Gender Differences in the Effects of Job Displacement: the Role of Firms

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Abstract

This paper investigates gender differences in the long-term effects of job loss on workers' labor market outcomes in Israel. Relative to displaced female workers, male counterparts experience a larger drop in earnings due to unexpected job loss, despite both genders seeing similar employment declines. Pre-displacement firm and individual attributes entirely account for this gap, with the displacing firm's wage premium and female share explaining the majority of it. Extending the analysis beyond mean effects to distributional impacts shows that these characteristics account for the observed gender gap across the income distribution. Our findings underscore the significant role of firms in shaping the dynamics of labor market disparities.

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1 Introduction

Although the gender wage gap has narrowed in the past decade, it remained significant, with women earning in the US 25 percent less than men on average (Goldin, 2014; Blau and Kahn, 2017). A large empirical literature in economics studies the sources of this gap, decomposing it to individual attributes, such as education and experience, and unexplained components, usually attributed to labor market discrimination and/or differences in expectations, information, and bargaining power (Oaxaca, 1973). Recent work has emphasized that firm sorting accounts for a non-negligible share of the contemporaneous wage gap (Card et al., 2016) while also explaining a significant share of workers' long-run earning losses due to displacement and outsourcing events (Goldschmidt and Schmieder, 2017; Lachowska et al., 2020; Schmieder et al., 2023). Taken together, these findings raise the concern that initial firm sorting contributes not only to the gender differences in earning levels but also to the gender differences in earning dynamics.

In this paper, we investigate the gender differences in labor market dynamics in the context of the long-run responses to unexpected job displacement as a consequence of mass layoff events using rich administrative data from Israel. We measure the raw gender gap in job loss effects and decompose it into components attributable to the displacing firm characteristics and individual characteristics by re-weighting the female workers to match the distribution of male workers' characteristics.

We find that the impact of job loss on earnings is larger and deeper for male workers. In the first year after job displacement, male workers experience a drop of 47 percent in earnings relative to pre-displacement. In contrast, female workers face a drop of only 43 percent in earnings, a 4 percent gap, which is 10 percent of the male effect. In the long run, 7 to 11 years after displacement, males' earnings are 19 percent less than their counterfactual, while females' are only 9 percent less, i.e., their long-run job loss effects are 50 percent of the impacts on males. While the gaps in earnings are substantial, the short- and long-run employment responses after the displacement of males and females are quantitatively similar.

Male and female displaced workers vary by their individual characteristics, which could result in different earning dynamics after displacement. Women are older at job displacement, have fewer children, and are less likely to belong to the Arab minority group. Moreover, compared to males, displaced female workers are more likely to work in large, female-dominated, and lower-paying firms. To study the explanatory power of each dimension in the observed gaps of the long-run impacts of job loss, we decompose the job loss effects into individual and firm characteristics. We do so by re-weighting the female workers to have similar characteristics as male workers using Inverse Probability Weighting (IPW) (DiNardo et al., 1996). Individual characteristics include demographics, ethnicity, location of residence, and post-secondary degree attainment. Firm characteristics include firm Abowd et al. (1999) (hereafter AKM) wage premium, number of employees, age, and share of female workers.

Re-weighting by both individual and firm characteristics explains the entire gap in job loss effects on earnings in Israel both in the short- and long-run, up to 11 years after displacement. This result is in contrast to Illing et al. (2021) in Germany, which finds that the long-run impacts of job displacements are deeper for females after accounting for covariates. Similarly, re-weighting female workers only by pre-displacement earnings also closes the gender gap entirely, which speaks with the evidence that wages are well approximated by a combination of firm and individual components (Abowd et al., 1999; Card et al., 2013).

Pre-displacement firm characteristics account for the majority of the gender gap, with decreasing importance over time. 2 to 6 years after displacement, firm characteristics account for almost 80 percent of the gender gap in relative earnings, while after 7 to 11 years from displacement, they account for 60 percent of the gap. Of all the firm characteristics explored, firm wage premium and female share account for most of the explanatory power of firm characteristics. These results altogether suggest that the initial sorting into firms with different productivity levels plays an important role in career progression and in the differences between male and female job ladders after displacement.

Interestingly, although there are no raw gender differences in the effects of job loss on employment, after accounting for covariates, we find that post-displacement, men experience smaller employment effects. Similar to previous findings on earnings, this result is primarily driven by accounting for pre-displacement firm characteristics. Taken together with the zero covariate-adjusted gaps in earnings (which include zeros), we conclude that in the long run, the average wage of women increases.

Extending the analysis beyond mean effects to the distributional impacts of job displacement on earnings, we find that job loss disproportionately affects men and women in different segments of the income distribution. For men, job loss leads to a reduced probability of earning above median pre-displacement earnings, which both shifts and compresses their post-displacement earning distribution. In contrast, women experience a more uniform drop in income across the earnings distribution. Similar to the mean responses, these gender differences eventually disappear when we control for both individual and firm characteristics. Specifically, re-weighting by individual characteristics partially closes some of the gender gaps in the probability of earning above top income deciles, and accounting for firm characteristics eradicates the gender differences in the bottom half of the income distribution. These findings suggest that the distribution of low-wage accepted offers is strongly related to the previous employers. In contrast, the shift in the probability of earning high salaries after displacement reflects heterogeneity by both individual and firm characteristics.

The empirical literature has demonstrated that firms account for a non-negligible share of wage variation. After correcting for sampling error, firms' wage premia typically explain around 5-13% of the overall static wage variation in various countries (Kline et al., 2020; Bonhomme et al., 2023; Lachowska et al., 2023). They also explain a fifth of the gender wage gap in Portugal with 15% and lower of the gap explained by sorting into firms (Card et al., 2016; Hennig and Stadler, 2023), and account for gaps across other groups in the society.[1]. Moreover, past employers are predictive of future earnings (Di Addario et al., 2023), and Lachowska et al. (2020) and Schmieder et al. (2023) show that firms are also important determinants for the dynamic evolution of wages after job displacement.

Our findings suggest that male workers experience deeper earnings loss mainly due to losing their connection to the high-paying firm they worked for. While the phenomenon that displacement from

[1]For example, Arellano-Bover and San (2020) find that firm wage premium explains 10-27% of the wage gap between immigrants and natives in Israel during the first 10 years after arrival. In Brazil, firms explain 10% of the racial wage gap (Gerard et al., 2021)

a high-wage firm leads to a larger job loss effect has been documented in other countries (Schmieder et al., 2023; Lachowska et al., 2020), our findings emphasize the consequences of this phenomenon on the gender wage gap. We find that the gender differences in the size and persistence of the job-loss scar are driven mostly by this firm dimension. That means that gender differences in firm sorting are not only crucial to the static wage distribution and the gender wage gaps but also affect the evolution of earnings the two groups face throughout life. Our results suggest that because male workers are more likely to work at higher-paying firms, they experience a sharper drop in labor market outcomes post-displacement, which serves to decrease gender wage disparities.

From a theoretical standpoint, our findings align with job ladder models such as on-the-job search (Burdett and Mortensen, 1998) or sequential auction models with firms poaching workers (Postel-Vinay and Robin, 2002). These frameworks suggest that wage reductions following displacement can be primarily attributed to the loss of benefits associated with a specific employer. This is because losing the current employer leads to a drop in the value of the outside option, resulting in a fall down the job ladder. Therefore, in these models, the firm wage premium plays a pivotal role in shaping the job ladder.

The remainder of the paper is organized as follows: Section 2 provides an overview of the data, sample restrictions, summary statistics, and the setting of our study. Section 3 outlines the empirical approach and presents the results. Within this section, we outline the methodology in Subsection 3.1, estimate the gender gap in Subsection 3.2, and explore the gender differences of the distributional impacts in Subsection 3.3. Section 4 concludes.

2 Data

We use administrative data assembled by the Israeli Central Bureau of Statistics (CBS). The data covers the entire registered Israeli citizens for the cohorts of 1950-1995, totaling roughly 100 thousand individuals per cohort on average. The data is composed of two main sources: Tax records and the population registry. From the Tax Authority, the data includes employer-employee and self-employed tax records at a yearly level for the years 1995-2019. At the firm level, the data includes a unique firm identifier, number of employees, 3-digit industry code, and total firm payroll for each year. At the worker level, this data records separate jobs on a yearly basis at each employer, with the number of months of employment at each job and gross yearly earnings. From the population registry records, we match detailed information on demographics, including gender, year of birth, date of immigration and country of origin, number of children, an identifier of a spouse, and the year of birth for every child.

The main labor market outcomes in our analysis are employment and yearly earnings from work. Employment status is defined by a dummy that receives a value of one if the worker earned more than 10,000 Israeli Shekels (around 3,000 US dollars) a year and 0 otherwise. Additionally, we present in the appendix the effects of job loss on the number of months worked each year and monthly earnings.

2.1 Sample Restriction and Job Loss Estimation

We focus on workers who are involuntarily separated from their jobs due to mass layoffs and firm closer events. Differentiating between workers who are fired due to such unexpected events and those who leave for other reasons is challenging since, similar to employer-employee records from other countries, we have no information on the explicit separation reasons. Therefore, we rely on methods established in previous literature to detect mass layoff events and worker displacement.[2]

A mass layoff event is defined in our data as an instance where a firm identifier disappears from the records and does not reappear or if a firm experiences a minimum of 30 percent reduction in full-job equivalent worker count within a year, which is not offset the following year. We consider mass layoff events between 1999 and 2009, a decade with a relatively high incidence of layoffs. We restrict our analysis to firms with at least 40 employees, and to mitigate concerns about firm mergers or re-identification, we track worker flows from closing firms to existing ones and omit those where over 20 percent of workers find employment in another continuing firm.

Our sample comprises two groups: displaced and non-displaced workers. Displaced workers are those who leave a firm during a mass layoff event and meet specific criteria. These include a minimum of three years of tenure at their primary employer, working at least 10 months each year for those three years, and no re-employment at the same firm post-displacement. The focus on tenured workers serves two purposes: it supports the assumption that the job loss is involuntary and unrelated to worker-specific characteristics, and it acknowledges that tenured workers experience greater losses when displaced.[3] In addition, we restrict our attention to workers between the ages of 25-54 and exclude workers who worked in the following sectors prior to their displacement: mining, public administration, and health, activities of private households and extra-territorial organizations, and industries that government-owned companies lead.[4]

For the non-displaced worker group, we consider all workers who do not belong to the displaced worker category and were not employed at firms undergoing mass layoffs. We apply the same tenure, age, and sector restrictions criteria as for the displaced group. Each year a non-displaced worker meets these conditions becomes a potential job loss year, and they enter the sample K times, weighted by $\frac{1}{K}$. Further details on the sample restrictions and construction procedure are in Appendix Section B.

Propensity Score Matching Having defined the treated (displaced) and non-treated populations in our data, we use one-to-one matching to pick a subset of non-displaced workers, such that they have similar observables as the treated workers. We estimate a logit-based propensity score to predict the probability of each worker experiencing a mass layoff event. We exploit the richness

[2] For a discussion on the efficacy of this approach, see (Flaaen et al., 2019).

[3] For more discussion on the implications of focusing on tenured workers, see Bertheau et al. (2022), Lachowska et al. (2020), and Rose and Shem-Tov (2023).

[4] Specifically, we omit workers from the following industries: B - Mining and quarrying, O - Local administration, public administration, and defense; compulsory social security, P - Education, Q - Human health and social work activities, R.91 - Libraries, archives, museums, and other cultural activities, T - Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use, U - Activities of extraterritorial organizations and bodies, H.51 - Air transport

of our data by including a long list of features in the propensity estimation, including a second-order polynomial of earnings in the three years prior to displacement independently interacted with gender, pre-displacement firm characteristics such as firm size rank decile dummies, total firm payroll decile dummies, dummies for the year of birth, firm tenure years, cubic age times gender, ethnic group, number of children born up to displacement year, commuting zone at the time of displacement, and spouse's earnings in the two years before displacement. We match displaced workers to control workers within bins of characteristics. These bins are defined according to the displaced worker's industry, year of job loss, gender, and prior yearly earning quartiles.

2.1.1 Summary Statistics

Table 1 presents the means and standard deviation of workers' pre-displacement characteristics. Column (1) presents the characteristics of the non-displaced population who follow the tenure restrictions we describe in Section 2, which is the sample from which we draw the set of one-to-one matched non-displaced workers. Columns (2) and (3) present the displaced and non-displaced match groups, while column (4) presents their mean differences.

The set of displaced workers depicted in Column (3) is negatively selected compared to the pool of non-displaced workers described in Column (1). Job loss workers are more likely to earn less on average, are less educated, work in smaller, lower-paying firms, and are more likely to be of minority groups, such as Arabs or new migrants from Ethiopia or the Former Soviet Union.[5] Following our matching procedure, column (4) shows that the covariates balance across the two groups after matching.

We identified 1,172 firms that underwent a mass layoff between 1999 and 2009, out of which 227 closed altogether. This population constitutes around 3% of the workers in firms that follow our sample restrictions. Job loss firms tend to be slightly smaller, with an average of 181 workers before the event compared to 195 in the non-event firms.

Columns (5) and (6) present the descriptive statistics of the 7,776 male and 5,692 female displaced workers. The gender gap in pre-displacement characteristics is substantial. Females' pre-displacement average earnings are less than 55% of the displaced males, less than the economy-wide gender earning gap, which is around 66% in these years. Their pre-displacement firm is almost twice as big as the males' and pays, on average, lower monthly wages. Women are also more likely to work in firms with a lower male share and with fewer children.

