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The Gender Gap in Earnings Losses After Job Displacement

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Abstract

We compare men and women who are displaced from similar jobs by applying an event study design combined with propensity score matching and reweighting to administrative data from Germany. After a mass layoff, women's earnings losses are about 35% higher than men's, with the gap persisting five years after displacement. This is partly explained by women taking up more part-time employment, but even women's full-time wage losses are almost 50% higher than men's. Parenthood magnifies the gender gap sharply. Finally, displaced women spend less time on job search and apply for lower-paid jobs, highlighting the importance of labor supply decisions.

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1 Introduction

A large literature in Economics has documented the high costs to workers who are displaced from stable jobs. Following a mass layoff, job losers face large earnings losses that last for many years (e.g., Jacobson et al., 1993; Couch and Placzek, 2010; Davis and von Wachter, 2011; Lachowska et al., 2020; Schmieder et al., forthcoming). A striking feature of this literature is that it has mostly focused on the experience of men, with women often not being studied at all or only as a side note. In particular, very few papers explore explicitly how the experience of women may differ from the experience of men after a job loss.

This is surprising in light of the large interest among labor economists in the gender pay gap and differences in careers between men and women. One recent strand of this literature has studied whether women respond differently than men to other "shocks" such as childbirth or marriage (recent examples include Angelov et al., 2016; Kuziemko et al., 2018; Kleven et al., 2019a,b). Perhaps most strikingly, there appear to be more papers on the "added worker effect" that study how women respond to job loss of their husbands (e.g. Lundberg, 1985; Stephens, 2002; Bredtmann et al., 2018; Fackler and Weigt, 2020; Halla et al., 2020) than papers that study how women's responses to a job loss of their own differs from men's (a few exceptions are Maxwell and D'Amico, 1986; Crossley et al., 1994; Kunze and Troske, 2015; Meekes and Hassink, 2022). Understanding how men's and women's labor market outcomes evolve in response to job displacement is not only important given the large economic and personal costs of job loss, but can also be helpful to understand reasons for differences in labor market experiences of men and women more broadly.

In this paper, we study labor market outcomes of displaced men and women using administrative data from Germany.[1] Following the seminal event study design of Jacobson et al. (1993), we document earnings losses of workers who lost their jobs during a mass layoff or plant closing, separately by gender. Men and women differ along many dimensions, such as pre-displacement earnings, occupations, or industry, which on their own affect the recovery path after job displacement. To better understand the underlying reasons for different experiences of men and women, we therefore distinguish between the raw (or unadjusted) gender gap in post-displacement outcomes and the adjusted gender gap, that compares women to men who are displaced from similar jobs and with similar labor market histories. The raw

[1] As discussed below, our main analysis focuses on married men and women, but our results also hold when we include singles.

gap is arguably the correct measure for understanding how the typical cost of job loss differs by gender and whether, given the distribution of jobs, men or women are more negatively affected. The adjusted gap, however, can shed more light on the mechanisms behind different experiences by gender, as it isolates the part that is not easily explained by pre-displacement characterstics.[2]

In a first step, we show that both men and women have large and lasting earnings losses of about 25% relative to pre-displacement earnings. These similar raw losses mask, however, that displaced women look very different from displaced men. In particular, women on average have much lower earnings, are much more likely to work part-time, and work in lower-paying industries before displacement, which are all characteristics typically associated with smaller earnings losses. Once we use reweighting or regression controls to generate the composition adjusted gender gap in earnings losses, we show that women experience about 35% larger earnings losses than men who are displaced from similar jobs.

One might expect that after controlling for observables, similar to the gender wage gap, the costs of job displacement should not differ by gender. The fact that the gender gap in earnings losses on the contrary *increases* if we compare men and women with very similar labor market characteristics suggests that a labor market shock, such as job displacement, is significantly more harmful to successful women's careers. Comparing the raw gap to the composition adjusted gap thus shows that women's labor market trajectories are much more fragile: for those who managed to fill comparable job positions as men, a labor market shock sets them back much more severly, and they do not recover for a long time. In the remainder of the paper, we focus on the composition adjusted differences between men and women, while continuing to report the raw gap for comparison as well.

In a second step, we investigate the main drivers that underly these persistent earnings losses. In particular, we show the relative importance of time spent in unemployment after a job loss, wage losses, and the incidence of working part-time in shaping earnings losses. Similarly to men, the short-term earnings losses for women are to a large degree driven by losses in days worked. In the longer term, daily wages become a more important factor, as they show no recovery as time passes. Furthermore, the composition adjusted gender gap is large both for employment and wages, with larger losses and slower recovery for women. While men's daily wages fall by around 20 log points, women's wages fall by close to 33 log points.

[2]The relationship between the raw and adjusted gender gap in the costs of job loss is thus similar to the relationship between the raw and composition adjusted gender pay gap.

The different wage losses are to a large part due to the much higher propensity of women to work part-time and in marginal "mini-jobs".[3] While mini-jobs and part-time explain some of the wage loss differences, even full-time wages fall more dramatically for women than for men. For example, 5 years after job loss, men's full-time wages are around 7 log points lower relative to non-displaced men, while for similar women, full-time wages fall by around 15 log points.

In a third step, we document how job characteristics after job loss such as employer size, occupations, industry, and commuting distance can explain the large differences in wage losses between men and women. Our results show that many of these characteristics do not change differentially between men and women after job loss and are not driving the gender gap in wage losses. One factor that does turn out to be important is establishment pay premiums, estimated using the two-way fixed effects model of Abowd et al. (1999) (AKM).[4] We find that in the long run (5 years post displacement), women are employed at establishments paying slightly lower wage premiums than men (9 log point loss for women vs. 6 log point loss for men), which in turn explains about a fourth of the gender gap in full-time wage losses. Thus, while men and women both fall down the job ladder (with little sign of climbing back up), women fall further and recover more slowly.[5]

What can explain the large differences in post-displacement outcomes for men and women who are displaced from similar jobs? One possibility could be that for married job losers, labor supply decisions are interdependent.[6] We therefore turn to the household level to better understand the experience of men and women after job loss. Since the household dimension

[3]Mini-jobs are an unusual feature of the German labor market in that they are jobs that are exempt from payroll and income taxes subject to an income threshold (450 Euro per month since 2013) and thus very low income (Tazhitdinova, 2020; Gudgeon and Trenkle, forthcoming).

[4]This builds on recent work that investigated the role of employer wage premiums in explaining the costs of job loss using the AKM model, such as Lachowska et al. (2020); Schmieder et al. (forthcoming); Gulyas and Krzystof (2020); Fackler et al. (2021).

[5]This is in line with the results in Card et al. (2016), showing that the distribution of men and women across establishments with different wage premiums plays an important role in explaining the gender wage gap.

[6]In particular, husbands and wives face a joint decision with respect to allocating time between participating in the labor market and home production / child care. Depending on each individuals potential for earning wages, cost and availability of childcare, as well as preferences and norms it may either be optimal for both spouses to work or for one spouse to specialize on market work while the other spouse focuses on home production. A shock such as job loss and the subsequent (often permanent) loss in expected wages will change the optimal allocation of household time. In particular, women might find home-production comparatively more attractive, either due to their often lower earnings potential (e.g. because of being married to older and higher income partners or because of the gender pay gap) or due to different preferences / norms for childcare. This would explain why women's labor supply may drop in response to job displacement relative to men's.

is key for understanding possible mechanisms, we focus our entire analysis (including the results described above) on married couples, though we show that all the previous results are similar when including singles. This has the advantage that we can observe the presence of children and explore the role of spousal earnings. We show that the recovery paths vary with the presence of children. Here, we find striking differences between men and women: while fathers of young children have substantially smaller earnings losses, mothers of young children have much larger earnings losses.[7] Thus, parenthood sharply widens the gender gap in earnings losses, as well as wage and employment losses. We further investigate the household dimension analyzing whether the displaced worker's share in household income (prior to job loss) affects earnings losses.

In a final step, we provide a partial answer to whether gender differences are due to labor supply differences, e.g. women wanting to work fewer hours, or labor demand differences, such as discrimination. Using stated job search preferences (from the unemployment insurance system) and novel survey data on job search, we provide evidence that at least part of the difference is likely explained by labor supply. In particular, we show that displaced women are on average 11-13 percentage points less likely to look for full-time work, with the effect magnified by motherhood. In addition, women have a somewhat more narrow geographic scope in job search, apply to lower paying jobs and report a lower search effort.

The paper makes several key empirical contributions to the existing literature. First, while some papers estimate earnings losses separately for men and women (e.g. Maxwell and D'Amico, 1986; Crossley et al., 1994; Kunze and Troske, 2015; Meekes and Hassink, 2022), there is usually no or very little attempt to control for the large differences in pre-displacement job and worker characteristics. Our paper is the first to systematically account for such pre-displacement differences and to focus on a set of similar men and women in the comparison. In contrast to these previous papers on the gender gap, we systematically investigate sources behind the earnings losses, such as wage vs. employment losses as well as a broad range of job characteristics (including AKM-style establishment wage premiums) and their ability to explain the gender gap in earnings and wage losses. Another important difference is the ability to investigate the household dimension in some detail in the same context, such as the role of children, the relative share in household income, and the added worker effect. Finally,

[7] This is consistent with evidence in Frodermann and Müller (2019) that for women, motherhood negatively affects job outcomes after displacement. It is also in line with Bertrand et al. (2010) who show, for a sample of MBA graduates, that mothers work shorter hours and face greater career disruptions.

in contrast to previous work we explicitly examine whether differences in labor supply can explain part of the differences in the cost of job loss by showing how women's job preferences and job search patterns after displacement differ from men's.

On the methodological side, a key contribution of our paper is to combine a matching algorithm to construct a suitable control group with a reweighting technique to make the sample of displaced women comparable to the sample of displaced men. In the first step, we use propensity score matching (as in Couch and Placzek, 2010 and Schmieder et al., forthcoming) to find a comparable non-displaced worker for each displaced worker. This provides for a clean counterfactual that easily passes visual inspections of the parallel trends assumption. We then use a reweighting technique in the spirit of DiNardo et al. (1996) (DFL), to reweight displaced women (and their matched controls) to match the characteristics of displaced men. A major advantage of this matching-cum-reweighting method is that it allows to directly study the different post-displacement earnings losses for men and women using event study figures that show outcomes for men and comparable women.

Our analysis also combines the reweighting approach with the matched difference-in-difference design proposed by Schmieder et al. (forthcoming). This design creates an individual-level difference in difference type estimate of earnings losses by comparing earnings changes of an individual before and after displacement with earnings changes of the matched control worker. The advantage of this design is that it is then straightforward to regress this individual-level estimate of the earnings losses on explanatory variables such as gender, but also on possible sources of earnings losses such as changes in job characteristics. While Schmieder et al. (forthcoming) focus on earnings losses over the business cycle, we use this design to estimate the gender gap in losses. We combine the design with the DFL reweighting approach to keep other job and worker characteristics similar between displaced men and women.

A third methodological contribution is that this paper is part of a research project at the Institute for Employment Research (IAB) to link married spouses to each other in the German social security data.[8] We created a dataset of matched married couples for each year from 2001 to 2014, building on Goldschmidt et al. (2017). This linkage gives us access to key variables typically not available in administrative datasets that have been used to study job loss. Most crucially, we can observe spousal income and labor market status and we can infer

[8]This paper here together with the data documentation in Bächmann et al. (2021) are the first papers that directly come out of this cooperation and use the newly linked couples data.

children and births for both partners, which otherwise would only be available for women.

Our paper is closely related to several strands in the literature exploring the reasons for differences in the labor market experience of men and women and sources of the gender pay gap. First, it ties into the literature investigating differences in job preferences. For example, Goldin (2014) finds that a significant part of the gender wage gap is due to employers rewarding men's relatively longer working hours. It moreover relates directly to papers documenting gender differences in the job search and application process. Le Barbanchon et al. (2021) show that women trade off shorter commutes against wages, and Cortes et al. (2022) show that women tend to accept jobs earlier on in the search process which also tend to be lower payed. In addition, Fluchtmann et al. (2021) and Lochner and Merkl (2022) provide evidence that women are more likely to apply for different, lower paying jobs. We document that gender differences in job search occur among involuntarily laid off workers with similar pre-unemployment characteristics, and that these differences are largest for mothers with young children.[9] While Card et al. (2016) document the importance of gender-specific firm sorting for the gender pay gap, we document how such sorting can occur for mid-career workers working in similar jobs after facing a labor market shock.

Second, our paper is also related to the literature on intra-household bargaining (e.g., Chiappori et al., 2002; Mincer and Polachek, 1974). For example, previous research shows that the gender pay gap is positively related to gender differences in home production (Albanesi and Olivetti, 2009). In line with Bertrand et al. (2015), we show that women with a relatively large share in household earnings pre-displacement have particularly large earnings losses, suggesting that they revert to male breadwinner norms. We moreover contribute to the active literature looking at the effect of job loss on household decisions, such as fertility choices (Huttunen and Kellokumpu (2016)).

