Early-Career Job Displacement and the Gender Wage Gap: Evidence from Brazil*

Kelly Santos†

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Abstract

This paper investigates the long-run effects of early-career job displacement by gender. We use employer–employee data from Brazil to show that displacement narrows the gender wage gap by eroding firm-sorting advantages that typically favor men. Exploiting mass layoffs as an exogenous shock, we find that women experience larger short-run earnings losses due to lower formal sector participation and transitions into formal part-time jobs. Evidence from a national household survey indicates that, in the short run, men are more likely to transition into self-employment or informal jobs following an unemployment spell, while women are more likely to exit the labor force. In the long run, men face larger and more persistent earnings losses as they transition to lower-paying firms. We also document asymmetric scarring, with employment gaps penalizing men more than women.

Keywords: Gender Wage Gap, Job Displacement, Informal Labor Market, Formal Employment, Worker Reallocation
JEL Classification Codes: J16, J31, J63, J64, O17, J21

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†Insper Institute of Education and Research - Rua Quatá, 300. Sao Paulo, SP, Brazil;
email: kellygs@inper.edu.br.

1 Introduction

Understanding the persistence of the gender wage gap remains a central question in labor economics. While a large literature documents the role of parenthood and the child penalty in shaping gender inequality (Kleven et al., 2019a,b; Berniell et al., 2021; Aguilar-Gomez et al., 2026), much less is known about how career interruptions affect long-term outcomes by gender. A well-established literature shows that job displacement leads to persistent earnings losses and lower employment (Jacobson et al., 1993; Kaplan et al., 2005; Oyer, 2006; Couch and Placzek, 2010; Kahn, 2010; Oreopoulos et al., 2012; Amarante et al., 2014; Farber, 2017; Kalleberg and von Wachter, 2017; Lachowska et al., 2020; Bertheau et al., 2023; Schmieder et al., 2023). Evidence on the gender-specific effects of job displacement remains limited. Previous studies, focused on developed economies, find that women tend to experience larger earnings losses than men, often attributed to labor supply constraints and lower geographic mobility (Meekes and Hassink, 2022; Illing et al., 2024). Evidence on long-run (more than five years after job loss) is even scarcer, particularly in developing economies, which are characterized by high job turnover and large informal sectors.[1]

This paper studies the gendered effects of early-career job displacement in Brazil. Focusing on workers aged 16 to 30 entering the formal labor market in the late 1990s and early 2000s, we show that displacement narrows the gender wage gap not through transitions into informality, which men are more likely to enter after unemployment, but through a deterioration in men's post-displacement job matches. Since the gender wage gap is largely driven by men's sorting into higher-paying firms, displacement disrupts access to high-quality matches, a mechanism that is especially relevant in developing economies with high labor turnover (Donovan et al., 2023).

Our empirical strategy proceeds in two steps. First, we establish stylized facts about

[1] On the one hand, informality may attenuate gender differences in earnings losses if it serves as a more important buffer for women due to greater flexibility (Goldin, 2014). On the other hand, informality may not mitigate gender gaps if men are more likely to transition into these sectors.

the gender wage gap using the two-way fixed effects framework proposed by Abowd, Kramarz, and Margolis (1999, henceforth AKM) and the firm-fixed-effect decomposition method from Card et al. (2016). Second, we exploit mass layoffs as exogenous shocks, tracking displaced workers and a matched control group of non-displaced peers for up to 15 years.

Our descriptive analysis reveals a striking pattern: the gender wage gap is significantly wider among workers with continuous employment histories (*stayers*) than among those who experience displacements. After controlling for education, experience, sector, and worker and firm fixed effects, we estimate a gender wage gap of 10 log points among *stayers*, compared with 9 log points among *displaced* workers. Firm pay premia account for a much smaller share of the gap among the displaced: the firm-fixed-effect gap is 7.1 log points, or 70% of the total gap, for *stayers*, but only 2.5 log points, or 27%, for *displaced* workers. The AKM decomposition shows that the sources of the gender wage gap vary by career trajectory. Among *stayers*, the gap is driven primarily by sorting across firms. In contrast, for workers who exit and later re-enter the formal sector, firm sorting plays a much smaller role in explaining the gap. In summary, firm sorting, with women disproportionately employed at lower-paying firms, explains a substantial share of the gender wage gap in Brazil, but this mechanism is driven primarily by workers with continuous attachment to the formal labor market.

In the second part of the paper, we exploit job losses triggered by mass layoffs as an exogenous shock. To ensure comparability, we employ exact matching on observable characteristics to construct a valid control group of non-displaced workers. Our results differ sharply across horizons, with distinct mechanisms driving short- and long-run effects. In the short run (first 5 years), women experience larger earnings losses than men. This initial penalty stems from the fact that displaced women are more likely to exit the formal labor force, transition to formal part-time jobs, and work fewer hours. Interestingly, we show that these earnings losses eventually reverse. Between 10 and 15 years post-displacement,

men experience significantly larger and more persistent penalties than women. While women's earnings stabilize relative to counterfactual trajectories as they return to the formal sector, displaced men face higher and increasing penalties even after 15 years.

Using national household survey data, we investigate the mechanisms driving the short-run outcomes. While men and women engage in active job search at similar rates, women are more likely to exit the labor force due to care responsibilities. Interestingly, women are less likely than men to enter the informal sector or self-employment after displacement. Unlike evidence on transition observed after childbirth, when women frequently move to informal jobs for flexibility (Berniell et al., 2021), job displacement does not trigger a similar shift. This suggests that in developing economies, the flexibility offered by informal and self-employment comes at the cost of unpredictable and unstable hours, differentiating these roles from formal part-time employment (Goldin, 2014).

The long-run earnings penalty is particularly pronounced among men displaced at very young ages (16–20) and among those who lose their first formal job. This pattern is concentrated among less-educated individuals, defined as those with at most a high school degree, who comprise the majority of our sample. Moreover, the long-run effects are driven by workers with lower initial wages and those employed at lower-paying firms prior to displacement. Taken together, these findings indicate that men's larger long-run earnings losses are concentrated among younger, less-educated workers at the lower end of the job ladder, suggesting that the loss of firm-specific experience and human capital is unlikely to be the primary mechanism (Kletzer, 1998).

We explore several mechanisms that may explain why men experience more persistent long-run earnings penalties than women. First, our results point to significant gender differences in post-displacement match quality: men re-enter employment at lower-paying firms than women. Second, we find evidence consistent with asymmetric CV scarring, whereby longer non-employment spells have a more negative impact on men's subsequent earnings. Men appear to be disproportionately penalized for extended periods

out of the workforce. This pattern suggests that employers interpret long unemployment spells as a stronger negative signal of productivity for men, whereas similar gaps for women are less stigmatized, likely because they are attributed to child-rearing or domestic responsibilities rather than unobserved ability (Eriksson and Rooth, 2014; Pedulla, 2016). Finally, we examine career progression and find only limited evidence of higher promotion rates for women and no evidence that women are more likely to hold managerial positions. Overall, differences in career progression explain little of the observed long-run gender gap.

Our findings suggest that, although job displacement penalizes women more heavily in the short run, it reduces the gender wage gap in the long run by permanently dampening men's earnings progression. Typically, non-displaced men benefit from steep wage trajectories driven by sorting into high-paying firms. Early-career displacement severs the job ladder, forcing men into lower-quality matches. In contrast, because women are historically less likely to sort into high-premium firms their relative loss in firm quality is less severe than the male counterfactual.

We are engaging with the literature on the long-term consequences of early labor market shocks. This literature investigates the adverse labor market consequences of recessions and weak economic conditions, as well as job displacement driven by plant closures and mass layoffs (Jacobson et al., 1993; Kaplan et al., 2005; Oyer, 2006; Couch and Placzek, 2010; Kahn, 2010; Oreopoulos et al., 2012; Amarante et al., 2014; Farber, 2017; Kalleberg and von Wachter, 2017; Lachowska et al., 2020; Bertheau et al., 2023; Schmieder et al., 2023). While this evidence primarily focuses on male workers in developed economies, the findings consistently reveal severe, persistent scarring effects on earnings. Specifically, displaced workers typically experience a sharp short-term earning loss of approximately 30% to 40%, which, although attenuating over time, stabilizes at a significant permanent loss of roughly 15% to 25% five to ten years after the initial shock (Jacobson et al., 1993; Couch and Placzek, 2010; Amarante et al., 2014; Kalleberg and von Wachter, 2017). Our

estimates are of similar magnitude in a developing-country setting.

Our study also contributes to the literature analyzing gender disparities in labor market outcomes and the sources of the gender pay gap (Meekes and Hassink, 2022; Ivandić and Lassen, 2023; Illing et al., 2024). Recent evidence indicates that, compared to men, displaced women face longer unemployment durations – often driven by the search for flexibility and lower commuting tolerance (Meekes and Hassink, 2022) – as well as larger relative earnings losses and higher unemployment risks (Ivandić and Lassen, 2023). Most closely related to our work, Illing et al. (2024) documents that women suffer larger earnings losses in the first five years post-displacement. While our short-run estimates align with Illing et al. (2024), we find that this pattern fades when examining outcomes ten years after displacement, as results for men and women converge. We also extend their analysis to a developing economy context by incorporating novel evidence on the informal sector and self-employment.

We also contribute to the broader literature on the determinants of the gender wage gap (Blau and Kahn, 2017). Specifically, building on Card et al. (2016) and Morchio and Moser (2024), we show that gender-specific firm sorting is a primary driver of earnings disparities among workers with continuous attachment to the formal sector, but is substantially less relevant for workers who experience job displacement. Furthermore, we connect our findings to the literature on the demand for temporal flexibility (Goldin, 2014) and its interplay with informality and self-employment (Berniell et al., 2021), highlighting how these alternative work arrangements operate in developing labor markets.

In summary, our paper makes several key empirical contributions to the literature. First, we document that firm-level job ladder mechanisms related to firm sorting are less relevant among displaced workers. Men disproportionately lose access to high-premium firms after displacement and face larger penalties following extended periods out of the formal labor market. Second, we provide long-run evidence showing that displacement effects are not persistent and that gender differences in earnings reverse over time. Third,

we provide new evidence on labor adjustments post-displacement in a developing-country context. Finally, we show that, as in developing economies, while women are more likely to transition into part-time work in the formal sector, they are less likely to move into informal work or self-employment, despite its greater flexibility.

The paper is organized as follows: Section 2 describes the data, and Section 3 documents the institutional background. Section 4 details the empirical strategy. Section 5 presents our main results, while Section 6 explores the underlying mechanisms. Finally, Section 7 concludes.

2 Data

Our analysis relies on longitudinal data from the formal sector (RAIS) and the national household survey (PNADC). We describe each data source in detail below.

Employer-employee registers. We use the longitudinal employer-employee data from *Relação Anual de Informações Sociais* (RAIS). These cover nearly all formal jobs in Brazil and is made available by the Ministry of Labor. Workers are identified by a unique tax code (CPF) and their full name. Each observation in RAIS corresponds to a worker-establishment match, representing a job in a given year. For each job, the dataset provides three categories of information: (i) worker-related variables, such as gender, age, education, and a unique worker identifier; (ii) firm-related variables, including sector of activity, establishment size, municipality, and unique identifiers for both the establishment and the firm; and (iii) job-related variables, such as average monthly earnings for the year, contractual weekly hours, tenure, occupation, months of hiring and separation, and the reason for separation.[2]

The RAIS dataset is compiled from legally mandated annual reports submitted by firms and includes formal workers (excluding informal workers), firm owners, and share-

[2] To compute real earnings, we deflate average monthly nominal earnings using the average *Índice de Preços ao Consumidor Amplo* (IPCA), normalized to December 2020.

holders, unless they are self-employed. In Brazil, formal employees are hired under the labor regulations established by the *Consolidação das Leis do Trabalho* (CLT). According to the CLT, employers must complete and sign the employee's work card (*Carteira de Trabalho*) upon formal hiring.

We construct an annual worker-level panel with one observation per worker-year. For workers holding multiple jobs in a given year, we keep the job with the highest earnings. If earnings are tied, we randomly select one of the job matches.

Household survey data. To study labor market dynamics for both formal and informal workers in Brazil, we use microdata from the Brazilian quarterly labor force survey *Pesquisa Nacional por Amostra de Domicílios Contínua* (PNADC), conducted by the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*, or IBGE). The survey has been conducted continuously since early 2012 and is used to calculate official unemployment statistics. We use variables such as worker ID, gender, age, monthly earnings, labor market status (employed or unemployed), and whether the individual holds a formal work card (*Carteira de Trabalho*).[3] In the survey, employees with a formal work card correspond to the population observed in the RAIS data, excluding domestic workers.

PNAD surveys employ a rotating panel structure similar to the U.S. Current Population Survey (CPS). Each household is interviewed in five consecutive quarters, then exits the sample. Interviews are distributed evenly throughout each month. This rotation ensures that new cohorts of households enter the survey as others leave, allowing for the panel structure to capture short-term changes while maintaining representative coverage of the population. Using the worker ID, we follow the same individual for five consecutive quarters. However, because this ID is distinct from the CPF (the identifier in RAIS), we are unable to link the PNADC results to the administrative records.

[3] As with the RAIS data, nominal earnings are deflated to December 2020 prices using the *Índice de Preços ao Consumidor Amplo* (IPCA).

3 Gender Earning Gap and Firm Pay Premium Decomposition

3.1 Evidence on the Gender Wage Gap in Brazil

We document key trends in the Brazilian labor market using RAIS, focusing on the period from 1995 to 2019. The sample is restricted to the 1978 birth cohort. It covers individuals who entered the formal labor market between 1998 and 2004. We follow these individuals from ages 20 to 41, yielding 11,793,141 observations.

We classify workers into three labor market trajectories. Stayers are workers with uninterrupted formal employment since entry, accounting for about 28% of the sample. The remaining workers experience employment disruptions. We separate these into displaced workers, who spend at least one full year out of the formal sector (72%), and dismissed workers, who experience at least one employer-initiated separation, with or without cause (81%). Dismissal does not necessarily imply displacement, since some workers transition to another formal job within the same year.

Figure 1 displays the lifecycle evolution of the average gender wage gap across the three trajectory categories.[4] The gap between men and women widens over the lifecycle, ranging from 10 to 35 log points. Notably, we observe distinct gaps by trajectory: among *stayers*, the gap is larger from the onset of their careers, whereas for the *displaced* and *dismissed* groups, the gaps are smaller and similar in magnitude. This suggests that the divergence in wage growth over the lifecycle is closely related to labor market turnover. Selection may also play an important role, as lower-ability workers may sort into firms or sectors with a higher risk of layoffs, potentially contributing to the observed gender gap. These considerations motivate the estimation of a two-way fixed effects model.

Therefore, we estimate an equation based on Abowd-Kramarz-Margolis (AKM) wage

[4] To estimate the gender wage gap, we regress log wages on a gender indicator and age dummies. We control for tenure, contracted hours, firm size, state, and education.

regression (Abowd et al., 1999) separately by gender:

$$lwage_{ijt} = \alpha_i + \psi_j^g + X_{it}'\beta^g + \varepsilon_{ijt}, \tag{1}$$

where $lwage_{ijt}$ is log earnings of individual i in year t working at employer $j = J(i,t)$, α_i is a person FE, ψ_j^g is a gender-specific employer FE, and g indexes gender (F or M). We control for X_{it}, including tenure, contractual hours, state, education (nonparametrically at four levels), and experience. ε_{ijt} is a residual.