Figure 1 plots the raw uncontrolled ratio of female to male earnings by years from displacement and across treatment groups. Among that sample of highly attached to the labor market and not displaced workers, the gender gap remains stable over time, with female workers earning between 52-54% of males' earnings. In contrast, the gender gaps among displaced workers narrow after displacement, with female workers' earnings reaching 60% of their male counterparts. The gaps between the blue and red lines can be interpreted as the gender gaps in the long-run effects of job loss. As we show next,

[5]The yearly salary of workers in our sample is around 130 thousand Israeli Shekels (\$1 US $\approx$ 3.4), which is higher than the population mean yearly earnings in the Israeli workforce. This is due to the tenure restrictions detailed in B we impose that include only workers who are highly attached to the labor market.

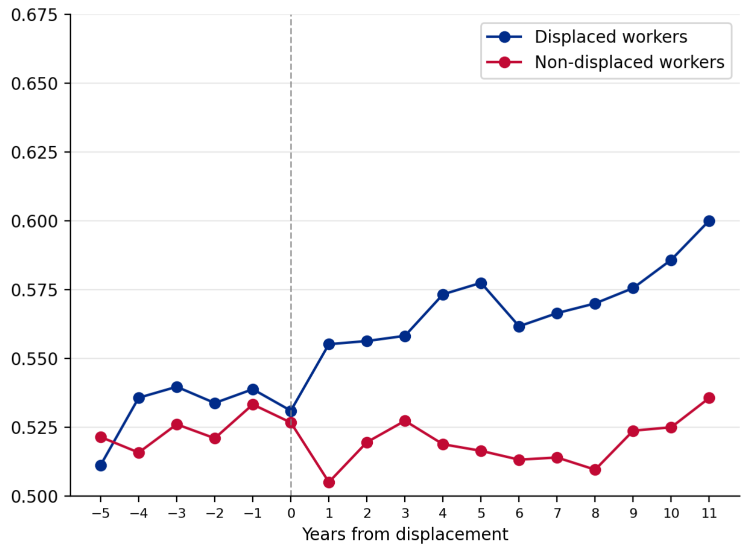
Table 1: Job loss balance table and descriptive statistics

Variable	(1) Population	Matched sample (2) Stayers	(3) Displaced	(4) Difference	Gender (5) Male	(6) Female
Panel A: workers						
t=-1 Yearly earnings	162,953	133,556	132,787	-769	164,698	89,192
				(1,642)		
t=-2 Yearly earnings	155,936	131,598	131,973	-375	163,666	87,974
				(1,919)		
t=-3 Yearly earnings	144,927	124,111	126,446	-2,336	156,541	84,387
				(2,050)		
Age at t=0	40.11	40.06	39.98	-0.09	39.4	40.8
				(0.11)		
t=0 # children in HH	1.96	1.92	1.94	0.02	2.30	1.37
				(0.02)		
Had a spouse	0.54	0.53	0.53	0.00	0.57	0.47
				(0.01)		
Spouse earnings at t=-1	70,010	61,933	61,364	-568	49,140	77,920
				(1,427)		
BA attainment	0.2	0.17	0.17	-0.00	0.18	0.16
				(0.00)		
Arab	0.08	0.11	0.12	0.00	0.15	0.08
				(0.00)		
FSU descendent	0.24	0.31	0.30	-0.00	0.24	0.38
				(0.01)		
Europe/Israel descendent	0.32	0.26	0.26	0.00	0.28	0.22
				(0.00)		
North-African descendent	0.33	0.29	0.29	0.00	0.30	0.29
				(0.01)		
Firm tenure	6.85	5.71	5.66	-0.04	5.61	5.72
				(0.03)		
Panel B: firms						
Firm age	8.04	8.04	7.77	-0.28	6.86	7.32
				(0.04)		
Hi-tech	0.11	0.11	0.12	0.01	0.12	0.11
				(0.00)		
Avg. age in firm	44.95	45.14	45.19	0.05	45.22	44.34
				(0.04)		
Firm share men	0.56	0.56	0.58	0.02	0.71	0.52
				(0.01)		
Firm mean earnings	70,295	70,295	75,360	5,065	63,598	60,574
				(823)		
Share firms closed	0	0	0.19		0.11	0.22
Firm size	167	157	136	-20.56	122	203
				(14.77)		
Num. firms	6,066	3,229	1,138	4,367	989	797
Num. individuals	443,778	13,361	13,361	26,722	7,812	5,549

This table presents a comparison of pre-displacement attributes of three distinct groups: displaced workers (column 3), a 1:1 matched sample of non-displaced workers (column 2), and a larger pool of non-displaced individuals who adhere to the baseline restrictions from which the matched sample is constructed (column 1). Column (4) presents the differences between columns (3) and (2), with standard errors in parentheses. Columns (5) and (6) present the average characteristics of displaced workers, broken down by gender. Panel A presents the characteristics of workers, while Panel B presents the characteristics of firms.

we find that male workers experience a deeper displacement scar, which explains the pattern displayed in Figure 1. In the next section, we formally define our parameter of interest, the gender gaps in the effects of job displacement, and explain how we decompose that gap into observed individual and firm characteristics.

Figure 1: The earnings gender gap by years from displacement and treatment group



Note: This figure displays the ratio between the earnings of female and male displaced workers and matched non-displaced workers by years from displacement.

3 Effects of Job Loss in Israel by Gender

3.1 Comparing Men and Women

We investigate the gender gap in job loss effects with two primary objectives. First, we quantify the gender gap in the long-term job loss scars and study both the raw gender gap and the gender gap adjusted for pre-displacement characteristics such as demographics and firm attributes. Second, we decompose the observed gender gap into attributes explained by pre-displacement firm characteristics and those related to individual characteristics. This decomposition sheds light on the channels underlying the disparities in effects. These objectives are intrinsically linked, as they both rest on the observation that displaced male and female workers differ in characteristics crucial to determining job loss impacts, as we show in Table 1. To isolate the different channels through which disparities might arise, we exploit the richness of our data and control for all of the relevant pre-displacement observables.

Formally, let $Y_{it}(1)$ be worker i's potential outcome in time t if displaced, and $Y_{it}(0)$ otherwise. Therefore, $\Delta_{it} \equiv Y_{it}(1) - Y_{it}(0)$ is the job displacement effect of worker i in time t. Each worker is characterized by a gender variable $G_i \in \{f, m\}$ and a set of pre-displacement covariates X_i, and we denote $F_f(x)$ and $F_m(x)$ the observed distribution of female and male characteristics. The average effect of unexpected job displacement at time t for gender $G = g$ is defined by:

$$\mathbb{E}[\Delta_{it}|G_i = g] = \int_x \mathbb{E}[\Delta_{it}|G_i = g, X_i = x] dF_g(x),$$

and the *raw* gender gap in the effects of job loss is $\mathbb{E}[\Delta_{it}|G = f] - \mathbb{E}[\Delta_{it}|G = m]$. The raw gender gap could reflect either the gaps due to differences in workers' characteristics or due to gender differences in treatment effects. Following the seminal work of DiNardo et al. (1996), and as similarly done in Germany (Illing et al., 2021), we use a re-weighting function $g(x)$ that maps between the distribution of female's characteristics to the distribution of male's characteristics. Specifically, we are interested in the impact of job loss on females, had they would have had the same characteristics as males:

$$\mathbb{E}\big[\mathbb{E}[\Delta_{it}|G_i = f, X_i]\big|G_i = m]\big] = \int_x \mathbb{E}[\Delta_{it}|G_i = g, X_i = x]g(x)dF_g(x),$$

and estimate the covariates-adjusted Average Treatment on the Treated (ATT) gender gap:

$$\mathbb{E}\big[\mathbb{E}[\Delta_{it}|G_i = f, X_i]\big|G_i = m]\big] - \mathbb{E}[\Delta_{it}|G_i = m]$$

which identifies the gender gap in the impacts of job loss that is not explained by the observed covariates that are included in X_i.

The re-weighting function, $g(x) = \frac{p}{1-p}$, is the well-known Average Treatment on the Treated weighting function (Imbens and Rubin, 2015), where $p \equiv \Pr(G = m|X)$ is the propensity score predicting a female worker given their characteristics. We estimate $\hat{p}$ using logistic regression with a wide set of covariates divided into two main groups: individual characteristics and firm characteristics. In our analysis, we also separately estimate $\hat{p}$ based on pre-displacement worker's earnings, which are a function of both individual and firm characteristics.

The ATT is identified as long as $\hat{p} < 1$ and as long as there is sufficient overlap between males and females. In our baseline analysis, we use a trimming cutoff of 99.7% on the propensity score that includes all the covariates. Appendix Figure A.1 verifies that our propensity score re-weighting indeed balances the gender differences in workers' characteristics. Furthermore, we show in Appendix section D that our results are robust different cutoffs and that our propensity scores satisfy the overlap restriction.

Firm characteristics - The literature suggests that firms serve as an important institution affecting wage determination (Abowd et al., 1999; Card et al., 2013), and job displacement impacts (Lachowska et al., 2020; Schmieder et al., 2023). The theory on job ladder models such as on-the-job search (Burdett and Mortensen, 1998) or sequential auction models (Postel-Vinay and Turon, 2014) predict that the lost displacement wage would be attributed to the loss of employer effects. Moreover, as manifested in the theory by Jovanovic (1979) and recently documented in the US context by Lachowska et al. (2020), wage displacement losses could reflect the losses of worker-employer specific match effects. Taken together, and given the unequal distribution of female and male workers across firm types reported in Table 1, one might suspect that at least part of the job loss gap is explained directly by the displacing firm.

As pre-displacement firm characteristics, we use the AKM firm fixed effects, firm size, industry dummies, the average age of workers, the share of women in the firm, and the age of the firm. We estimate firm effects by running a two-way fixed effect wage equation with both firm and individual fixed effects:

$$logY_{it} = \alpha_i + \psi_{j(i,t)} + x'_{it}\beta + \epsilon_{it}, \tag{1}$$

where $logY_{it}$ denotes the log average monthly earnings of worker i at firm $j(i,t)$ in year t, α_i is a worker-specific fixed effect, reflecting productive characteristics of the worker that can be transferred across employers and over time, $\psi_{j(i,t)}$ is an employer-specific fixed effect, reflecting employer wage premium of all firm j's workers, x_{it} is a vector of year effects, and workers' age and age squared, and ϵ_{it} is the error component. We estimate equation 4 on the full sample of workers aged 23-67 in the years 1995-2019, excluding the workers who experienced a job displacement and their matched control group. Finally, the AKM firm premium is the estimated $\hat{\psi}_j$ of each worker pre-displacement firm. We provide more detail on the AKM estimation and its results in Appendix C.

Individual characteristics - Wages and their evolution over time vary dramatically with individual characteristics. For example, Seim (2019) finds that young workers' wages recover faster than those of older workers after job loss. In Aloni and Avivi (2023), we find that the effects of job loss in Israel vary with family size and time due to changes in the welfare system. In a recent paper, Flinn et al. (2023) highlight the importance of gender differences in noncognitive skills in explaining the gender wage gap, and Card et al. (2023) show how wages vary by location of residence.

To account for the potential gender heterogeneity by individual characteristics, we additionally control for individual characteristics. They include dummies for ages at the time of job loss, region of residence, birth cohort, ethnic group, recent immigration status, degree attainment, and marital status. We also approximate the individual wage effect by taking the average difference between the individual pre-displacement monthly wage in the 3 years prior to displacement and the firm average monthly wage. This variable serves as a proxy for an employee's ability or excess contribution to wage beyond the firm average.[6]

Equation 4 suggests that wages are comprised of a third component, the firm-employee match effect. While we don't control for it directly, we provide an additional re-weighting exercise that includes only the pre-displacement earnings in the 3 years prior to displacement. A similar approach was taken in Illing et al. (2021), who find that pre-displacement earnings prove to be a strong predictor for the effects of job loss in Germany.

[6] While this measure does not residualize the time-invariant firm component as in Equation 4, it serves as a more precise proxy for individual effects, thereby avoiding the ramifications of measurement errors.

3.2 Estimation Results

We estimate the gender difference in the effects of job loss by running the following regression:

$$y_{it} = \alpha_{m(i)} + \sum_{\tau} \gamma_\tau 1\{t = t_i^* + \tau\} + \sum_{\tau} \beta_\tau 1\{t = t_i^* + \tau\} \times D_i \\ + \sum_{\tau} \delta_\tau 1\{t = t_i^* + \tau\} \times \text{Female}_i \times D_i + \epsilon_{it}, \tag{2}$$

where y_{it} is worker i's labor market outcome t years after the displacement year t_i^*. In our baseline analysis, y_{it} is either annual earnings relative to pre-displacement year $t = -1$ or employment status. D_i is an indicator for displacement and $\alpha_{m(i)}$ is a matched-pair fixed effect where $m(i)$ is the matched pair identifier of worker i. We set $t = -1$ as the base-level year, and therefore β_τ captures the effect of job loss on men in each period τ relative to $t = -1$, while δ_τ provides the difference in effects for women relative to men.[7]

Table 2 presents the results. Column (1) presents the job loss effect on men β_τ, column (2) presents the raw gender gap δ_τ, and columns (3)-(6) present the covariate-adjusted δ_τ coefficients by re-weighting the sample using different inverse probability weighting schemes. We group the years post-displacement into three periods: 1 year after job loss (short-term), 2-6 years (medium-term), and 7-11 years (long-term). In Panel A, we present the effects on annual earnings relative to pre-displacement earnings, and in Panel B, the effects on employment status.

We start by discussing the raw gender differences in the displacement effects on relative earnings (Panel A). Column (1) shows that in the short run, men experience an earnings drop of almost 48 percent relative to pre-displacement earnings. Earnings drops shrink by half to 24 percent in the mid-term and to 19 percent in the long term. From Column (2), we learn that women's earnings drops are of similar magnitude in the short run, at almost 44 percent relative to pre-displacement earnings, more than 90 percent the impact of men. Conversely, the recovery trajectory in the mid and long-term differs substantially between genders. The gender gap in the mid-term is 6 percent, meaning that women's post-displacement drop in earnings is 25% of the drop of men. The long-term gap is even wider, as women experience a job loss scar that is over 50 percent smaller than men's. This raw gap is comparable to the results from Jacobson et al. (1993), who find that in the US, women's job loss effects are less severe than those of men, by around 35 percent five years post displacement.