Finally, our work connects to the recent "child penalty" literature. For example, Kleven et al. (2019a), Kleven et al. (2019b), and Angelov et al. (2016) show that while men and women typically have similar career trajectories early on in their life, a dramatic gap opens up after childbirth. Similarly, Gunnsteinsson and Steingrimsdottir (2019) show that women are much more likely than men to drop out of the labor force or reduce hours after the birth of a disabled child. Our paper complements this literature by showing that women are also more adversely

[9]Relatedly, Kunze and Troske (2012) document gender differences in life-cycle patterns of job search which they hypothesize to stem from child-related constraints, a hypothesis the authors can't test due to data limitations.

affected by the exogenous shock of job displacement. In addition, we document that having children sharply increases the gender gap in earnings losses after displacement.[10]

The paper proceeds as follows: In Section 2 we describe the data sources and our methodology of combining a matched event study analysis and matched difference-in-difference design with reweighting. In Section 3 we document the gender gap in earnings, employment, and wage losses, both for a broad sample of men and women and when comparing men and women displaced from similar jobs. In Section 4 we explore potential mechanisms with a focus on changes in job characteristics, the role of children, within-household earnings inequality, and gender differences in job preferences and job search. Section 5 discusses the robustness of our results and Section 6 concludes.

2 Data and Methods

2.1 German Administrative Data

For our empirical analysis, we combine worker-level data from the German social security system (provided by the Institute for Employment Research IAB) with a newly available couple identifier, which enables us to link the employment history of workers' to that of their spouses. The worker-level data covers the universe of German workers subject to social security contributions[11]. It contains day-to-day information on earnings and time worked in each employment spell, as well as spell information on unemployment duration and benefit receipts. In addition, the data comprises basic demographic characteristics, such as education, occupation, and industry. We use the couple identifier to generate a dataset with information on workers and their spouses; we complement it with information on mothers, using the algorithm provided by Müller et al. (2017).[12]

From the universe of workers, we select all workers in an identified mixed-sex couple, where at least one partner was displaced from a mass layoff in 2002-2012 after they are observed in a couple.[13] We combine this with a sample of couples where no partner experienced a

[10]This is consistent with evidence in Frodermann and Müller (2019) that for women, motherhood negatively affects job outcomes after displacement but without comparisons to men.

[11]We use the Integrated Employment Biographies (IEB), Version 14.00. This data does not include self-employed and civil servants.

[12]Note that since the algorithm relies on mothers being observed in the social security data before they give birth, it is most reliable in identifying the first child. Throughout the analysis below, we will therefore focus on the oldest child in a household.

[13]We drop individuals who appear in multiple couples over this time period.

displacement. After matching, our sample has 80,655 displaced workers (48,849 men and 31,806 women). All workers in our sample are born in 1950 or later. After applying the imputation method for the education variable suggested by Fitzenberger et al. (2006), and following Dauth and Eppelsheimer (2020), we construct a yearly panel spanning 1997 through 2017. Information on couples is available from 2001 through 2014. The couples we identify are a somewhat selected group, where both partners are in the labor force and covered by social security.[14] In particular, partners can be in marginal employment or receive unemployment benefits, but they cannot be self-employed or civil servants. We only identify couples if one partner changes their name at marriage. While this is still very common in Germany we are more likely to identify older, more conservative couples. Our algorithm is moreover more likely to pick up couples in smaller homes (e.g. single-family) and with less common names.

2.2 Measuring Job Displacement

In our definition of job displacement, we follow Schmieder et al. (forthcoming). This comes with the advantage that like them, we can compare our results to state-of-the-art studies on job loss from the U.S. literature. Thus, we define a worker as displaced if she leaves her main employer in the course of a mass layoff event. We focus on workers with at least two years of tenure prior to displacement. Our focus is thus workers who most likely did not expect the mass layoff and lost their job involuntarily.

Like Schmieder et al. (forthcoming), we work with two definitions of a mass layoff event. We define a mass layoff as a workforce decline of more than 30% between June 30 of two consecutive years. In addition, we consider permanent establishment closings. We exclude establishments with less than 30 employees in the year before the mass layoff, and we exclude establishments with large employment fluctuations prior to displacement.[15] Our focus is on mass layoffs occurring in 2002-2012; thus, we can observe each worker at least 5 years before and 5 years after displacement.

We follow Hethey-Maier and Schmieder (2013) to make sure we exclude events such as mergers, takeovers, or changes in employer identification numbers from our mass layoff data. For this purpose, we construct a complete cross-flow matrix of worker flows between establish-

[14] Appendix A.1 provides a brief description of the identification algorithm developed by Goldschmidt et al. (2017) and the recent data update by Bächmann et al. (2021).

[15] That is, we exclude establishments where the workforce increased by more than 30% in at least one of the two years preceding the layoff.

ments using the universe of the German social security data. We consider only displacements where no more than 30% of the laid-off workers go to a single new establishment.

2.3 Constructing a Sample of Displaced and Non-Displaced Workers

We construct our main analysis sample in two steps: First, we choose a sample of workers who fulfill our baseline restrictions. Second, we use propensity-score-matching (PSM) to assign an appropriate control group to our displaced workers.

To make our study comparable to the existing literature, we again follow Schmieder et al. (forthcoming) in our baseline restrictions. One difference to the previous literature is that our restrictions allow for part-time employment before displacement, which makes the baseline sample more representative of women in Germany where in recent years almost 50% of women work part-time (Fitzenberger and Seidlitz, 2020). We denote the year prior to displacement the baseline year $c-1$. For each baseline year $c-1$ we consider all workers that satisfy the following on June 30 for that year: the individual is aged 24 to 50, she works in an establishment with at least 30 employees, has at least two years of tenure, and was not in marginal employment in the four years preceding displacement.[16] Another important requirement for our main analysis sample is that workers have to be identified as part of a couple in at least one of the five years prior to displacement. This comes with the advantage that we can observe a large set of household variables (e.g., children and relative income) for these workers. We moreover exclude displaced workers who left the displacing establishment for reasons such as death, sick leave, parental leave, or conscription in the baseline year. We do this to make sure we do not falsely identify workers as displaced who in reality took up, e.g., parental leave. Within this sample, a worker is displaced between year $t = c-1$ and $t = c$ if she fulfills the following two conditions: First, she leaves the establishment between $t = c-1$ and $t = c$ and is not employed at the year $c-1$ establishment in any of the following 10 years. Second, the establishment she works at has a mass layoff between year $t = c-1$ and $t = c$. We exclude potential comparison workers who move establishments between $t = c-1$ and $t = c$. Note, however, that control workers can be displaced in future years.

Our baseline restrictions ensure that displaced and non-displaced workers are somewhat

[16] We also exclude individuals working in the construction and mining sectors. Very few women work in these sectors so that it is essentially impossible to compare displaced men from these sectors to similar women. To keep our sample constant throughout the analysis below, we impose this restriction from the beginning, though it makes little difference for the raw gender gap (before reweighting).

comparable before the mass layoff. However, they may still differ in many ways that will make it difficult for us to estimate the causal effect of displacement. We thus use a propensity score step-matching estimator, matching displaced workers to suitable controls within cells of 1-digit industries, gender, and location in East or West Germany. Our list of matching variables includes a worker's log wage in $t = c - 3$ and $t = c - 4$, full-time employment status in $t = c - 3$, and age, years of education, tenure, and log establishment size in $t = c - 1$. Each displaced worker is assigned the non-displaced worker with the closest propensity score without replacement.

Observable characteristics of displaced and matched non-displaced workers prior to displacement are very similar as shown in Appendix Table 1. Thanks to the matching, the displaced men and women are very similar to their respective controls and there are virtually no differences in individual characteristics (education, experience, tenure, earnings) as well as establishment characteristics (size, share of female/full-time workers) between displaced and non-displaced workers.

Table 1 shows summary statistics for the displaced women and men in our sample. As a reference point, the table includes characteristics for a random sample of all women, Column (1), and all men, Column (4) in the German administrative data during our sample period. Column (2) shows characteristics of displaced women in our sample. Compared to the overall sample of women in Column (1), displaced women are positively selected in terms of labor force attachment and earnings due to our baseline restrictions on tenure and establishment size (and ruling out workers working only in mini-jobs). For example, prior to displacement women in our sample earn about 26,600 Euro per year as opposed to only around 15,300 in the overall population. Similarly, displaced men in our sample (Column 5) are also positively selected compared to all male workers (Column 4), and also have about 50% higher earnings.

While both our sample of displaced men and women is positively selected with comparatively high levels of earnings and labor force attachment, there are also large differences when comparing the sample of displaced women (Column 2) to displaced men (Column 5). For example, 2 years before displacement displaced men have earnings of around 36,700 Euro compared to women's 26,600 Euro. Similarly, log daily wages are around 36 log points higher for men. One key driver for these differences is that while men rarely work part-time in this sample (on average only 8 days per year), for women around 1/3 of total time worked is part-time (on average 115 days per year). By contrast traditional measures of human capital,

such as education, tenure, or experience are quite similar for men and women. Strikingly, our baseline sample contains substantially fewer women with a child in kindergarten age or younger (3%) compared to men (12%), reflecting the low labor force attachment of women with young children. Women also work at somewhat different employers: they typically work for larger establishments that pay lower wage premiums (as measured by the AKM establishment effect). For example, women in our baseline sample work at establishments where the average establishment effect is -0.265 (-0.164 after reweighting); for men it is -0.193.

2.4 Comparing Men and Women Displaced from Similar Jobs: Reweighting

Our goal is to compare earnings losses after job displacement for men and women. If we think of the post displacement earnings loss of a treatment effect, this means we are interested in comparing the estimated treatment effects for two populations. The complication is that there may be differences in treatment effects either because of gender per se, or because of other pre-displacement characteristics that determine earnings losses. As the previous discussion showed, displaced men and women, who satisfy the same baseline restrictions, nevertheless show important differences in labor market variables prior to displacement. For example, workers displaced from high-paying jobs may have relatively larger losses than workers from low-paying jobs.

To define precisely what we are striving to estimate, consider the following potential outcomes framework (loosely inspired by Hotz et al. (2005)). Let earnings in the case of job loss be denoted by Y_1 and in the absence of job loss be denoted by Y_0. The earnings loss on the individual level is then simply the difference between these two potential outcomes: $\Delta \equiv Y_1 - Y_0$. Let gender be denoted by $D \in \{m, f\}$. We can then define the unconditional gender gap in earnings losses as:

$$Gap_{unc} \equiv E[\Delta|D = f] - E[\Delta|D = m] \tag{1}$$

Now consider a vector of covariates $X \in \mathcal{X}$ for each individual, which are potentially determinants of individual earnings losses, i.e. Y_1 and Y_0 are functions of X. Earnings losses for women $E[\Delta|D = f]$ may then differ from the earnings losses for men $E[\Delta|D = m]$ either because of differences in the Xs or because of gender itself.

We can write the earnings loss conditional on gender and the covariates as: $E[\Delta|D, X]$

and express the expected earnings loss for women adjusted to the male characteristics as:

$$E[E[\Delta|D=f,X]|D=m] = \int_{\mathcal{X}} E[\Delta|D=f,x]dF_X^m(x) \tag{2}$$

where $F_X^m(x)$ denotes the distribution of covariates for men. Since we cannot observe the state as described in Equation (2) in reality, we follow DiNardo et al. (1996) and use a reweighting function $\phi_x(x)$ to map the distribution of women's characteristics to the distribution of men's characteristics, all measured before displacement. Formally, we express this as follows:

$$E[E[\Delta|D=f,X]|D=m] = \int_{\mathcal{X}} E[\Delta|D=f,x]dF_X^f(x)\phi_x(x) \tag{3}$$

Thus, women who are more similar to men before the job displacement (e.g., in terms of working hours), receive a higher weight in the regression estimation. We can implement this strategy as long as $\mathcal{X}^m \subseteq \mathcal{X}^f$, that is as long as there is sufficient overlap in the observables between the two groups. We can then define the composition adjusted gender gap:

$$Gap_{adj} \equiv \int_{\mathcal{X}} E[\Delta|D=f,X]dF_X^f(x)\phi_x(x) - E[\Delta|D=m] \tag{4}$$

The composition adjusted gender gap thus amounts to a test for the hypothesis that earnings losses are independent of gender, conditioning on the covariates: $\Delta \perp D|\, X$.[17] This means that after netting out the part of the gap driven by differences in pre-displacement characteristics, we can attribute the remaining adjusted gap to the effect of gender per se (e.g., labor supply vs. labor demand mechanisms).

To calculate the composition adjusted gender gap, we follow the non-parametric approach in DiNardo et al. (1996) (hereafter DFL) and use a weighting procedure to reweight displaced women to displaced men. To do this, we estimate a probit regression, where the dependent variable is a dummy for being male. We include the same individual and establishment characteristics as controls which we used in the propensity score matching. These are: log wage in $t = c-3$ and $t = c-4$, full-time employment in $t = c-3$, and age, years of education, tenure, log establishment size, 1-digit industry dummies, and location in East or West Germany in $t = c-1$. We obtain the predicted propensity score from this regression $\hat{p}$

[17] Note that this is essentially a test of the unconfoundedness assumption in Hotz et al. (2005).

and use $\hat{\phi}(x) = \frac{\hat{p}}{1-\hat{p}}$to reweight women in our sample to match their male counterparts.[18]

Table 1, Column (3) shows the sample of displaced women reweighted using the weights described above. After reweighting, displaced women now look very similar to displaced men along most dimensions, even along characteristics that we did not match on such as earnings. Not shown here is that there are also substantial industry differences between men and women and now we are upweighting women in the industries where they are underrepresented (Appendix Table 6). Compared to the overall sample of displaced women, the reweighted women have much higher earnings, work mostly full-time, commute longer and work in smaller establishments that pay higher wage premiums.