We can only identify the fixed effects in equation (1) for firms connected by worker mobility, requiring at least one observation per worker. We therefore restrict our analysis to the "dual-connected sample," defined as the intersection of the largest connected sets for men and women. Table 1 presents descriptive statistics by sample: Column 1 displays the full sample, while Columns 2 through 5 focus on the AKM estimation sample, broken down by labor market trajectories. Differences between the dual-connected set and the full sample are negligible; indeed, the observation counts indicate that we can estimate equation (1) for 96% of the original sample.

Table 1 also details other key characteristics. Most individuals work full-time, with a roughly even split between white- and blue-collar occupations. The average age is 31, and the majority of workers hold a high school degree or lower. We also observe notable heterogeneity across labor market trajectories. Compared to *displaced* or *dismissed* workers, *stayers* earn higher wages, are more likely to hold white-collar positions, possess higher levels of education, and are employed by larger firms.

Previous studies normalize firm effects relative to the average effect in the hotel and restaurant sector, which is argued to consist of "low-surplus" firms that pay, on average, zero wage premia to both genders (Card et al., 2016). In our setting with gender-specific groups, we normalize the firm-fixed effect by lower sector within each gender, that is, the education sector for women and lodging and food for men. Figure 2 confirms sectors with the lowest average firm fixed effects for men and women separately, supporting this

choice of normalization.

Table 2, Column (1), reports the gender gap estimated using the AKM model. In the full sample, the gender gap is 9.1 log points, smaller than the raw wage gap shown in Figure 1. The reduction in the gap when firm fixed effects are included implies that part of the gender wage gap is explained by women sorting into lower-paying firms.[5] Nevertheless, a substantial gap persists even after accounting for worker selection and sorting across firms.

Within the dual-connected sample, the gender gap remains substantial at 8.9 log points. However, this aggregate figure masks meaningful heterogeneity across labor market trajectories: the gap is widest among *stayers* (10.0 log points), compared to *dismissed* (9.7) and *displaced* (9.0) workers. Thus, even after conditioning on worker and firm selection, displacement is associated with a narrower gender gap.

We now turn to the role of firm fixed effects (Columns (2) and (3) of Table 2). In both the full and the dual-connected samples, the gender gap in firm pay premia is 3.7 log points. This gap varies substantially across labor market trajectories. Among *stayers*, the gap reaches 7.1 log points, compared with 2.5 log points among *displaced* workers and 2.9 log points among *dismissed* workers. In relative terms, firm pay premia account for approximately 70% of the gender gap among *stayers*, in sharp contrast to only about 30% among *displaced* and *dismissed* workers.

This pattern indicates that sorting of women into lower-paying firms plays a much larger role in explaining the gender gap for workers with uninterrupted formal careers. In contrast, among displaced workers, firm sorting becomes less relevant. The tendency of displaced workers to accept lower-quality job matches appears to affect men more strongly, thereby narrowing the gender gap. An important question is whether the reduction in the gender gap in firm pay premia among displaced workers operates through a narrowing of gender differences in within-firm wage growth, driven by bargaining along

[5] This result is consistent with the literature; see, for example, Casarico and Lattanzio (2024) and Morchio and Moser (2024).

the job ladder, or through a reduction in gender differences in sorting into lower-paying firms. To address this question, we implement a Kitagawa–Blinder–Oaxaca decomposition following Card et al. (2016).

3.2 Between-firm versus within-firm decomposition

Our primary objective is to determine whether the gender wage gap in our sample is driven more by within-firm wage progression or by sorting into specific firms. To this end, we first estimate equation (1) separately for each gender. As we aim to compare fixed effects across genders, we normalize the estimates within each group. This normalization re-centers and rescales the fixed effect distributions to ensure comparability. Finally, we decompose the gender difference in firm pay premia into between-firm and within-firm components by implementing the Kitagawa-Blinder-Oaxaca decomposition (Card et al., 2016) as follows:

$$\begin{aligned}\mathbb{E}\left[\psi_j^M \mid g = M\right] - \mathbb{E}\left[\psi_j^F \mid g = F\right] =& \mathbb{E}\left[\psi_j^M - \psi_j^F \mid g = M\right] \\ &+ \mathbb{E}\left[\psi_j^F \mid g = M\right] - \mathbb{E}\left[\psi_j^F \mid g = F\right].\end{aligned} \tag{2}$$

We decompose the difference $\mathbb{E}\left[\psi_j^M \mid g = M\right] - \mathbb{E}\left[\psi_j^F \mid g = F\right]$, which captures the contribution of firm selection to the gender wage gap, into two distinct channels: a between-firm component (sorting channel) and a within-firm component (bargaining channel). The first term on the right-hand side represents the within-firm channel. It captures the average difference between firm fixed effects for men and women, assuming that women are distributed across firms in the same proportion as men, that is, holding sorting fixed. The remaining terms represent the sorting, or between-firm, channel. This corresponds to the difference between the average firm effect for women and what it would be if they were represented across firms in the same proportion as men.

Table 2, Columns (4) to (7), report the decomposition results. The decomposition reveals distinct mechanisms across labor market trajectories. Among *stayers*, the gender

gap is largely driven by between-firm differences. In contrast, for workers who experience a career interruption, whether through displacement or dismissal, firm sorting plays a smaller role. Instead, the remaining gap is driven primarily by within-firm pay differences.

In sum, the gender wage gap is smaller for displaced workers compared to those with continuous employment, as the male advantage derived from firm sorting is attenuated. This is consistent with mechanisms where men sort into better firms and climb job ladders faster than women (Casarico and Lattanzio, 2024; Morchio and Moser, 2024). Job loss interrupts this progression, severing access to the firm wage premia that men disproportionately capture.

4 Empirical Strategy: Job Displacement Effects

We exploit job loss due to firm-level mass layoffs as an exogenous shock to employment status, following Bhalotra et al. (2025). This strategy ensures that men and women experience job loss for the same underlying reason and reduces concerns about endogenous separation. By focusing on mass layoffs driven by firm-level shocks rather than worker behavior, we strengthen the identification strategy's plausibility. The pool of potential control workers includes individuals employed in firms that do not experience mass layoffs during the sample period. This approach ensures that the actual year of job loss for a displaced worker represents the potential year of job loss for a non-displaced worker.

We use RAIS data from 1995 to 2019 and focus on mass layoffs occurring between 1998 and 2004. This ensures that we observe at least three pre-displacement periods for all treated workers. Because our interest lies in long-run effects, we focus on workers in the early stages of their careers and restrict the sample to individuals aged 16 to 30 at the time of displacement.

We then implement an event-study framework to estimate the dynamic effects of job

displacement, estimating the following regression separately by gender:

$$Y_{it} = \alpha + \gamma Treat_i + \sum_{k=K_0, k\neq 0}^{K_1} \delta_k (Treat_i \times I_{(t=k)}) + \sum_{k=K_0, k\neq 0}^{K_1} \gamma_k I_{(t=k)} + \varepsilon_{it}, \tag{3}$$

where Y_{it} is the outcome of interest of worker i in year t, $Treat_i$ is a dummy variable indicating whether worker i was displaced during a mass layoff. The term $I_{(t=k)}$ represents a set of dummy variables for each period k relative to the displacement year. The coefficients of interest are δ_k, which measure the differential evolution of outcomes for displaced workers relative to the control group (non-displaced workers). The time window is measured in years, with $K_0 = -3$ and $K_1 = 15$ corresponding to the period from three years prior to displacement up to the fifteenth year following the event.

To assess gender differences in responses to job displacement, we also estimate the following regression model:

$$\begin{aligned} Y_{it} = &\alpha + \gamma Treat_i + \sum_{k=K_0, k\neq 0}^{K_1} \gamma_k I_{(t=k)} + \beta Male_i + \sum_{k=K_0, k\neq 0}^{K_1} \eta_k (Treat_i \times I_{(t=k)}) + \delta (Treat_i \times Male_i) \\ &+ \sum_{k=K_0, k\neq 0}^{K_1} \lambda_k (Male_i \times I_{(t=k)}) + \sum_{k=K_0, k\neq 0}^{K_1} \delta_k (Treat_i \times Male_i \times I_{(t=k)}) + \varepsilon_{it}, \end{aligned} \tag{4}$$

where $Male_i$ is a gender indicator, and all other variables are defined as in equation (3). To summarize the magnitude of post-displacement effects, we also estimate specifications in which the set of event-time indicators $I_{(t=k)}$ in equations (3) and (4) is replaced by a single indicator, $Post_t$, equal to one for all periods after the layoff.

Following Bhalotra et al. (2025), we define mass layoffs as cases where firms with 15 or more employees dismiss at least 33% of their workforce without just cause in a given year. In Brazil, labor law allows these dismissals if severance is paid. Most private sector contracts are open-ended, full-time (93%), and layoffs without just cause account for 65% of separations; the remaining cases are predominantly voluntary resignations.

The control group consists of non-displaced workers employed in formal jobs at firms that did not experience mass layoffs during the same period (1998–2004). To enhance comparability, we implement an exact matching procedure based on observable characteristics. Specifically, for each displaced worker, we identify control workers who share the same birth cohort, gender, earnings category (in R$25/month bins), occupation code, job tenure (in years), firm size (quartiles), and state (27 categories). When a displaced worker matches several controls, one is selected at random. For all control workers, the dismissal date is set to match the corresponding displaced worker's dismissal date. This procedure ensures the control group mirrors the characteristics of the displaced group at the time of displacement and controls for observed heterogeneity.

Our main analysis relies on RAIS data. In addition, we use PNADC, which does not allow the identification of mass layoffs. In this case, we focus on workers who experience an unemployment spell. We restrict the sample to individuals aged 16 to 30 who were initially employed in the formal sector. To construct a counterfactual, we select individuals in the same age range who are not unemployed and match them on birth cohort, state, gender, and pre-displacement earnings category (R$ 50 bins). We further restrict the sample to treated and control individuals who were active in the labor market in the year prior to the unemployment spell. The final dataset includes 93,070 observations, drawn from 14,942 displaced workers and 13,596 matched controls.

Sample Characteristics. The final sample from RAIS consists of 602,169 workers aged 16 to 30 who lost a formal job due to a mass layoff between 1998 and 2004 and who are matched to a control worker.[6] The resulting panel includes 22,882,422 worker-year observations. Table 3 presents descriptive statistics for laid-off workers and the matched control group in the displacement year, along with mean differences and corresponding p-values. The two groups are well balanced across most observable characteristics. Where differences are statistically significant, they are small in magnitude. The sample consists

[6] The mass-layoff sample represents 11.5% of the initial sample, and the matching rate is 95%.

primarily of younger, lower-wage workers, with relatively few college-educated individuals, compared with the full worker sample reported in Table 1.

Beyond the standard treatment-control comparison, we verify whether covariate balance differs by gender, given that we analyze men and women separately. Figure 3 plots the triple-difference coefficients from the balance regression (capturing the difference in treatment-control gaps between genders). We find that the groups are largely balanced, except for firm size: treated women are more likely to work in small firms (up to 5 employees) and less likely to work in medium-sized firms (5–20 employees) than control women, whereas this differential is smaller for men. Although the magnitude of this discrepancy is modest (approximately 2 percentage points), we perform a heterogeneity analysis by firm size to hold this dimension fixed. We discuss these results in Section 5.

In general, we conclude that there are no economically significant pre-displacement differences between the treatment and control groups by gender. However, it is possible that displaced men are assigned to different occupations and firms than displaced women. While this compositional difference does not pose a threat to our identification strategy – since the difference-in-differences design relies on the parallel trends assumption rather than identical baseline levels (a condition we validate in our event study results) – it suggests that pre-existing characteristics, such as higher earnings or older age, could potentially drive the observed heterogeneity in treatment effects.

To investigate potential compositional differences, we examine the characteristics of men and women in the year of displacement, focusing on age, earnings, and average firm pay. Panel (a) of Figure 4 shows the age distribution at displacement. Women are slightly younger than men. To address this difference, we conduct a robustness check restricting the sample to workers aged 21 to 26, where the age distributions overlap closely (Appendix Figure A1). Panel (b) presents the distribution of average monthly earnings in the displaced job, with vertical lines indicating the mean. Average monthly earnings, expressed in 2020 prices, are around R$1,100 and display nearly identical distributions

for men and women. Panel (c) reports the distribution of average firm wages. While the distributions and means are similar, men are somewhat more likely to be employed at higher-paying firms. We further examine heterogeneity along these dimensions in Figures 11 and 12.

Beyond these characteristics, men and women may sort into different occupational roles prior to displacement. Prior to displacement, women were more likely to hold white-collar positions (53% vs. 21% for men), whereas men were concentrated predominantly in blue-collar roles (62% vs. 31% for women). Disaggregating these categories reveals that this disparity is driven primarily by the concentration of men in manual labor roles (e.g., construction assistants) and women in sales and administrative support roles (e.g., secretaries and receptionists). Excluding these specific occupations eliminates the pre-displacement occupational differences. Consequently, we perform a robustness check excluding these roles; as shown in Appendix Figure A2, our results remain robust.

5 Results

We begin by examining gender-specific effects of job loss on monthly earnings relative to the year of layoff. Figure 5 reports the results. Both genders suffer immediate declines – approximately 40% for men and 45% for women in the first year. While women experience deeper losses in the short run (Panel (a)), their trajectory stabilizes and converges with men's after five years. By the tenth year, this pattern reverses: men face larger and more persistent penalties, as illustrated by the widening gender gap in Panel (b). Table 4 confirms these dynamics across four horizons (1, 5, 10, and 15 years post-displacement). In the first year, men fare relatively better, losing R$ 48 (4% of baseline) less than women. This advantage erodes quickly; the gap becomes statistically insignificant from year 5 through year 10. In the long run (year 15), the trend inverts, with men suffering losses R$ 49 higher than women.

We next examine exits from formal employment. Figure 6 shows that one year after displacement, formal employment falls by about 30 percentage points for men and 34 percentage points for women (Panel (a)). Both genders begin to return after two years, but men re-enter more quickly. This widens the gap in the second year (Panel (b)). Women gradually catch up. By year 10, employment rates converge, with displaced workers about 3 percentage points below the baseline. A small share of displaced men and women remain permanently out of formal employment, even after 15 years.

Figure 7 further explores part-time status and contractual hours, defined for employed workers only. Part-time employment is defined as holding a formal contract with under 35 weekly hours at any point in the year. Among those who remain formally employed after displacement, women see a 1.3 percentage-point increase in part-time work, compared to 0.2 for men (Panel (a)). The gender gap narrows over time and becomes less significant, as shown in Panel (b). Consistent with previous findings, women in Brazil are more likely to enter part-time employment after displacement. This effect is small, however, because formal employment is overwhelmingly full-time, as Table 3 shows. Additionally, Panels (c) and (d) show results for contractual hours relative to baseline. After displacement, women reduce their contractual hours more than men do, but this difference narrows over time. In the long run, the gap between men and women is minimal: only 0.124 hours, or about 0.2% of the baseline, as Table 4 details.

