{2-1}$$

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:

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

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., 2018; Azar, Marinescu e Steinbaum, 2022; Felix, 2022; Schubert, Stansbury e Taska, 2024), geography × sector boundaries (Urena, Manelici e Vasquez, 2021; Berger, Herkenhoff e Mongey, 2022), and geography only (Dix-Carneiro e 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 definition used is micro-region × occupation.[6] 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. Therefore, I use the full six-digit occupational code, and the municipality as a geography instead of micro-region.[7]

[6] The author uses the first two-digit occupational code. For more information on occupational codes, see footnote 7.

[7] 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 47 categories. The third and fourth digits identify the Occupational Subgroup, dividing occupations into 192 categories. The fifth digit denotes the Occupational Family, dividing occupations into 596 categories. Finally, the last digit defines the full six-digit Occupation code, which consists of 2,422 different occupations. 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:

$$Y_{imt} = \beta_1 HHI_{mt} + \beta_2 HHI_{mt} \times Male_i + \beta_3 Male_i + \beta_4 \mathbb{X}_{imt} + \delta_t + \delta_m + \delta_{zm} + \delta_i + \epsilon_{imt}, \tag{3-1}$$

where Y_{imt} is the real December wage[1] 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,

[1]Real value from January 2010.

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.[2]

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 3-1 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.[3]

[2]In fact, Robinson (1934) has brought up the model for monopsonistic discrimination a long time. Yet, 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 e Dale-Olsen (2009), Sharma (2022), Caldwell e Oehksen (2023).

[3]It is clear to see why that is the case. If there were no movers, it would not be possible

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 variations.[4] 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 3.1 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.

3.3 Results

I show the results of the estimates of Equation 3-1 in Table 3.2. 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 first result is how the coefficient associated with 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

to distinguish the labor market and individual fixed effects.

[4]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 3.1: 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.

the gender gap in Table 3.1. When we include the HHI variable alone in the second column, the coefficient 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 3.1.

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 $\times$ 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, Cardoso e Kline (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%.

The coefficient of interest in this analysis is HHI $\times$ $Male$, which captures the impact of labor market concentration on the gender wage gap. The estimates for this interaction term suggest that labor market concentration has a modest direct effect on the gender wage gap. Based on the estimate in the third column, transitioning from a monopsony to perfect competition would reduce the gender wage gap by nearly 14 percentage points, which initially appears substantial. However, considering that the average worker operates in

Table 3.2: 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 3-1 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 ≤ 0.01, **: p_value ≤0.05, *: p_value ≤ 0.1).

a market with an HHI of 315 points, moving this average market to perfect competition would only decrease the gap by approximately 0.44 percentage points.[5] This translates to a gender wage gap reduction of just 1.55%. When controlling for firm-labor market fixed effects, this impact becomes negligible.

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 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.

[5]This calculation is performed by multiplying $\frac{315}{10{,}000} \times 0.139$.

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, e.g., productivity, cost structures, and different demands, are jointly determined with HHI_{mt}. Given the endogeneity of the labor market concentration variable, exogenous variation is required to properly identify the causal effect.

I use mass layoffs as a source of variation in labor market concentration. Note 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, and many of them are confounded with productivity. Suppose a shock affects a key firm in a labor market, leading it to implement mass layoffs. As a result, the labor market power of other firms changes as well. Firms should adjust wages accordingly. However, the sector's productivity has decreased since a key firm was impacted. Given that wages are tied to productivity, wages are now lower.

I focus on 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.[1] The sectors are human health, information, textile, and construction sectors.[2] 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 selected occupations that are present across various sectors in order that the mass layoff shocks significantly varied the labor market concentration. Additionally, selecting specific sectors enables me to analyze how changes in labor market power within those sectors affect the gender gap.

While the choice of occupations is closely tied to the empirical strategy, the selection of sectors was more flexible as it does not directly influence

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

[2]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.

the strategy. I chose the four sectors—construction, health, information, and textile—for the following reasons: Construction was selected because it has the lowest female representation in the sample. Health was chosen due to its highest female representation. The information sector was included as it represents a "median" level of female participation among the sectors. The textile sector was selected because it is also intermediate. Finally, the inclusion of the last two sectors allows for comparison with, respectively, Goldin (2014) and Sharma (2022).

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

$$\begin{aligned} Y_{imjt} = \beta_1 HHI_{mt} + \beta_2 \Delta\text{Projected HHI}_{mt} + \beta_3 \Delta\text{Projected HHI}_{mt} \times Male_i + \\ + \beta_4 Male_i + \beta_5 \mathbb{X}_{imjt} + \delta_t + \delta_m + \delta_{zm} + \epsilon_{imt}. \end{aligned} \tag{4-1}$$

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.

Including labor market and firm-labor market fixed effects improves identification. While the timing of the shock in ΔProjected HHI$_{mt}$ is likely exogenous, the size of the shock may not be. Fixed effects for labor markets should address this issue. Simultaneously, mass layoffs might impact firms differently, with some experiencing them more frequently than others. I aim to account for this variation by incorporating firm-labor market fixed effects.

Now, I define the projected changes in HHI due to mass layoffs, referred to as the Projected HHImt variable. Let $szmjt$ represent the share of employees as previously defined, with the subscript j indicating sector j. Since a labor market m is defined as occupation $\times$ municipality, it can be segmented at the sector level without conflict. In other words, the HHI for the janitors' labor market depends on the share of employees from each firm that hires janitors in the health sector, the construction sector, and so on. 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 note 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 other than j.[3]

To define mass layoff events, I follow two steps. First, I calculate the difference in active contracts within a firm for each year. Following Britto, Pinotti e Sampaio (2022), I define a mass layoff as occurring if a firm with more than 50 workers (of any occupation) lays off more than 30% of them.