Despite the marked gender differences in relative earnings post-displacement, the effects on employment in Panel B show almost no raw gender differences. Appendix Figure A.2 visually presents the effects of job loss year-by-year separately by gender. In addition, Appendix Figure A.3 presents the effects on earnings in Shekels instead of earnings relative to pre-displacement earnings.

Next, we turn to study the importance of workers' characteristics in predicting gender disparities in job loss recovery. Column 3 reports the job loss gender gap after re-weighting the female workers to

[7] Note that the matched pairs $\alpha_{m(i)}$ are within gender, hence there is no $Female_i$ dummy term separately. Also, since matching is performed within the treatment year as well, this is akin to a matched-pair-cohort FE, which under treatment effect heterogeneity, addresses the concerns of estimating biased effects due to negative weights across treatment effect and cohort's groups (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021).

Table 2: Job loss effects on men's earnings and employment and the gender gap in effects

Period	Job loss effect on men (1)	The Difference in JL effect (female minus male): Raw gender difference (2)	Individual char. (3)	Firm char. (4)	Ind. & firm char. (5)	Earnings (6)
A: yearly earnings						
$t < -1$	0.003	0.008	0.013	0.003	0.029	-0.002
	(0.018)	(0.017)	(0.021)	(0.017)	(0.023)	(0.017)
$t = 0$	-0.111	-0.009	-0.003	-0.003	0.016	-0.021
	(0.020)	(0.017)	(0.020)	(0.018)	(0.023)	(0.018)
$t = 1$	-0.476	0.040	0.051	0.014	0.030	0.013
	(0.029)	(0.026)	(0.026)	(0.020)	(0.023)	(0.025)
$2 \leq t \leq 6$	-0.239	0.061	0.038	0.013	0.003	-0.033
	(0.017)	(0.017)	(0.018)	(0.018)	(0.022)	(0.021)
$7 \leq t \leq 11$	-0.190	0.100	0.052	0.038	-0.003	-0.021
	(0.025)	(0.024)	(0.030)	(0.024)	(0.030)	(0.027)
R sq. adj.	0.237	0.237	0.256	0.265	0.282	0.247
B: employment						
$t < -1$	-0.006	0.010	0.015	0.002	0.007	-0.001
	(0.008)	(0.007)	(0.009)	(0.007)	(0.012)	(0.009)
$t = 0$	0.000	0.001	0.004	-0.004	-0.005	-0.005
	(0.005)	(0.005)	(0.008)	(0.007)	(0.011)	(0.008)
$t = 1$	-0.221	-0.012	-0.010	-0.017	-0.028	-0.008
	(0.018)	(0.018)	(0.019)	(0.015)	(0.018)	(0.022)
$2 \leq t \leq 6$	-0.086	-0.005	-0.003	-0.010	-0.024	-0.032
	(0.010)	(0.009)	(0.010)	(0.008)	(0.013)	(0.016)
$7 \leq t \leq 11$	-0.065	0.007	0.006	-0.008	-0.007	-0.023
	(0.009)	(0.008)	(0.010)	(0.010)	(0.014)	(0.016)
R sq. adj.	0.207	0.207	0.236	0.225	0.254	0.223
Observations	26,694	26,694	26,694	26,694	26,694	26,694

Note: This table presents the effects of job loss on men and the gender difference between women and men, with the effects aggregated over the time periods in the left column. Column (1) presents the job loss effects for men, and columns (2) to (6) present the difference between the effect on women and men. Column (2) presents the raw gender difference, while columns (3) to (6) show the gender differences with women observations weighted by different sets of pre-displacement coefficients. **Individual characteristics** (column 3) include dummies for age, region of residence, birth cohort, ethnic group, recent immigration status, degree attainment, and marital status, as well as the individual firm wage premium, calculated as the difference between the individual monthly wage and the firm average. **Firm characteristics** (column 4) include the 3rd polynomial of firm fixed effect, firm total payroll, 10 firm size rank dummies, 1-digit industry, the share of men in the firm, and the firm's age. Column (5) includes both sets of firm and individual characteristics. Column (6) includes only **yearly earnings** in the 3 years prior to displacement, each as decile dummies. Panel A presents the effects on the average yearly earnings relative to the pre-displacement year, and Panel B presents the effects on employment status. Standard errors, clustered at the firm level, are in parentheses.

have the same individual characteristics as male workers. We find that after adjusting for individual characteristics, the gaps in earnings in the medium and long term close by less than half. In Column 4, we repeat the same exercise, but this time re-weighting based on firm characteristics. We find that firm characteristics alone account for 80 percent of the gap in the mid-term and more than 60 percent of the gap in the long run. Combining the individual and firm characteristics in the re-weighting scheme (Column 5) closes the gender gap entirely. This result suggests that women and men with similar characteristics experience very similar job loss earnings scars.[8][9]

[8] Appendix Table A.1 presents similar patterns with monthly earnings.

[9] Appendix Figure A.6 plots the corresponding job loss effects graphically separately for men and women, with additional graphs for the weighted impacts on women.

Panel B of Table 2 presents the estimates of short- and long-run effects of job displacement on employment. The gender gap in job loss recovery on employment remains zero in all time periods after accounting for individual characteristics. When observations are re-weighted based on firm characteristics, the point estimates of the gender gap widen in the opposite direction of the earnings gap. That is, men's probability of being employed after job loss is larger than women's. In the medium run, the gap is one percentage point, which is 12% of the base-level male job loss scar, and in the long run, the job loss effect gap is 0.8 lower probability for female workers, which is 12% of male base-level effect. In column (5), when we combine all of the characteristics, the gaps in the short and medium-term widen even more, with a gap of around 28% in the mid-term and 10% in the long-term, where the medium-run estimates are marginally statistically significant. Taken together with the finding mentioned above in which the covariate-adjusted effect on earnings (including zeros) is the same on average for both genders, we conclude that conditional on working, men's wages show a lower decrease post-displacement compared to women's.

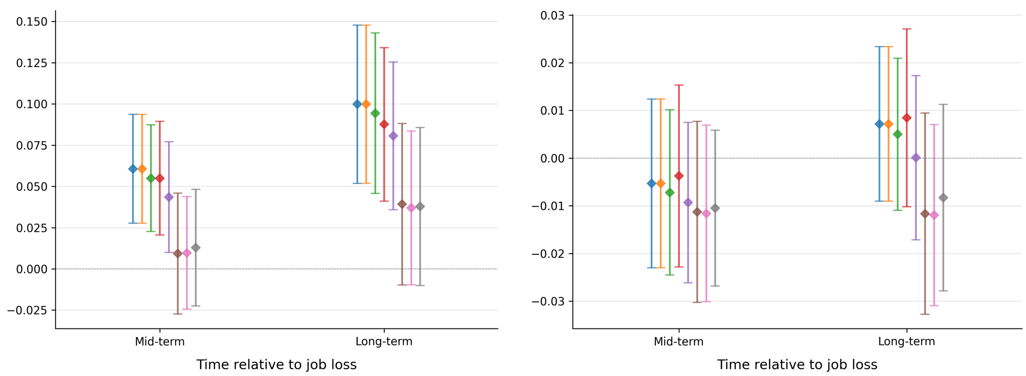
Lastly, in Column (6) of Table 2, we re-weight the observations only using the pre-displacement annual earnings in the three years preceding the displacement. We find a qualitatively similar result to that of re-weighting by all individual and firm covariates, namely that this weighting scheme closes the raw gap in job loss effects on earnings. This aligns with recent findings suggesting wages are well approximated by a function of firm and individual characteristics.

Our findings from Israel are in contrast with recent results in Illing et al. (2021) from Germany. First, they find no raw gender gap in earnings, whereas we find a significant gap in favor of women. Second, after adjusting for pre-displacement earnings, Illing et al. (2021) find that the women suffer from substantially larger effects on earnings, whereas we find no significant excess job loss effect on women.

Firm Characteristics - Firm characteristics are highly predictive of the gender gap in the long-run impacts of job loss, even more so than workers' characteristics. To further investigate which firm characteristics account for most of the explanatory power, in Figure 2, we repeat the same exercise and re-weight the female observations separately by each of the firm covariates. Each dot in the figure represents the estimated gender gap in job loss recovery, re-weighting the sample using a different firm feature. In Panel (a), we show gender gaps in the effects of job loss on relative earnings. We find that out of the six characteristics that are included in our firm variables, only two of them account for most of the explanatory power: the share of men in the firm and the AKM firm fixed effects. Each on its own shrinks the earnings scar gap as much as all the variables combined, from a 6 percentage points gap to less than one in the mid-term and from 10 percentage points to below 4 in the long-term. As was also documented in other settings, Appendix Figure A.8 shows that firms with high fixed effects have a lower share of females. Weighting by other attributes, such as firm size, age, and payroll, has little to no effect on the gap at all, and weighting by the one-digit industry code does slightly shrink the gap by around 25 percent.

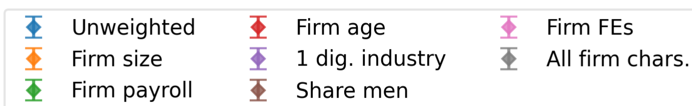
In Panel (b), with employment as an outcome, we find similar results, albeit noisier. Firm fixed effects and the share of men in the firm both have the largest effects on the gender gap, bringing it to the level of the gaps after re-weighting using all firm covariates combined. Lastly, we document in Appendix Figure E.1b that not only does the firm wage premia explain the majority of the gender gaps, but even just a crude split of the sample by above and below median firm fixed effect shrinks the gender gaps on relative earnings almost entirely. That is, the gender gap in the effects of job loss on earnings can be explained even with the most degenerate firm effects split.

Figure 2: The gender gap in medium and long-run effects of job loss, firm characteristics breakdown



(a) Yearly earnings means rel. to $t < 0$

(b) Employment



Note: This figure plots the gender gap in the effects of job loss on yearly relative earnings and employment. The figure plots the effects in the mid-term (2-6 years) and long-term (7-11 years) after displacement. We present the raw unweighted gender difference, as well as the re-weighted gaps by different firm characteristics: 10 firm size rank dummies, firm total payroll, the 2nd order polynomial of the age of the firm, 1-digit industry, the share of men in the firm, 3rd polynomial of firm fixed effect, and all of these characteristics combined. Panel (a) presents the effects on the average yearly earnings, and Panel (b) presents the effects on employment. Confidence intervals are based on standard errors clustered at the firm level. Appendix Table A.2 presents these coefficients with additional information.

The literature has demonstrated that firms account for a large share of the variation in determining wage inequality and the static wage gap. Firms' wage premia typically explain around 5-13% of the overall wage variation, after correcting for sampling error (Kline et al., 2020; Bonhomme et al., 2023; Lachowska et al., 2023), account for a fifth of the gender wage gap in Portugal, with 15% and lower of the gap explained by sorting into firms (Card et al., 2016; Hennig and Stadler, 2023), and account for 10-27% of the wage gap between immigrants and natives in Israel during the first ten years after arrival (Arellano-Bover and San, 2020). Lachowska et al. (2020) and Schmieder et al. (2023) find that firms are important determinants for the dynamic evolution of wages. While past employers have been shown to predict future earnings (Di Addario et al., 2023), our findings suggest that they are also predictive of displacement effects and the rate of recovery years after. As a result, we show that firms are important for the evolution of the gender wage gap of workers with similar characteristics. Since the drop in earnings is deeper among workers at high-wage premium firms, and since male workers are more likely to work at these firms, an unexpected job displacement decreases the gender earning gaps.

3.3 Distributional Impacts

Next, we study the impact of job loss on the earning distribution. We do so by estimating the following equation, separately by gender $g \in \{f, m\}$:

$$\mathbf{1}\{y_{it} > Y_p\} = \alpha_{m(i)} + \theta^g_{p,t}\mathrm{D}_i + \varepsilon^g_{it}, \tag{3}$$

where y_{it} is worker i's annual earnings t years after job displacement and Y_p is the pre-displacement earnings percentile p among the sample of displaced and matched control workers. Therefore, the outcome variable is an indicator function for whether worker i earned more than the pth pre-displacement percentile t years after displacement. D_i is a displacement indicator, and $\alpha_{m(i)}$ is a matched-pair fixed effect, where $m(i)$ is of worker i's pair. The parameter of interest is $\theta_{p,t}$, describing the impact of job loss on the probability of earning above the p percentile earnings t years after displacement. The full set of coefficients $\{\theta_{p,t}\}^{100}_{p=1}$ depicts how the entire distribution of earnings t years from displacement changes as a result of job loss.

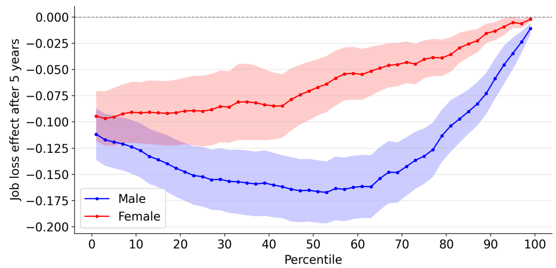
Figure 3 displays the results for the effects five years after job displacement.[10] The left sub-figures present the $\theta^g_{p,5}$ for each gender and percentile, and the right sub-figures present the gender difference in the effects of job loss on earning above each percentile. Sub-figures (a) and (b) present the raw job loss effects, sub-figures (c) and (d) display the covariate-adjusted effects, including only individual characteristics, sub-figures (e) and (f) present the effects after adjusting for firm characteristics alone, and sub-figures (g) and (h) present the results after accounting for both individual and firm characteristics. Note that by construction, in all the figures, β^0 is lower than zero. Because we measure earnings effects compared to the pre-displacement earnings distribution, there is a substantial proportion of workers who don't work post-displacement. Additionally, we find that $\theta^g_{p,5} = 0$ for both men and women, implying that, on average, job loss did not widen the support of the earning distribution.