2.5 Estimation Strategies: Event Study and Matched Diff-in-Diff Design

Event Study

To estimate the dynamic impact of displacement effects for men and women, we use an event study analysis for a variety of outcome variables. Let y_{itc} be the outcome of interest for a worker i, with baseline year $c-1$ observed in year t. Furthermore, let $Disp_i$ be a dummy variable for whether worker i is a displaced worker. We estimate the following regression model separately by gender:

$$y_{itc} = \sum_{k=-5}^{5} \delta_k \times I(t = c + k) \times \text{Disp}_i + \sum_{k=-5}^{5} \gamma_k \times I(t = c + k) + \pi_t + \alpha_i + X_{it}\beta + \varepsilon_{itc} \quad (5)$$

where y_{itc} denotes the outcome (e.g., log earnings) for worker i at time t, in "cohort" c. The main coefficients of interest are δ_j, which measure the change in earnings of displaced workers relative to the evolution of earnings of non-displaced workers (with δ_0 being the first year post-displacement). To avoid perfect collinearity, we omit $k = c - 3$ from the regression.

Like Schmieder et al. (forthcoming) we control for "year relative to baseline year" fixed effects (coefficients γ_k).[19] In addition, we include year fixed effects π_t, worker fixed effects α_i, and time-varying control variables $X_{it}\beta$ (age polynomials). Standard errors are clustered

[18] As a robustness check, we also reweight men to women (that is, weight all male observations by $\frac{1-\hat{p}}{\hat{p}}$).

[19] The reason for this is that due to our baseline restrictions (e.g., 2 years tenure), workers in both the treatment and control group are on an upward earnings profile before treatment. This means that even in the control group, which does not experience job loss, earnings may decrease once we lift these restrictions. For a detailed overview on alternative job loss specifications, see Schmieder et al. (forthcoming), Online Appendix.

at the worker level. We estimate this model unweighted both for our sample of men and women. We also estimate the model reweighting women to match the baseline characteristics of displaced men, as discussed above.

Matched Diff-in-Diff Design

The reweighted event study design traces out the time path of labor market effects of job displacement, and the reweighting makes it straightforward to compare men and women with similar characteristics. We complement this analysis with a matched difference in difference design that allows us to obtain an individual-level estimate of the displacement effect. This makes it straightforward to investigate heterogeneity in the displacement effect and to what extent various factors (such as changing job characteristics) can explain the direct displacement effects and gender differences in these effects.

To do so, we use the fact that for each job loser we have a matched control worker. We then calculate an individual-level estimate of the earnings loss after displacement

$$\Delta_{dd} y_{ic} = \Delta_{d} y_{ic} - \Delta_{nd} y_{ic}$$

where $\Delta_{d} y_{ic}$ is the individual change in earnings from before (-5 to -2 years) to after (0 to 3 years) job displacement for a displaced worker i with baseline year $c-1$, while $\Delta_{nd} y_{ic}$ is the earnings change for the matched non-displaced worker. The difference between the two, $\Delta_{dd} y_{ic}$, is an estimate of the individual treatment effect from job displacement.

Based on the individual level estimate of the treatment effect it is now straightforward to estimate the unconditional gender gap in the cost of job loss Gap_{unc} as: $E[\Delta_{dd} y_{ic} | D = f] - E[\Delta_{dd} y_{ic} | D = m]$, which we can obtain by running the simple univariate regression:

$$\Delta_{dd} y_{ic} = \beta \, Female + \varepsilon_{ic} \tag{6}$$

The coefficient estimate $\hat{\beta}$ will be an estimate of Gap_{unc}. To estimate the composition adjusted gender gap Gap_{adj}, we estimate Equation (6) using the $\hat{\phi}(x)$ weights to reweight women to the sample of men.

As an alternative to the reweighting approach, we can also estimate Equation (6) but including controls for the covariates. This assumes that the unconditional gap can be modeled as the sum of the adjusted gap and the effect of the covariates: $Gap_{unc} = Gap_{adj} + X\theta + u$.

In this case we can estimate:

$$\Delta_{dd} y_{ic} = \beta \, Female + X\theta + \varepsilon_{ic} \tag{7}$$

and the coefficient estimate $\hat{\beta}$ will again be an estimate of Gap_{adj}. In practice, this parametric approach to estimating Gap_{adj} provides similar estimates as the non-parametric reweighting approach and we will provide both for comparison. One advantage of the parametric approach is that it is straightforward to include interaction terms between the $Female$ dummy and other covariates.

With the matched Diff-in-Diff approach, it is also straightforward to investigate whether changes in job characteristics Z_{ic} explain the earnings and wage losses. For this we compute Diff-in-Diff estimates of changes in these characteristics on the individual level, e.g. establishment size or the establishment wage premium. We then estimate regressions of the form:

$$\Delta_{dd} y_{ic} = \beta \, Female + \gamma \Delta_{dd} Z_{ic} + \varepsilon_{ic} \tag{8}$$

To the extent that women have large wage losses because they are more likely to move to low-paying firms or change industry or occupations, adding these controls for changes in job characteristics should reduce the magnitude of the coefficient estimate $\hat{\beta}$.

3 Earnings and Employment Losses after Job Displacement of Men and Women

3.1 Comparing Raw Earnings Losses for Men and Women

Figure 1 provides first evidence on how earnings losses between female and male workers differ. Results are presented relative to the displacement year, such that 0 corresponds to $t = c$, the first year after displacement, and -1 corresponds to the baseline year $c-1$. Panels (a) and (b) show the raw means of total annual earnings from 5 years before to 5 years after job loss for the displaced workers as well as their matched control workers. Pre-trends for the treatment and control groups line up very well up to $t = c-1$, the baseline year, which is not surprising given the matching algorithm. In year $t = c-1$ a small gap opens up driven by the fact that displacement occurs at some point between June 30 of $t = c-1$ and $t = c$. In the displacement year $t = c$, earnings drop sharply for men and women, and only recover slowly in subsequent years. Comparing Panels (a) and (b) highlights that while the overall pattern is very similar

for men and women, women have much lower pre-displacement earnings.

Panel (c) plots the event study coefficients from Equation (5) for annual earnings in levels. Given the matching design, the additional controls make virtually no difference and the event study coefficients are very close to the simple difference in the means of the two lines in Panels (a) and (b). This figure shows that in levels, women have substantially smaller losses of around 9,000 Euro in the first post-displacement year, while men lose around 13,000 Euro. The recovery path looks similar, but even 5 years out women's losses are smaller. The higher losses in levels stem largely from the fact that men have more to lose given their higher baseline earnings. Panel (d) thus shows the earnings losses using as an outcome earnings in the respective year divided by each individual's earnings in year $t = c - 2$, that is the year before the baseline year, we denote this as $\tilde{y}_{i,t} \equiv \frac{y_{i,t}}{y_{i,c-2}}$. This outcome variable has the distinct advantage that it expresses the effect in percentage terms and is thus easily interpretable.

Using $\tilde{y}_{i,t}$ also provides for a very natural way of including observations with 0 earnings, as in that case we simply have: $\tilde{y}_{i,t} = 0$. More commonly papers use log(earnings) or log(earnings + 1) as an outcome. The former has the disadvantage that zero earnings observations are excluded and that for many individuals, earnings fall by very large values (e.g. some workers go to mini-jobs where annual earnings are just a few thousand Euro), so that the typical percentage interpretation of log(earnings) becomes a bad approximation. Similarly, while log(earnings+1) allows for including zeros, the magnitudes are difficult to interpret (e.g. in our case the change in log(earnings+1) is around -2, but obviously this is not a decline of 200%). Using $\tilde{y}_{i,t}$ as an outcome, Figure 1 (d) reveals that in percentage terms men and women in this unweighted sample experience virtually identical losses and recovery paths. Furthermore, the magnitudes are very large: in the first year, earnings decline by almost 40% relative to pre-displacement earnings. In the following years, there is some recovery, but 5 years out earnings are still about 20% lower relative to the pre-displacement year.

Table 2 shows the corresponding estimates from our matched Diff-in-Diff design, that is estimates of Equation (6). The unit of observation in this regression is the number of displaced workers, where for each displaced worker we calculated $\Delta_{dd} y_{ic}$ for various outcomes. Each row corresponds to a different outcome variable. Column (1) shows the mean change in the outcome variable for men, Column (2) shows the unadjusted gender gap from estimating Equation (6).

The results in Columns (1) and (2) confirm the impression from Figure 1. Men experience

large earnings losses both in levels (around 9,400 Euro per year) and relative to the baseline (around 26%). For women, the earnings losses are smaller in levels (a loss of about 6,200 Euro per year), but very similar in relative earnings or when using log earnings. Using the inverse hyperbolic sign (IHS) transformation of earnings allows for including 0s, but the mean value of the variable (−1.51) shows why the interpretation is not very intuitive.

Overall, there are large earnings losses which are comparable to those found, for example, by Schmieder et al. (forthcoming) for Germany or various studies for the U.S. using administrative data (e.g., Jacobson et al. (1993), Couch and Placzek (2010) or Lachowska et al. (2020)).

3.2 The Gender Gap in Earnings Losses for Men and Women Displaced from Comparable Jobs

We now turn to estimating the gender gap in earnings losses when we compare women who are displaced from comparable jobs as men using the DFL reweighting technique described in Section 2.4.

Figure 2 shows event study graphs for the main earnings outcomes. Each panel shows four lines: the event study estimates for men (solid blue line), for women without reweighting (solid red line), for women reweighting using individual characteristics such as education, age and pre-displacement tenure and wages (dashed pink line) and for women reweighting using both individual characteristics and establishment characteristics, such as industry and establishment size (dashed orange line). Figure 2 (a) shows a striking result: while wage losses for our broad sample of women were smaller than for men, once we reweight women to closely match the men their earnings losses become substantially larger. For example, in the first year after displacement losses are around 1,000 Euro higher for women than for men. Strikingly, this gap grows as time passes and 5 years post displacement earnings are around 3,000 Euro lower for displaced women than for men.

A similar pattern emerges when looking at our preferred measure of earnings relative to pre-displacement in Panel (b): women lose about 5 percentage points more earnings immediately after job loss and the gap grows over time to around 15 percentage points 5 years after job loss. Figure 2 (c) and (d) show log earnings and the IHS of earnings, respectively. The pattern is similar for these two outcomes and both show a large gender gap in earnings losses once we compare similar women and men, although there is somewhat more convergence for IHS

earnings. Appendix Table 8 shows how the gender gap in earnings losses changes as we include reweighting variables one by one. The full-time employment dummy and the establishment characteristics play a particularly important role.

Table 2 Columns (3) and (4) show regression estimates of the gender gap when accounting for job characteristics between women and men. In Column (3), we estimate our matched Diff-in-Diff specification but including the same pre-displacement characteristics of individual and establishment-level variables as linear controls. The second row shows that the gender gap grows sharply to 7.7 percentage points, closely in line with the reweighted event study results from Figure 2 (b). We find similarly large gender gaps when looking at log earnings and $sinh$(earnings). Column (4) uses DFL reweighting instead of the linear controls, applying the reweighting weights discussed in Section 2.4 and used in Figure 2. This specification is more general than the linear controls and provides a consistent estimator for the gender gap even if the other controls have a non-linear effect on earnings losses. The results are broadly similar, though the gender gap is slightly larger (e.g. 9.2 percentage points for earnings relative to pre-displacement).

3.3 The Role of Wage and Employment Losses after Job Displacement

Earnings losses after job loss occur partly due to workers being unemployed or leaving the labor force, and partly due to losses in wages and hours worked. While the German social security data does not contain information on hours worked, it has detailed information on days worked (for each employment spell the exact start and end date is reported) and it provides an indicator for whether workers are working full-time, part-time or in a mini-job. There is also no information on hourly wages, but we can compute daily wages and daily wages conditional on working in a full-time job.

Figure 3 shows wage and employment outcomes to better understand the patterns of earnings losses. Panel (a) shows that log daily wages decline dramatically after job loss for both men and women. Even unweighted, women have larger losses in daily wages but this gap becomes much larger when reweighting women to their male counterparts and women lose around an extra 8 log points immediately after displacement, a gap that grows to around 20 log points 5 years out. Turning to full-time log wages in Panel (b), we find that men and women experience similar losses without weighting, but there is again a very substantial gender gap once we reweight women to match the men. Overall women lose about an extra 5

log points conditional on working full-time.

Panels (c) and (d) show that after reweighting, women have only slightly larger employment losses than men when measured as any employment in a given year or annual days worked. This however masks a large gap in days worked full-time (Panel (e)) when comparing similar men and women, where women work around 30 days less full-time per year.[20] This implies that women are much more likely to take on part-time jobs than men and indeed even women who worked full-time before often switch to working part-time afterward, something rarely observed for men (for results on part-time employment, see Appendix Figure 6 (b).