The coefficient of interest in Equation 4-1 is β_3. If the gender gap widens with increased labor market power, then β_3 should be positive. Conversely, β_2 is expected to be negative, as Projected HHI_{mt} captures the causal effect of labor market power; thus, greater labor market power should correspond to lower wages.

The coefficient of HHI_{mt}, β_1, should not be interpreted causally, however. As previously mentioned, the pre-mass layoff HHI level is endogenous.[4] Nonetheless, its inclusion as a control is crucial. A shock in ΔProjected HHImt may be correlated with the pre-mass layoff HHI level. For example, a 50-point shock in ΔProjected HHImt 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.

There are two main identification hypotheses. First, the timing and which firms are carrying out the mass layoffs are unanticipated by other firms. For example, both hospitals and real estate firms employ janitors. It seems unlikely that a specific hospital can predict which real estate firms will perform mass layoffs or when they will do so. Therefore, the variation in labor market concentration should be considered exogenous. Consequently, this strategy enables me to examine the impact on the gender wage gap for janitors in the health sector when the labor market power of janitors varies.

Second, the selected mass layoff shocks should not be confounded with productivity shocks. If real estate firms are carrying out mass layoffs, I would expect productivity shocks for janitors working in the real estate sector. However, the productivity of janitors in the health sector should remain unaffected by these mass layoffs. Therefore, any observed variation in the gender wage gap should stem from changes in the labor market power of

[3]This is a common analysis related to market concentration. For instance, if two large firms were to merge, Projected HHImt captures how this merger would affect the market, assuming all else remains constant.

[4]See Appendix A for a more detailed discussion.

these janitors. If these two hypotheses hold, then Projected HHI_{mt} should be exogenous in Equation 4-1.

The main limitation of this approach is that the magnitude of the shock might not be exogenous. The magnitude of the shock is likely correlated with the size of the market. For example, in larger metropolitan areas, the shocks are expected to be smaller, as 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.

4.2 Sample Selection and Descriptives

In subsection 4.1, I discussed the rationale for focusing on office assistants, janitors, and security guards across the human health, information, textile, and construction sectors. Additionally, I restrict the analysis to new contracts. Identifying wage adjustments for existing contracts can be challenging, as firms cannot reduce wages. By focusing on new contracts, I aim to achieve a clearer identification of changes in labor market power and their impact on the gender wage gap.

As an additional restriction, I exclude markets with shocks smaller than 20 points in $\Delta\text{Projected HHI}_{mt}$, in absolute value. This is because the majority of shocks are very close to zero. It occurs because mass layoffs are defined at the firm level, meaning that while a company may conduct a mass layoff, it may terminate only a few employees in the occupations of interest.[5] With many near-zero shocks, the quality of inference could be compromised due to high variance in this small range.[6]

Moreover, it aligns with the goal of this analysis to focus on shocks larger than 20 points in absolute value. These are the shocks that effectively alter market power to a meaningful degree. 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 are typically defined as those exceeding 100 or 200 points, depending on the context.[7] I define a significant shock as one that results in

[5]Despite this limitation, defining mass layoffs at the firm level remains more appropriate than defining them at the occupation level. For instance, requiring a firm to have at least 50 janitors and lay off at least 30% of them would be excessively restrictive.

[6]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 enhances the robustness of the results without fundamentally altering the findings.

[7]The DOJ would classify a merger as potentially creating a monopsony if it increased the HHI by 100 points and either resulted in an HHI market level greater than 1800 or a firm with a market share greater than 30%. The report by Azar et al. (2019) considers a change

a change of more than 100 HHI points. By excluding shocks smaller than 20 points in absolute value, I retain smaller shocks for comparison purposes.

The descriptive statistics for the workers used in this section are presented in Table 4.1. The sample for the mass layoff quasi-experiment differs notably from the sample used in section 3. Both women's and men's average wages are significantly lower. 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.

One potential concern is the mobility of individuals across occupations and sectors. On the one hand, I defined the labor market as occupation $\times$ municipality, but I specifically chose occupations that were not strongly tied to any particular sector. If individuals can easily switch out of these occupations, this could be a conflicting concern. On the other hand, due to the nature of the empirical strategy, it would be desirable for individuals to have high mobility across sectors within the same occupation so that mass layoffs could effectively shift labor market concentration. The table on occupation and sector mobility is available in Appendix B. It shows that mobility within occupations is reasonably high, while sector mobility appears to be somewhat higher in comparison.

This sample is also more frequently employed in markets with significantly higher concentration compared to the previous sample. Additionally, women and men now appear to be working in markets with similar concentration levels, whereas a larger disparity was observed previously. The ΔProjected HHI$_{mt}$ shocks are very similar for men and women, and are generally less than 100 HHI points, classifying them as not significant.

When analyzing the distribution of mass layoff shocks, it is evident that more than half of the shocks were negative. Figure 4.1 plots all the shocks used in the analysis, with pre-mass layoff HHI on the horizontal axis and projected HHI on the vertical axis. Each point represents a shock in a specific labor market and year. The points are predominantly located below the 45° line, indicating that most mass layoff shocks decreased labor market concentration. In Appendix B, Table B.5 reveals that the average shock was a decrease of 99 HHI points, and the median shock was a decrease of 35 points. Approximately 33% of the shocks were classified as significant. Figures B.1 and B.2 in Appendix B illustrate that, although the majority of shocks were less than 20 points in absolute value, there is substantial variation in shocks that can be utilized.

Table 4.1 indicates no correlation between the gender wage gap and labor

of 200 HHI points sufficient to increase labor market power.