Sub-figure (a) shows that unexpected job displacement dramatically shifts the distribution of men's earnings downwards, substantially reducing the probability of earning more than the median, therefore compressing their post-displacement earning distribution. In contrast, the corresponding effects for women change linearly throughout the income percentiles, meaning that women experience a more uniform distributional shift in earnings. Accordingly, sub-figure (b) shows that the raw gender gap in the impact of job loss arises across all income distributions and is deepest at the middle and the high end of the income distribution. This means that the impact of job loss is not only bigger for men on average, but it especially reduces men's probability of earning relatively high wages compared to women. Job loss both compresses and shifts downwards men's earnings distribution while women experience only a shift.

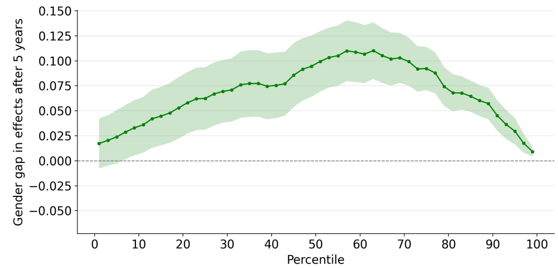
As we note throughout the paper, men and women differ by their pre-displacement characteristics,

[10] Appendix Figure A.10 presents similar qualitative results for $t = 10$.

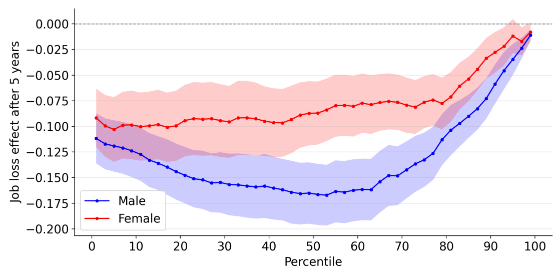
Figure 3: The distributional effect of job loss on earnings 5 years after displacement by gender



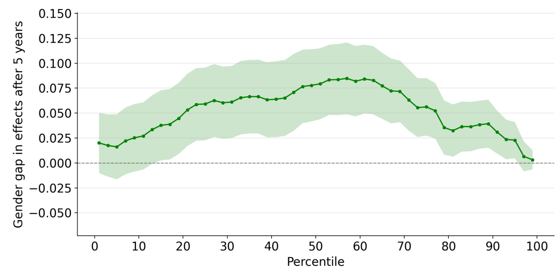
(a) Effects by gender, not weighted



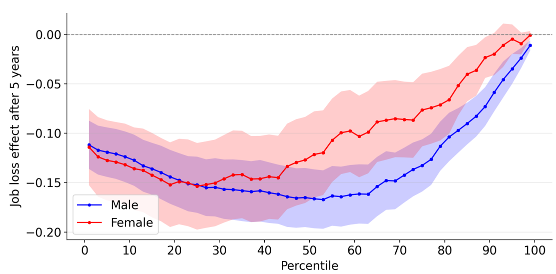
(b) Gender gap, not weighted



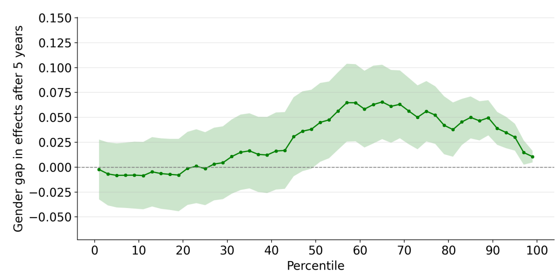
(c) Effects by gender, weighted by ind. char.



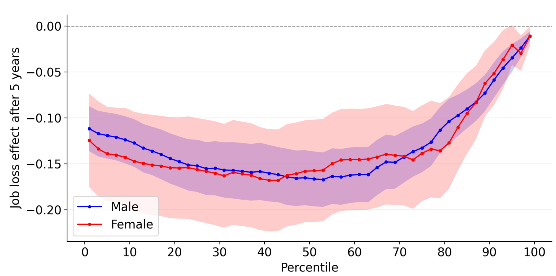
(d) Gender gap, weighted by ind. char.



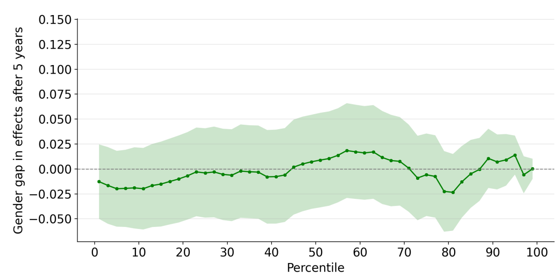
(e) Effects by gender, weighted by firm char.



(f) Gender gap, weighted by firm char.



(g) Effects by gender, weighted by all char.



(h) Gender gap, weighted by all char.

Note: These figures present the effects of job loss 5 years after displacement, where the outcome variables are dummies for whether the individual earns more than the p'th percentile (on the x-axis), with respect to the pre-displacement distribution of average earnings in period $t = -1$. The left panels show the effects separately by gender, and the right panels show the gender gaps. Each point in this figure represents a different regression coefficient. Regressions include the matched pair fixed effects. We present non-weighted estimates (Panels (a) and (b)) and IPW estimates that include individual characteristics (Panels (c) and (d)), firm characteristics (Panels (e) and (f)), and both individual and firm characteristics combined (Panels (g) and (h)). Standard errors used to construct the confidence intervals are clustered at the firm level.

which could explain the differences in the distributional impacts. Therefore, we turn to study the gender gaps after accounting for pre-displacement workers' and firms' characteristics. Sub-figures (c) and (d) show that re-weighting by individual characteristics barely closes the gap, with some impact of the re-weighting on the distribution apparent towards the top two deciles. In contrast, sub-figures (e) and (f) suggest the opposite with respect to firm characteristics. Accounting for firm characteristics closes the gender difference entirely in the bottom half of the earning distribution while partially shrinking it at the top. These findings might suggest that the distribution of low-wage accepted offers is strongly related to past firms (Di Addario et al., 2023). As such, the gender differences in job-loss impacts on the bottom of the distribution are explained entirely by the type of displacing firm. In contrast, the shift in the probability of earning high salaries after displacement reflects heterogeneity by both individual and firm characteristics.

Lastly, Figure (h) shows that after adjusting for both firm and individual characteristics, there is no significant difference in the impact of job loss on the distribution of earnings between men and women across the full distribution. Workers of different genders but identical individual and firm characteristics face the same impact of job loss on their future earnings.

4 Conclusions

This paper examines the gender differences in earnings losses due to unexpected job loss events using administrative data from Israel. We find that in Israel, the impacts of job loss vary substantially across gender groups, where the long-run earnings losses of male workers are bigger than those of female workers. However, we find that the entire gender gap across all the income distribution is explained by observable pre-displacement factors. Our analysis reveals that the pre-displacement firm characteristics alone account for 60-80% of the gender difference in post-displacement outcomes in the medium and long run, where the firm wage premium is the principal attribute of firms that most significantly explains the gender difference.

A large body of literature in labor economics focuses on measuring and explaining the long-run consequences of job loss. Recent studies emphasize the role of displacing firms in shaping earnings and employment dynamics. A parallel literature has investigated the roots of gender wage gaps. Our findings emphasize the dynamic role of firms in shaping labor market outcomes and gaps. Disentangling the mechanisms through which firms shape those results, and in particular whether they reflect supply vs. demand factors, is an important avenue for future research.

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A Appendix Tables and Figures

Table A.1: Job loss effects on women's monthly earnings and months worked and the gender gap in effects

		The Difference in JL effect (female minus male)				
Period	Job loss effect on men	Raw gender difference	Individual char.	Firm char.	Ind. & firm char.	Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
A: monthly earnings						
$t < -1$	0.002	0.008	0.015	0.001	0.027	-0.000
	(0.017)	(0.016)	(0.020)	(0.017)	(0.023)	(0.017)
$t = 0$	-0.016	-0.010	-0.014	0.011	0.003	-0.015
	(0.018)	(0.017)	(0.022)	(0.017)	(0.021)	(0.016)
$t = 1$	-0.396	0.032	0.025	0.000	-0.002	-0.004
	(0.027)	(0.026)	(0.025)	(0.020)	(0.024)	(0.026)
$2 \leq t \leq 6$	-0.225	0.057	0.033	0.013	0.003	-0.034
	(0.017)	(0.017)	(0.018)	(0.018)	(0.023)	(0.022)
$7 \leq t \leq 11$	-0.190	0.093	0.049	0.027	-0.014	-0.024
	(0.024)	(0.025)	(0.030)	(0.025)	(0.030)	(0.027)
R sq. adj.	0.223	0.223	0.242	0.249	0.262	0.228
B: months worked						
$t < -1$	-0.055	0.129	0.144	0.032	0.132	-0.057
	(0.100)	(0.092)	(0.119)	(0.097)	(0.152)	(0.110)
$t = 0$	-1.121	-0.032	0.101	-0.183	0.019	-0.160
	(0.103)	(0.120)	(0.123)	(0.121)	(0.156)	(0.157)
$t = 1$	-4.514	0.287	0.446	0.023	-0.103	0.155
	(0.246)	(0.211)	(0.221)	(0.186)	(0.209)	(0.241)
$2 \leq t \leq 6$	-1.676	0.279	0.289	0.063	0.001	-0.116
	(0.132)	(0.120)	(0.132)	(0.119)	(0.155)	(0.192)
$7 \leq t \leq 11$	-1.124	0.398	0.328	0.167	0.205	-0.026
	(0.111)	(0.105)	(0.139)	(0.125)	(0.180)	(0.194)
R sq. adj.	0.244	0.244	0.27	0.264	0.291	0.259
Observations	26,694	26,694	26,694	26,694	26,694	26,694

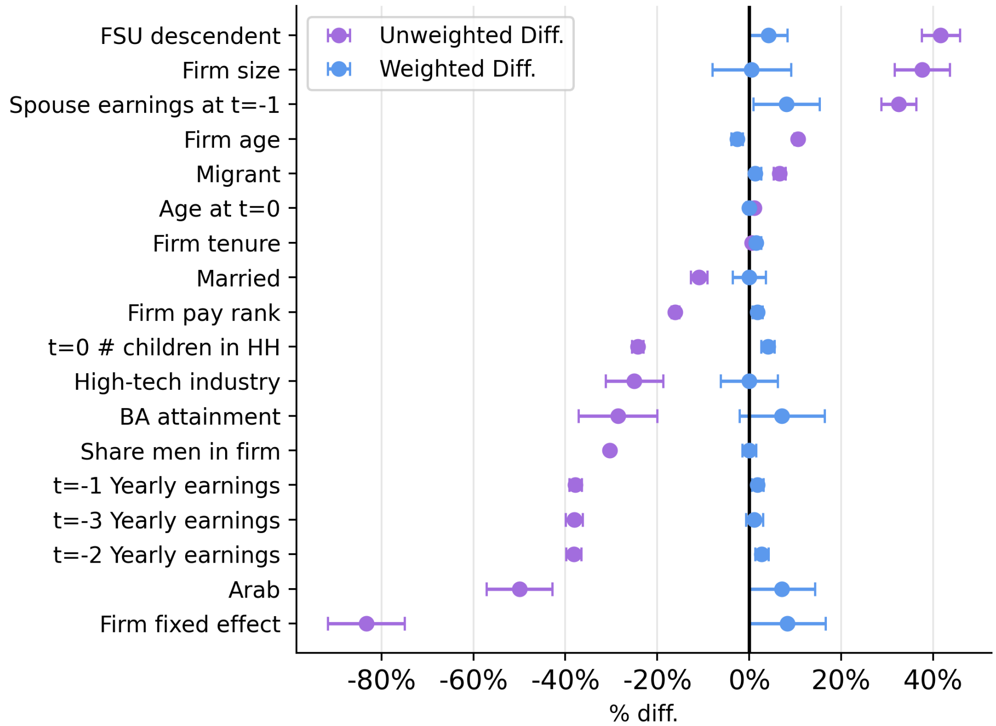
Note: This table presents the effects of job loss on men and the gender difference between women and men, with the effects aggregated over the time periods in the left column. We estimate the effects via Equation 2. Column (1) presents the job loss effects for men (β_t). Columns (2) to (6) present the difference in the effect for women relative to men for each period (δ_t). Column (2) presents the raw gender difference while Columns (3) to (6) show the gender differences with women observations weighted by different sets of pre-displacement coefficients. **Individual characteristics** (column 3) include dummies for age, region of residence, birth cohort, ethnic group, recent immigration status, degree attainment, and marital status, as well as the individual firm wage premium, calculated as the difference between the individual monthly wage and the firm average. **Firm characteristics** (column 4) include the 3rd polynomial of firm fixed effect, firm total payroll, 10 firm size rank dummies, 1-digit industry, the share of men in the firm, and the firm's age. Column (5) includes both sets of firm and individual characteristics. Column (6) includes **yearly earnings** in the 3 years prior to displacement, each as decile dummies. Panel A presents the effects on the average monthly earnings, and Panel B presents the effects on yearly months worked. Standard errors, clustered at the firm level, are in parentheses.