To separate employment effects from wage effects, we estimate displacement impacts on earnings for those remaining in the formal sector. Table 4 shows that, when restricting the sample to displaced workers who return to the formal sector in the first year (Row *Earnings (R$) | Employed After 1 Year*), the gender difference in earnings losses shrinks from R$ 48 to R$ 16. Conditioning on formal-sector participation at later horizons (5, 10, or 15 years) shows that women's short-run earnings losses become more pronounced.

Taken together, these patterns indicate that women's larger short-run earnings losses stem partly from lower formal-sector participation and transitions into part-time work.

This effect fades and does not persist beyond the first decade after displacement. By ten years post-layoff, gender gaps in employment and full-time status converge, supporting women's earnings recovery.

5.1 Heterogeneous Effects

This section examines heterogeneity across pre-displacement characteristics. We find that the baseline reversal – larger short-run losses for women versus persistent long-run penalties for men – is driven primarily by younger, less educated workers at the lower end of the job ladder.

Figure 8 stratifies the results by education level. The long-run reversal is concentrated among workers with a high school degree or less. Among college graduates, men experience larger earnings losses immediately after displacement. Post-displacement formal employment rates are similar for both genders among college graduates. This differential is thus driven by a sharper wage decline for men, not differences in labor force attachment.

To test if the loss of firm-specific human capital drives our results (Kletzer, 1998), we examine heterogeneity by age and tenure to assess whether this mechanism explains the observed earnings differences. If loss of firm-specific human capital is the main driver, we would expect earnings gaps to widen with age. Figure 9 presents estimates for three age groups: 16–20, 21–25, and 26–30. Contrary to this prediction, the long-run reversal is statistically significant only for the youngest cohort, suggesting that the mechanism may not fully account for the observed pattern. We find consistent evidence when restricting the sample to workers displaced from their first formal job (Figure 10), indicating the finding holds under a more specific definition of initial firm attachment. Men suffer larger long-run earnings losses than women, even as formal employment recovery is similar, implying potential gender differences in post-displacement earnings trajectories beyond those explained by firm-specific human capital loss.

Figures 11 and 12 report results by pre-displacement individual wages and firm aver-

age wages. The long-run male penalty is most pronounced among workers with lower starting wages and those who worked at lower-paying firms, suggesting that initial earnings levels and firm pay structure play a role in determining the magnitude of the penalty experienced after displacement. These findings suggest that destruction of firm-specific human capital probably does not explain the gendered costs of job loss. We analyze alternative mechanisms in Section 6.

6 Understanding the Gender Gap in Earning Losses

Our results show that women experience larger short-run earnings losses, while men face steeper long-run losses. These patterns point to distinct mechanisms at different horizons. Accordingly, we organize this section by first examining short-run mechanisms and then long-run mechanisms.

6.1 Short-Run Result: Labor Market Participation and Care Responsibilities

We use the National Household Survey (PNADC) to capture short-run transitions into informal employment. This complements our primary analysis based on RAIS administrative records. Data linkage between these sources is not possible. Therefore, we construct the PNADC sample to mirror the restrictions used in RAIS, ensuring comparability. The restrictions are described in Section 4.

We classify labor market status into five categories: out of the labor force, unemployed (actively searching), formal employment (employees with a registered work card, *Carteira de Trabalho*), informal employment (employees without a registered work card); and self-employment (own-account workers without a registered work card). Figure 13 displays labor market status one year post-unemployment. Job search rates are similar across genders. However, re-employment patterns differ substantially, suggesting gender influences

post-unemployment labor outcomes. Women are more likely to leave the labor force, which may contribute to lower re-employment rates. In contrast, men are more likely to re-enter formal, informal, or self-employment, indicating a gender difference in employment transitions.

We estimate event-study specifications following the methodology in Section 4, applying sample weights. Figure 14 reports results for monthly earnings in formal and non-formal jobs and for labor market status. Panel (a) shows the impact of unemployment on total monthly earnings relative to the pre-displacement quarter. Women suffer larger short-run losses than men. This holds even after accounting for income from the informal sector and self-employment.

Our results show that informal work and self-employment serve as insurance after unemployment by providing alternative employment options. These options help both genders find work after job loss. Transitions into informal wage employment do not differ significantly between genders. However, among those leaving formal jobs, men are about 2 percentage points more likely to transition into self-employment, while women are roughly 3 percentage points more likely to exit the labor force entirely. Figure 15 summarizes these dynamics with pooled estimates across post-shock quarters. The results confirm a gender divergence. Women are more likely to exit the labor force. Men are more likely to transition into informal and self-employment. These results indicate that job loss leads men and women into different post-unemployment trajectories, with men transitioning toward flexible informal work and women exiting the labor force.

Household Pressure vs. Care Penalties. We now test whether the presence of children influences post-unemployment transitions. The presence of a child in the household may create pressure to smooth consumption immediately, encouraging faster re-entry into the labor market. At the same time, the high opportunity cost of childcare may induce workers to remain at home, an effect likely stronger for women.

Figure 16 stratifies results by the presence of children. Female labor force exit is most

pronounced among women with children, particularly those with children under age five. While transitions into informal wage employment appear to be less responsive to the presence of children, women with young children are significantly less likely to enter self-employment. This suggests a divergence in mechanisms: while consumption smoothing motives drive men back into employment (often via self-employment), childcare constraints dominate for women, leading to market exit. Furthermore, these results imply that self-employment may not serve as a viable flexible alternative for mothers of young children compared to informal jobs.[7]

In summary, women are significantly more likely to exit the labor force following short-term unemployment, a phenomenon driven largely by mothers. For men, the pressure to maintain household consumption appears to drive a faster return to work, utilizing self-employment as a key insurance mechanism. Women, facing higher opportunity costs due to childcare, are less likely to transition into these "insurance" jobs in the short run, opting instead for non-employment.

Job Search Behavior and Care Responsibilities. Although we are not able to perfectly separate demand-side from supply-side drivers, the survey data allow us to characterize the nature of the labor supply response. We examine job search duration and stated reasons for non-participation to distinguish between market frictions and voluntary withdrawal.[8]

Figure 17 Panel (a) shows that job search duration increases symmetrically for men and women following unemployment. One year after the shock, active job seekers in both groups report an average search duration of approximately 2.5 months. Panels (b)

[7] We test for potential endogeneity regarding fertility decisions. Using the presence of a child under one year of age in the household as a proxy for fertility response, Appendix Figure A3 shows no significant change in fertility behavior in response to unemployment within our four-quarter window, but a negative trend. This is consistent with evidence finding negative long-term fertility effects of job loss (Del Bono et al., 2012; Huttunen and Kellokumpu, 2016).

[8] The specific questions are: for search duration, "How long had you been without work and trying to get work (in months)?"; for not searching, "What was the main reason for not taking action to find work in the reference period?"; and for non-participation, "What was the main reason for not wanting/being able to start working in the reference week?" Care-related responsibilities are defined by the answer: "Had to take care of child(ren), other dependent(s), or domestic chores."

and (c) examine whether care responsibilities affect job search behavior or the decision to start working. We find little evidence that women stop searching for jobs due to care responsibilities in the months immediately following displacement. Instead, the divergence arises in the decision to work: women are significantly more likely to report being unable to start working because of care duties.

In summary, we find no significant gender differences in job search duration or in the reasons for not searching. This contrasts with the findings of Illing et al. (2024), who show that women spend fewer minutes on job search activities. Instead, our findings indicate that the gender divergence operates on the extensive margin: women are more likely to exit the labor force to care for dependents. This confirms that the larger short-term earnings losses and lower formal participation among women are driven by labor supply constraints. Importantly, this supply channel is not explained by lower search effort among active job seekers, but rather by the decision to withdraw from the labor market.

6.2 Long-Run Result: Matches Quality, Career Progression, and CV Scars

We next investigate potential explanations for the long-run results using the RAIS sample. We focus on three main channels: job match quality, penalties for jobless spells, and career progression.

Firm Pay Premium. We start by examining whether men's larger long-run earnings losses reflect reallocation to lower-quality firms following displacement. We proxy firm quality using the firm's average monthly wage, with results shown in Figure 18. Beginning in the first year after displacement, men are employed in firms with lower average wages than women, indicating that displaced men transition to lower-quality firms. Table 4, *Panel B: Occupation and Industry*, reports the average effect on the gender gap in firm pay premia, expressed in *reais*. This gap increases over time. Fifteen years after displacement,

men are employed at firms that pay, on average, R$40.5 more than the firms employing women.

As highlighted in the short-run results, men may face stronger household pressure to return to work quickly due to consumption needs, while women are more constrained by care responsibilities. This asymmetry contributes to larger short-run earnings losses for women, who are more likely to remain out of the labor force in the years immediately following displacement. At the same time, this pressure may push men to accept lower-quality job matches. Rapid re-employment can come at the cost of moving to lower-paying firms, slowing wage growth over the life cycle, and contributing to larger long-run earnings losses for men. In contrast, women return more slowly, but, conditional on re-entry, they tend to match into higher-paying firms than men do.

As discussed in Section 3, women's sorting into lower-paying firms accounts for a sizable share of the overall gender wage gap. However, this mechanism is less relevant for the displacement-induced gender difference. This result is consistent with the idea that displacement lowers men's average firm quality, thereby narrowing the sorting gap between men and women. As a result, firm sorting becomes less important in explaining the gender difference among displaced workers.

Penalties for Jobless Spells. We next examine how time spent out of the formal labor market affects post-displacement wages. Extended non-employment spells are associated with the depreciation of job-specific human capital, which lowers productivity and reduces wages upon re-entry (Arulampalam et al., 2001). Employers may also interpret long jobless spells as a negative signal of worker quality, further depressing wage offers (Eriksson and Rooth, 2014). If such stigma is more severe for men than for women, given that female career interruptions are more commonly attributed to caregiving rather than low productivity, this mechanism could help explain men's larger long-run earnings losses.[9]

[9] Pedulla (2016) shows that men are penalized for part-time employment histories, whereas women are not. The author argues that because women are often perceived as being on the "mommy track" or deviating from the ideal worker norm due to caregiving, employers view their non-standard employment histories as a common demographic experience rather than a negative signal of competence.

As shown in Table 4, when we restrict attention to workers who return quickly, wage losses are more similar for men and women (see row *Earnings | Employed After 1 Year*). Thus, the larger long-run earnings losses for men appear to be smaller when workers return quickly to formal employment. This suggests that delayed re-entry amplifies the gender difference in the long run. In other words, men may face particularly large penalties when they return to the labor market after spending extended periods out of formal employment.

Figure 19 Panel (a) shows that women spend more months out of the formal sector after displacement than men. This result is consistent with responses along the extensive margin, as women are significantly less likely to participate in the formal labor market in the short run. Figure 19 Panel (b) investigates the scarring effect by splitting the sample into workers who return to formal employment within one year and those who remain out for more than 36 months. Among workers who re-enter shortly after displacement, earnings losses are similar by gender. In contrast, the long-run earnings losses are concentrated among men who experience extended periods of non-employment. This pattern reinforces the idea that employment interruptions carry larger long-run penalties for men and suggests that long gaps may worsen match quality upon re-entry, potentially reallocating men toward lower-paying firms.

Career Progression. Beyond firm sorting, career progression may also be a channel that explains our findings. If women advance in the job ladder more quickly than men after returning to the labor market, the narrowing of the gender wage gap could partly reflect differential post-displacement career advancement. In Table 4, *Panel B: Occupation and Industry* reports the effects of job displacement on four measures of career progression.

We first estimate the effect of displacement on the probability of receiving a promotion, defined as a wage increase exceeding the firm's average annual wage growth. Men experience a short-term increase in the probability of promotion. In the long run, however, this pattern reverses, indicating that displaced men are less likely to be promoted than

women. Nonetheless, the magnitude of these differential effects is economically modest.

We also examine whether workers change industries or occupations relative to their pre-displacement positions, as reported in the rows *Changed Industry* and *Changed Occupation*. Men are less likely than women to switch either occupation or industry. In this case, displacement-induced losses of occupation- or industry-specific experience appear to contribute to women's short-run earnings losses but do not explain the larger long-run earnings losses observed among men.

Finally, we show that there are no meaningful gender differences in the probability of holding managerial positions, suggesting that managerial sorting does not explain the long-run gender differences in earnings losses (see Figure 20). Overall, career progression appears to have limited explanatory power for long-run outcomes.

7 Discussion

Using matched employer–employee records from Brazil, we show that in the absence of labor market shocks, men disproportionately benefit from firm-based career ladders through sorting into high-paying firms and accumulating firm-specific wage premia, making firm sorting a central driver of the gender earnings gap. In contrast, among workers who experience job displacement, firm sorting plays a much smaller role, as displacement disrupts men's access to high-quality firm matches.

Our results from mass layoffs reveal a temporal dichotomy. In the short run, women experience larger earnings losses primarily because care responsibilities lead them to exit the labor force, directly reducing their income, though this choice helps them avoid the instability of informal sector work. In the long run, however, men face more persistent penalties; this arises because men who become unemployed are more likely to re-enter lower-paying firms and experience greater employment gap scarring.

Furthermore, our analysis offers new insights into the role of the informal sector in

Latin American labor markets. Contrary to the view that informality serves as a seamless buffer or a flexible option for mothers, we find that displaced women are less likely than men to transition into informal work or self-employment. This divergence suggests that in developing economies, the flexibility of the informal sector often comes bundled with instability and unpredictability, rendering it an incompatible substitute for formal employment for primary caregivers. While men may use self-employment as an insurance mechanism to smooth consumption, women facing childcare constraints appear to have a higher reservation utility for job stability, leading them to opt out of employment.

Finally, our evidence on scarring points to the persistent influence of social norms. The asymmetric penalty for long non-employment spells – where men suffer larger earnings losses than women for similar gaps in CV – suggests that employers interpret labor market detachment differently by gender. For men, extended gaps may signal unobserved productivity; for women, these gaps are likely viewed as care-related interruptions. This implies that the "male breadwinner" norm cuts both ways: it protects men's earnings when employed but penalizes them more severely when they fall off the ladder.

These dynamics have profound implications for policy design. First, our results clarify that the gender wage gap is widest among workers with uninterrupted careers, a pattern causally driven by female sorting into lower-paying firms, possibly due to firm-specific pay practices. Second, effective mitigation strategies must address the distinct temporal profiles of post-displacement costs, shaped by differences in labor market re-entry dynamics for men and women. For women, short-run costs are causally linked to labor force exit following displacement, frequently due to barriers in obtaining childcare or accessing retention policies; thus, interventions should target these mechanisms rather than rely on the informal sector to absorb supply shocks. For men, the long-run penalty arises from delayed re-attachment, with potential mechanisms including human capital depreciation and employer discrimination. More research is needed to investigate how unemployment insurance and childcare availability causally mitigate these effects, and to further disen-

tangle the drivers behind persistent long-run penalties for men.