Figure 4.1: 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 4.1: 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

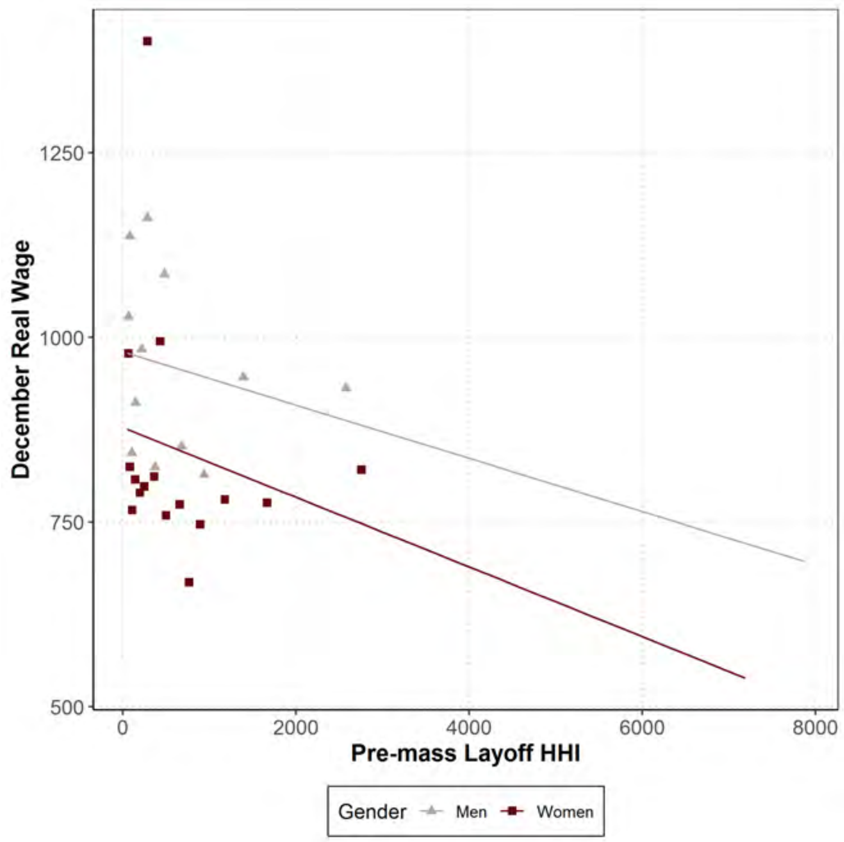
Notes: This Table presents descriptive statistics for workers utilized in the mass layoff quasi-experiment. The sample comprises exclusively new contracts and labor markets that experienced shocks greater than 20 points in absolute value. The first column depicts these statistics for all workers pooled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

market concentration. As in the previous sample, the gender gap is evident, but both men and women are employed in labor markets with similar levels of concentration. Women are slightly more likely to be in markets with higher concentration, suggesting a potential weak association between labor market concentration and the gender wage gap. To further investigate this association, I conducted a binscatter regression analysis, following Cattaneo et al. (2024).[8]

The binscatter regression analysis presented in Figure 4.2 weakly suggests that the gender wage gap may not widen with increased labor market concentration. As expected, higher labor market concentration is associated with lower wages for both men and women. It is also evident that men earn higher wages than women across nearly all levels of labor market concentration. However, if the gender gap were to widen with increased labor market concentration, we would expect to see a difference in the slopes of the lines. The dark red line is slightly steeper, which could be consistent with a higher gender gap in more concentrated labor markets. Nonetheless, the difference in slopes might be influenced by the uncertainty associated with the data points further to the right.

[8]Binscatter is commonly used for visualizing bivariate relationships and performing informal specification testing. Cattaneo et al. (2024) enhance this method by incorporating optimal binning for estimating conditional means and techniques to quantify uncertainty.

Figure 4.2: 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.

4.3 Main Results

Table 4.2 presents the results estimated using Equation 4-1 for all selected occupations and sectors. In the first column, only year-fixed effects are included. In the second column, labor market fixed effects are added, meaning the results capture variation within labor markets. In the third column, firm-labor market fixed effects are incorporated. Since ΔProjected HHI$_{mt}$ is measured at the labor market level, the variation remains within labor markets. In all specifications, standard errors are clustered at the labor market level.

In all columns, the coefficient of interest, ΔProjected HHI$mt \times Malei$, is positive, indicating that men tend to earn higher wages than women in more concentrated labor markets. Going from a perfectly competitive market to a monopsony would increase the gender wage gap between 45% and 76%.

Table 4.2: 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}	-0.1230	0.2343	0.0274
	(0.1808)	(0.3196)	(0.1659)
ΔProjected HHI_{mt}	0.3400	0.3224	-0.3304
	(0.4080)	(0.7503)	(0.2123)
ΔProjected $\text{HHI}_{mt} \times Male$	0.7561**	0.4525*	0.4837**
	(0.3698)	(0.2441)	(0.1964)
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 4-1. 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).

Since the majority of mass layoffs led to negative shocks in labor market concentration, the average effect across markets was a reduction in the gender wage gap.

This finding aligns with the initial hypothesis that labor market power influences the gender wage gap. Specifically, the results suggest that firms with greater monopsony power may be better positioned to exploit differences in labor supply elasticities between men and women, resulting in wage disparities. The observed gender wage gap could therefore be driven not solely by discrimination in a competitive sense, but by the strategic behavior of firms facing less elastic female labor supply, as proposed in monopsonistic models.

To quantify the impact of the mass layoff shocks, it is necessary to translate the coefficient of interest into changes in the wage gap. This is done by multiplying the coefficient by a shock of relevant magnitude. I use the first quartile shock, a negative shock of 132 HHI points.