Table A.2: Job loss effects on women's monthly earnings and months worked and the gender gap in effects, firm characteristics breakdown

Period	Job loss effect on men	The Difference in JL effect (female minus male)							
		Raw gender difference	Firm payroll	Firm size	1 dig. industry	Share men	Firm age	Firm FEs	All chars.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A: earnings									
$t < -1$	0.003	0.008	0.007	0.008	0.007	-0.000	0.005	0.009	0.003
	(0.018)	(0.017)	(0.018)	(0.017)	(0.015)	(0.016)	(0.015)	(0.016)	(0.017)
$t = 0$	-0.111	-0.009	-0.008	-0.009	-0.013	-0.005	-0.010	-0.017	-0.003
	(0.020)	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.015)	(0.017)	(0.018)
$t = 1$	-0.476	0.040	0.038	0.040	0.024	0.009	0.039	0.015	0.014
	(0.029)	(0.026)	(0.025)	(0.026)	(0.022)	(0.020)	(0.024)	(0.022)	(0.020)
$2 \leq t \leq 6$	-0.239	0.061	0.055	0.061	0.044	0.009	0.055	0.010	0.013
	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.019)	(0.017)	(0.017)	(0.018)
$7 \leq t \leq 11$	-0.190	0.100	0.094	0.100	0.081	0.039	0.088	0.037	0.038
	(0.025)	(0.024)	(0.025)	(0.024)	(0.023)	(0.025)	(0.024)	(0.024)	(0.024)
R sq. adj.	0.237	0.237	0.238	0.237	0.236	0.266	0.237	0.242	0.265
B: months worked									
$t < -1$	-0.055	0.129	0.103	0.129	0.101	-0.024	0.095	0.049	0.032
	(0.100)	(0.092)	(0.090)	(0.092)	(0.087)	(0.098)	(0.098)	(0.094)	(0.097)
$t = 0$	-1.121	-0.032	-0.025	-0.032	-0.137	-0.202	-0.086	-0.198	-0.183
	(0.103)	(0.120)	(0.120)	(0.120)	(0.123)	(0.113)	(0.115)	(0.144)	(0.121)
$t = 1$	-4.514	0.287	0.273	0.287	0.123	-0.060	0.287	0.127	0.023
	(0.246)	(0.211)	(0.205)	(0.211)	(0.192)	(0.189)	(0.201)	(0.194)	(0.186)
$2 \leq t \leq 6$	-1.676	0.279	0.244	0.279	0.192	-0.005	0.273	0.035	0.063
	(0.132)	(0.120)	(0.118)	(0.120)	(0.119)	(0.128)	(0.129)	(0.126)	(0.119)
$7 \leq t \leq 11$	-1.124	0.398	0.369	0.398	0.306	0.132	0.385	0.118	0.167
	(0.111)	(0.105)	(0.104)	(0.105)	(0.112)	(0.135)	(0.121)	(0.122)	(0.125)
R sq. adj.	0.244	0.244	0.244	0.243	0.243	0.265	0.245	0.252	0.264
Observations	26,694	26,694	26,694	26,694	26,694	26,694	26,694	26,694	26,694

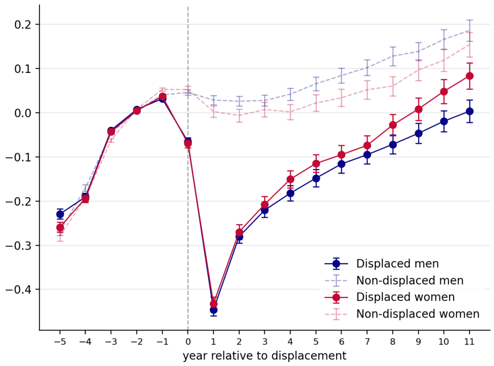
Note: This table presents the effects of job loss on men and the gender difference between women and men, with the effects aggregated over the time periods in the left column. We estimate the effects via Equation 2. Column (1) presents the job loss effects for men (β_t). Column (2) presents the raw gender difference while Columns (3) to (9) show the gender differences with women observations weighted by different sets of firm characteristics (δ_t): (3) firm total payroll, (4) 10 firm size rank dummies, (5) 1-digit industry, (6) the share of men in the firm, (7) the 2nd order polynomial of the age of the firm, (8) 3rd polynomial of firm fixed effect, (9) all the above combined. Panel A presents the effects on the average monthly earnings, and Panel B presents the effects on yearly months worked. Standard errors, clustered at the firm level, are in parentheses. A visual summary of this table is presented in Figure 2.

Figure A.1: Balance between men and women using propensity score re-weighting

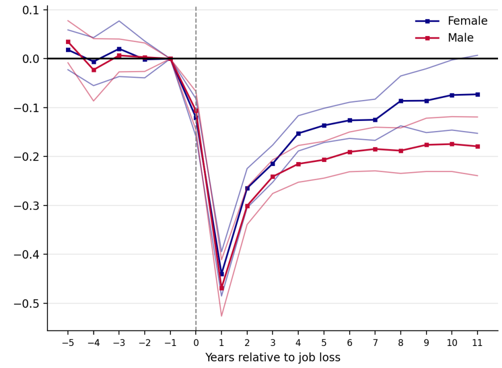


Note: This figure presents the difference in pre-displacement characteristics between displaced men and women, before and after re-weighting male observations by the inverse of the probability of being a female, predicted using logistic regression as described in Section D, with all covariates combined as in last column of Table 2. Values are as a percent of the average value of women.

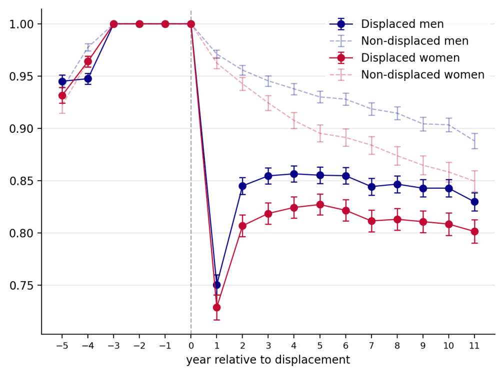
Figure A.2: Effects of job loss on earnings and employment, by gender



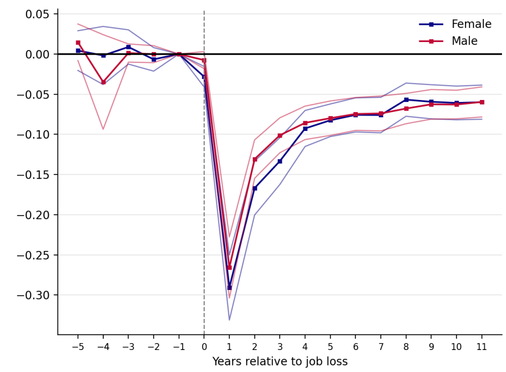
(a) Yearly earnings means rel. to $t < 0$



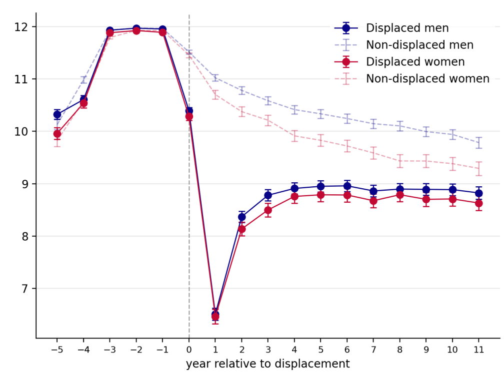
(b) Yearly earnings coefs. rel. to $t < 0$



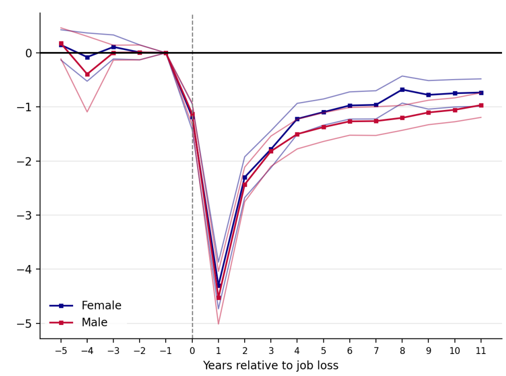
(c) Employment means



(d) Employment coefs.



(e) # of months employed means



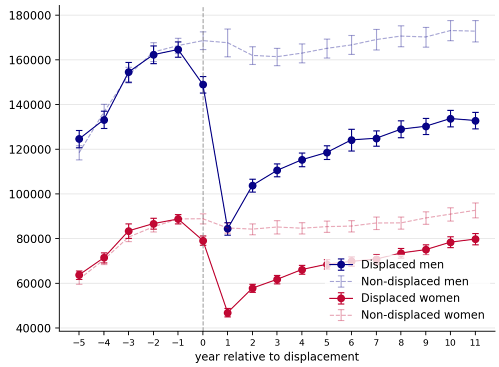
(f) # of months employed coefs.

Note: These figures present the job loss effects by gender. Left panels: means and standard deviations of displaced/control by years relative to displacement. Right panels: the θ_t^g coefficients from the following regression by gender $g \in \{F, M\}$:

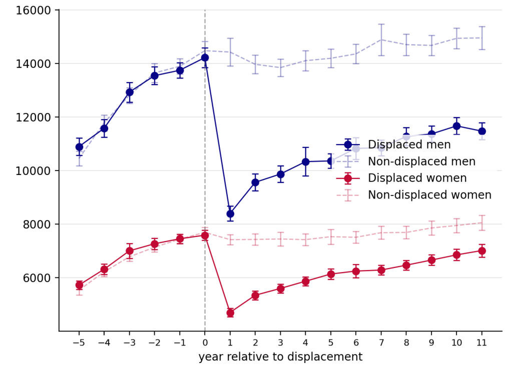
$$y_{it}^g = \sum_{\tau=-5,\tau\neq-1}^{\tau=11} \gamma_\tau^g \mathbf{1}\{t = t_i^* + \tau\} + \sum_{\tau=-5,\tau\neq-1}^{\tau=11} \theta_\tau^g \mathbf{1}\{t = t_i^* + \tau\} \times \mathrm{D}_i + \alpha_{m(i)}^g + \varepsilon_{it}^g,$$

where y_{it} is worker i's outcome t years after job loss. t_i^* is the job loss year, and D_i is a displacement indicator. $\alpha_m(i)$ is a matched-pair fixed effect, where $m(i)$ is of worker i's pair. Earnings are measured in ratio to earnings in the three years preceding displacement, with no-earnings years coded as 0. Employment is defined as earning above 10,000 Shekels ($\approx 3,000$ USD) annually. Work months are the number of months with positive earnings. Standard errors are clustered at the firm level.

Figure A.3: Effects of job loss on earnings levels, by gender



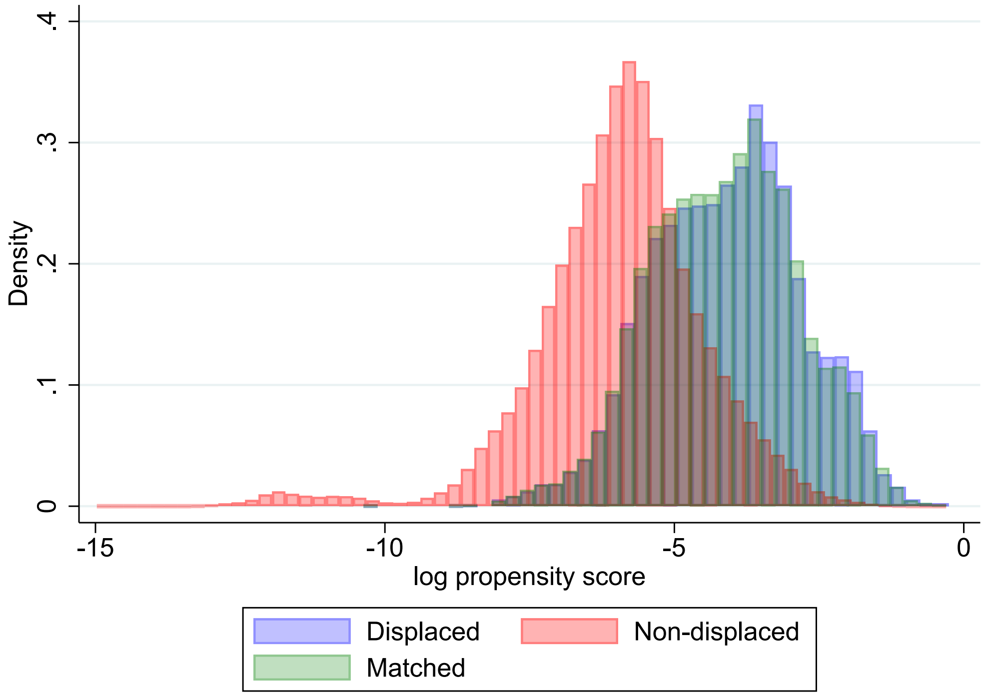
(a) Yearly earnings (1NIS ≈ 0.3$) means



(b) Monthly earnings (1NIS ≈ 0.3$) means

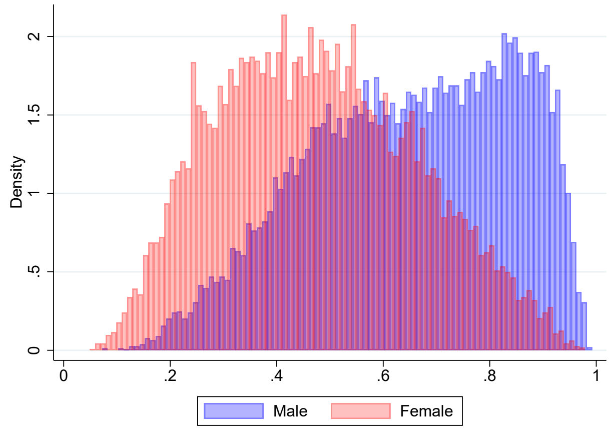
Note: These figures present means and standard deviations of displaced/control by years relative to displacement. Earnings are measured in Shekels, with no-earnings years coded as 0. Monthly earnings are calculated as annual earnings divided by the number of months of work reported. In cases of missing values for the number of months, we divide the annual earnings by the average number of months worked conditional on working. Standard errors are clustered at the firm level.