This is also supported by Panel (f), which shows the number of days worked in a mini-job. Mini-jobs are a special type of marginal employment in the German labor market. For most of our observation period, mini-jobs define an employment contract with remuneration not exceeding 400 Euros per month.[21] They are exempt from social security contributions and are particularly common among female workers, partly because they make it easy to combine work and family life. Note that given our baseline restrictions, we exclude workers working only in mini jobs, though they can work a mini-job on the side. Following job loss there is essentially no uptake of mini-jobs for men, however, there is a big increase for the broad sample of women of around 15 days, and about an 8 day increase after reweighting. In fact, the large increase in part-time and min-jobs for women after displacement is an important factor behind the large daily wage losses for women in Panel (a) compared to men.

The visual results from Figure 3 are also confirmed in Table 2, rows 5 to 10. Overall, holding pre-displacement characteristics constant, women experience much larger employment losses than men, are more likely to switch to part-time work or mini-jobs and have larger wage losses, even when conditioning on working full-time. All factors together produce the large and lasting earnings losses that we documented in Section 3.2.

[20] The unweighted gap for days full-time goes in the other direction, but this is mainly because women work so much less full-time to begin with and thus have less to lose.

[21] Prior to 2003, the threshold on monthly earnings was 325 Euros, with an additional limit of 15 working hours per week. Since 2013, the income threshold is 450 Euro per month (Gudgeon and Trenkle (forthcoming); Tazhitdinova (2020)).

4 Understanding the Gender Gap in Wage Losses

4.1 Changes in Job and Establishment Characteristics after Job Displacement

The previous section showed that there is a large gender gap in earnings, but also employment and wage losses for displaced women compared to men. Yet how does the nature of jobs change after displacement? As one measure of the type of employer quality, we show log establishment size in Figure 4 (a). Recall from Table 1 that women tend to work at larger establishments before reweighting. In this broad sample, women move to much smaller establishments post job loss. However, after reweighting the difference disappears and women displaced from comparable jobs as men also do not move to smaller employers.

As another measure of establishment characteristics, we show the share of women working in an establishment as an outcome variable in Panel (b). The figure shows that while the share of female coworkers remains similar for men after displacement, women move to establishments with much more female coworkers. Unweighted, women move to establishments with a female share that is 4 percentage points higher, while after weighting this increases to around 6 percentage points. This complements the evidence on the establishment wage premiums, and is consistent with the evidence from Card et al. (2016) that women tend to be concentrated in low-paying establishments.[22] Strikingly, this suggests that even women with similar careers as men fall back to more typical female employers.

Figure 4 (c) and (d) show the probability of switching industry or occupation, which previous papers have highlighted as an important channel for wage losses after displacement since they are usually correlated with losses in human capital (e.g., Topel (1990); Neal (1995)). Approximately 30% of job losers switch industry and about 40-50% switch occupations immediately after job loss. However, gender differences here are pretty modest, especially after reweighting. If anything, women are slightly less likely to switch occupations. Thus at least along this measure it does not seem that the gender gap in earnings losses is due to larger human capital losses of women.

A more direct measure of employer quality are estimated establishment fixed effects from an AKM model (Abowd et al. (1999)). A recent version of the AKM model for our time

[22] Appendix Figure 4 shows that the share of women in an establishment is strongly negatively correlated with the establishment wage premium. In turn, an establishment's size is positively correlated with the establishment wage premium.

period was estimated by Bellmann et al. (2020)[23] who generously made them available to us. Figure 4 (e) shows the evolution of the estimated establishment effect after job loss. The estimated establishment effect drops by around 8 log points for men. This corresponds almost exactly to the drop in log full-time wages for men, confirming the result in Schmieder et al. (forthcoming) that the change in establishment effects fully accounts for the change in log wages for displaced men for a slightly earlier time period. For women, the unweighted loss in the establishment effect is slightly smaller than for men, with around 6 log points losses, while after reweighting the loss is larger, around 9 log points in year 5. These establishment effect losses mirror the losses in log full-time wages for women in Figure 3 (b) and suggest that at least part of the gender gap in log full-time wages (and thus earnings) is due to women moving to worse paying firms relative to men after job loss.

Finally, Figure 4 (f) shows how commuting distances are affected by job loss. Our measure of commuting distance (in km) is the straight line distance between the geographic center of the municipality of residence and the municipality of work. This is relatively granular since many German towns and villages are geographically small, but it is a noisy measure when it comes to large urban areas. The result on the broad sample of women is in line with Le Barbanchon et al. (2021), showing that women substantially reduce commuting distance after job loss, by almost 8 km (relative to a 30 km commute prior to displacement), while men's commuting distance is essentially unchanged. However, when we reweight women to match men, the gap in commuting disappears completely and women's commutes remain unchanged relative to their pre-displacement job.

4.2 Sources Underlying the Gender Gap in Wage Losses

Given the changes in job characteristics shown above, we can now turn to whether these observable post-displacement job characteristics can explain the losses in wages and the gender gap in particular. For this, we estimate Equation (8), including changes in job characteristics $\Delta_{dd}Z_{ic}$ as explanatory variables. We complement these estimates with a Kitagawa-Oaxaca-Blinder decomposition to quantify the contribution of each of these factors to the gender gap in job loss. Table 3 shows these estimates both for overall daily wages (Panel A) and full-time wages (Panel B). All regressions are weighted so that women match their male counterparts.[24] Column (1) reproduces the benchmark results from Table 2 Column (4) for the two outcomes.

[23] In turn closely following Card et al. (2013).

[24] Appendix Table 9 shows the same table using regression adjustment instead of weights.

Column (2) and (3) include variables capturing changing job characteristics. These include changes in industry and occupation, differences in employment size, the establishment share of women, commuting distance, and changes in the AKM establishment fixed effect. In addition we also include switches to parttime and mini jobs in Panel (A). The various job characteristics show the expected signs: switching to parttime (mini-job) is associated with a 17 (70) log point loss in wages, industry and occupation changes are associated with a loss of 8-9 log points in wages and going to establishments that are smaller or have a larger share of female workers reduces wages. The AKM effect also has a clear negative effect, close to the theoretically expected value of 1.[25]The inclusion of these controls reduces the gender gap in wage losses from 13 to 9.6 log points or about 25 percent.

Imposing the theoretical coefficient of 1 on the AKM effects (that is if we assume that the AKM model provides a fully accurate description of the wage generating process), only has a marginal effect on the gender gap.

Based on Le Barbanchon et al. (2021), we might expect that women trade off a higher wage for a shorter commute after job loss and that this would explain some of the gender gap, however we find no clear evidence of this either for wage losses.

To better understand how much each of the job characteristics explains the gender gap in earnings losses, we turn to the Kitagawa-Oaxaca-Blinder decomposition. For this we estimate the wage loss model separately by gender and then compute the part of the wage loss that is explained by gender as $\left(\bar{X}_{female} - \bar{X}_{male}\right)\beta_{male}$. Column (4) shows these endowment contributions for each variable, while column (5) expresses the contribution as percent of the total gender gap in earnings losses. Interestingly the most important factor is the share of women at the employing establishment, which explains almost 7 percent of the gender gap. Parttime and mini-job status explain just a little bit less (around 6 percent) and occupation goes in the opposite direction (women are less likely to switch occupations). The AKM effect explains about 5 percent of the gap, but this is imprecisely estimated.

Panel B does the same analysis but restricting observations to workers working full-time

[25]If the AKM model is not misspecified, the true coefficient should in principle be 1, but due to measurement error in the estimates of the AKM model we would expect the coefficient to be downward biased (Kline et al., 2020; Bonhomme et al., 2019). Indeed, Schmieder et al. (forthcoming) show that using a two sample IV leads to a coefficient close to 1 in this type of regression. Appendix Table 10 shows results using establishment effects estimated from AKM models estimated separately by gender and using the Kmeans hybrid approach proposed in Schmieder et al. (forthcoming). The gender specific AKM establishment effects have somewhat more explanatory power and explain about 40% of the fulltime wage loss. The kmeans hybrid effects have somewhat less explanatory power for the gender gap, likely because a lot of within group variation is lost.

(before and after job-loss). We can explain 22.5 percent of the gender gap with the observables. Interestingly, by far the most important job characteristic is the AKM establishment effect of the employer, which explains about 18 percent of the gap. Given that the AKM model is geared towards capturing establishment wage premia for full-time workers, it is not surprising that its explanatory power is much larger for log wages of workers remaining in full-time employment.

4.3 The Role of Children

We now turn to whether the earnings losses after displacement are affected by whether young children are in the household. Ex-ante one can imagine different channels for why children may matter. On the one hand, holding income constant, the presence of children may increase the marginal value of consumption since household income is spread thinner. This may increase search effort during spells of unemployment following job loss or increased hours worked once a job is found. On the other hand, the presence of children may increase the opportunity cost of working. Especially if there is a permanent loss in wage prospects for job losers, as we showed in Section 3.3, this may make it relatively more attractive to focus on childcare instead of labor market participation.

To estimate the effect of job displacement separately by the age of the oldest child in the household, we extend the model in Equation (7):

$$\Delta_{dd} y_{ic} = \sum_a \left(\alpha_a + \beta_a \, Female_i\right) I_{KidAge_i=a} + X_i\theta + \varepsilon_{ic} \tag{9}$$

where $KidAge_i$ is the age of the oldest child of the displaced worker (or an indicator if there is no child) and a indicates the possible age of the oldest child. All the covariates X_i are demeaned, so that the estimated α_a provide estimates of the cost of job loss for men with a child aged a (or no child), while the estimated β_a provide the respective gender age gap.[26]

Figure 5 plots the estimated effects for men α_a and for women $(\alpha_a + \beta_a)$. Note that we plot the estimates for men and women without children on the far right of the graph. Panel (a) shows our main estimate: earnings relative to $t = c - 2$. For men and women without young children, the results correspond to those in Section 3.3: women have significantly larger earnings losses than men when holding pre-displacement characteristics constant. A striking

[26] We use regression adjustment here rather than reweighting as this is intuitively easier to understand in the presence of many interaction terms. In practice, this makes little difference.

result emerges, however, when comparing these to parents: displaced men who have a child at home have smaller earnings losses than men without young children. In stark contrast, mothers of very young children have much larger earnings losses in the order of 80% of pre-displacement earnings. Mothers with older children (around 3 years and older) have comparatively much smaller earnings losses, albeit still larger than men. We observe a similar pattern for log wages in Panel (b). A plausible explanation for the trend break at age 3 might be that this is when children typically join kindergarten and then elementary school, in effect reducing the opportunity cost of working.

Panels (c) and (d) show that women with very young children also have huge losses in days working full-time without a parallel increase in working part-time. However, once children are 3 or older there appears to be more a substitution effect from full-time to part-time rather than dropping out of the labor force.

Interestingly, for mothers with teenage children, the gap seems to largely disappear. It is noteworthy that we can only observe children who are born while the mother is employed so that the 'without children' group likely also contains some mothers who we misclassify. Thus one possibility might be that the gender gap for childless job losers is in fact 0 (as the figure suggests for parents with children older than 15), and that the gender gap is entirely driven by mothers.[27]

Table 4 shows comparable results from a regression model, where we estimate Equation (8) but include dummies for children younger than 16, both interacted with gender. The omitted category is men without children. The results suggest that for job-losers without children, there is still a gender gap but only 3.8 percentage points, and thus less than the overall gender gap. The coefficient on the dummy for child (0.013) and its interaction with a female dummy (-0.026) show that the presence of young children substantially reduces the earnings losses for men, but sharply increase earnings losses for women.

The remaining columns of Table 4, as well as the other panels of Figure 5, complete the story: The presence of children has a positive effect on men's post-displacement trajectories: they work more, have lower wage losses, show a higher probability of working full-time. For women, the effects are reversed with larger losses in days worked and wages, and a higher propensity to work part-time or mini-jobs. Women also move to lower-paying employers if they

[27]We also explored whether these large losses for mothers of young children are transitory by replicating our baseline eventstudy analysis. Figure 5 in the Appendix shows that at least over a 5 year horizon, the larger losses for mothers of young children are very persistent. Similarly, the smaller losses for fathers of young children compared to other men also seem to be persistent and are still apparent 5 years after job loss.

have young children.Interestingly, mothers of young children also have a pretty large (though statistically insignificant) decline in commuting distances after displacement, potentially to be able to better reconcile childcare with work.

4.4 The Role of Within-Household Earnings Inequality

Ex-ante it seems plausible that whether the job loser was the main breadwinner (that is, contributing more than 50% of household income) or just a small contributor, may affect post-displacement outcomes. Moreover, gender identity norms, as in Bertrand et al. (2015), could make it undesirable for either or both partners that the wife makes more money than the husband. In this case, the pre-displacement within household income distribution may be an important determinant for post-displacement outcomes.[28]

In Table 4 Panel B we show estimates of our main regression Equation (7) where we add the share of household income of the job loser both by itself and interacted with the female dummy. A simple interpretation of Bertrand et al. (2015) would be that having a higher share of household income is associated with higher earnings losses for women relative to men (and thus a negative coefficient on the interaction term in Column (1)). The opposite seems to be the case: while men's earnings losses get larger as their share of household income increases, women's earnings losses are less affected by their pre-displacement share. Similar patterns hold for wages and employment

A more nuanced view of Bertrand et al. (2015) would, however, suggest that the effect may be non-linear: if women (or their spouses) have a strict preference to make less money than their husband, then losses should be highest for women who make significantly more than their husband and who may actually move to a less than 50% household share post-displacement. However, for everyone close to 50% pre-displacement earnings no such motivation exists and household share should not affect earnings losses through the gender identity channel.