The results are presented in Counterfactual A of Table 4.3. Interestingly, the negative shock in labor market concentration had a limited effect on the gender wage gap, reducing it by at most 1 percentage point. However, in relative terms, this reduction is more notable, amounting to a decrease of up to 10.4%.

An important extension of the analysis involves examining the potential impact of eliminating labor market concentration entirely. The average labor market concentration stands at 934 HHI points, so I replicate the previous exercise using a shock of this magnitude. The results, summarized in Counterfactual B of Table 4.3, suggest that the relative reduction in the gender wage gap would range from 38% to 73%. This indicates that enhancing competition could substantially reduce the gender wage gap. However, even in fully competitive labor markets, a residual gender wage gap would likely persist.

Table 4.3: 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: Reducing HHI by 132 points			
Effect 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 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 4-1. 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 4.2. 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 Equation 4-1 for all mass layoff shocks, including those smaller than 20 HHI points. The results are shown in Table C.1. Although the estimates for the coefficient of interest, ΔProjected HHImt ×

$Malei$, are not statistically significant, their magnitude remains similar to those in Table 4.2. As expected, the large number of near-zero observations likely complicates inference. The similarity in the estimates suggests they follow the same trend.

In addition, I remake this exercise without controlling for HHI_{mt}. The results are shown in Table C.2. The estimates for the coefficient of ΔProjected HHImt × $Malei$ remain similar to those in Table 4.2.

A key limitation of these findings is their external validity. The sample is composed of workers in labor markets with meaningful variation in labor market concentration. Persistent, highly concentrated labor markets may not be captured in this sample, and such markets might be structurally concentrated beyond the reach of policy interventions. Additionally, the sample includes occupations that are prevalent across various sectors, and the results may not apply to sector-specific occupations, such as physicians in the health sector or engineers in construction.

4.4 Heterogeneity by Occupations and Sectors

In this section, I present the results separately for each selected occupation and sector. I estimate Equation 4-1 for each occupation and sector combination, with the regression tables provided in Appendix D.[9] To replicate the analysis of the impact of labor market concentration on the gender wage gap from Subsection 4.3, I use the coefficients from the second specification, which includes year and labor market fixed effects only.[10]

Looking at the first panel of Table 4.4, it is clear that all occupations exhibit a positive gender wage gap. In the second panel, which presents Counterfactual A, it is notable that most changes in labor market concentration reduced the gender wage gap. Many of these reductions appear small at first glance, with the exception being security guards in the information sector. In the third panel, we observe that many of the relative changes in the gender wage gap are also modest, with five of them being less than 10%. However, three changes stand out as potentially significant, with reductions ranging between 19% and 33%.

[9]To mimic the last section, I also remake this exercise excluding the HHI_{mt} variable in D.

[10]Within each occupation and sector, the coefficients for ΔProjected HHI_{mt} are of similar magnitude across specifications. While statistical significance may vary, this is likely due to the lower statistical power in the occupation-sector subsamples. It is also possible that labor market concentration is not always relevant in explaining the gender wage gap. In any case, choosing a coefficient from a different specification would likely not alter the analysis significantly.

Table 4.4: 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: Reduction in HHI by the 1st Quartile Shock		
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 4-1 for each combination of sector and occupation. In the Counterfactual A panel, I multiply the coefficient ΔProjected $\text{HHI}_{mt} \times Male$ by the first quartile shock for each relevant labor market, as measured 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.

Four results deviate from expectations: 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.

Table D.6 in appendix C shows that security guards in the information sector come from a very small sample, and none of the estimates are significant. Table D.5 indicates that the sample of security guards in the human health sector is more substantial. However, tables B.3 and B.4 reveal that the sample had more than five times as many male security guards as female ones, which may explain why the results for this occupation in this sector are less reliable.

In contrast, the results for office assistants in the construction sector and janitors in the textile sector are based on substantial sample sizes with similar proportions of men and women. Despite this, the estimates for both occupations are not statistically significant.

The gender gap at baseline results in the health sector is the smallest among the sectors analyzed. This aligns with the findings of Goldin (2014), who also documented the smallest gender gaps in the health sector. She argues that this is likely due to how time flexibility interacts non-linearly with wages in different occupations, less likely in health-related occupations, where the relationship appears to be more linear. This could explain why the gender wage gap is smaller in the health sector, both in her findings and in my results.

On the other hand, comparing the relative reduction in the gender wage gap due to the decrease in labor market concentration with Goldin's results is more challenging. It is difficult to determine how time flexibility might interact with market concentration. This creates limitations in drawing direct comparisons between the two studies, particularly regarding the dynamics of how market power could affect time flexibility and, in turn, the gender wage gap.

When I compare my results with those of Sharma (2022), my estimates are notably smaller. While Sharma finds that gender differences in monopsony could account for an 18 percentage point gender wage gap among equally productive men and women, explaining over half of the observed 42% gender wage gap in the textile industry, my results suggest that a first-quartile negative shock to labor market concentration represents at most a reduction of less than 1 percentage point, and relatively up to a 10% reduction.

However, it is important to note that the results are not directly comparable. Sharma (2022) estimates an average markdown, which may conceal heterogeneous effects across different contexts. In contrast, I examine the impact of a first-quartile reduction in the distribution of HHI shocks. Even so, as shown in Table B.5, the average shock and the first-quartile shock are relatively close. Thus, there may be some comparability between my shocks and those analyzed by Sharma, and her results are indeed more pronounced.

Overall, the heterogeneity analysis aligns with the results from section 4.3. Eight out of twelve estimates are within the expected range. Among the four unexpected results, two can be explained by sample issues. Thus, the majority of findings suggest that a reduction in labor market concentration could potentially decrease the gender wage gap.