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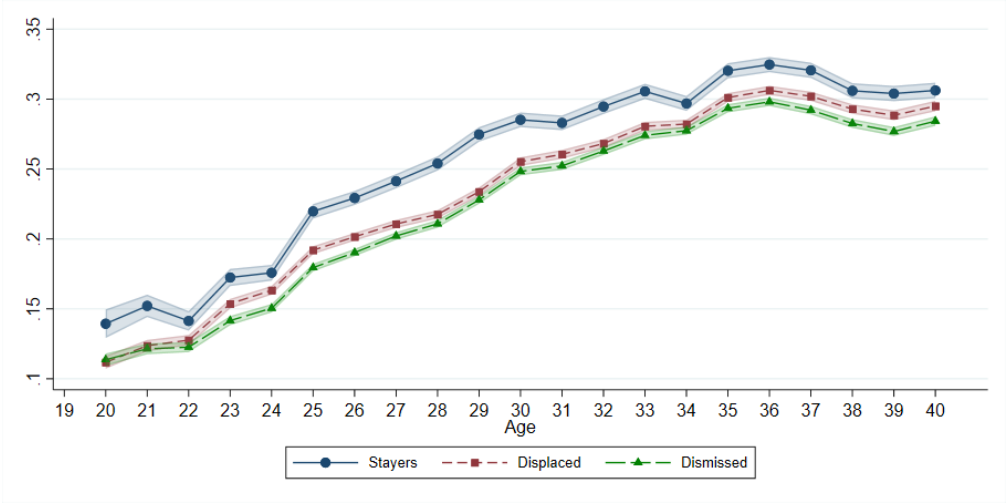
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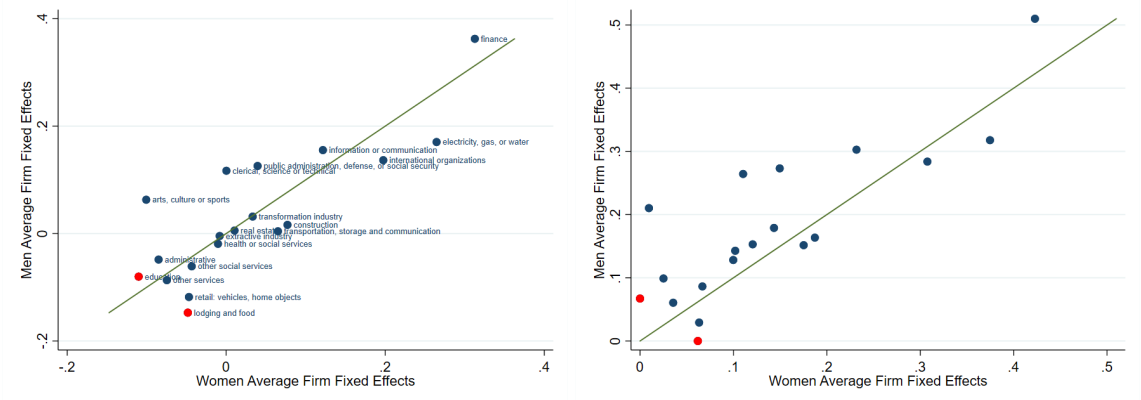
A Figures

Figure 1: Gender Earnings Gap across Employment Trajectories



This figure plots the gender gap in earnings by age for three employment trajectories. *Stayers* are workers continuously employed in the formal sector. *Displaced* workers experience at least one employment interruption lasting one year or more. *Dismissed* workers are those separated from their jobs through dismissal. The gender gap is estimated by regressing log wages on a gender indicator, controlling for tenure, contracted hours, firm size, state, education, and year fixed effects. Shaded areas represent 95% confidence intervals. The data come from RAIS and cover the period 1995–2019 for workers who entered the formal labor market between 1998 and 2004 and were born in 1978.

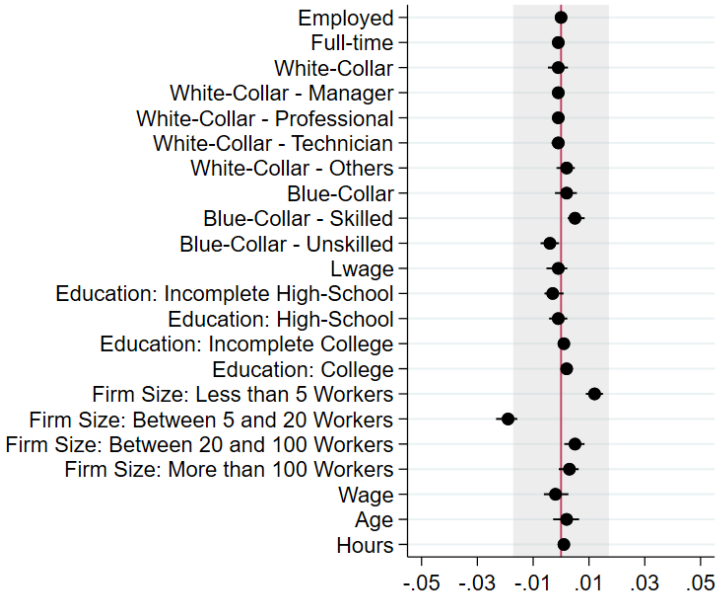
Figure 2: Firm Fixed Effects by Gender and Sector



(a) Level (b) Normalized

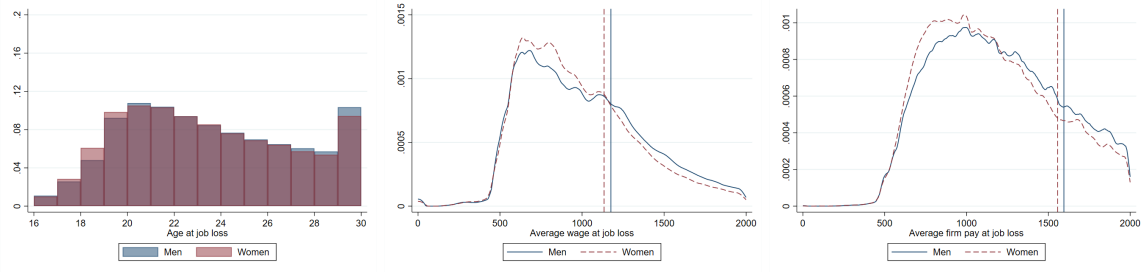
This figure plots firm fixed effects estimated from an AKM model, separately by gender and sector. Panel (a) reports the level of firm fixed effects, while Panel (b) reports normalized firm fixed effects, using the sectors highlighted in red as the normalization benchmark. Each point corresponds to a sector. The data come from RAIS and cover the period 1995–2019 for workers who entered the formal labor market between 1998 and 2004 and were born in 1978.

Figure 3: Gender Differences in Pre-Layoff Covariates: Laid-Off vs. Matched Controls



This figure reports covariate balance for the matched sample of workers affected by layoffs. Each point shows the gender gap in the difference between laid-off workers and matched controls for observable characteristics measured one year prior to the layoff. We show 95% confidence intervals. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

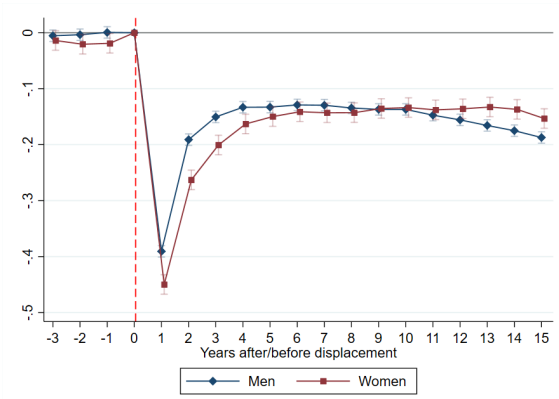
Figure 4: Distribution of Worker Characteristics Pre-Layoff, by Gender



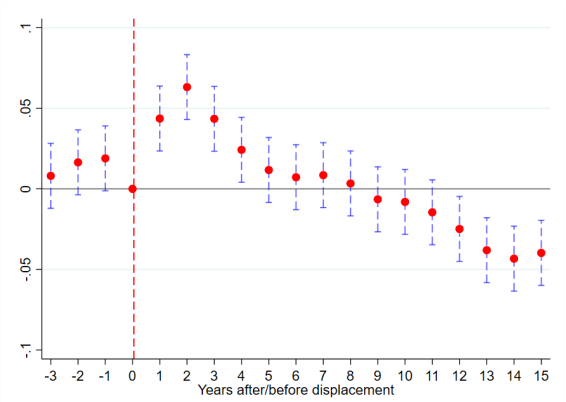
(a) Age (b) Monthly Wage (c) Firm Pay

This figure shows the distribution of selected worker characteristics pre-layoff, separately by gender. Panel (a) reports age, Panel (b) reports monthly wages, Panel (c) reports average firm pay. Solid and dashed lines correspond to men and women, respectively. Vertical lines indicate gender-specific means where applicable. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 5: Effects of Job Displacement on Earnings Loss



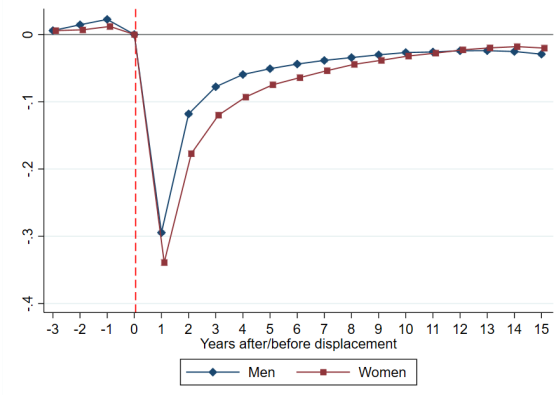
(a) Level (Relative to the Pre-Displacement Year)



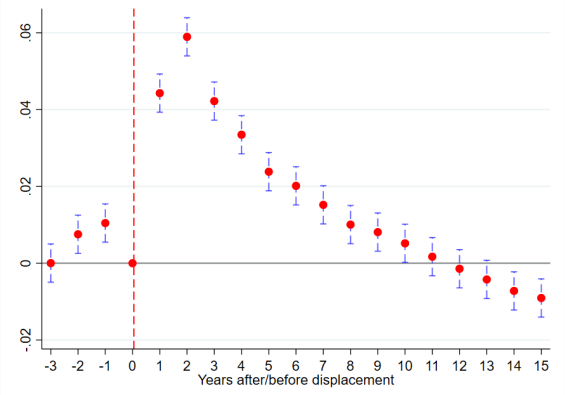
(b) Gender Gap

This figure shows the dynamic effects of job displacement on earning loss. Panel (a) reports event-study estimates for men and women, while Panel (b) reports the corresponding gender gap. Estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 6: Effects of Job Displacement on Formal Labor Market Participation



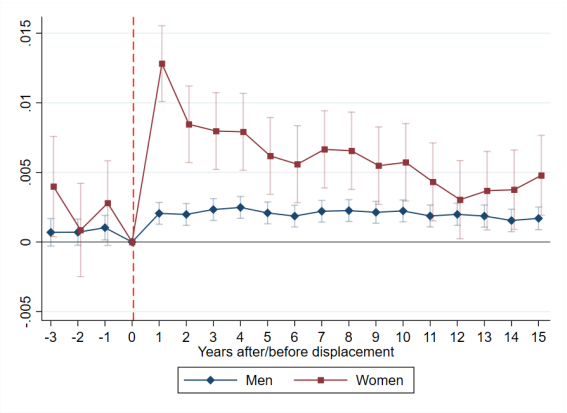
(a) Level (%)



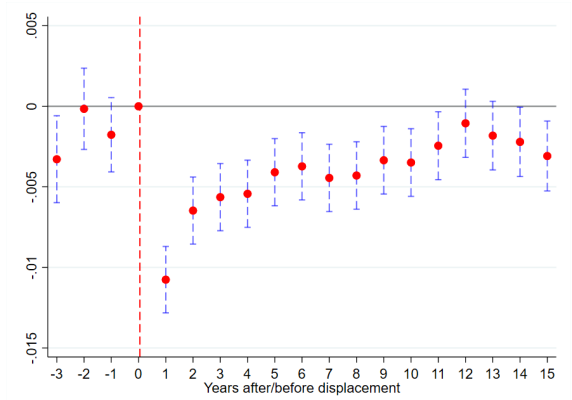
(b) Gender Gap

This figure shows the dynamic effects of job displacement on formal labor market participation. Panel (a) reports event-study estimates for men and women, while Panel (b) reports the corresponding gender gap. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

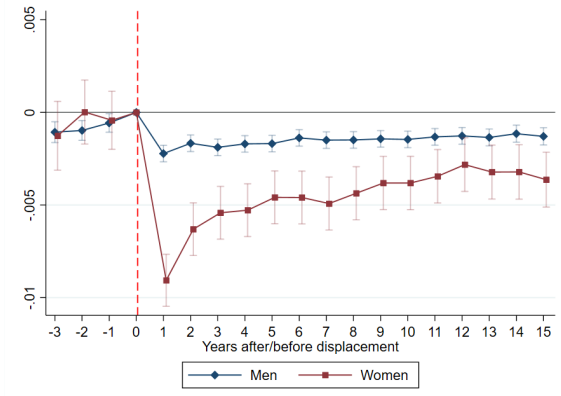
Figure 7: Effects of Job Displacement on Job Characteristics



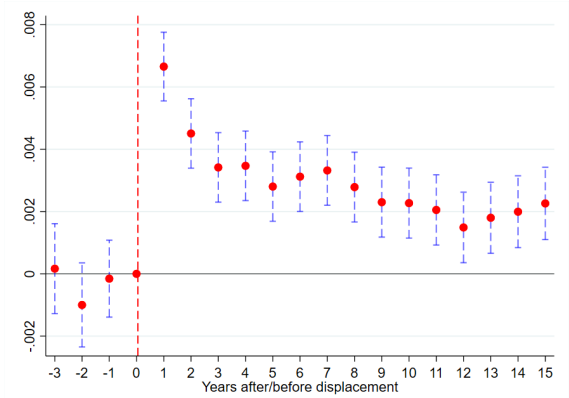
(a) Part-time - Level (%)



(b) Part-time - Gender Gap



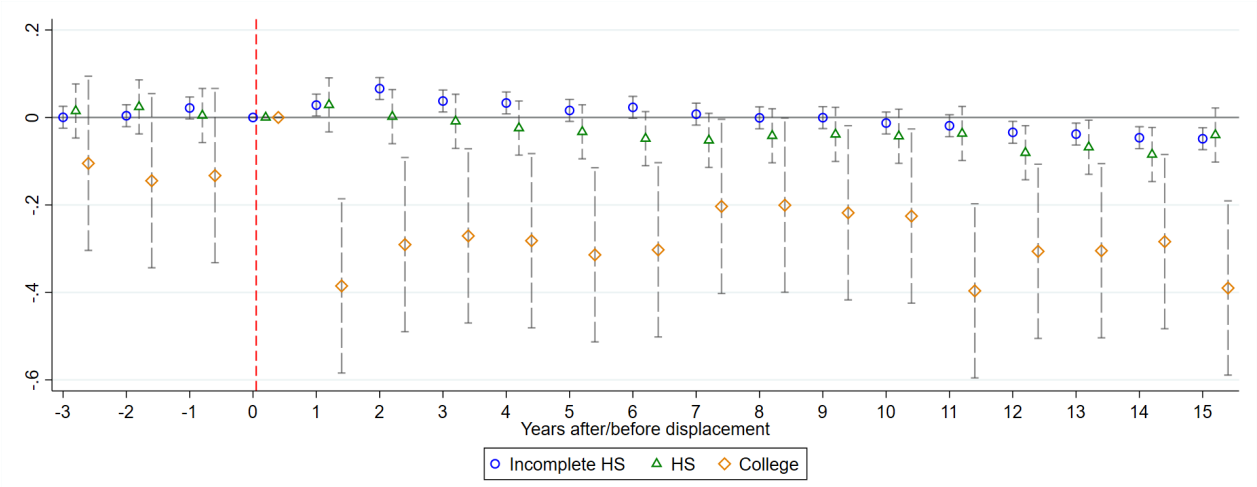
(c) Hours - Level (Relative to the Pre-Displacement Year)