Figure A.4: Job loss propensity score overlap histogram

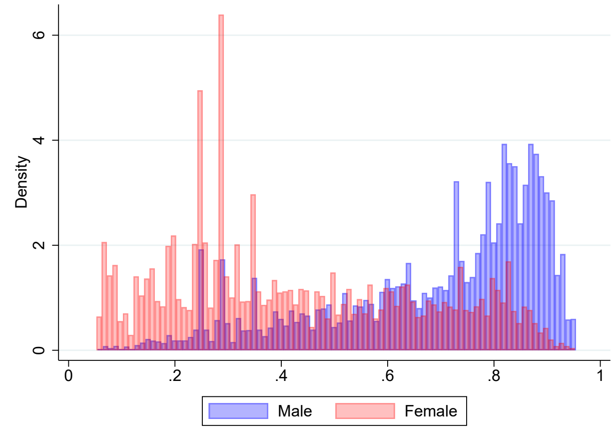


Note: This figure presents the distributions of the log of predicted probability of being displaced for the displaced and non-displaced population, before and after the 1:1 matching procedure described in D.

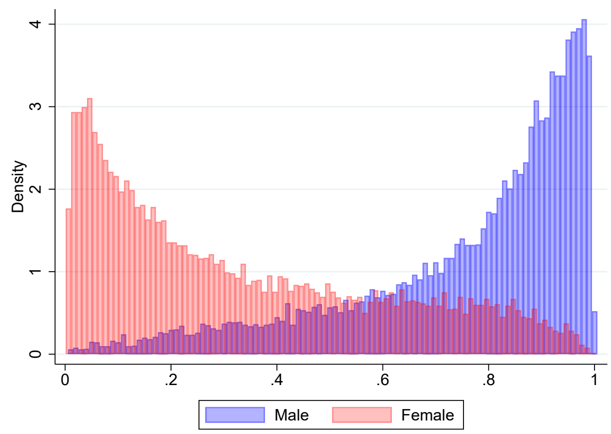
Figure A.5: Gender propensity scores overlap histogram



(a) Individual characteristics



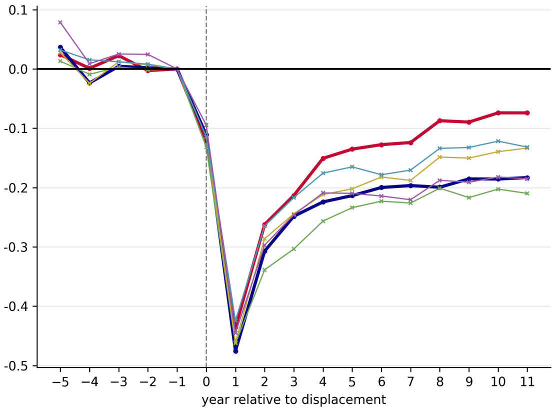
(b) Firm characteristics



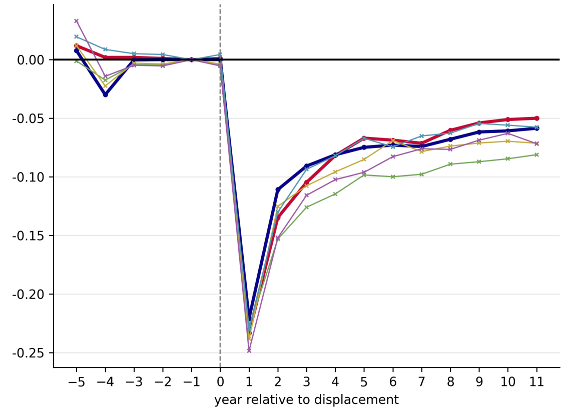
(c) All characteristics

Note: This figure presents the distributions of predicted probabilities of being male estimated via the logistic regression described in D, separately by males and females. **Individual characteristics** include dummies for age, region of residence, birth cohort, ethnic group, recent immigration status, degree attainment, and marital status, as well as the individual firm wage premium, calculated as the difference between the individual monthly wage and the firm average. **Firm characteristics** include firm fixed-effects, firm size, the average age of workers and share of women in the firm, and the firm's age. The histograms were trimmed according to the common support of the two groups, and to extreme weights, as described in D.

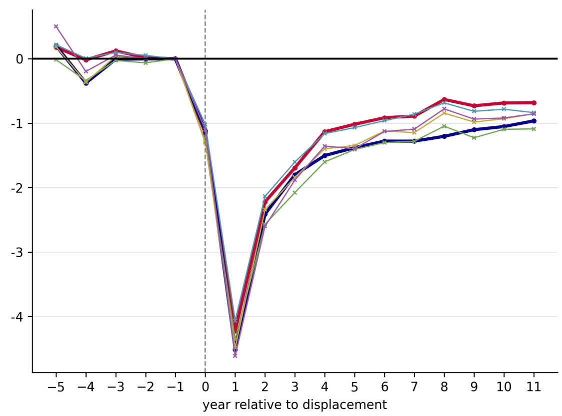
Figure A.6: Effects of job loss by gender, event study coefficients, re-weighting



(a) Yearly earnings rel. to $t < 0$



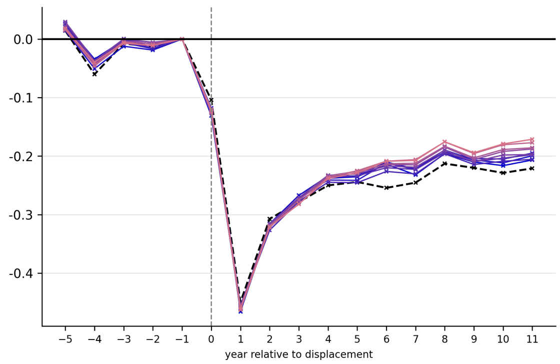
(b) Employment status



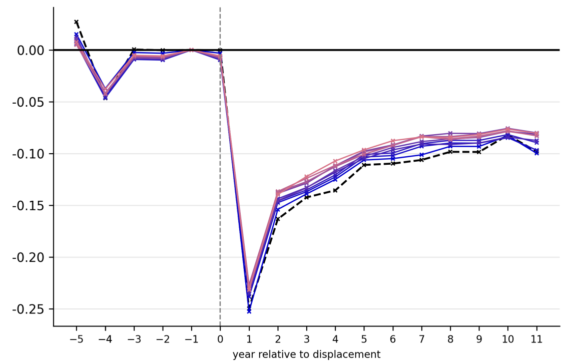
(c) # of months employed

Note: This figure presents the effects of job loss on labor market outcomes separately by gender. Each line corresponds to a different inverse probability weighting scheme for women observations according to the predicted propensity scores estimated via separate logistic regressions for the probability of being female using different sets of explanatory variables. **Weighting by earnings** includes the yearly earnings in the 3 years prior to displacement, each with ten decile dummies. **Firm characteristics** include the 3rd polynomial of firm fixed effect, firm total payroll, 10 firm size rank dummies, 1-digit industry, the share of men in the firm, and the firm's age. **Individual characteristics** include dummies for age, region of residence, birth cohort, ethnic group, recent immigration status, degree attainment, and marital status, as well as the individual firm wage premium, calculated as the difference between the individual monthly wage and the firm average.

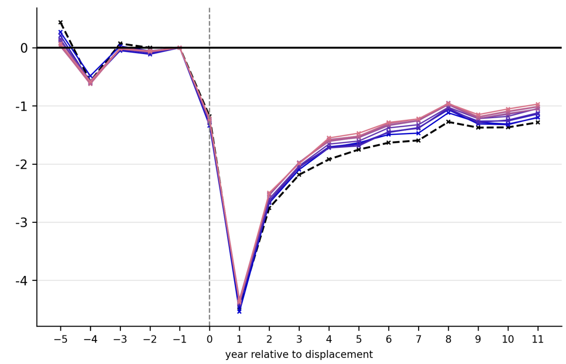
Figure A.7: Effects of job loss by gender, event study coefficients, omitting extreme weights



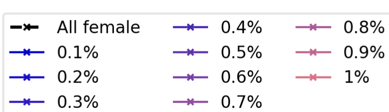
(a) Yearly earnings rel. to $t < 0$



(b) Employment status

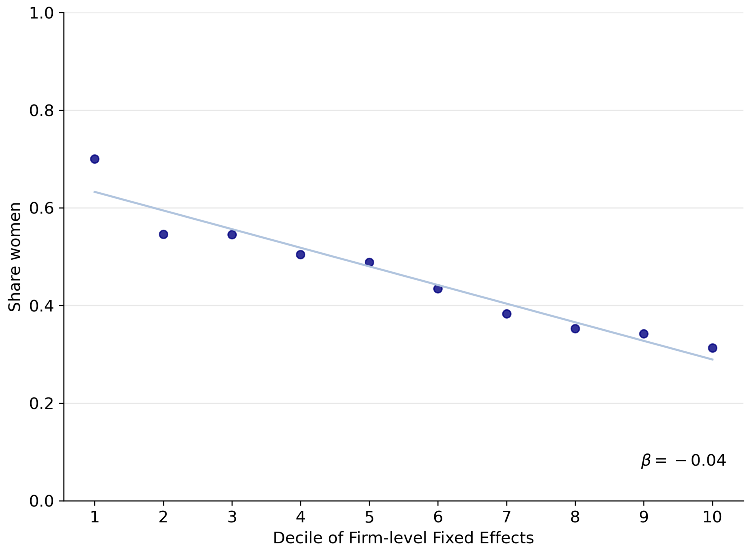


(c) # of months employed

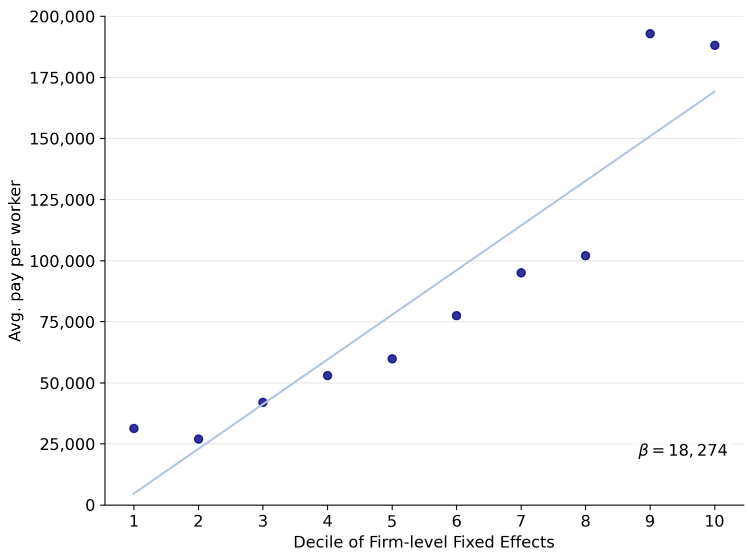


Note: This figure presents the effects of job loss on labor market outcomes for women after re-weighting observations according to the inverse of the predicted propensity scores, with the full set of individual and firm covariates as detailed in Section **??**. Each line corresponds to a different subset of displaced women, trimmed according to the predicted probability. For instance, 0.1% corresponds to a trimming of the top 0.1 percent of observations according to their inverse probability weights.

Figure A.8: Worker characteristics in the firm, binned by firm fixed effect deciles



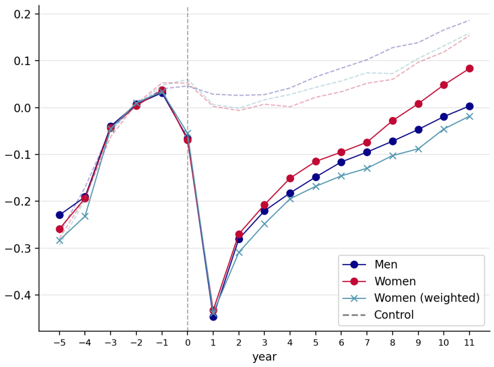
(a) Share women



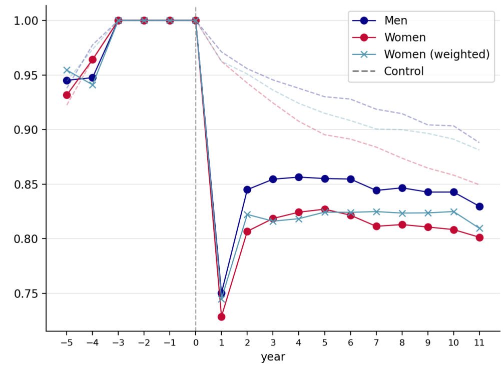
(b) Avg. pay per worker

Note: This figure presents the average share of women in the firm and the average pay per worker in the firm for each firm fixed effect decile. We fit the bin scatter with a linear line and present the coefficient β at the right bottom corner.