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.

6
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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%. [1] The resulting HHI in both markets is 5,288. Table A.1 summarizes this situation.

Table A.1: 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 A.1. They would find a positive correlation between HHI and wages.

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

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. 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 A.2 and A.3. 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 A.2: 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 A.3: 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 B.1: 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 B.2: 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 B.3: 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 B.4: 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.

Table B.5: 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 B.6: 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.

Table B.7: Mobility of Occupations

Office Assistant	Security Guard	Janitor
47.76%	63.94%	65.83%

Notes: This Table presents the mobility of occupations within the mass layoff experiment sample. The number corresponds to given that a person is changing jobs, how many of them stay in that occupation.

Table B.8: Mobility of Sectors

Human Health	Information	Textile	Construction
62.55%	80.44%	69.61%	71.91%

Notes: This Table presents the mobility of sectors within the mass layoff experiment sample. The number corresponds to given that a person is changing jobs, how many of them stay in that sector.

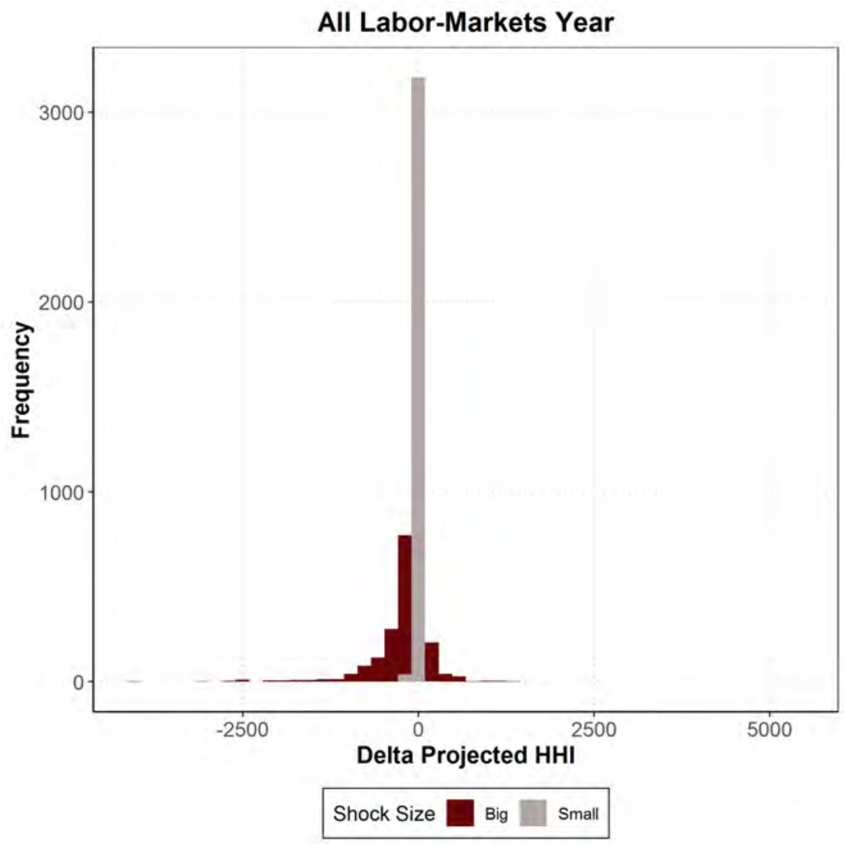

Figure B.1: Histogram of ΔProjected HHI with mass layoffs variation, by size of shock

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.

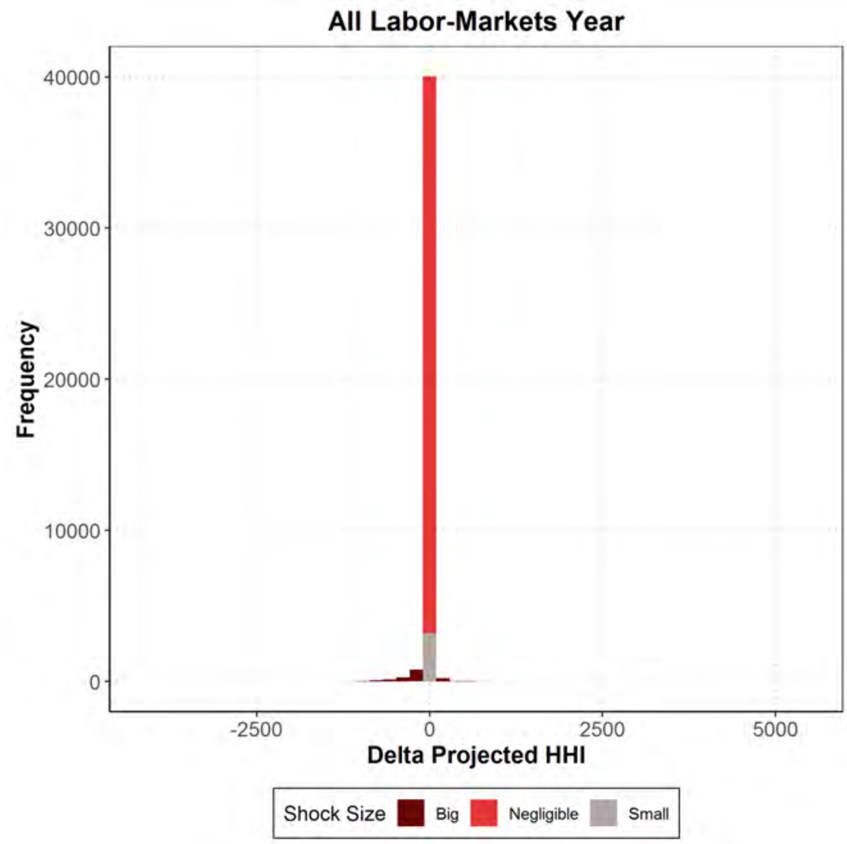

Figure B.2: Histogram of ΔProjected HHI with mass layoffs variation, by size of shock

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.