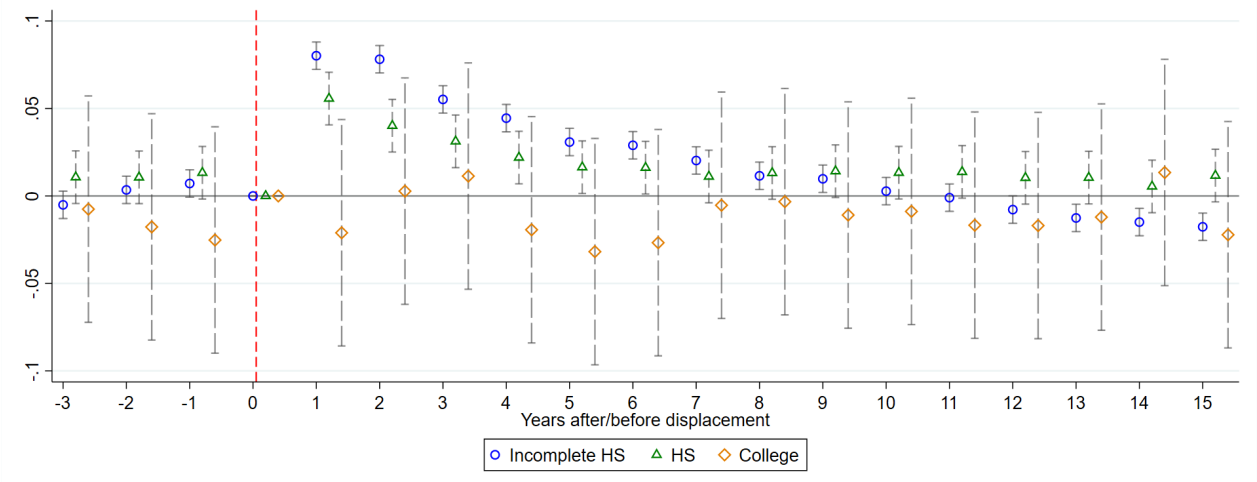
(d) Hours - Gender Gap

This figure shows the dynamic effects of job displacement on job characteristics. Panels (a) and (b) for part-time employment, and Panels (c) and (d) for contracted hours. Left panels report level effects for men and women, while right panels report the corresponding gender gaps. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 8: Effect of Job Displacement on Gender Gap in Earning Loss and Formal Market Participation, By Education



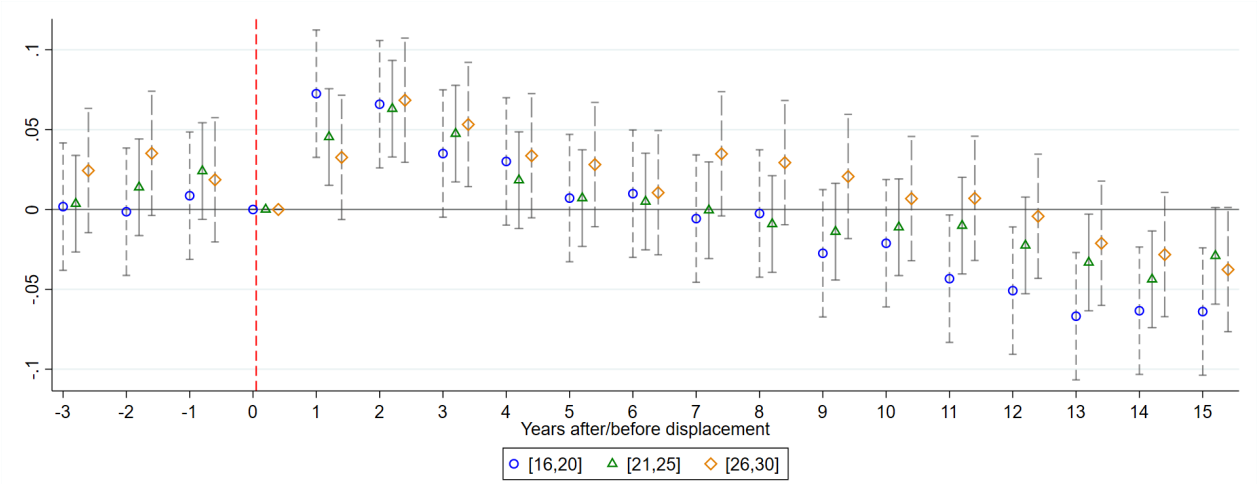
(a) Earning Loss



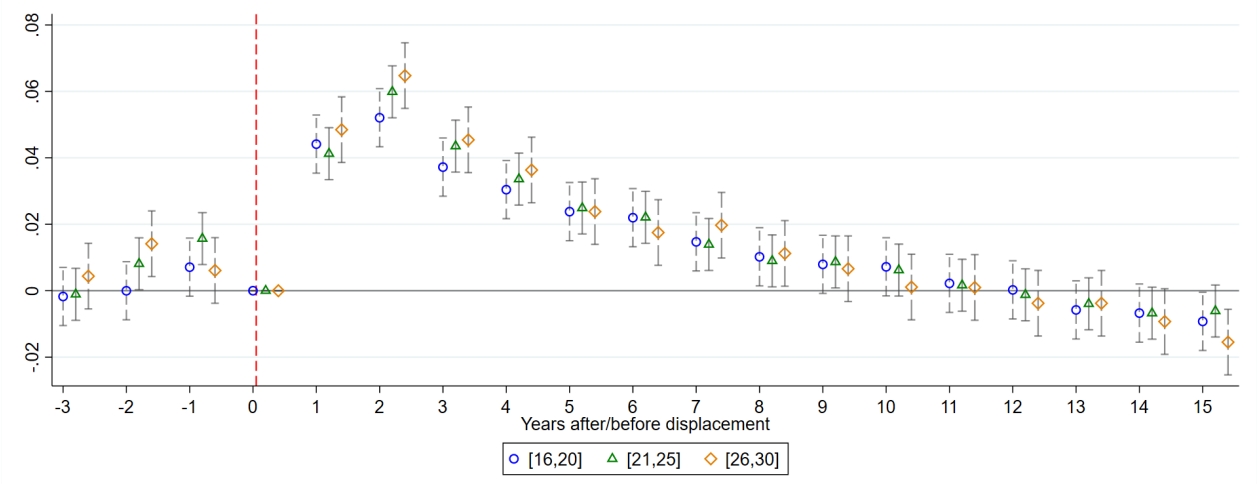
(b) Employment

This figure shows event-study estimates of the effects of job displacement on gender gaps in earnings losses (Panel (a)) and formal employment (Panel (b)). Estimates are shown separately for workers with incomplete high school, high school, and college education. All estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male − Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 9: Effect of Job Displacement on Gender Gap in Earning Loss and Formal Market Participation, By Age



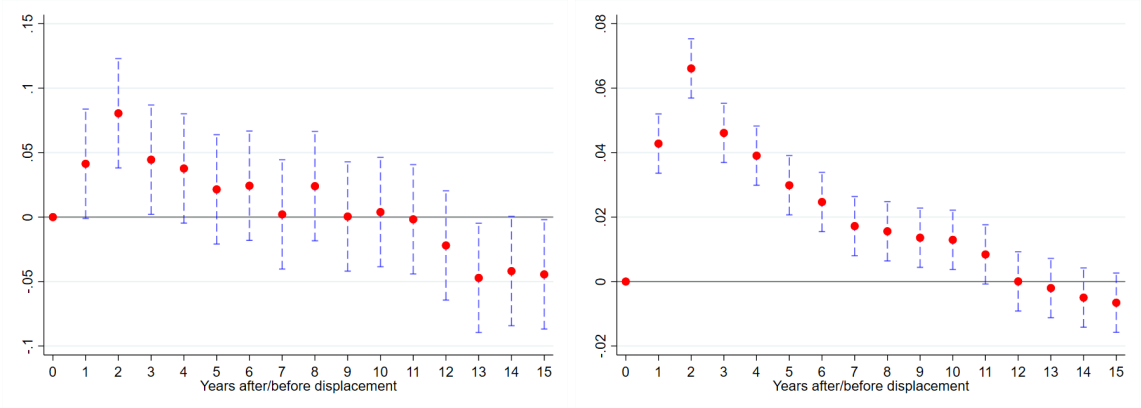
(a) Earning Loss



(b) Employment

This figure shows event-study estimates of the effects of job displacement on gender gaps in earnings losses (Panel (a)) and formal employment (Panel (b)). Estimates are reported separately for workers aged 16–20, 21–25, and 26–30 at the time of displacement. All estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

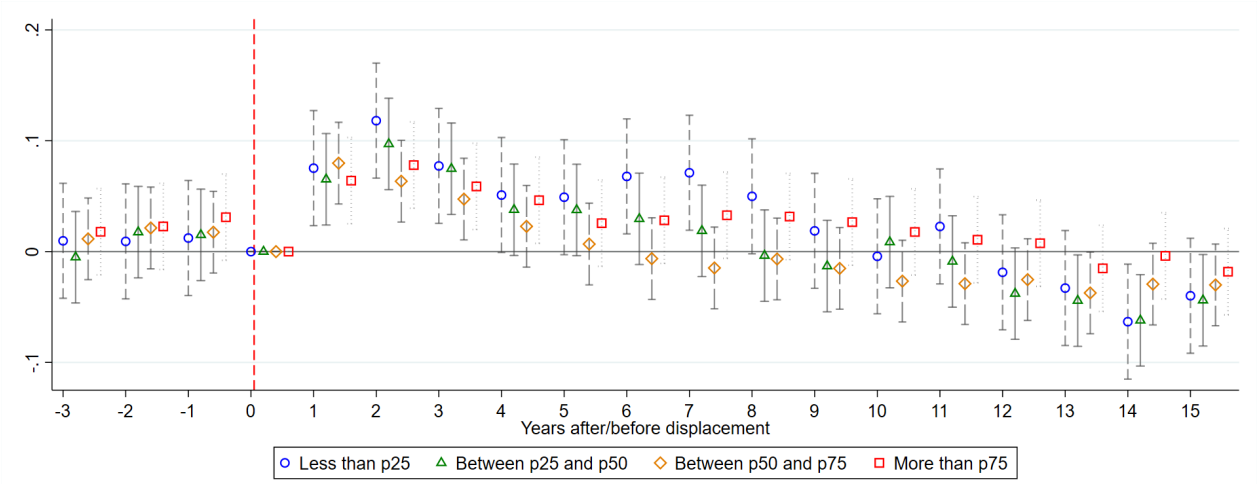
Figure 10: Effects of Job Displacement on Gender Gap in Earning Loss and Formal Market Participation, Only First Job



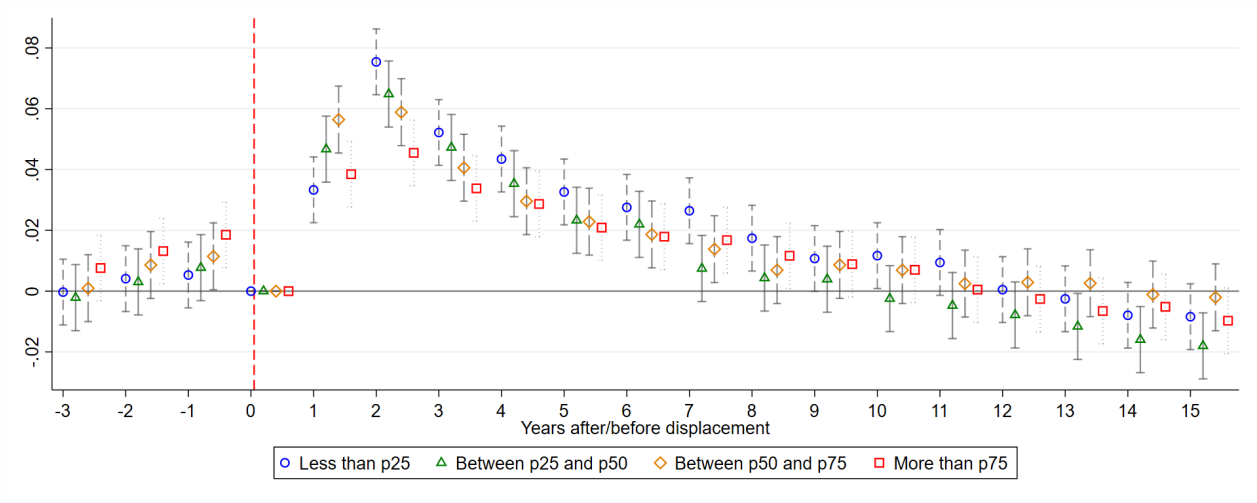
(a) Earning Loss (b) Employment

This figure reports first job loss effects on gender gaps in earnings losses (Panel (a)) and formal employment (Panel (b)). Estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 11: Effect of Job Displacement on Gender Gap in Earning Loss and Formal Market Participation, By Earnings