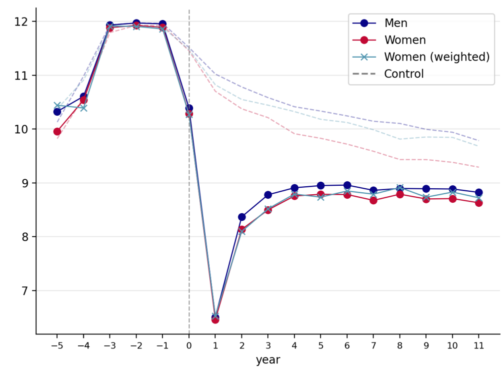
Figure A.9: Effects of job loss by gender, outcome means, re-weighting



(a) Means of earnings rel. to $t < 0$



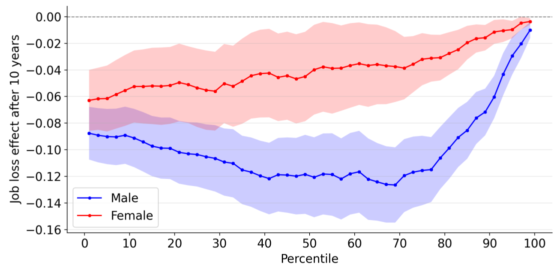
(b) Means of employment



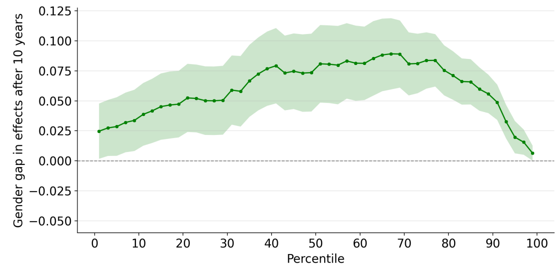
(c) Means of # of months employed

Note: These figures present the sample means of labor market outcomes by period relative to the event year with dashed lines depicting the control group. We present the raw means of men, and women, as well as the IPW re-weighted means of women, based on all individual and firm characteristics listed in Section D.

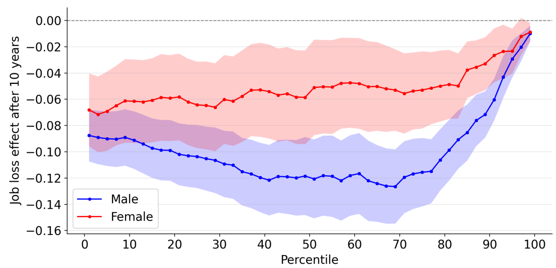
Figure A.10: The distributional effect of job loss on earnings 10 years after displacement by gender



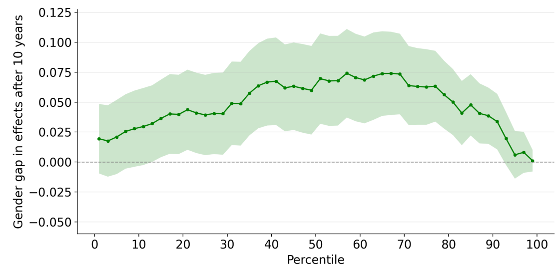
(a) Effects by gender, not weighted



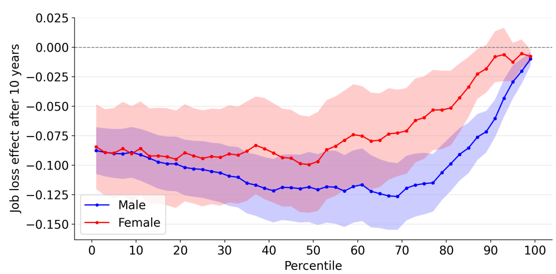
(b) Gender gap, not weighted



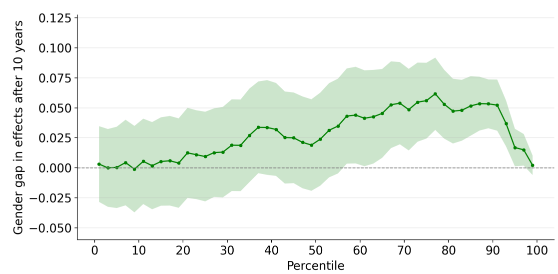
(c) Effects by gender, weighted by ind. char.



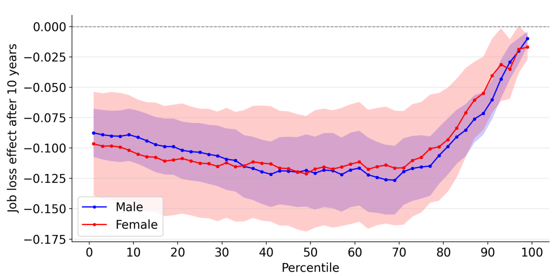
(d) Gender gap, weighted by ind. char.



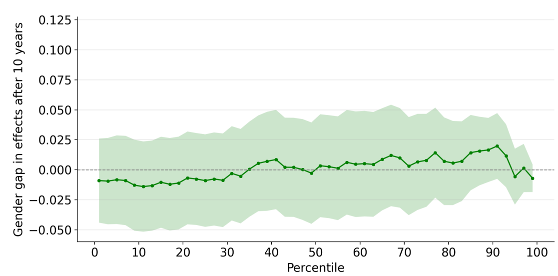
(e) Effects by gender, weighted by firm char.



(f) Gender gap, weighted by firm char.



(g) Effects by gender, weighted by all char.



(h) Gender gap, weighted by all char.

Note: These figures present the effects of job loss 5 years after displacement, where the outcome variables are dummies for whether the individual earns more than the p'th percentile (on the x-axis), with respect to the pre-displacement distribution of average earnings in period $t = -1$. The left panels show the effects separately by gender, and the right panels show the gender gaps. Each point in this figure represents a different regression coefficient. Regressions include the matched pair fixed effects. We present non-weighted estimates (Panels (a) and (b)) and IPW estimates, that include individual characteristics (Panels (c) and (d)), firm characteristics (Panels (e) and (f)), and both individual and firm characteristics combined (Panels (g) and (h)). Standard errors used to construct the confidence intervals are clustered at the firm level.

Table A.3: Descriptive statistics of laid-off sample, by groups

	Income		Firm FE quartile				Age			Gender	
Variable	Above Med.	Below Med.	1st	2nd	3rd	4th	Age $\leq$ 30	31-50	Age $>$ 50	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: workers											
Male	0.77	0.39	0.37	0.48	0.59	0.71	0.58	0.60	0.48	1.00	0.00
	(0.42)	(0.49)	(0.48)	(0.50)	(0.49)	(0.46)	(0.49)	(0.49)	(0.50)	(0.00)	(0.00)
Age	40.0	40.0	42.1	39.4	39.4	40.0	27.8	40.3	53.7	39.4	40.8
	(8.0)	(9.4)	(9.6)	(9.0)	(8.6)	(8.0)	(1.7)	(5.8)	(2.2)	(8.4)	(9.0)
Earnings	204,816	61,205	63,554	84,473	113,989	211,763	96,999	145,008	116,717	164,698	89,192
	(158,398)	(20,235)	(38,759)	(64,020)	(88,112)	(157,932)	(81,779)	(141,675)	(135,454)	(153,675)	(81,992)
# children under 18	2.15	1.67	1.58	1.81	1.88	2.10	2.25	2.11	0.49	2.30	1.37
	(1.59)	(1.74)	(1.66)	(1.77)	(1.66)	(1.61)	(1.62)	(1.68)	(0.94)	(1.79)	(1.35)
Multiple jobs	0.06	0.13	0.22	0.11	0.06	0.04	0.11	0.09	0.11	0.07	0.13
	(0.24)	(0.34)	(0.41)	(0.32)	(0.24)	(0.19)	(0.32)	(0.28)	(0.31)	(0.26)	(0.33)
Arab	0.07	0.16	0.14	0.13	0.16	0.07	0.20	0.11	0.03	0.15	0.08
	(0.26)	(0.37)	(0.35)	(0.33)	(0.37)	(0.26)	(0.40)	(0.31)	(0.18)	(0.35)	(0.27)
Ethiopia descendant	0.00	0.03	0.04	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
	(0.07)	(0.18)	(0.20)	(0.13)	(0.11)	(0.09)	(0.14)	(0.14)	(0.13)	(0.15)	(0.13)
FSU descendant	0.21	0.38	0.37	0.33	0.30	0.24	0.19	0.30	0.44	0.24	0.38
	(0.41)	(0.49)	(0.48)	(0.47)	(0.46)	(0.43)	(0.39)	(0.46)	(0.50)	(0.43)	(0.49)
Mizrahi	0.34	0.25	0.27	0.31	0.29	0.31	0.24	0.31	0.28	0.30	0.29
	(0.47)	(0.43)	(0.44)	(0.46)	(0.45)	(0.46)	(0.43)	(0.46)	(0.45)	(0.46)	(0.46)
Ashkenazi	0.35	0.16	0.16	0.21	0.21	0.36	0.35	0.24	0.20	0.28	0.22
	(0.48)	(0.37)	(0.37)	(0.41)	(0.41)	(0.48)	(0.48)	(0.43)	(0.40)	(0.45)	(0.42)
Post-secondary degree	0.25	0.09	0.08	0.11	0.12	0.29	0.25	0.17	0.08	0.18	0.16
	(0.43)	(0.29)	(0.27)	(0.32)	(0.32)	(0.45)	(0.44)	(0.37)	(0.27)	(0.38)	(0.37)
Married	0.56	0.53	0.61	0.53	0.53	0.52	0.29	0.56	0.76	0.55	0.53
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.45)	(0.50)	(0.43)	(0.50)	(0.50)
Tenure	5.88	5.44	5.90	5.28	5.73	6.19	4.68	5.67	6.85	5.61	5.72
	(2.35)	(2.25)	(2.40)	(2.25)	(2.29)	(2.44)	(1.49)	(2.22)	(2.93)	(2.22)	(2.43)
Panel B: firms											
# workers in firm	173	209	365	183	143	275	198	182	253	122	223
	(642)	(609)	(1,118)	(310)	(218)	(1,191)	(868)	(525)	(615)	(338)	(710)
Firm pay decile	7.28	5.36	3.42	4.91	6.80	9.00	5.38	6.26	5.49	6.27	6.05
	(2.78)	(2.55)	(1.47)	(2.29)	(2.29)	(1.91)	(2.60)	(2.81)	(2.74)	(2.81)	(2.80)
Firm share men	0.63	0.54	0.52	0.52	0.61	0.67	0.61	0.58	0.53	0.71	0.52
	(0.22)	(0.25)	(0.27)	(0.23)	(0.24)	(0.20)	(0.23)	(0.24)	(0.24)	(0.20)	(0.24)
Firm age	7.24	7.13	7.58	6.84	7.32	7.11	6.60	6.97	9.64	6.86	7.32
	(2.92)	(2.93)	(3.13)	(2.97)	(3.03)	(2.91)	(2.62)	(2.79)	(3.11)	(2.81)	(2.96)
Observations	6,713	6,755	2,397	2,258	2,707	2,983	2,343	9,283	1,842	7,776	5,692

Note: This table presents means and standard deviations of pre-displacement characteristics of workers who were displaced, by income level categories, defined using the pre-displacement median income within job-loss year.

B Job Loss Sample Construction

Differentiating between workers who are involuntarily fired and workers who leave a firm due to any other reason is not immediate, given that we do not explicitly observe separation reasons, as is the case in all comprehensive administrative data.[11] Therefore, we build on previous work and focus on mass layoff events, where for reasons that are not worker-specific, firms either have to let go of a substantial fraction of their workers or close altogether. We closely follow the literature to detect such events in the data. Specifically, we rely on Schmieder et al. (2023), who themselves utilize the common methods established in the literature that use administrative data, to detect mass layoff events and worker displacement.

We define a mass layoff event in the data if a firm identifier disappears from the records in a certain year between 1999 and 2009 and does not appear again, or if between two consecutive years, there is a drop of at least 30% in full-job equivalent worker count in the firm, and this drop is not offset a year later. We restrict our attention to firms with at least 40 workers at the year of the event since larger firms exhibit higher stability in worker count, and are more likely to capture mass layoff events. For example, in a firm of 3 workers, a drop of a third in the number of employees cannot convincingly be independent of worker characteristics. Another concern when using administrative data is that some firms appear to close, but in fact undergo mergers, outsourcing, or changes to firm identifiers. To address this concern, we examine worker flows from each firm that is closed to all other firms. If more than 20% of the workers from the closing firm are employed in another firm that keeps existing in the year following the event, we omit it from the analysis. In addition, we exclude workers who worked in the following sectors prior to their displacement: mining, public administration, and health, activities of private households and extra-territorial organizations, and industries that are led by government-owned companies.[12]

The displaced workers' group includes all workers who leave a firm that undergoes a mass layoff event in the same year. We consider tenured workers, who work at the firm for at least three consecutive years for at least 10 months each year, and who do not work in that firm again after the separation event. This job stability condition is implemented in almost all papers that document the persistent scarring effects of job loss (Bertheau et al., 2022). There are two main reasons to include this condition: (1) decreasing separation hazard rate with tenure implies unexpected displacement, supporting the identifying assumption that displacement is involuntarily and orthogonal to unobserved worker ability, and absent the mass layoff event, workers would have remained employed in these firms, and (2) tenured workers stand to lose more when displaced, due to, e.g., firm-specific accumulated human capital, or higher match quality, which lead to larger effects estimated (for a discussion on this see e.g. Lachowska et al. (2020)).

[11] It has been shown, however, that this approach yields very good results in terms of the effect size of job loss on workers (Flaaen et al., 2019).

[12] Specifically, we omit workers from the following industries: B - Mining and quarrying, O - Local administration, public administration and defense; compulsory social security, P - Education, Q - Human health and social work activities, R.91 - Libraries, archives, museums, and other cultural activities, T - Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use, U - Activities of extraterritorial organizations and bodies, H.51 - Air transport

To construct the sample of the non-displaced workers' group, we consider all workers who do not belong to the above population of displaced workers at any period in the data. We apply the same conditions above, such as on tenure, earnings, and sector restrictions. The only difference in sample restrictions between the displaced and non-displaced is that these workers do not work at firms that we tag as mass-layoff or closing firms. This implies that we do not consider "survivors" of firm-level events in our comparison group. Each year in the data for which a non-displaced worker follows the conditions on tenure, earnings, etc., is a potential job loss year. Finally, note that if a non-displaced worker has K potential job loss years, she enters the non-displaced pool of workers separately K times. We, therefore, weight the data by K.