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

Table C.1: 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}	-0.3420	-0.2090	-0.4650**
	(0.3600)	(0.2740)	(0.2060)
ΔProjected HHI_{mt}	0.0755	0.1350	-0.5170*
	(0.5160)	(0.5390)	(0.2860)
ΔProjected $\text{HHI}_{mt} \times Male_i$	0.5440	0.1990	0.3250
	(0.4480)	(0.2730)	(0.2210)
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 4-1. 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 $\leq$ 0.01, **: p_value $\leq$0.05, *: p_value $\leq$ 0.1).

Table C.2: Regression Table of mass layoff quasi-experiment

	Log Real Wage		
	(1)	(2)	(3)
Male	0.1422***	0.1110***	0.0645***
	(0.0193)	(0.0134)	(0.0113)
ΔProjected HHI_{mt}	0.4337	0.1833	-0.3471**
	(0.3929)	(0.6083)	(0.0113)
ΔProjected $\text{HHI}_{mt} \times Male$	0.7082**	0.4651*	0.4869**
	(0.3379)	(0.2528)	(0.2008)
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	0.28786	0.45751	0.75350
Within R^2	0.26584	0.24266	0.13161

Notes: This Table shows the estimates from Equation 4-1. 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).

D
Complementary Results from Heterogeneity in Mass Layoff Quasi-Experiment

D.1
Full Regression

D.1.1
Office Assistants

Table D.1: Regressions of office assistants in the human health sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-0.8840	1.0000	2.0000
	(0.5370)	(1.0000)	(2.0000)
$\Delta\text{Projected HHI}_{mt}$	-2.0000	0.2630	0.9920
	(1.0000)	(1.0000)	(1.0000)
$Male$	0.0471***	0.0473***	0.0307***
	(0.0156)	(0.0126)	(0.0106)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	3.0000**	1.0000	2.0000**
	(1.0000)	(0.7800)	(0.9020)
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 4-1 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 D.2: Regressions of office assistants in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	4.0000*	5.0000***	3.0000
	(2.0000)	(2.0000)	(4.0000)
$\Delta\text{Projected HHI}_{mt}$	10.0000***	6.0000***	3.0000
	(4.0000)	(2.0000)	(4.0000)
$Male$	0.0597***	0.0673***	0.0513**
	(0.0179)	(0.0143)	(0.0225)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	-2.0000***	0.2580	0.2320
	(0.8160)	(0.4460)	(0.5880)
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 4-1 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 D.3: Regressions of office assistants in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-0.6580	-2.0000*	-3.0000***
	(0.6450)	(1.0000)	(1.0000)
ΔProjected HHI_{mt}	0.1680	-2.0000	-3.0000**
	(1.0000)	(1.0000)	(1.0000)
$Male$	0.0600*	0.0737***	0.0608**
	(0.0348)	(0.0227)	(0.0268)
ΔProjected $\text{HHI}_{mt} \times Male_i$	-0.4810	0.1250	0.5120
	(0.4960)	(0.4730)	(0.4510)
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 4-1 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 D.4: Regressions of office assistants in the construction sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	0.0705	2.0000	2.0000
	(0.7130)	(3.0000)	(2.0000)
ΔProjected HHI_{mt}	0.8100	1.0000	3.0000
	(0.7200)	(3.0000)	(2.0000)
$Male$	1.7790***	1.5630***	1.1240***
	(0.3080)	(0.3000)	(0.2100)
ΔProjected $\text{HHI}_{mt} \times Male_i$	0.2530	-0.5450	-0.6740
	(0.6260)	(0.4310)	(1.0000)
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 4-1 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.1.2
Security Guards

Table D.5: Regressions of security guards in the human health sector subsample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	1.0000*	0.5100	-0.5530
	(0.5180)	(0.7950)	(0.7120)
ΔProjected HHI_{mt}	2.0000**	0.4860	0.1640
	(0.7250)	(0.4490)	(0.4720)
$Male$	2.8500	7.2000***	7.9000***
	(3.2100)	(2.6900)	(2.6800)
ΔProjected $\text{HHI}_{mt} \times Male_i$	-0.3160	-0.5760**	-0.5230**
	(0.4660)	(0.2740)	(0.2280)
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 4-1 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 D.6: Regressions of security guards in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-0.2390	-6.0000**	
	(0.4640)	(2.0000)	
$\Delta\text{Projected HHI}_{mt}$	-17.0000	-74.0000	2906.0000
	(31.0000)	(49.0000)	(3353.0000)
$Male$	10.1300	26.0800*	1.2800
	(6.2600)	(13.8300)	(19.5900)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	17.0000	69.0000	60.0000
	(31.0000)	(48.0000)	(43.0000)
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 4-1 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 D.7: Regressions of security guards in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-0.1920	-1.1900	-20.0000
	(0.2950)	(2.0000)	(1.0000)
ΔProjected HHI_{mt}	1.0000	-2.0000	3.0900
	(1.0000)	(2.0000)	(2.0000)
$Male$	0.0270	0.1639***	0.0814**
	(0.0452)	(0.0600)	(0.0348)
ΔProjected $\text{HHI}_{mt} \times Male_i$	-0.7980	2.0000	1.0000
	(1.0000)	(1.0000)	(1.0000)
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 4-1 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 D.8: Regressions of security guards in the construction sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	-0.4280**	-0.4930	0.8030**
	(0.2090)	(0.3180)	(0.3480)
$\Delta\text{Projected HHI}_{mt}$	-3.0000	-2.0000	0.3900
	(4.0000)	(3.0000)	(4.0000)
$Male$	0.1129**	0.0887**	0.1096***
	(0.0474)	(0.0404)	(0.0360)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	2.0000	0.7570	-0.6470
	(3.0000)	(3.0000)	(4.0000)
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 4-1 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.1.3 Janitors