To capture this nonlinearity, Appendix Figure 1 shows the effects of displacement on earnings losses by bins of pre-displacement household income share. In this figure, male earnings losses are not much affected by their share of household earnings, but female earnings losses show some non-linearity and resemble an inverse U-shape with the lowest earnings losses close to earnings parity between both spouses, and a slight decline if women have a higher household income share (though note that we have few observations where women have a

[28] See Kuehnle et al. (2021) for a replication of Bertrand et al. (2015) in the German context.

substantially larger than 50% share of household income). Interestingly, for low income shares, women's earnings losses also become larger. This might be because their income is relatively less important to the financial situation of the household, making dropping out of the labor force or working part-time to look after children potentially more appealing. This impression is even stronger when looking at days worked full-time and part-time. Overall, this may be viewed as weak evidence in support of the identity model in Bertrand et al. (2015).

An additional question related to the household level is whether the losses on the household level are larger when the husband or the wife lose their job. Given the literature on the added worker effect (Lundberg, 1985; Halla et al., 2020) it seems possible that losses of a male job loser are more likely to be compensated to some extend by additional labor supply of his wife, compared to the other way around. Our context is not ideal for studying the added worker effect due to the restriction that we can only observe couples where both partners are in the labor force, but we provide some analysis of this in the appendix (Table 14), where we find virtually no evidence of an added worker effect, likely due to correlated economic shocks, since many spouses work in the same industry or firm. Furthermore, declines in total household earnings are similar for male and female job losers after adjusting for observables, where the larger earnings losses for women are weighed against higher household income shares for men.

4.5 Labor Supply or Labor Demand? Gender Differences in Job Preferences and Job Search Behavior after Job Loss

The gender differences in labor market outcomes after job loss beg the question whether they are due to differences in labor supply or labor demand. For example, the labor supply channel may operate through women searching less for a job (e.g. because of increased childcare duties at home) or wanting to work fewer hours after a job loss, in comparison to men. On the other hand, the labor demand channel may operate through women facing discrimination by potential employers thus having a harder time than men to recover from job loss.

Job Seekers in Baseline Displaced Worker Sample While we cannot fully disentangle these two channels, we leverage two additional datasources to shed some light on what is arguably the labor supply side. First we use self-reported job search preferences for workers in our sample, which we obtained from the UI system (so called "ASU" data). Workers who are displaced typically have contact with the UI system soon after being notified of the upcoming

lay-off (the employer has to notify the UI agency in advance of a mass-layoff). If they are assigned a caseworker to assist with job search, the worker fills out a number of questions regarding what type of employment he or she is looking for and what the scope of the search is. In our sample about 70% of displaced workers register as job searchers in the year of the mass-layoff and we have valid information on job preferences for about 53,000 individuals in our sample.[29] Appendix Table 4 shows that along observable characteristics workers with ASU information look very similar to the full sample of workers, with the main difference being that earnings are about 6% lower.

The key variables we focus on are whether a worker is looking only for a full-time job (as opposed to parttime or full- or part-time); whether or not a worker is looking broadly in terms of geography (i.e. willing to commute significantly or move); and whether a worker is looking for a permanent (i.e. open ended) contract as opposed to a fixed term contract.

Table 5 presents this information in the same format as Table 2 with the difference that in this table we only use post displacement outcomes for displaced worker, since these outcomes are naturally not available for non-displaced workers and prior to job loss. Panel A shows quite strikingly that 98% of men are looking only for a full-time job (Column 1), in contrast to women where less than 70% are looking only to work full-time in the overall sample (Column 2). After the controlling for observables via regression (Column 3) or reweighting (Column 4), the gender gap shrinks but women are still about 11-13 percentage points less likely to look for a full-time job, despite the fact that in this reweighted sample almost all women were working full-time before. Looking at the geographic dimension of job search, we see that women are about 4 percentage point less likely to search broadly (40% compared to 44%), which shrinks to around 2 percentage points after adjusting for observables (and on the margin of statistical significance). The table also shows that women are somewhat less likely to look for permanent contracts, but the difference disappears or becomes even slightly positive after adusting for composition.[30]

UI Recipients Survey Data As a second data source we use a survey of UI recipients by DellaVigna et al. (2022). The survey followed a sample of around 7,800 UI recipients over a period of 18 weeks and asked them regularly via text message (SMS) about the job search

[29]This information comes from the Job-Seeker History Panel, in particular, we use "ASU" version V06.11.00 and "XASU" version V02.03.00-201904.

[30]Appendix Table 13 provides some additional outcome variables from the ASU.

process. We focus on two questions: time spent on job search on the previous day in minutes (asked twice a week for the full survey length) and the approximate wage of the last job the person applied to, which we refer to as "target wage" (asked once every 4 weeks). The sample of the SMS survey does not overlap with our sample of job losers (the SMS survey was conducted between 2017 and 2019, while our job loss sample is restricted to job losses between 2002 and 2012). Appendix Table 5 shows summary statistics for the SMS sample, highlighting that this group is of a similar age and gender composition as our main sample, but with about 1 year less education, lower wages and shorter tenure duration. Despite these demographic differences (explained by the sampling frame of the SMS data) the individuals come from a similar context (German job losers) who lost somewhat stable jobs involuntarily.[31] We restrict the sample to responses from individuals who were still unemployed on the date of their response, which yields a total of 116,159 valid responses to the time spend on job search question and 5,541 for the target wage. Table 5 shows that men spend on average 94 minutes on job search, while strikingly women only spend 76 minutes, or almost 20% less (and the difference is very precisely estimated). After controlling for obervables, the gap between men and women shrinks somewhat to around 7-9 minutes per day, still an almost 10% difference. In order to use the target wage as a measure for what type of jobs workers apply to, we divide it by the pre-unemployment wage and take the log and call the result the log target wage ratio, similar to the log reservation wage ratio in Krueger and Mueller (2016). Our results show a log target wage ratio of 0.075 for men, thus job seekers on average apply to jobs paying more than their previous job. The log target wage ratio for the average women in the sample is on average even higher (0.12), which appears to be due to the higher incidence of working part-time among women. However, after adjusting for observables to make women comparable to men, the log target wage ratio falls significantly and is now about 5-8 log points lower than for men.

Overall these results suggest that labor supply (preferences and job search behavior), plays a significant role both for the raw and the composition adjusted gender gap in post-displacement outcomes. For the raw gap, women are much less interested in full-time employment and show a narrower scope of job search (geographic and type of contract), they also spend much less time searching for a job, though they do report a slightly higher target wage

[31] While in Germany also voluntary quits qualify for UI, they are sanctioned with an off time that reduces the potential benefit duration. Since the survey selects only individuals that have not been sanctioned, we view these as involuntary separations.

ratio. For the composition adjusted gap, women are still substantially less likely to look for a full-time job, have narrower geographic scope, spend less time on job search and apply to lower paying jobs (compared to their pre-displacement jobs).[32]

The Role of Children for Job Preferences As discussed above, a plausible driver for differences in labor supply could be the division of labor in households with children. In Panels B and C, we therefore show the analysis separately by whether or not the job losers have children (age 15 or younger). These results show that men with and without children are very similar in terms of job preferences and job search behavior (Column 1). In contrast, for women the differences by presence of children are quite stark. For the raw comparison, women with children are much less likely to search for a full-time job (compared to men but also to women without young children) and similarly have a more narrow geographic scope of job search, and spend less time on job search. For the composition adjusted gap, the differences are somewhat more muted, but women with children are still much less likely to look for full-time jobs, have a narrower scope of job search and a lower log target wage ratio. Overall, this further supports that the gender gap is at least in part driven by labor supply differences between men and women, possibly stemming from women being more likely to substitute child care for work in the labor market. It also highlights the importance of the job search process itself for shaping gender differences in labor market outcomes and is broadly consistent with the results in Le Barbanchon et al. (2021) on commuting / wage trade-offs and the results in Cortes et al. (2022) on risk-aversion and overconfidence.

5 Robustness of Main Results

Table 6 provides a range of robustness checks for our main results. For comparison, Column (1) replicates the baseline estimates for the composition adjusted gender gap in the costs of job loss using the reweighting method from Table 2 Column (4) for four key outcomes. We show additional outcomes in Appendix Table 15.[33]

Sample Construction:

[32] Appendix Table 14 shows results that are similar to Table 3, but control for the observed job search preferences. The table shows that differences in stated job search preferences explain some of the gender gap in wage losses and especially of the gap in fulltime log wages, though a smaller part than that explained by job-differences in Table 3. Given that stated job search preferences are a noisy measure of differences in labor supply this analysis thus likely only provides a lower bound for the importance of the labor supply channel.

[33] We also reproduce this table without controls and with regression adjustment instead of reweighting in Appendix Tables 16 and 17.

While our baseline specification estimates the cost of job loss over a 5-year-horizon after displacement, Table 6 Column (2) presents a result for a 10-year post-displacement horizon. Since we have to drop displacement events after 2007 to observe the full time horizon, we lose about 30% of our observations. Strikingly, even over this longer time horizon results are very similar as before, suggesting that wage and earnings losses are highly persistent. This is also shown in Appendix Figure 7 (a) and (b), where earnings and full-time log wages show virtually no recovery after 10 years.

Our main estimates impose a 2 year tenure restriction in the baseline year. Column (3) shows that relaxing this restriction to only 1 year does not substantially alter the result and in fact leads to an even larger gender gap. Similarly, we show in Appendix Table 18 Column (6) that imposing the stricter restrictions (3 years tenure, baseline establishment size larger than 50) from Schmieder et al. (forthcoming) leads to similar results and again a somewhat larger gender gap.

One downside of propensity score matching is that while on average, displaced and non-displaced workers have very similar characteristics, this does not have to be the case on the individual level. As an alternative, we show in Table 6 Column (4) estimates based on Mahalanobis distance matching using the same covariates, which leads to close covariates within each pair. In this specification, we also force the treatment and control worker to be in the same pre-displacement earnings decile. The results are fairly similar and the wage losses even slightly larger.

Alternative Reweighting Algorithm:

A key contribution of our approach is to hold pre-displacement characteristics constant when comparing men and women. Appendix Table 22 shows that occupations of displaced workers are also quite different between men and women. For example, before the layoff displaced men often have blue-collar jobs, such as Trucker, Warehouseman or Bricklayer and the broad white-collar occupation "Qualified Office Employee" only accounts for about 7.3% of job losers. Women on the other hand are much more likely to be in white-collar jobs with almost 40% being "Qualified Office Employees" or Salesperson. Table 6 Column (5) shows that when we also reweight on 1-digit occupations, the gender gap becomes even larger, especially for wages.

Another way to ensure that we compare men and women who experience similar shocks is to compare men and women displaced in the same mass layoff event. Table 1 showed

that women tend to work at different establishments than men (larger, lower-paying, different industries). While these differences become substantially smaller after reweighting (Table 1), this may not capture all the relevant differences. It could be for example that women are still, on average, laid off during mass layoff events that are more destructive, e.g. particularly large, or in particularly depressed regions. To account for this we estimate the gender gap by comparing men and women displaced from the same establishment by adding pre-displacement establishment fixed effects to the regression. The results are shown in Table 6 Column (6). Earnings losses in this specification are still substantially larger for women (8.6 percentage points) and the gender gap in wage losses is increased relative to the baseline.

Another concern is that our reweighting algorithm puts a lot of weight on women who may have been particularly lucky. In the presence of a gender wage gap in the economy, by conditioning on pre-displacement wages, we may pick up women who were either particularly lucky or particularly successful in landing a good job relative to a man with the same wage. In that case, conditioning on the pre-displacement wage may lead to women showing essentially more mean reversion than men which would somewhat change the interpretation of the gender gap in earnings losses. Column (7) shows that when we implement the reweighting algorithm without matching on pre-displacement wages (or earnings) we get almost the same results.

So far, we compared men and women displaced from similar jobs by reweighting women to the characteristics of displaced men. An obvious alternative is to reweight men to the characteristics of women. One practical issue is that there are very few men working part-time in our sample (and in general), so that in some cells we have almost no men to reweight leading to very large standard errors (since some individuals get a huge weight). To deal with this, we drop observations with a propensity score greater than 0.99 (that is observations that based on observables have a more than 99% probability of being women). The resulting estimates in Table 6 Column (8) show a similar pattern as the baseline results. While the gender gap in relative earnings losses is slightly smaller, it is larger for wage losses and days worked full-time.