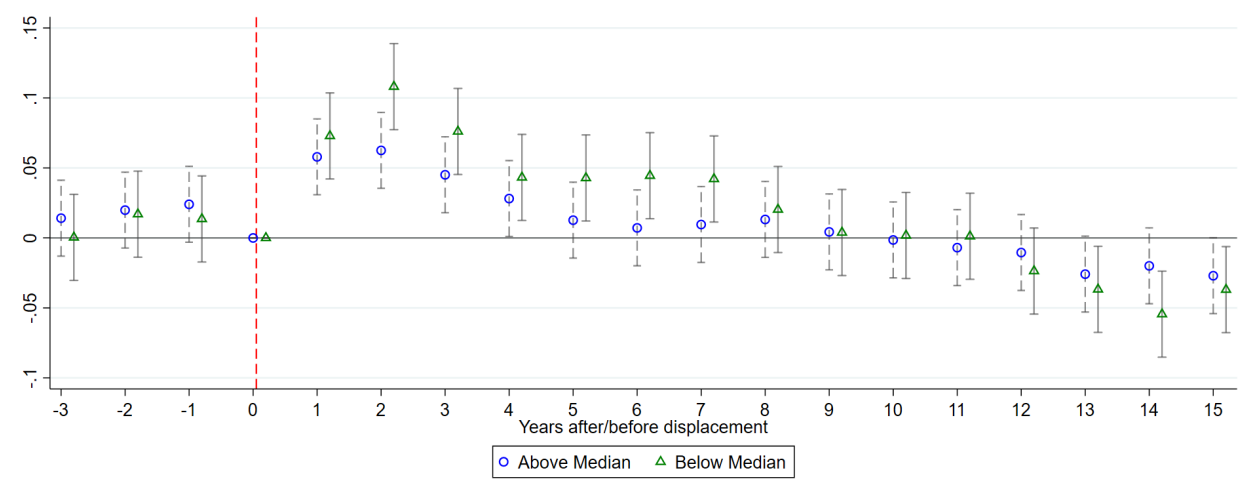
(a) Earning Loss



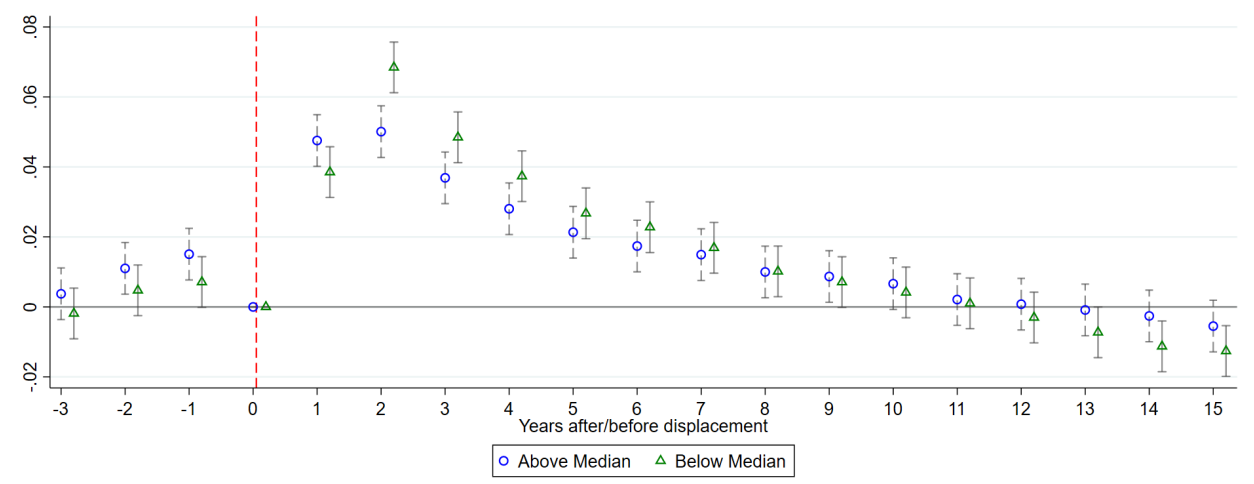
(b) Employment

This figure shows event-study estimates of the effects of job displacement on gender gaps in earnings losses (Panel (a)) and formal employment (Panel (b)). Estimates are reported separately for workers with earnings below the 25th percentile, between the 25th and 50th percentiles, between the 50th and 75th percentiles, and above the 75th percentile. All estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male − Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 12: Effect of Job Displacement on Gender Gap in Earning Loss and Formal Market Participation, By Firm Pay



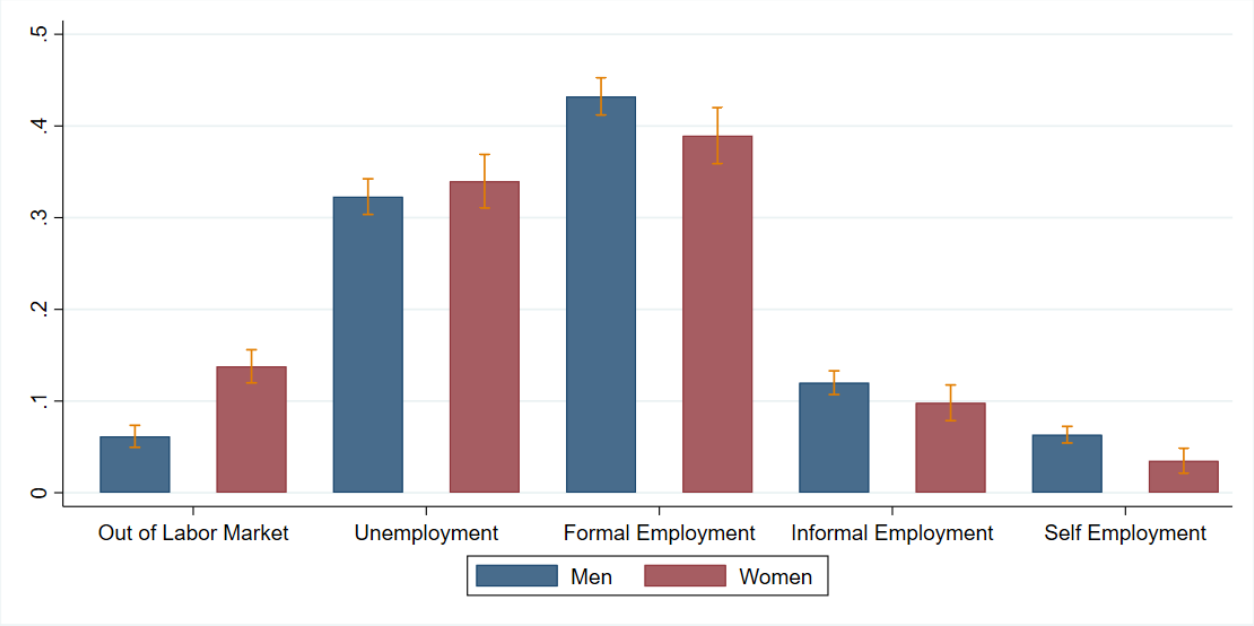
(a) Earning Loss



(b) Employment

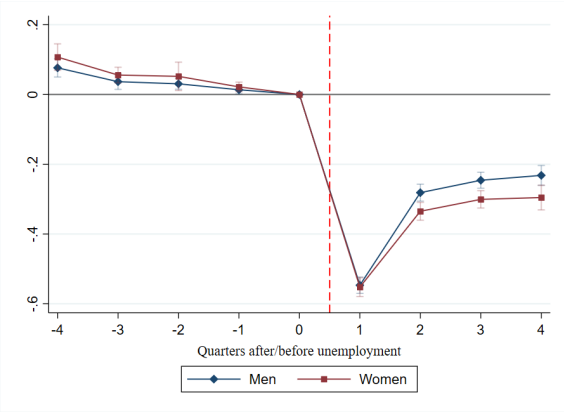
This figure shows event-study estimates of the effects of job displacement on gender gaps in earnings losses (Panel (a)) and formal employment (Panel (b)). Estimates are reported separately for workers employed at firms with average pay above and below the median prior to displacement. All estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 13: Employment Status One Year After Unemployment

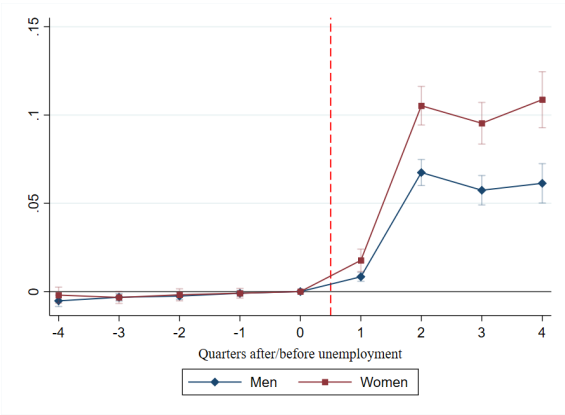


This figure displays the distribution of labor market status four quarters after an unemployment spell. Blue bars denote men, and red bars denote women. The sample consists of workers aged 16 to 30 who were initially employed in the formal sector. Treated workers are matched to non-displaced controls based on cohort, state, gender, and pre-displacement earnings bins. The analysis uses data from the PNADC rotating panel from 2012 to 2024. We show 95% confidence intervals

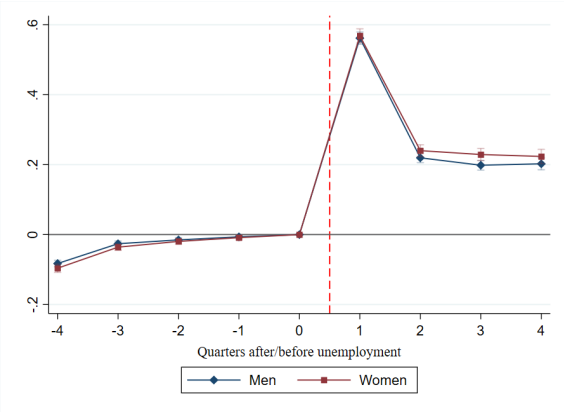
Figure 14: Short-Term Impact of Unemployment on Labor Market Outcomes by Gender



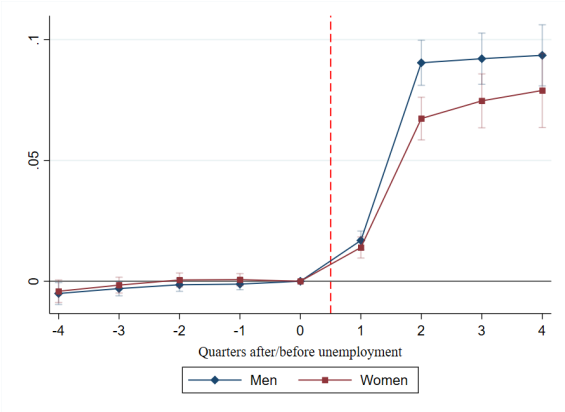
(a) Earnings (Relative to the Pre-Displacement Quarter)



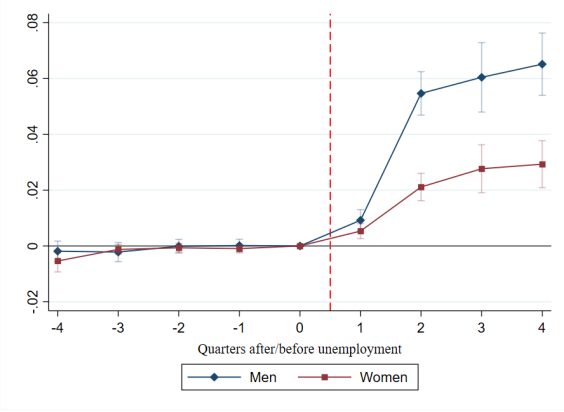
(b) Out of Labor Market (%)



(c) Unemployment (%)



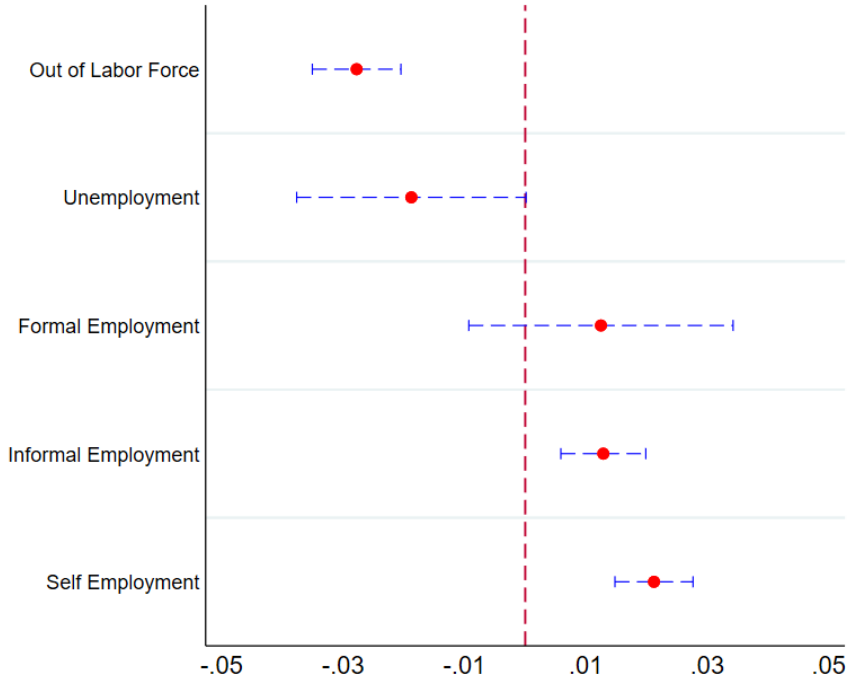
(d) Informal Employment (%)



(e) Self-Employment (%)

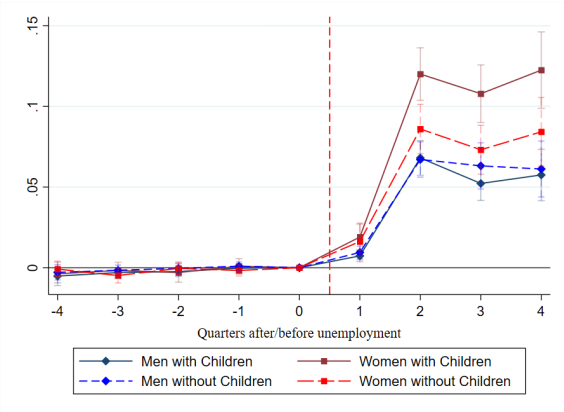
This figure plots the event-study coefficients estimating the impact of an unemployment spell on earnings and labor force status, separately for men (blue diamonds) and women (red squares). The x-axis represents quarters relative to the event, where $t = 0$ is the last quarter of employment (reference period). Panel (a) displays the effect on total monthly earnings (including zeros for non-employed individuals) relative to the baseline. Panels (b) through (e) show the impact on the probability of being in a specific labor market state: (b) Out of the Labor Force; (c) Unemployed (actively searching); (d) Informal Employment (unregistered); and (e) Self-Employment. The sample consists of workers aged 16 to 30 who were initially employed in the formal sector. Treated workers are matched to non-displaced controls based on cohort, state, gender, and pre-displacement earnings bins. The analysis uses data from the PNADC rotating panel from 2012 to 2024. We show 95% confidence intervals.

Figure 15: Average Gender Gap in Labor Market Outcomes Following Unemployment

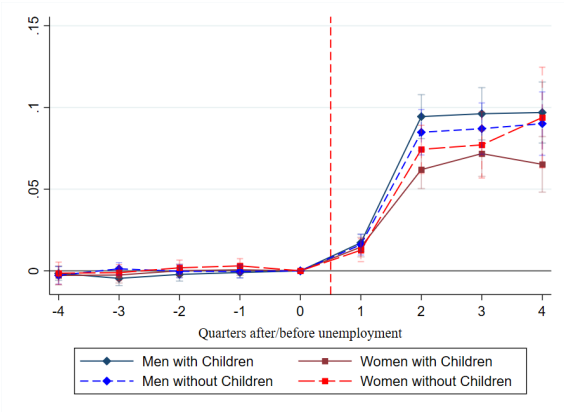


This figure displays the average gender difference in treatment effects over the four quarters following an unemployment spell. The coefficients are obtained from a difference-in-differences specification where the treatment indicator is interacted with a gender dummy. The estimates represent the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The sample consists of workers aged 16 to 30 who were initially employed in the formal sector. Treated workers are matched to non-displaced controls based on cohort, state, gender, and pre-displacement earnings bins. The analysis uses data from the PNADC rotating panel from 2012 to 2024. We show 95% confidence intervals.