Table D.9: Regressions of janitors in the human health sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	0.2660**	-0.2540	0.1840
	(0.1270)	(0.2750)	(0.1490)
ΔProjected HHI_{mt}	0.3230	-0.9330	0.0143
	(0.2360)	(0.6000)	(0.2070)
$Male$	0.0108	0.0291***	0.0186**
	(0.0107)	(0.0068)	(0.0073)
ΔProjected $\text{HHI}_{mt} \times Male_i$	0.3530	0.0439	0.2860
	(0.5460)	(0.2940)	(0.2570)
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 4-1 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 D.10: Regressions of janitors in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	0.1010	0.1920	0.8580*
	(0.2140)	(0.3320)	(0.4440)
ΔProjected HHI_{mt}	0.9810*	0.2900	2.0000**
	(0.5520)	(0.9420)	(0.6740)
$Male$	0.0521***	0.0696***	0.0570***
	(0.0173)	(0.0161)	(0.0213)
ΔProjected $\text{HHI}_{mt} \times Male_i$	0.2550	1.0000**	0.3210
	(0.5330)	(0.5140)	(0.5030)
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 4-1 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 D.11: Regressions of janitors in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	1.0000***	0.1520	-0.1320
	(0.2510)	(0.4810)	(0.3130)
$\Delta\text{Projected HHI}_{mt}$	0.3090	-0.8020*	-0.8570
	(0.4170)	(0.4730)	(0.6010)
$Male$	0.0701**	0.0857***	0.0572***
	(0.0349)	(0.0157)	(0.0191)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	0.1020	-0.0981	-0.0269
	(0.7670)	(0.4870)	(0.4930)
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 4-1 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 D.12: Regressions of janitors in the construction sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
HHI_{mt}	0.1890	-0.0688	-2.0000*
	(0.2290)	(0.2240)	(1.0000)
$\Delta\text{Projected HHI}_{mt}$	-0.3520	0.0581	-3.0000**
	(0.6320)	(0.3920)	(1.0000)
$Male$	0.1472***	0.1213***	0.0825*
	(0.0349)	(0.0356)	(0.0441)
$\Delta\text{Projected HHI}_{mt} \times Male_i$	0.6970	0.8150	0.7660
	(0.7050)	(0.6730)	(0.8500)
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 4-1 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).

D.2 Without Controlling for Pre Mass Layoffs HHI

D.2.1 Office Assistants

Table D.13: Regressions of office assistants in the human health sector subsample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.0430***	0.0465***	0.0304***
	(0.0146)	(0.0126)	(0.0106)
ΔProjected HHI_{mt}	-0.6610	-0.5012	-0.0277
	(0.8099)	(0.5703)	(0.5285)
$Male \times \Delta$Projected HHI_{mt}	2.002**	1.003	2.060**
	(0.7855)	(0.8050)	(0.9034)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	1,010	1,010	1,010
N.o of Big HHI shocks:	128	128	128
Observations	11,266	11,266	11,266
R^2	0.50134	0.59213	0.75396
Within R^2	0.47600	0.46113	0.26299

Notes: This Table shows the estimates from Equation 4-1 for office assistants in the human health. 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.14: Regressions of office assistants in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.0546***	0.0674***	0.0521**
	(0.0185)	(0.0147)	(0.0230)
ΔProjected HHI$_{mt}$	6.671**	1.704***	0.3159
	(2.742)	(0.4986)	(0.9580)
$Male \times \Delta$Projected HHI$_{mt}$	-2.750**	0.0493	0.1358
	(1.117)	(0.3632)	(0.5894)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	927	927	927
N.o of Big HHI shocks:	96	96	96
Observations	7,049	7,049	7,049
R^2	0.56366	0.68977	0.80586
Within R^2	0.31406	0.23011	0.14823

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.15: Regressions of office assistants in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.0488	0.0705***	0.0563**
	(0.0348)	(0.0232)	(0.0277)
ΔProjected HHI$_{mt}$	0.7882	-0.0617	-0.4836
	(0.8699)	(0.3284)	(0.6866)
$Male$ × ΔProjected HHI$_{mt}$	-0.6338	0.0483	0.3500
	(0.5162)	(0.4548)	(0.4234)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	951	951	951
N.o of Big HHI shocks:	144	144	144
Observations	4,192	4,192	4,192
R^2	0.38896	0.61316	0.78895
Within R^2	0.32419	0.29641	0.29000

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.16: Regressions of office assistants in the construction sector subsample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.1777***	0.1562***	0.1126***
	(0.0311)	(0.0300)	(0.0210)
ΔProjected HHI_{mt}	0.7812	-0.2938	0.6794
	(0.6062)	(0.4788)	(0.5916)
$Male \times \Delta$Projected HHI_{mt}	0.2323	-0.5568	-0.6581
	(0.5664)	(0.4323)	(1.066)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	1,025	1,025	1,025
N.o of Big HHI shocks:	142	142	142
Observations	9,539	9,539	9,539
R^2	0.42374	0.52461	0.76333
Within R^2	0.38291	0.36813	0.31801

Notes: This Table shows the estimates from Equation 4-1 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