Evidence on Non-Couples:

Our main analysis focuses on individuals who we identified as married as described above. While this is an important sample in itself (and the relevant sample when looking at job displacement in the household context as in the next section), it is also somewhat restrictive. Therefore, we replicate our baseline analysis for a random sample of individuals who are

not identified as couples (Column 9) and a combined sample of couples and non-couples (corresponding to a random sample of the overall population of workers in Germany). Table 6 Column (9) shows that the gender gap is somewhat smaller for non-couples, though the basic pattern is still very similar. It is noteworthy that just because we do not observe someone in the data as a married couple does not mean that they are not married (the partner could be self-employed, for example). Finally, Column (10) shows that a representative sample of couples and non-couples again show similar patterns as the baseline, with just slightly smaller gender gaps.[34]

East vs. West:

One might expect that the results differ between East and West Germany, given that culture may influence women's labor supply (Boelmann et al. (2020)). Appendix Table 18, Columns (2) and (3), show that costs of job loss indeed differ between women working in East compared to West Germany in t=c: Earnings losses are about twice as large for West German women. Interestingly, East German women lose more in terms of full-time wages and employment. This is partly because - along with East German men - they have a much higher propensity to switch to mini-job employment after job displacement (see Appendix Figure 11).

Complete Closure vs. Mass Layoff:

Finally, one worry could be that the gender gap differs between workers displaced from a complete establishment closure versus a mass layoff. Workers displaced from a mass layoff could constitute a negative selection, because firms may lay off low productivity workers first (Gibbons and Katz (1991)). As Columns (4) and (5) of Appendix Table 18 show, the gender gap is remarkably stable for these two groups of workers.

6 Discussion and Conclusion

In this paper, we used administrative employer-employee data from Germany to investigate how the costs of job loss differ between men and women. Whereas existing research from both the U.S. and Germany has shown that displaced men suffer large and persistent earnings losses, evidence for women is scarce. A key contribution of this paper is to compare men and women who are displaced from comparable jobs with similar pre-displacement careers. This

[34]Note that for practical reasons we use a random sample of non-couples and the universe of displaced workers in couples in Column (10) but then reweight both groups to correspond to a random sample of the overall population.

distinction is crucial for understanding the impact of job loss since the costs of job loss are heterogeneous along many dimensions that would otherwise confound the gender differences. With the help of detailed and high-quality administrative labor market data from the IAB, we can compare men and women in terms of individual (e.g., age, education, and tenure) and establishment (e.g., establishment size and 1-digit industries) characteristics.

We showed that when taking these differences in pre-displacement characteristics into account through a reweighting approach, women's earnings losses are much higher than men's, with the difference persisting and, in fact growing, five years after job displacement. This difference is due to a gender gap in both wage and employment losses. One important reason for women's higher earnings losses is their much higher propensity to take up part-time or mini-job employment after displacement. Another explanation for the large gender gap in earnings losses is the presence of children in a household: women with young children at time of displacement face the largest earnings, wage, and employment losses. In contrast, men with young children have the smallest losses.

An obvious and important question is whether the gender gap is due to men and women facing different labor demand or whether it is due to differences in labor supply. Disentangling the role of demand from supply in this context is very challenging. The fact that mothers of young children have by far the largest earnings losses and are often moving to part-time employment seems consistent with a labor supply effect where women decide to stay at home to look after children. However, another possible explanation is that mothers of young children face discrimination in the labor market, making it harder for them to find any or at least a full-time job. We provided some evidence based on stated job preferences and time spend on job search that at least some differences are due to labor supply, but we cannot rule out that there is also substantial scope for a labor demand channel, e.g. in the form of discrimination against displaced women or mothers. Fully disentangling the role of demand and supply will surely be an important area for future research.

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Table 1: Summary Table of Displaced Workers in the Year Before Displacement

	(1) All Workers Women	(2) Baseline Sample Women	(3) Reweighted Women	(4) All Workers Men	(5) Baseline Sample Men
Panel A: Individual Characteristics					
Log Wage in t=c-3*	3.54	4.18	4.60	4.11	4.54
	[1.06]	[0.471]	[0.370]	[1.02]	[0.356]
Earnings in t=c-2	15320.9	26623.3	38498.4	24695.4	36677.8
	[15273.2]	[11881.2]	[13403.6]	[20570.7]	[12881.5]
Days per Year Working Fulltime	122.0	226.9	325.0	218.8	335.5
	[165.0]	[162.0]	[82.9]	[168.7]	[64.4]
Days per Year Working Parttime	76.4	114.8	16.7	11.9	8.23
	[142.8]	[160.7]	[69.9]	[60.1]	[50.2]
Years of Education*	11.9	11.4	11.4	12.1	11.3
	[1.92]	[1.45]	[1.63]	[2.11]	[1.58]
Tenure*	3.25	7.54	7.32	3.35	7.74
	[2.61]	[4.06]	[4.12]	[2.67]	[4.45]
Age*	39.5	41.7	40.4	39.5	41.0
	[13.2]	[5.87]	[6.33]	[13.4]	[5.93]
Commuting Distance	.	29.4	36.3	.	39.4
		[71.8]	[89.0]		[88.4]
Has child under 7	.	0.031	0.038	.	0.119
		[0.173]	[0.192]		[0.324]
Has child aged 7 or older	.	0.214	0.126	.	0.245
		[0.410]	[0.332]		[0.430]
Panel B: Establishment Characteristics					
Log Estab. Size*	4.07	5.19	4.70	4.58	4.77
	[2.11]	[1.37]	[1.07]	[2.14]	[1.10]
AKM Estab FE, 2003-2010	-0.331	-0.265	-0.164	-0.254	-0.193
	[0.288]	[0.222]	[0.210]	[0.264]	[0.230]
Panel C: Household Characteristics					
Total Yearly Household Earnings	.	61018.3	69234.7	.	54330.4
		[21149.3]	[24121.2]		[20061.8]
Total Yearly Earnings - Partner	.	34245.6	36777.8	.	17727.0
		[15300.5]	[15847.2]		[13892.7]
Share of Household Income	.	45.0	47.6	.	69.9
		[16.9]	[15.7]		[18.0]
Same Establishment as Spouse	.	0.059	0.068	.	0.040
		[0.235]	[0.252]		[0.197]
Same Industry as Spouse	.	0.099	0.116	.	0.075
		[0.298]	[0.320]		[0.263]
Number of Individuals	399615	31806	31806	418127	48849

Notes: This table summarizes characteristics of different samples of (displaced) men and women. Columns (1) and (4) show characteristics of a random sample of workers in Germany 2003-2012. Columns (2) and (5) represent all displaced workers in the couple dataset fulfilling our baseline restrictions. We measure characteristics in t=c-1. We exclude individuals working in the construction and mining sectors. Column (3) contains women in the couple dataset reweighted to men. In Panel C, we refer to the 2-digit industry. Partner earnings are missing if the partner is not working. Variables with * are used in reweighting. Additional reweighting variables are the following: Log wage in t=c-4 and fulltime employment on June 30 in t=c-3. Standard deviations in brackets.

Table 2: The Gender Gap in Earnings Losses and Other Characteristics After Displacement

	(1) Mean Change in Outcome Variable for Men		(2) Unadjusted Gender Gap		(3) Composition Adjusted Gender Gap Regression-Adj.		(4) Composition Adjusted Gender Gap Reweighted		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Earnings, Wages, and Employment									
Total Yearly Earnings	-9418.0	[313.8]	**3214.6**	[371.2]	**-1115.8**	[239.0]	**-2491.1**	[339.6]	80,655
Earnings r.t. t=c-2	-0.258	[0.0066]	0.014	[0.012]	**-0.077**	[0.0072]	**-0.092**	[0.012]	80,655
Log Earnings	-0.405	[0.0077]	-0.030	[0.020]	**-0.155**	[0.012]	**-0.128**	[0.017]	76,321
Sinh(Earnings)	-1.55	[0.064]	**0.165**	[0.079]	**-0.193**	[0.050]	**-0.294**	[0.060]	80,655
Log Wage Loss	-0.201	[0.0053]	**-0.066**	[0.013]	**-0.166**	[0.0098]	**-0.133**	[0.013]	73,598
Fulltime Log Wage	-0.094	[0.0029]	0.013	[0.0085]	**-0.045**	[0.0052]	**-0.039**	[0.0084]	52,996
Days Worked	-67.7	[2.01]	**9.04**	[2.97]	-2.97	[1.73]	**-7.05**	[2.13]	80,655
Days Worked Fulltime	-75.5	[2.11]	**31.4**	[3.24]	**-24.9**	[2.51]	**-23.1**	[2.84]	80,655
Days Worked Parttime	-0.154	[0.380]	**-33.8**	[1.72]	**12.6**	[1.49]	**11.3**	[1.66]	80,655
Days Worked in Minijob	1.09	[0.516]	**14.3**	[1.10]	**10.6**	[1.08]	**4.88**	[1.51]	80,655
Panel B: Job Characteristics									
Commuting Distance	2.59	[1.54]	**-8.76**	[1.62]	-0.505	[1.46]	-0.321	[2.11]	73,027
Log Establishment Size	-0.740	[0.029]	**-0.571**	[0.077]	**-0.066**	[0.023]	-0.041	[0.036]	72,811
Industry Change	0.536	[0.0066]	**-0.061**	[0.020]	**0.034**	[0.0086]	**0.046**	[0.011]	73,564
Occ. Change	0.417	[0.0067]	**-0.105**	[0.015]	**-0.017**	[0.0076]	**-0.043**	[0.012]	73,598
Estab Share Women	0.019	[0.0024]	**0.019**	[0.0032]	**0.043**	[0.0035]	**0.042**	[0.0049]	72,370
Temp Work	0.034	[0.0014]	**-0.012**	[0.0018]	**-0.0099**	[0.0021]	**-0.0087**	[0.0026]	72,811
Business Service Estab	0.064	[0.0023]	**-0.019**	[0.0032]	**-0.024**	[0.0033]	**-0.028**	[0.0040]	72,811
New Estab	0.195	[0.0067]	**0.085**	[0.018]	0.0086	[0.0075]	0.0063	[0.0087]	72,811
AKM Estab FE	-0.086	[0.0063]	0.011	[0.0066]	**-0.024**	[0.0043]	-0.0097	[0.0054]	63,452

Notes: Each row represents a separate regression of the mean change in the outcome variable over a five year period after job loss on a constant and a dummy for female. The first column shows the constant, representing the mean effect for men. The second column presents the coefficient on a female dummy without any controls. The third column presents the coefficient on the female dummy controlling for all covariates. The fourth column uses reweighting. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Sinh(Earnings) refers to the inverse hyperbolic sine transformation of earnings. We measure commuting distance as the km distance between two municipality centroids. Industry and occupation changes are defined on the 2-digit and 3-digit levels, respectively. "Temp Work", "Business Service Estab.", and "New Estab." are variables indicating whether workers changed their job to temporary work, to a business service establishment, or to a new establishment (5 years old or younger), respectively. Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Coefficients in bold are statistically significant at the 5%-level.

Table 3: Explaining the Gender Gap in Wage Losses After Displacement

	(1)	(2) OLS	(3)	(4) Kitagawa-Oaxaca-Blinder Decomp. Endowments	(5) Decomp. % Explained
Panel A: All Workers: Log Wage					
Female	-0.13	-0.096	-0.095		
	(0.013)**	(0.011)**	(0.011)**		
Parttime Job		-0.17	-0.17	-0.0084	6.31
		(0.018)**	(0.018)**	(0.0012)**	(0.90)**
Minijob		-0.70	-0.69	-0.0079	5.91
		(0.026)**	(0.026)**	(0.0024)**	(1.81)**
Industry Change		-0.090	-0.084	-0.0033	2.49
		(0.010)**	(0.0098)**	(0.00083)**	(0.62)**
Occ. Change		-0.082	-0.077	0.0028	-2.12
		(0.0084)**	(0.0081)**	(0.00081)**	(0.61)**
Log Estab Size		0.036	0.032	-0.0013	0.96
		(0.0032)**	(0.0035)**	(0.0012)	(0.93)
Estab Share Women		-0.22	-0.20	-0.0089	6.71
		(0.027)**	(0.027)**	(0.0012)**	(0.94)**
Commut. Distance		-0.000069	-0.000064	-0.0000017	0.0013
		(0.000060)	(0.000061)	(0.000016)	(0.012)
AKM Estab FE		0.83	1	-0.0066	4.94
		(0.057)**		(0.0039)	(2.90)
Observations	73598	73598	73598	73598	73598
R^2	0.010	0.319	0.219		
Mean Dep. Var Men	-.201	-.201	-.201	-.201	-.201
	(.003)	(.003)	(.003)	(.003)	(.003)
Total Gap				-0.13	100.0
				(0.016)**	(11.8)**
Explained Gap				-.035	26.258
Panel B: Full-time Workers: Full-time Log Wage					
Female	-0.039	-0.030	-0.028		
	(0.0084)**	(0.0076)**	(0.0076)**		
Industry Change		-0.031	-0.021	-0.0011	2.86
		(0.0067)**	(0.0062)**	(0.00040)**	(1.02)**
Occ. Change		-0.0096	-0.0019	0.00059	-1.51
		(0.0054)	(0.0050)	(0.00021)**	(0.53)**
Log Estab Size		0.012	0.0053	0.000018	-0.045
		(0.0018)**	(0.0027)*	(0.00040)	(1.03)
Estab Share Women		-0.056	-0.024	-0.0012	3.18
		(0.016)**	(0.015)	(0.00032)**	(0.81)**
Commut. Distance		0.000054	0.000066	0.000028	-0.072
		(0.000040)	(0.000041)	(0.00015)	(0.39)
AKM Estab FE		0.70	1	-0.0072	18.2
		(0.055)**		(0.0035)*	(9.01)*
Observations	52996	52996	52996		
R^2	0.003	0.228	0.015		
Mean Dep. Var Men	-.094	-.094	-.094	-.094	-.094
	(.002)	(.002)	(.002)	(.002)	(.002)
Total Gap				-0.039	100.0
				(0.014)**	(35.4)**
Explained Gap				-.009	22.492