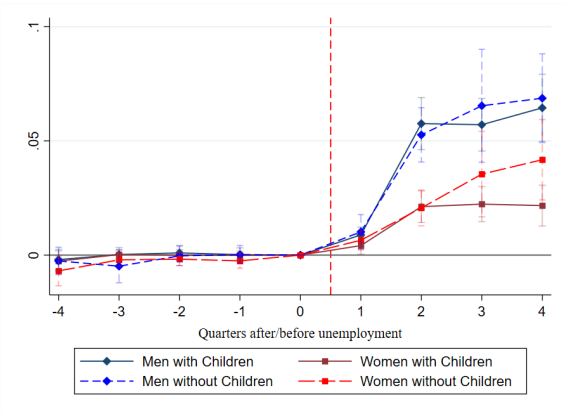
Figure 16: Short-Term Impact of Unemployment on Labor Market Outcomes by Gender and Children



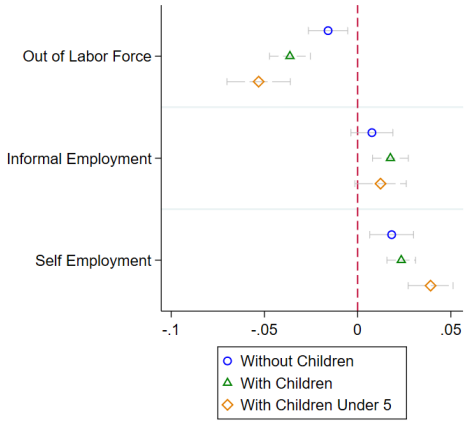
(a) Out of Labor Market (%)



(b) Informal Employment (%)



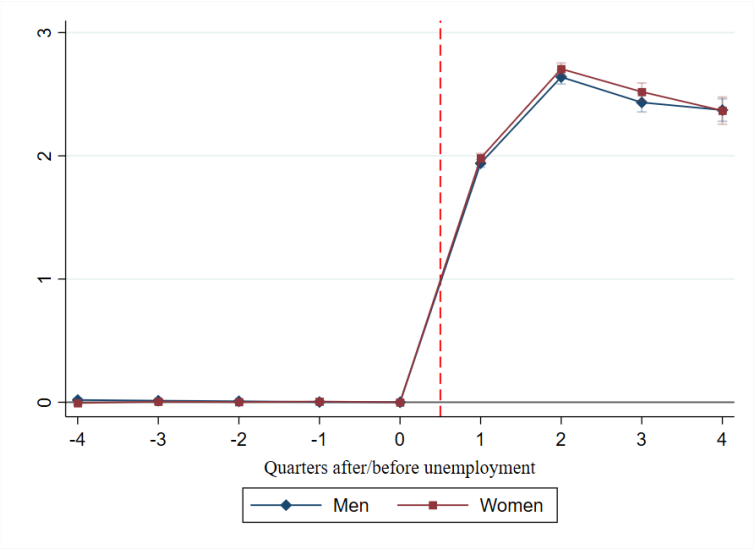
(c) Self-Employment (%)



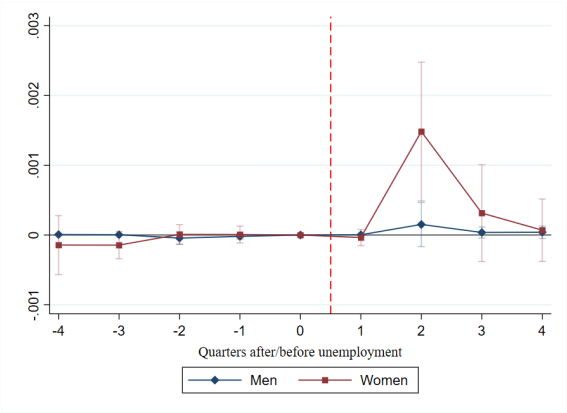
(d) Gender Gap

This figure displays the average gender difference in treatment effects over the four quarters following an unemployment spell. Panel (a) to (c) plot the event-study coefficients estimating the impact of an unemployment spell on earnings and labor force status, separately for men (blue diamonds) and women (red squares). The x-axis represents quarters relative to the event, where $t = 0$ is the last quarter of employment (reference period). The coefficients in Panel (d) are obtained from a difference-in-differences specification where the treatment indicator is interacted with a gender dummy. The estimates represent the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The sample consists of workers aged 16 to 30 who were initially employed in the formal sector. Treated workers are matched to non-displaced controls based on cohort, state, gender, and pre-displacement earnings bins. The analysis uses data from the PNADC rotating panel from 2012 to 2024. We show 95% confidence intervals.

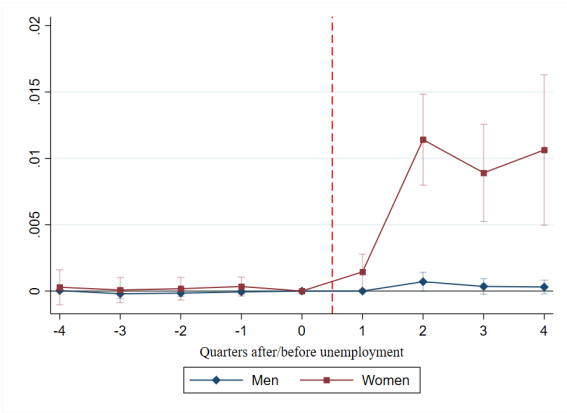
Figure 17: Short-Term Impact of Unemployment on Job Search Behavior



(a) Months Looking for a Job



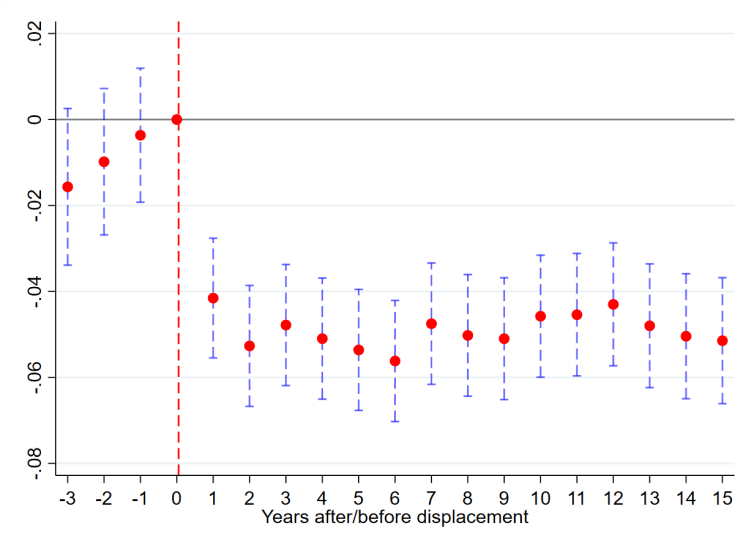
(b) Not Looking for a Job to Care (%)



(c) Not Working to Care (%)

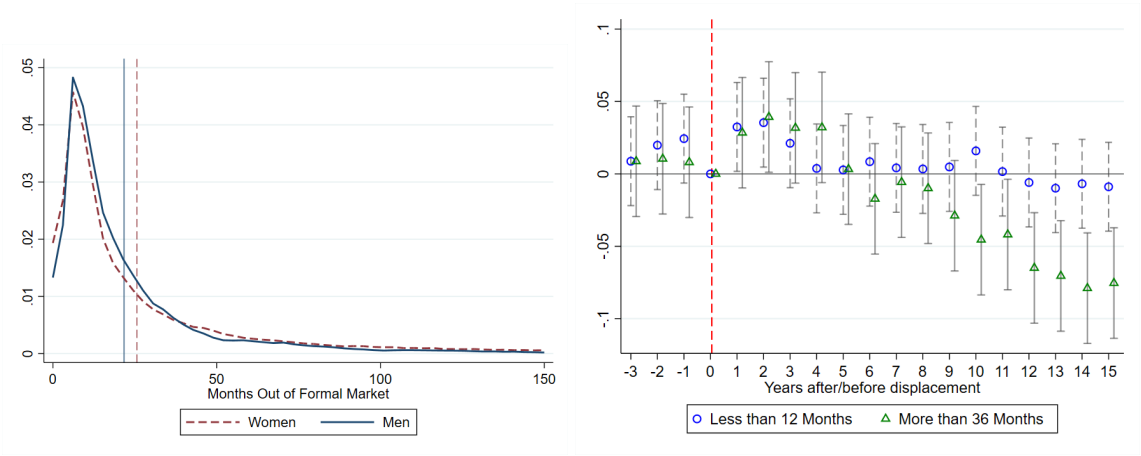
This figure investigates potential mechanisms driving the gender difference in labor supply. Panel (a) shows the effect on the self-reported duration of job search (in months) for those actively looking for work. Panels (b) and (c) analyze care responsibilities as a barrier to employment. Panel (b) plots the probability of citing "care for children, dependents, or domestic chores" as the main reason for not taking action to look for a job (among those out of the labor force). Panel (c) plots the probability of citing the same care responsibilities as the main reason for not being available to start working in the reference week (regardless of search status). The sample consists of workers aged 16 to 30 who were initially employed in the formal sector. Treated workers are matched to non-displaced controls based on cohort, state, gender, and pre-displacement earnings bins. The analysis uses data from the PNADC rotating panel from 2012 to 2024. We show 95% confidence intervals.

Figure 18: Effects of Job Displacement on Gender Employment in High-Paying Firms Gap



This figure examines employment at high-paying firms, defined as firms with average pay above the median. All estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

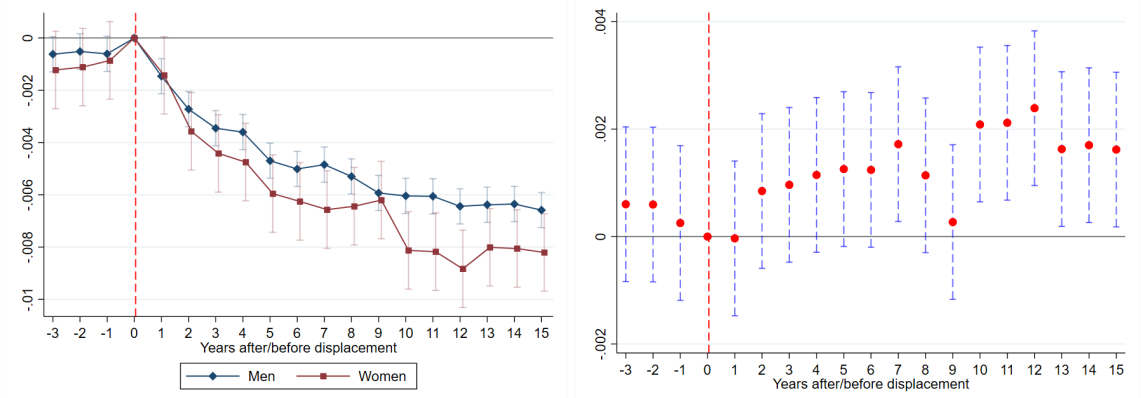
Figure 19: Effects of Job Displacement on Earnings Loss and Formal Employment Gaps, by Duration of Non-Employment



(a) Months Separeted (b) Gender Gap in Earning Loss

This figure examines the role of non-employment duration in shaping the effects of job displacement by gender. Panel (a) shows the distribution of months spent out of the formal labor market following displacement, separately for men and women. Solid and dashed lines correspond to men and women, respectively. Vertical lines indicate gender-specific means. Panel (b) reports event-study estimates of the effects of job displacement on gender gaps in earnings losses, separately for workers with short non-employment spells (less than 12 months) and long non-employment spells (more than 36 months). All estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure 20: Effects of Job Displacement on Managerial Position



(a) Managerial Position (%) (b) Gender Gap

This figure shows the dynamic effects of job displacement on managerial positions. Panel (a) reports event-study estimates of holding a managerial position for men and women, while Panel (b) reports the corresponding gender gap. The analysis covers a window of 3 years before and 15 years after displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

B Tables

Table 1: Descriptive Statistics of Workers by Employment Trajectory

		AKM sample			
	Complete	Dual-Connected	Stayers	Displaced	Dismissed
	(1)	(2)	(3)	(4)	(5)
Full-Time	0.919	0.919	0.884	0.932	0.944
	(0.273)	(0.273)	(0.320)	(0.251)	(0.230)
Earnings	2594.016	2632.152	3274.180	2380.694	2316.888
	(3656.446)	(3684.063)	(4311.923)	(3373.628)	(3069.273)
Ln(Earnings)	7.502	7.508	7.708	7.430	7.437
	(0.750)	(0.750)	(0.794)	(0.717)	(0.690)
White-Collar	0.454	0.456	0.536	0.425	0.411
	(0.498)	(0.498)	(0.499)	(0.494)	(0.492)
White-Collar – Manager	0.042	0.043	0.051	0.040	0.039
	(0.202)	(0.203)	(0.220)	(0.196)	(0.193)
White-Collar – Professional	0.098	0.100	0.143	0.083	0.074
	(0.297)	(0.300)	(0.350)	(0.276)	(0.261)
White-Collar – Technician	0.119	0.121	0.154	0.108	0.106
	(0.324)	(0.326)	(0.361)	(0.310)	(0.308)
White-Collar – Others	0.194	0.191	0.187	0.193	0.193
	(0.395)	(0.393)	(0.390)	(0.395)	(0.395)
Blue-Collar	0.540	0.537	0.456	0.570	0.586
	(0.498)	(0.499)	(0.498)	(0.495)	(0.493)
Blue-Collar – Skilled	0.235	0.237	0.225	0.241	0.249
	(0.424)	(0.425)	(0.417)	(0.428)	(0.432)
Blue-Collar – Unskilled	0.212	0.213	0.175	0.224	0.223
	(0.409)	(0.409)	(0.380)	(0.417)	(0.416)
Age	31.030	31.018	31.642	30.774	30.889
	(5.774)	(5.736)	(5.746)	(5.714)	(5.741)
Hours	41.516	41.495	40.572	41.857	42.157
	(5.901)	(5.897)	(6.653)	(5.531)	(5.176)
Education: Incomplete High-School	0.376	0.374	0.285	0.408	0.406
	(0.484)	(0.484)	(0.451)	(0.492)	(0.491)
Education: High-School	0.423	0.424	0.443	0.416	0.430
	(0.494)	(0.494)	(0.497)	(0.493)	(0.495)
Education: Incomplete College	0.043	0.043	0.047	0.041	0.041
	(0.202)	(0.202)	(0.212)	(0.198)	(0.198)
Education: College	0.158	0.160	0.224	0.134	0.123
	(0.365)	(0.366)	(0.417)	(0.341)	(0.329)
Firm Size: Less than 5 Workers	0.153	0.144	0.093	0.165	0.163
	(0.360)	(0.351)	(0.290)	(0.371)	(0.369)
Firm Size: Between 5 and 20 Workers	0.197	0.192	0.152	0.207	0.213
	(0.398)	(0.394)	(0.359)	(0.405)	(0.410)
Firm Size: Between 20 and 100 Workers	0.199	0.201	0.186	0.207	0.216
	(0.400)	(0.401)	(0.389)	(0.405)	(0.412)
Firm Size: More than 100 Workers	0.450	0.463	0.569	0.421	0.408
	(0.498)	(0.499)	(0.495)	(0.494)	(0.491)
Observations	11,793,141	11,313,828	3,184,103	8,129,725	9,226,801

This table reports descriptive statistics for workers by labor market trajectory. Columns (1) and (2) report statistics for the full sample and the dual-connected sample, respectively. Columns (3)–(5) report statistics separately for stayers, displaced, and dismissed workers. All variables are measured at the worker–year level. Reported values are means, with standard deviations in parentheses. *Full-Time* indicates full-time employment (35 hours or more) in a given year. Earnings denote average monthly earnings and, *Ln*(Earnings) denotes log monthly wages. Occupational categories distinguish white-collar and blue-collar jobs and their subgroups (manager, professional, technician, skilled, and unskilled). *Age* is measured in years, and *Hours* denote contracted weekly hours. Education variables indicate the worker's highest completed level of schooling. Firm size categories are defined by the number of employees at the firm. The data come from RAIS and cover the period 1995–2019 for workers who entered the formal labor market between 1998 and 2004 and were born in 1978.