D.2.2
Security Guards

Table D.17: Regressions of security guards in the human health sector subsample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.0037	0.0719***	0.0790***
	(0.0567)	(0.0269)	(0.0268)
ΔProjected HHI$_{mt}$	1.647	0.5283	0.1043
	(1.087)	(0.4562)	(0.4431)
$Male \times \Delta$Projected HHI$_{mt}$	-0.8121	-0.5976**	-0.4979**
	(0.6623)	(0.2792)	(0.2232)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	324	324	324
N.o of Big HHI shocks:	84	84	84
Observations	1,187	1,187	1,187
R^2	0.16259	0.54605	0.77058
Within R^2	0.11088	0.04986	0.07965

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.18: Regressions of security guards in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
Male	0.1000	0.2588*	0.0128
	(0.0659)	(0.1380)	(0.1959)
ΔProjected HHI$_{mt}$	-16.73	-72.14	-8.036
	(32.23)	(48.16)	(56.95)
Male $\times$ ΔProjected HHI$_{mt}$	16.81	68.44	6.439
	(32.24)	(48.34)	(43.35)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	206	206	206
N.o of Big HHI shocks:	60	60	60
Observations	249	249	249
R^2	0.38984	0.57149	0.89295
Within R^2	0.10458	0.18378	0.27335

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.19: Regressions of security guards in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.0270	0.1639***	0.0817**
	(0.0459)	(0.0600)	(0.0347)
ΔProjected HHI$_{mt}$	1.139	-2.090	0.3357
	(1.072)	(1.513)	(2.043)
$Male \times \Delta$Projected HHI$_{mt}$	-0.6497	2.339	1.358
	(1.247)	(1.418)	(1.285)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	332	332	332
N.o of Big HHI shocks:	104	104	104
Observations	652	652	652
R^2	0.14044	0.59561	0.72813
Within R^2	0.04204	0.08337	0.07429

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.20: Regressions of security guards in the construction sub-sample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.1110**	0.0886**	0.1094***
	(0.0491)	(0.0404)	(0.0360)
ΔProjected HHI$_{mt}$	-3.872	-1.404	0.1418
	(4.055)	(2.770)	(3.721)
$Male \times \Delta$Projected HHI$_{mt}$	2.650	0.6970	-0.6930
	(3.606)	(2.787)	(3.665)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	397	397	397
N.o of Big HHI shocks:	88	88	88
Observations	4,117	4,117	4,117
R^2	0.16449	0.41589	0.76771
Within R^2	0.02402	0.01099	0.02094

Notes: This Table shows the estimates from Equation 4-1 for security guards in the construction. 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

D.2.3 Janitors

Table D.21: Regressions of janitors in the human health sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
Male	0.0071	0.0288***	0.0188**
	(0.0114)	(0.0070)	(0.0073)
ΔProjected HHI_{mt}	0.0573	-0.7670	-0.1365
	(0.1914)	(0.4937)	(0.1936)
Male $\times$ ΔProjected HHI_{mt}	0.5192	0.0063	0.3047
	(0.5520)	(0.3008)	(0.2600)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	669	669	669
N.o of Big HHI shocks:	179	179	179
Observations	18,386	18,386	18,386
R^2	0.08960	0.29033	0.69079
Within R^2	0.03962	0.05742	0.03656

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.22: Regressions of janitors in the information sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
Male	0.0517***	0.0693***	0.0549**
	(0.0172)	(0.0161)	(0.0213)
ΔProjected HHI$_{mt}$	1.028*	0.2834	1.901**
	(0.5372)	(0.9637)	(0.7866)
Male $\times$ ΔProjected HHI$_{mt}$	0.2285	1.075**	0.2786
	(0.5408)	(0.5191)	(0.4987)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	492	492	492
N.o of Big HHI shocks:	112	112	112
Observations	2,285	2,285	2,285
R^2	0.05445	0.30055	0.79297
Within R^2	0.02375	0.02894	0.06070

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.23: Regressions of janitors in the textile sector sub-sample

	Log Real Wage		
	(1)	(2)	(3)
$Male$	0.0474	0.0857***	0.0571***
	(0.0364)	(0.0157)	(0.0190)
ΔProjected HHI$_{mt}$	0.5022	-0.8703*	-0.8069
	(0.4313)	(0.4547)	(0.5301)
$Male \times \Delta$Projected HHI$_{mt}$	1.269	-0.0900	-0.0311
	(0.8195)	(0.4860)	(0.4917)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	527	527	527
N.o of Big HHI shocks:	136	136	136
Observations	3,289	3,289	3,289
R^2	0.10854	0.55402	0.76314
Within R^2	0.04327	0.04964	0.05193

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).

Table D.24: Regressions of janitors in the construction sub-sample

	Log Real Wage		
Model:	(1)	(2)	(3)
$Male$	0.1453***	0.1213***	0.0824*
	(0.0357)	(0.0356)	(0.0441)
ΔProjected HHI$_{mt}$	-0.4457	0.0467	-2.751**
	(0.6327)	(0.3969)	(1.308)
$Male \times \Delta$Projected HHI$_{mt}$	0.6894	0.8128	0.7283
	(0.7164)	(0.6724)	(0.8473)
Municipal Fixed Effects		×	×
Firm-Municipal Fixed Effects			×
Total N.o of Municipalities	526	526	526
N.o of Big HHI shocks:	127	127	127
Observations	11,855	11,855	11,855
R^2	0.18047	0.39660	0.65873
Within R^2	0.07837	0.05881	0.03563

Notes: This Table shows the estimates from Equation 4-1 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 includes 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 parenthesis. (Signif. Codes: ***: p_value $\leq$ 0.01, **: p_value $\leq$ 0.05, *: p_value $\leq$ 0.1).