Notes: This table shows to what extent changes in contract type, industry, occupation, and establishment characteristics can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. In all columns, we reweight women to men using individual and establishment characteristics pre displacement. The coefficients in columns (1)-(3) are estimated from OLS regressions. In column (3), the coefficient on the AKM establishment effect is forced to be equal to 1. Column (4) shows the explained part, or endowment effects, from an Kitagawa-Oaxaca-Blinder decomposition, corresponding to $(E(X|female) - E(X|male))\beta_{male}$. Column (5) shows the % of the total wage gap explained by each variable. Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Standard errors (in brackets) are clustered at the dispalcement establishment level (constant within matched worker pairs). * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 4: The Gender Gap in Labor Market Outcomes by Household Characteristics

	(1) Earnings Rel. To t=c-2	(2) Log Wage	(3) Log Wage Fulltime	(4) Days Worked	(5) Days Worked Fulltime	(6) Days Worked Parttime	(7) Days Worked In Minijob	(8) Commuting Distance	(9) Log Estab Size	(10) Estab FE	(11) Partner's Earn. Rel. to Job Loser's
Panel A: Regression Adjusted Gender Wage Gap - Adding Family Controls											
Female	-0.038	-0.13	-0.028	1.20	2.48	-13.0	15.0	-3.13	-0.11	-0.018	-0.033
	(0.0078)**	(0.011)**	(0.0053)**	(1.81)	(2.67)	(1.48)**	(1.13)**	(1.44)*	(0.026)**	(0.0046)**	(0.0090)**
Child	0.013	0.016	0.0040	4.01	3.57	0.93	-0.71	-0.070	0.026	0.0078	0.0099
	(0.0037)**	(0.0046)**	(0.0024)	(1.01)**	(1.17)**	(0.53)	(0.67)	(0.78)	(0.014)	(0.0021)**	(0.0037)**
Female*Child	-0.026	-0.027	-0.011	-5.23	-2.74	-3.47	1.31	-0.60	-0.019	-0.011	-0.020
	(0.0076)**	(0.0091)**	(0.0075)	(1.91)**	(2.57)	(1.96)	(1.32)	(1.28)	(0.025)	(0.0037)**	(0.015)
Observations	161310	147196	105992	161310	161310	161310	161310	146054	145622	126904	161310
R^2	0.030	0.034	0.029	0.025	0.054	0.058	0.009	0.027	0.170	0.057	0.002
Mean Dep. Var Men	-.258	-.201	-.094	-67.66	-75.471	-.154	1.086	2.59	-.74	-.086	-.02
	(.002)	(.002)	(.001)	(.414)	(.541)	(.4)	(.317)	(.312)	(.006)	(.001)	(.003)
Panel B: Regression Adjusted Gender Wage Gap - Adding Household Income Controls											
Female	-0.055	-0.15	-0.036	-3.21	-1.44	-13.8	15.4	-3.32	-0.14	-0.024	-0.035
	(0.0077)**	(0.011)**	(0.0055)**	(1.81)	(2.63)	(1.50)**	(1.14)**	(1.47)*	(0.026)**	(0.0049)**	(0.011)**
Earn. Share in HH Inc.	-0.029	-0.036	-0.011	-6.93	-12.5	2.88	0.10	-0.44	-0.18	-0.0050	0.052
	(0.013)*	(0.014)**	(0.0079)	(2.90)*	(3.36)**	(1.62)	(1.75)	(3.26)	(0.045)**	(0.0078)	(0.015)**
Female*Earn. Share	-0.0013	0.015	0.00044	-6.92	4.79	-5.12	-4.23	-0.64	0.16	-0.0055	0.0030
	(0.019)	(0.022)	(0.016)	(4.29)	(5.80)	(4.50)	(2.82)	(3.65)	(0.064)*	(0.010)	(0.039)
Observations	126151	115338	82784	126151	126151	126151	126151	114466	114139	98161	126151
R^2	0.034	0.036	0.030	0.028	0.055	0.059	0.010	0.026	0.174	0.057	0.002
Mean Dep. Var Men	-.258	-.201	-.094	-67.66	-75.471	-.154	1.086	2.59	-.74	-.086	-.02
	(.002)	(.002)	(.001)	(.414)	(.541)	(.4)	(.317)	(.312)	(.006)	(.001)	(.003)

Notes: This table shows the role of children and household dynamics in explaining gender-specific labor market outcomes after displacement. All outcome variables are based on the individual difference-in-differences estimate. Panel (A) shows the regression adjusted gender gap controlling for having children younger than 16. Panel (B) shows the regression adjusted gender gap controlling for the job loser's earnings share in household income measured in t=c-2. The share in household income is set to missing if the partner is not working. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 5: Gender Differences in Job Preferences and Search Behavior after Job Loss

	(1) Mean Outcome Men		(2) Unadjusted Gender Gap		(3) Composition Adjusted Gender Gap Regression-Adj.		(4) Composition Adjusted Gender Gap Reweighted		(5) Number of Observations	(6) Data Source
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.		
Panel A: All										
Seeking full-time job	0.979	[0.0016]	**-0.314**	[0.0061]	**-0.136**	[0.0054]	**-0.113**	[0.0060]	45,087	ASU
Broad geographic search	0.439	[0.0051]	**-0.040**	[0.0073]	**-0.024**	[0.0085]	-0.019	[0.012]	31,349	ASU
Permanent contract	0.745	[0.0075]	**-0.035**	[0.0091]	**0.020**	[0.0094]	-0.0066	[0.010]	45,131	ASU
Minutes job search	94.0	[1.62]	**-18.0**	[2.09]	**-7.05**	[2.21]	**-9.18**	[2.68]	116,159	SMS
Target wage ratio	1.17	[0.016]	**0.077**	[0.023]	**-0.097**	[0.022]	**-0.054**	[0.027]	5,541	SMS
Log-Target wage ratio	0.075	[0.012]	**0.053**	[0.018]	**-0.084**	[0.017]	**-0.054**	[0.024]	5,541	SMS
Panel B: Age Youngest Child ≤ 15										
Seeking full-time job	0.981	[0.0019]	**-0.550**	[0.011]	**-0.323**	[0.013]	**-0.272**	[0.020]	12,735	ASU
Broad geographic search	0.446	[0.0073]	**-0.050**	[0.013]	-0.032	[0.018]	**-0.069**	[0.028]	8,884	ASU
Permanent contract	0.759	[0.0083]	**-0.081**	[0.013]	-0.028	[0.016]	**-0.095**	[0.023]	12,731	ASU
Minutes job search	91.5	[3.37]	**-22.2**	[3.94]	-3.15	[3.93]	-8.28	[6.00]	30,581	SMS
Target wage ratio	1.20	[0.031]	**0.132**	[0.044]	**-0.118**	[0.047]	**-0.168**	[0.074]	1,607	SMS
Log-Target wage ratio	0.098	[0.024]	**0.087**	[0.034]	**-0.108**	[0.034]	**-0.169**	[0.067]	1,607	SMS
Panel C: Age Youngest Child > 15/No Children										
Seeking full-time job	0.978	[0.0019]	**-0.252**	[0.0061]	**-0.103**	[0.0055]	**-0.085**	[0.0057]	32,352	ASU
Broad geographic search	0.435	[0.0056]	**-0.036**	[0.0080]	**-0.021**	[0.0092]	-0.0093	[0.013]	22,465	ASU
Permanent contract	0.738	[0.0078]	**-0.020**	[0.0095]	**0.030**	[0.0098]	0.013	[0.011]	32,400	ASU
Minutes job search	94.7	[1.84]	**-15.8**	[2.49]	**-7.64**	[2.63]	**-8.89**	[3.00]	85,578	SMS
Target wage ratio	1.16	[0.018]	0.046	[0.027]	**-0.087**	[0.024]	-0.032	[0.028]	3,934	SMS
Log-Target wage ratio	0.068	[0.014]	0.032	[0.021]	**-0.071**	[0.019]	-0.029	[0.024]	3,934	SMS

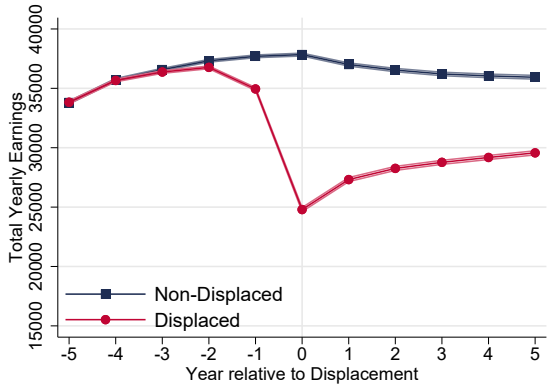
Notes: Each row represents a separate regression of the outcome variable on a constant and a dummy for female for a sample of displaced workers, only. In Panels B and C we restrict the sample to individuals with young children $\leq$ the age of 15 and above the age of 15 respectively. Data source ASU refers to the job-search preference data collected by the caseworkers at the local UI agency and is based on the subset of about 70% workers of the baseline job-loss sample for whom this information is available. SMS refers to the high-frequency job-search data among unemployed workers between 2017 and 2019 as collected and described in DellaVigna et al. 2022, with number of observations referring to the person $\times$ survey-date level. The first column shows the constant, representing the mean effect for men. The second column the coefficient on a female dummy without any controls. The third column the coefficient on the female dummy controlling for all covariates. The fourth column uses reweighting. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Coefficients in bold are statistically significant at the 5%-level.

Table 6: The Gender Gap in Earnings Losses - Robustness Checks

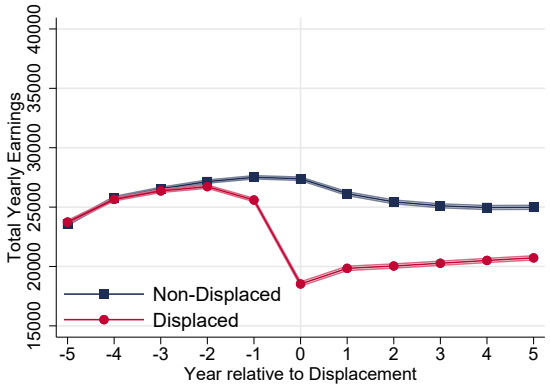
	(1) Baseline	(2) 10 Years Post Displ.	(3) Shorter Tenure Restr.	(4) Mahalanobis And Exact Matching	(5) Random Control Group	(6) Reweight. With Occupations	(7) Displ. Estab. FE	(8) Matching Without Wages	(9) Reweight. Men to Women	(10) Non Couples	(11) Couples + Non-Couples
Panel A: Earnings Rel. to Year -2											
Female	-0.092	-0.093	-0.11	-0.093	-0.092	-0.12	-0.086	-0.087	-0.068	-0.017	-0.048
	(0.012)**	(0.018)**	(0.014)**	(0.012)**	(0.012)**	(0.025)**	(0.0089)**	(0.012)**	(0.020)**	(0.013)	(0.013)**
Observations	80655	55107	93755	80707	80755	80423	77144	80706	78695	16422	96158
R^2	0.007	0.006	0.008	0.007	0.007	0.013	0.352	0.006	0.003	0.000	0.002
Mean Dep. Var Men	-.258	-.203	-.268	-.245	-.269	-.258	-.258	-.258	-.259	-.297	-.287
	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.006)	(.002)
Panel B: Log Wages											
Female	-0.13	-0.14	-0.16	-0.15	-0.13	-0.22	-0.16	-0.13	-0.16	-0.079	-0.075
	(0.013)**	(0.017)**	(0.013)**	(0.013)**	(0.013)**	(0.036)**	(0.013)**	(0.013)**	(0.017)**	(0.016)**	(0.015)**
Observations	73598	51670	85092	73626	73672	73369	70058	73634	71758	14551	87342
R^2	0.010	0.009	0.013	0.013	0.010	0.025	0.347	0.009	0.014	0.004	0.003
Mean Dep. Var Men	-.201	-.187	-.205	-.188	-.209	-.201	-.201	-.201	-.202	-.201	-.203
	(.003)	(.004)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.007)	(.003)
Panel C: Log Full-time Wages											
Female	-0.039	-0.046	-0.052	-0.067	-0.033	-0.090	-0.061	-0.051	-0.045	-0.039	-0.044
	(0.0084)**	(0.012)**	(0.0079)**	(0.0077)**	(0.0096)**	(0.027)**	(0.0074)**	(0.0086)**	(0.0099)**	(0.011)**	(0.012)**
Observations	52996	39002	60891	56077	51162	52939	49526	53169	52938	10944	63191
R^2	0.003	0.003	0.005	0.009	0.002	0.015	0.360	0.005	0.004	0.003	0.003
Mean Dep. Var Men	-.094	-.091	-.094	-.084	-.1	-.094	-.094		-.094	-.086	-.09
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
Panel D: Days Worked Full-time											
Female	-23.1	-32.5	-30.4	-10.1	-26.7	-31.9	-22.3	-17.4	-25.4	-6.68	-14.4
	(2.84)**	(3.73)**	(2.73)**	(2.74)**	(2.87)**	(6.66)**	(2.87)**	(2.86)**	(4.64)**	(4.20)	(4.07)**
Observations	80655	55107	93755	80707	80755	80423	77144	80706	78695	16422	96158
R^2	0.005	0.009	0.008	0.001	0.007	0.009	0.335	0.003	0.004	0.000	0.002
Mean Dep. Var Men	-75.47	-56.298	-77.46	-74.628	-77.428	-75.471	-75.47	-75.8	-75.664	-88.476	-84.705
	(.766)	(.976)	(.717)	(.727)	(.765)	(.766)	(.766)	(.763)	(.765)	(1.706)	(.716)