C AKM Estimation

We estimate firm effects by running a two-way fixed effect wage equation with both firm effects and individual effects, also known as the AKM model (Abowd et al., 1999):

$$logY_{it} = \alpha_i + \psi_{j(i,t)} + x'_{it}\beta + \epsilon_{it} \tag{4}$$

where $logY_{it}$ denotes the log average monthly earnings of worker i with employer $j(i)$ in year t, α_i is a worker-specific fixed effect, reflecting the productive characteristics of the worker that can be transferred across employers and over time, $\psi_{j(i,t)}$ is an employer-specific fixed effect, reflecting employer wage premium for all workers at firm j, x_{it} is a vector of time effects, and workers' age and age squared, and ϵ_{it} is the error component.

Sample construction and restrictions:

We estimate the AKM model with Equation 4 over the full employer-employee data, spanning the years 1995 to 2019. To construct our sample, we first omit the job loss workers to avoid the concern that these workers may bias the estimated effects, along with the matched comparison sample of non-displaced workers[13].

Then, similarly to Lachowska et al. (2020), we define the employer for each worker year as the highest paying employer in that year. In this sample, we impose several additional restrictions. We include all worker-year observations when workers are 23 to 67 of age, with yearly earnings higher than 5,000 ILS, in firms with at least 3 workers. We include workers who have worked in a firm for at least two years. We also restrict our sample to workers with at least 3 years of worker-year observations. In our individual fixed effect and firm fixed effect estimation, we exclude the post-job-loss periods for workers who experienced a job loss or who serve as controls. To estimate match effects, we run a separate regression and include post-job-loss periods, similarly to Lachowska et al. (2020).

This restricted sample includes 43.4 million worker-year observations, with 269k firms and 3.5 million workers. The identification of employer fixed effects in equation 4 is possible only among the connected set of transitioning workers (Abowd et al., 1999). In our data, the largest connected set is somewhat similar in size to the full restricted sample, with only 1k firms and 200k workers excluded. The descriptive statistics for the connected set are in Table C.1.

Estimating the model over this large year span helps to cope with the limited mobility bias. As discussed in Bonhomme et al. (2019), the concern with a short panel is that it may not provide enough variation in the data to accurately estimate the parameters of the model. This can lead to biased or inconsistent estimates, and reduce the precision of the results. In our sample, we calculate 11 movers per employer, compared to 10 moves in the Washington data as reported in Lachowska et al. (2020). We also find a mobility rate of 0.104 - the number of moves (4,526,340) divided by the number of

[13] Including them does not change our results. In fact, similarly to Lachowska et al. (2020), the correlation between the firm fixed effects estimated with and without the sample of job losers is 0.985.

worker-year observations (43,417,211). This is similar to the mobility rate found in the Washington data (0.097) and larger than the figure found in Germany (0.03) Lachowska et al. (2020); Card et al. (2013).

In our estimation, we find that firms account for around 11 percent of the variance in average monthly earnings. This is similar to the value found in Israel by Dobbin and Zohar (2021), which reaffirms the validity of our estimation.

Table C.1: AKM sample descriptives statistics

	Gender		
	Male	Female	All
Monthly earnings	13,711	8,702	11,198
	(20,120)	(9,113)	(15,806)
Yearly earnings	151,742	95,136	123,337
	(169,079)	(89,334)	(137,992)
Age	39.78	40	39.81
	(10.37)	(10)	(10.36)
Number of matches	2.37	2.26	2.31
	(1.35)	(1.29)	(1.32)
Number of moves	1.37	1.26	1.31
	(1.35)	(1.29)	(1.32)
Number of workers	1,764,734	1,730,649	3,495,383

D Gender Propensity Score

Propensity score matching:

Having defined the treated (job displaced) and non-treated populations in our data, we estimate a logit-based propensity score to predict the probability of belonging to the treatment group of workers displaced in a mass layoff event. The logit equation for estimating the propensity score is given by:

$$\text{logit}(P(T = 1|X)) = \alpha + \beta X$$

where $\text{logit}(P(T = 1|X))$ represents the log-odds of belonging to the treatment group given the covariates X. We exploit the richness of our data by including a long list of features in our estimation:

- 2nd order polynomial of earnings in the three years prior to displacement
- Gender
- Pre-displacement firm characteristics (firm size rank decile dummies, total firm payroll decile dummies)
- Firm tenure years
- Cubic age times gender
- Ethnic group
- Commuting zone at the time of displacement
- Spouse's earnings in the two years prior to displacement

With the predicted propensity score for the non-treatment population, we employ a one-to-one matching within characteristics bins. We define bins according to the displaced worker's 1-digit industry, job loss year, gender, and yearly earning quartiles prior to displacement.

Appendix Figure A.4 shows the overlap in the predicted propensity to be displaced for each of the groups, and after the matching procedure.

Gender inverse probability weighting: After obtaining a balanced sample of displaced and non-displaced workers via the matching procedure, we estimate an additional predicted probability of being a female, based on different sets of characteristics.

To learn about the gender differences in the impact of job loss, we conduct an inverse probability weighting exercise in which we reweight the female characteristics distribution to match the male's characteristics distribution, similar to Illing et al. (2021). We estimate the composition-adjusted gender gap, using a re-weighting of female observations to ensure that displaced men and women exhibit comparable observable characteristics[14]. To that end, we estimate a logistic regression similar

[14] We conduct a similar analysis, weighting male observations, and get the same qualitative results.

to the above propensity estimation, where the outcome variable is a dummy for male. We then use the predicted probabilities ($\hat{p}$) to construct the inverse probability weights $\hat{w} = \frac{\hat{p}}{1-\hat{p}}$ for women.

In the logit regression, we use three categories of covariates for our predictions: individual demographics, firm characteristics, and earnings. Individual characteristics include age, dummies for the number of children, family origin or ethnicity dummies, region of residence, recent migration status dummy, and marital status, as well as the individual firm wage premium, calculated as the difference between the individual monthly wage and the firm average. Firm characteristics include firm fixed effects, firm size, the average age of workers and share of women in the firm, and the age of the firm. Earnings variables are the earnings in each year in the three years pre-displacement, flexibly estimated by earnings deciles in each year.

We construct weights for each set separately and for all covariates together. This approach allows us to examine the importance of the differences in each category on the gender gap in job loss effects separately.

To deal with extremely large weights, in cases where the propensity that was estimated is close to 1, we trim the sample by the top 0.1 percentile of predicted probabilities from the full covariates logit regression. Figure A.7 presents a sensitivity analysis dropping extreme observations using different cutoffs. In addition, we trim the sample once more according to the common support of predicted probabilities. This results in dropping 0.3 percent of the observations.

Figure A.1 presents the gender differences between covariates before and after re-weighting by the full list of covariates. This provides evidence that the re-weighting approach effectively achieves similarity between the groups. Notably, pre-displacement earnings, a crucial element of heterogeneity in effects, demonstrate no significant difference between men and women for each of the three years leading up to the displacement event.

Appendix Figures A.5 present the distribution of predicted probabilities, by each of the explanatory variable sets: individual characteristics, which include demographics and the within-firm individual wage premium, firm characteristics, which include firm fixed effects and other time-varying variables, and both of these sets combined. First, note that in all histograms there exists substantial overlap, which is required for the validity of our estimation. Second, the predictive power of firm characteristics appears to be higher than that of individual characteristics, which is in line with our IPW results for the ability of these sets to explain the gender gap in job loss effects.

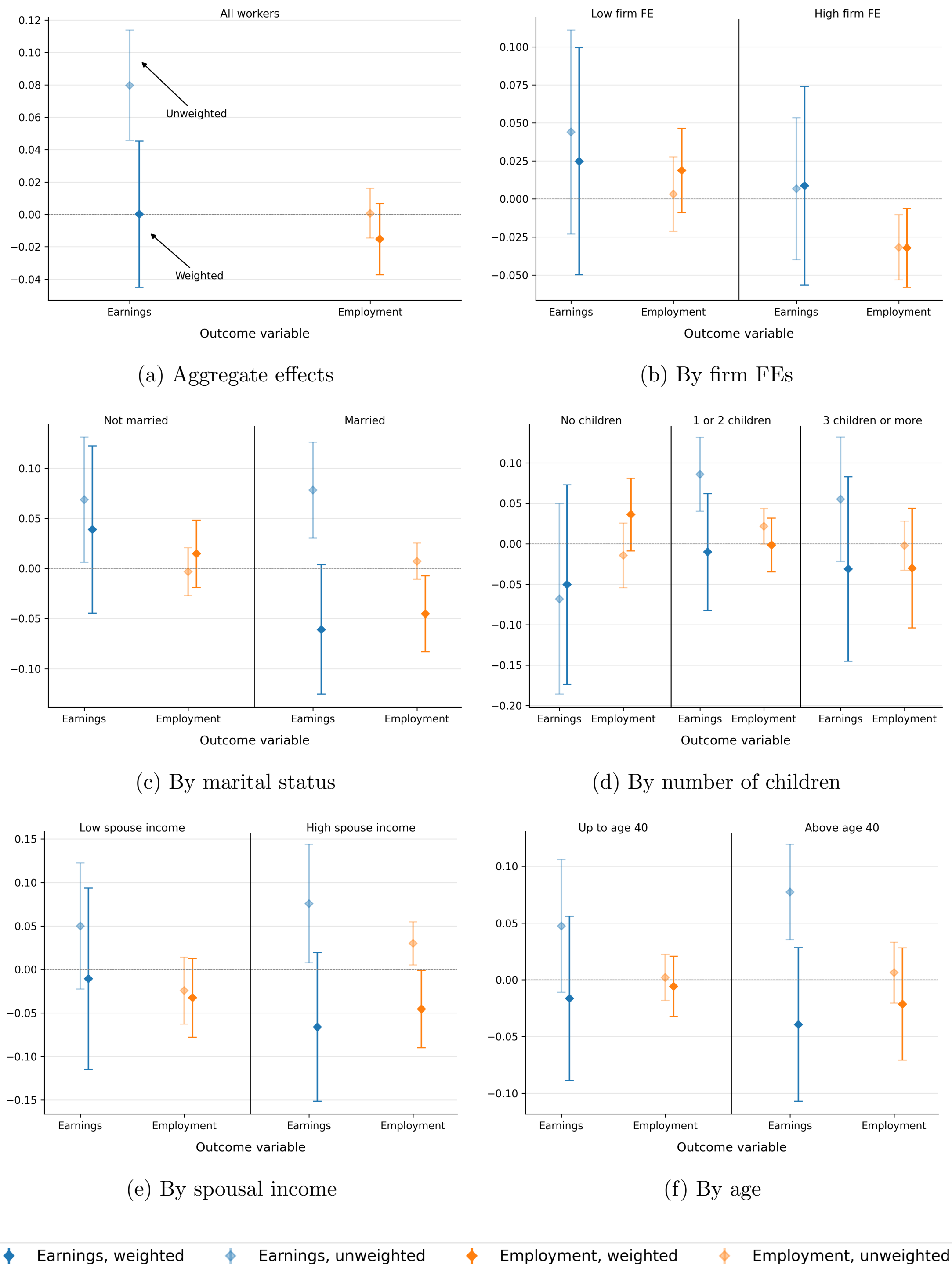
E Heterogeneity

The gender gap in the impacts of job loss masks some heterogeneity. Figure E.1 plots the raw and covariate-adjusted gender gaps stratifying the sample according to five pre-displacement characteristics that are potentially relevant to the effects of job loss. In sub-figure E.1a, we first present the gaps for the whole sample, visually reiterating the results discussed above, and in the rest, we present the job loss gaps on various sub-samples.

Sub-figure E.1b displays the gender gap separately for workers with above and below median firm fixed effects. We find that the gender gap in the effects on relative earnings shrinks substantially even just with that crude split of the sample, regardless of whether we use re-weighting or not. The gaps are less than one percentage point for high firm fixed effects workers and 2.5 percentage points for low firm fixed effects workers. This means that the job-loss gap in earnings can be explained even with the most degenerate matching firms split. In addition, we find that the negative gap in employment status stems solely from the high firm fixed effects workers, with a gap of -2.7 percentage points, while low firm fixed effect workers exhibit a positive 2.3 percentage points gap.

The gender gap in the impacts of job loss varies by individual characteristics. Sub-figure E.1c displays heterogeneity in effects by marital status. While there is no gap in the effects of job loss on non-married workers, after adjusting for covariates, we find that married female workers experience a five percentage point lower relative earnings and four percentage points lower employment compared to married males. This means that married women are less likely to return to work after job loss compared to married men with exactly the same individual and firm characteristics. Subfigure E.1d suggests that this pattern is not driven by the number of children in the household. This finding rules out the possible explanation that this pattern reflects traditional differences in the gender roles in the household, where women serve as the main parent responsible for childcare and, therefore, experience a higher opportunity cost of working after job loss. In contrast, in Figure E.1e, we find evidence that the gender gaps among married workers stem from families with high-earning spouses, while married workers with low-earning spouses do not exhibit a gender difference. Lastly, in Figure E.1f, we find some imprecise evidence that age wage penalty is higher for women after job loss.

Figure E.1: The gender gap in medium and long-run effects of job loss by pre-displacement characteristics



(a) Aggregate effects

(b) By firm FEs

(c) By marital status

(d) By number of children

(e) By spousal income

(f) By age

Note: This figure plots the gender gap in job loss effects on earnings (relative to pre-displacement levels) and employment status in the long-run. The raw gender difference is presented in semi-transparent colors, while the re-weighted gaps adjusted for all variables are depicted in solid colors. Panel (a) shows the gaps for the entire sample. Panels (b) to (f) dissect the gaps by group: based on median firm Fixed Effects (FE) (b), marital status (c), number of children (d), age (e), and spouse's median income (including employment and self-employment earnings) (f). Confidence intervals are based on standard errors clustered at the firm level.