Table 2: Decomposing the Gender Wage Gap

	Gender Wage Gap	Gender gap in employers FEs		Between-employer gap		Within-employer gap	
		Level	Share (%)	Level	Share (%)	Level	Share (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All	0.091	0.037	41.0	0.029	32.0	0.008	9.0
Dual-Connected	0.089	0.037	41.6	0.028	31.8	0.009	9.8
Stayers	0.100	0.071	70.5	0.083	82.3	-0.012	–
Displaced	0.090	0.025	27.4	0.007	8.0	0.018	19.4
Dismissed	0.097	0.029	30.0	0.006	5.9	0.024	24.1

This table decomposes the gender wage gap using firm fixed effects estimated from an AKM model. Column (1) reports the overall gender wage gap. Columns (2)–(3) report the contribution of firm fixed effects to the gap, in levels and as a share of the total gap. Columns (4)–(5) report the between-firm component, and columns (6)–(7) report the within-firm component, following the decomposition in Card et al. (2016). Rows report results for the full sample, dual-connected sample and by labor market trajectory (*stayers*, *displaced*, *and dismissed*). The data come from RAIS and cover the period 1995–2019 for workers who entered the formal labor market between 1998 and 2004 and were born in 1978.

Table 3: Descriptive Statistics for Laid-Off Workers and Matched Controls

	Laid-Off (1)	Matched (2)	Difference (3)	P-value (4)
Full-Time	0.978	0.976	0.002	0.000
	(0.147)	(0.154)		
Earnings	1170.597	1159.625	10.972	0.000
	(1197.782)	(1034.731)		
Ln(Earnings)	6.930	6.925	0.005	0.000
	(0.456)	(0.454)		
White-Collar	0.294	0.295	-0.001	0.090
	(0.456)	(0.456)		
White-Collar – Manager	0.004	0.003	0.001	0.000
	(0.061)	(0.057)		
White-Collar – Professional	0.008	0.008	0.000	0.022
	(0.088)	(0.090)		
White-Collar – Technician	0.072	0.071	0.001	0.024
	(0.259)	(0.257)		
White-Collar – Others	0.210	0.213	-0.003	0.001
	(0.407)	(0.409)		
Blue-Collar	0.539	0.536	0.003	0.002
	(0.498)	(0.499)		
Blue-Collar – Skilled	0.171	0.165	0.006	0.000
	(0.377)	(0.371)		
Blue-Collar – Unskilled	0.217	0.221	-0.004	0.000
	(0.412)	(0.415)		
Age	23.183	23.166	0.017	0.014
	(3.809)	(3.776)		
Hours	43.247	43.166	0.081	0.000
	(3.622)	(3.730)		
Education: Incomplete High-School	0.764	0.730	0.034	0.000
	(0.424)	(0.444)		
Education: High-School	0.203	0.228	-0.025	0.000
	(0.402)	(0.420)		
Education: Incomplete College	0.020	0.025	-0.005	0.000
	(0.141)	(0.155)		
Education: College	0.013	0.017	-0.004	0.000
	(0.112)	(0.129)		
Firm Size: Less than 5 Workers	0.164	0.174	-0.010	0.000
	(0.370)	(0.379)		
Firm Size: Between 5 and 20 Workers	0.316	0.313	0.003	0.007
	(0.465)	(0.464)		
Firm Size: Between 20 and 100 Workers	0.268	0.263	0.005	0.000
	(0.443)	(0.440)		
Firm Size: More than 100 Workers	0.253	0.249	0.004	0.000
	(0.435)	(0.433)		
Observations	602,169	602,169		

This table reports descriptive statistics for laid-off workers and their matched control group. Columns (1) and (2) report means for the laid-off and matched samples, respectively. Column (3) reports differences in means, and column (4) reports p-values from tests of equality of means. All variables are measured one year prior to displacement. Reported values are means, with standard deviations in parentheses. *Full-Time* indicates full-time employment (35 hours or more) in a given year. Earnings denote average monthly earnings and, *Ln*(Earnings) denotes log monthly wages. Occupational categories distinguish white-collar and blue-collar jobs and their subgroups (manager, professional, technician, skilled, and unskilled). *Age* is measured in years, and *Hours* denote contracted weekly hours. Education variables indicate the worker's highest completed level of schooling. Firm size categories are defined by the number of employees at the firm. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

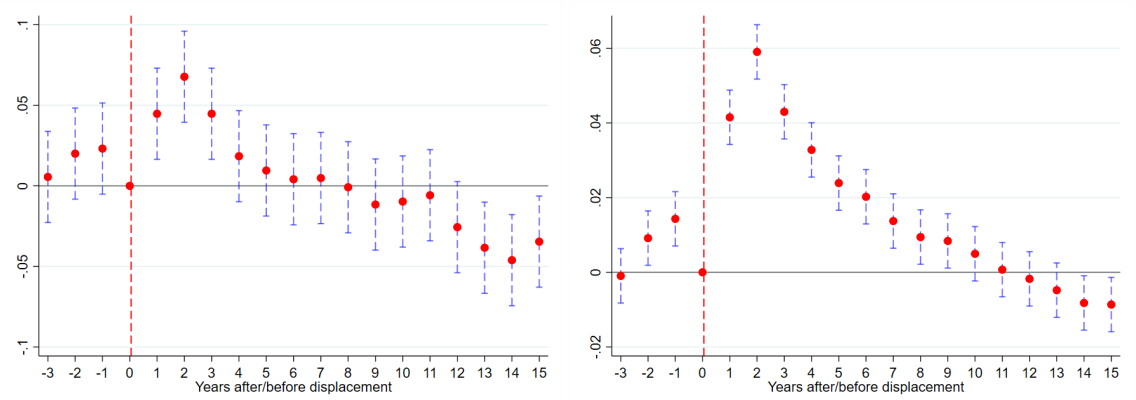
Table 4: Effects of Job Displacement on Gender Gap

	+1 Years (1)		+5 Years (2)		+10 Years (3)		+15 Years (4)	
Panel A: Main Earnings and Employment Results								
Earnings (R$)	48.219***	(5.366)	11.092	(6.852)	-11.403	(9.164)	-49.073***	(10.624)
Employment	0.044***	(0.002)	0.024***	(0.002)	0.005***	(0.002)	-0.009***	(0.002)
Part-time	-0.006***	(0.001)	-0.002***	(0.001)	-0.003***	(0.001)	-0.002	(0.001)
Hours	0.192***	(0.017)	0.124***	(0.019)	0.136***	(0.021)	0.124***	(0.028)
Earnings (R$) | Employed After 1 Year	15.757**	(6.818)	0.464	(9.041)	8.339	(12.210)	-26.866*	(14.006)
Earnings (R$) | Employed After 5 Years	38.443***	(7.219)	-9.199	(9.497)	-13.617	(12.936)	-50.041***	(15.121)
Earnings (R$) | Employed After 10 Years	55.177***	(7.472)	5.764	(9.627)	-30.340**	(12.758)	-42.443***	(15.579)
Earnings (R$) | Employed After 15 Years	66.002***	(8.293)	14.000	(10.443)	0.536	(13.917)	-30.064*	(16.620)
Panel B: Occupation and Industry								
Firm Avg. Pay (R$)	-8.381	(6.027)	-33.019***	(8.441)	-31.532***	(10.579)	-40.459***	(12.812)
Promotion	0.019***	(0.003)	-0.005	(0.003)	0.001	(0.003)	-0.007**	(0.004)
Changed Industry	-0.006**	(0.003)	-0.029***	(0.003)	-0.025***	(0.003)	-0.016***	(0.003)
Changed Occupation	-0.009*	(0.005)	-0.026***	(0.004)	-0.018***	(0.003)	-0.015***	(0.003)
Managerial Position	-0.001*	(0.000)	0.001	(0.001)	0.002***	(0.001)	0.001	(0.001)

This table reports gender differences in the effects of job displacement. Columns present average displacement effects *X* years after layoff, with standard errors in parentheses. *Earnings* denote average monthly real earnings in 2020 reais. *Part-Time* indicates employment in a formal job with fewer than 35 weekly hours. *Hours* denote contracted weekly hours. *Earnings (R$) | Employed After X Years* reports average monthly real earnings conditional on being employed in the formal sector *X* years after layoff. *Firm Avg. Pay* is the average monthly wage paid by the employing firm and serves as a proxy for firm quality. *Promotion* equals one if the worker's wage growth exceeds the firm's average annual wage growth. *Changed Industry* equals one if the worker is employed in a different industry than in the pre-displacement job. *Changed Occupation* equals one if the worker switches occupation relative to the pre-displacement job. The matched sample is constructed using observable worker and job characteristics as described in Section 4. ***p< 0.01, ** p< 0.05, * p< 0.1.

Appendix

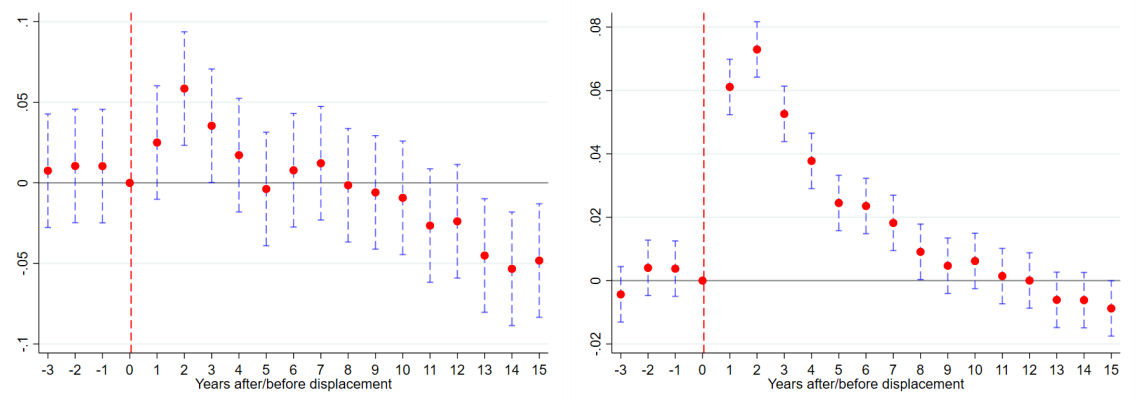
Figure A1: Robustness by Age: Effects of Job Displacement on Gap in Earning Loss and Formal Market Participation



(a) Earning Loss (b) Employment

This figure reports robustness checks restricting to ages 21-26 for the event-study estimates of the effects of job displacement on gender gaps in earnings losses (Panel (a)) and formal employment (Panel (b)). Estimates are relative to the year immediately before displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. The analysis covers a window of 3 years before and 15 years after displacement. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

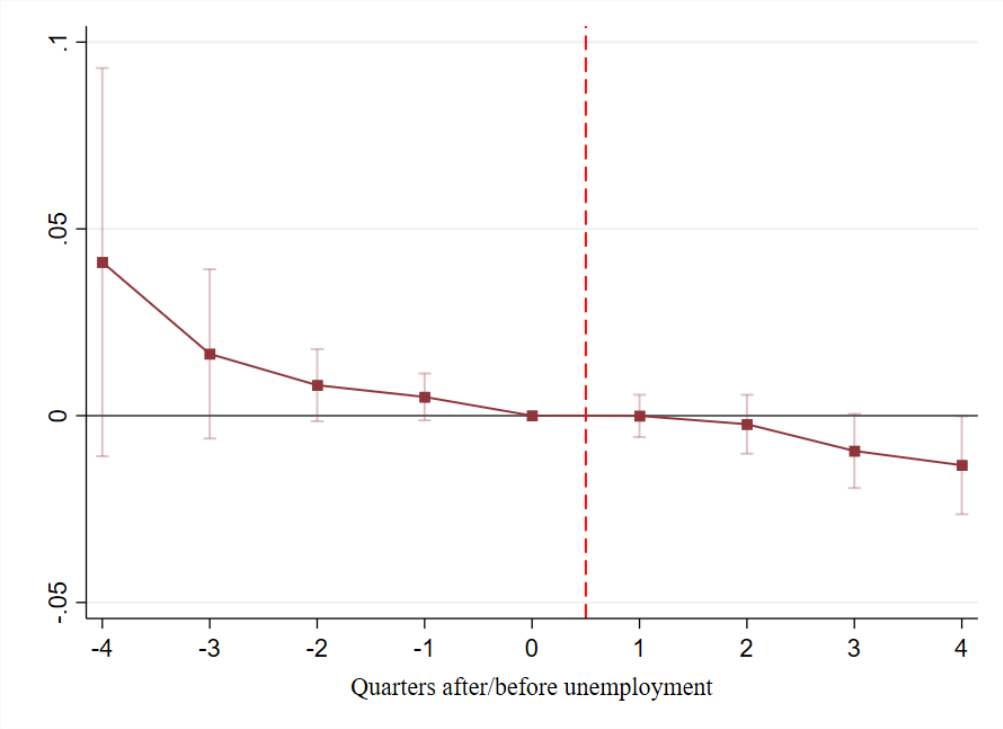
Figure A2: Robustness by Occupation: Effects of Job Displacement on Earnings Loss and Formal Employment Gaps



(a) Earning Loss (b) Employment

This figure reports robustness checks by occupation for the event-study estimates of the effects of job displacement on gender gaps in earnings losses (Panel (a)) and formal employment (Panel (b)). Estimates are relative to the year immediately before displacement. The analysis covers a window of 3 years before and 15 years after displacement. Gender gap represents the differential impact for men relative to women (*Male* − *Female*). Consequently, a positive coefficient indicates that the post-displacement outcome is higher (or the decline is smaller) for men compared to women. Robust standard errors are clustered at the worker level, and 95% confidence intervals are shown. The matched sample is constructed using observable worker and job characteristics as described in Section 4.

Figure A3: Short-Term Impact of Unemployment on Children Aged Less Than One Year



This figure plots the impact of unemployment on fertility, defined as the probability of observing a new child aged less than 1 year in the household in the quarters following job loss. The sample consists of workers aged 16 to 30 who were initially employed in the formal sector. Treated workers are matched to non-displaced controls based on cohort, state, gender, and pre-displacement earnings bins. The analysis uses data from the PNADC rotating panel from 2012 to 2024. We show 95% confidence intervals.