Notes: Each column in this table represents a different robustness check. All specifications are estimated using weights. Column (1) reports the baseline coefficients. Column (2) reports results for a longer post-displacement time window (10 years). Column (3) reports results for shorter tenure workers (1 year at time of displacement). Column (4) reports results when using Mahalanobis matching in combination with exact matching of pre-displacement earnings deciles. Column (5) reports results with a random (non-matched) control group of workers who fulfill the baseline restrictions. Column (6) reports results when reweighting with 1-digit occupations in addition to industries and individual characteristics. Column (7) reports regression coefficients controlling for pre-displacement establishment fixed effects. Column (8) reports regression coefficients for a sample of treated and control workers, where the propensity score matching did not include log wages. Column (9) reports results when reweighting men to women. Trimmed at 99%. Column (10) reports regression coefficients for a dataset of non-couples. Column (11) reports regression coefficients for a combined dataset of couples and non-couples in our sample. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

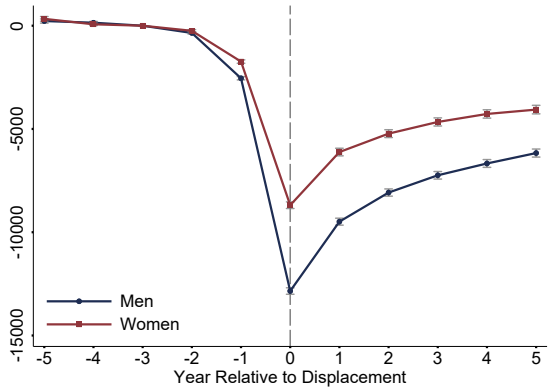
Figure 1: The Gender Gap in Earnings Losses after Displacement without Controlling for Pre-Displacement Characteristics



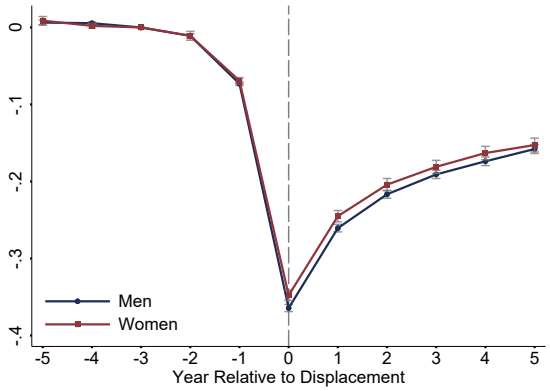
(a) Total Earnings in Year - Men



(b) Total Earnings in Year - Women



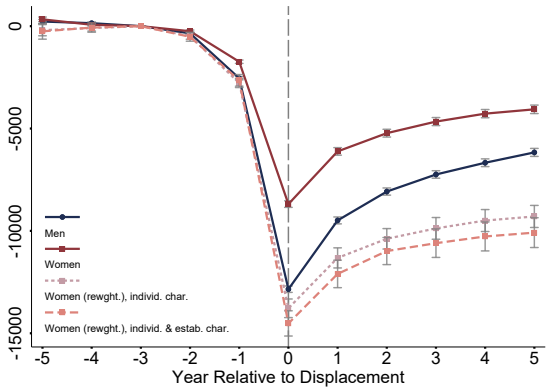
(c) Total Earnings in Year - Men and Women



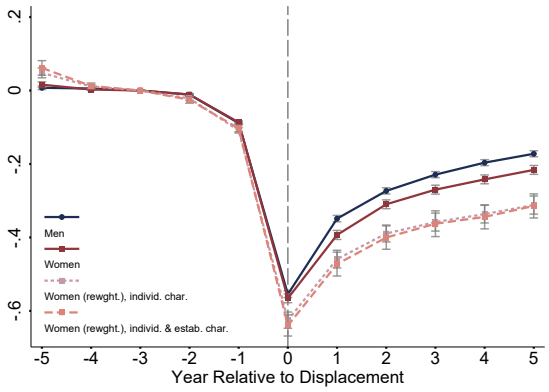
(d) Earnings Relative to t=c-2 - Men and Women

Notes: The figures show earnings losses for displaced and non-displaced workers. Panels (a) and (b) show total yearly earnings for displaced and non-displaced men (a) and women (b). The red line corresponds to workers who are displaced from year t=c-1 to t=c, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group. Panels (c) and (d) show eventstudy coefficients, controlling for person FE, year FE, years since separation, and age polynomials. Panel (c) shows event study coefficients for total yearly earnings as outcome. Panel (d) shows event study coefficients for earnings relative to t=c-2 as outcome. The red line corresponds to women, the blue line corresponds to men. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

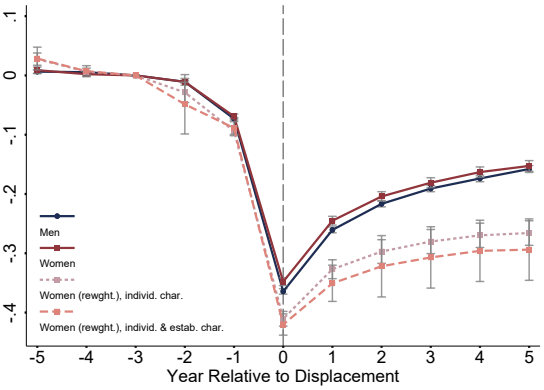
Figure 2: The Gender Gap in Earnings Losses after Displacement, Controlling for Pre-Displacement Job and Worker Characteristics



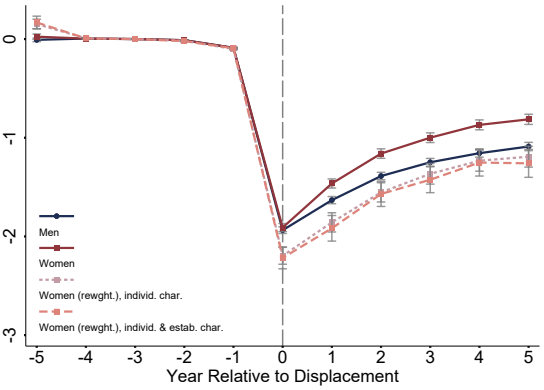
(a) Total Earnings



(b) Log Earnings



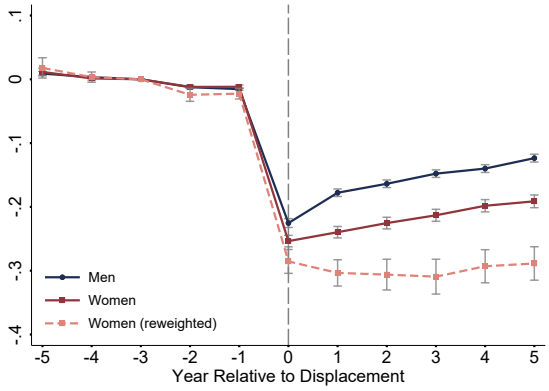
(c) Earnings Relative to t=c-2



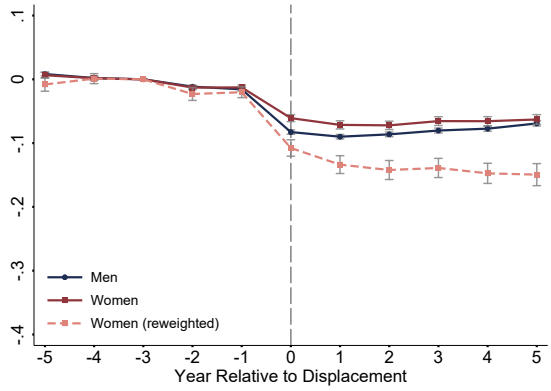
(d) Inverse Hyperbolic Sine Earnings

Notes: This figure shows how earnings losses from displacement differ for men and women. Panels (a)-(d) show eventstudy coefficients for total yearly earnings, log earnings, earnings relative to t=c-2, and inverse hyperbolic sine earnings. The four lines correspond to four event study regressions: Men only, women only, women reweighted with individual characteristics, and women reweighted with individual characteristics and establishment characteristics. Individual characteristics are a worker's log wage in t=c-3 and t=c-4, fulltime employment in t=c-3, and age, years of education, tenure, and location in East or West Germany in t=c-1. Establishment characteristics are 1-digit industry dummies and log establishment size in t=c. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

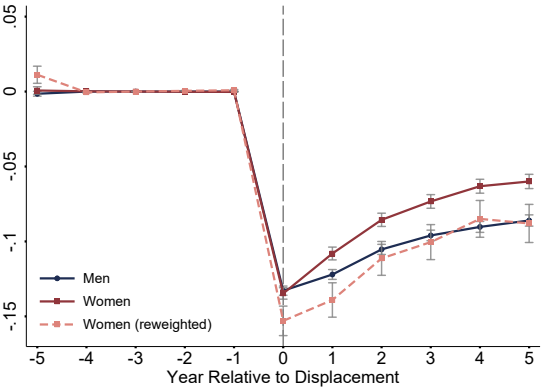
Figure 3: The Gender Gap in Wage and Employment Losses after Displacement



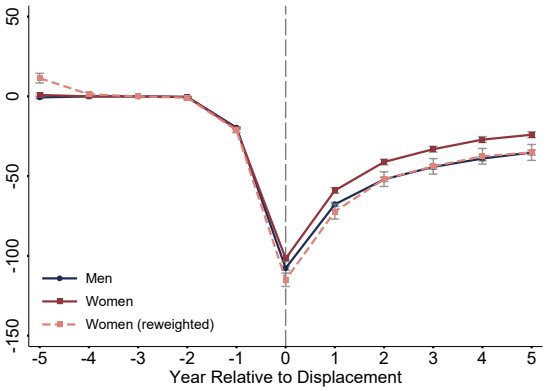
(a) Log Wage



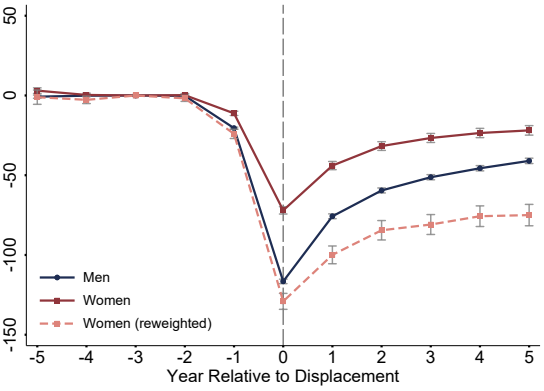
(b) Log Wage Fulltime Job



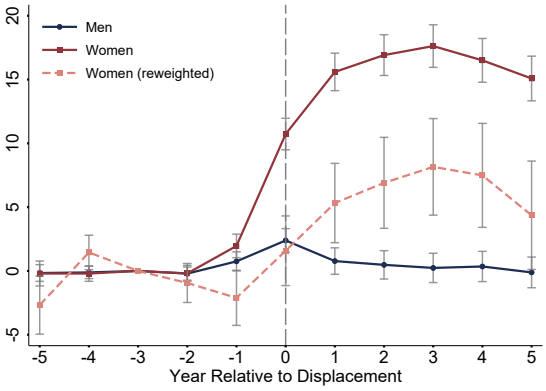
(c) Any Employment in Year



(d) Days Worked



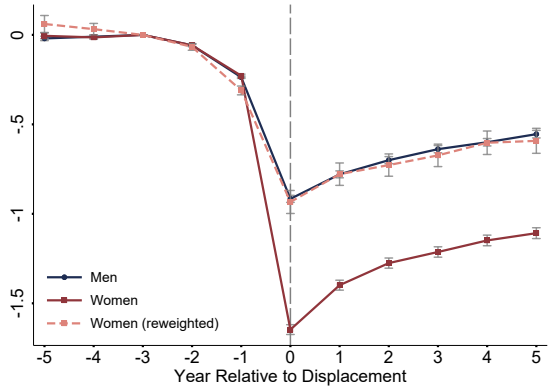
(e) Days Worked Fulltime



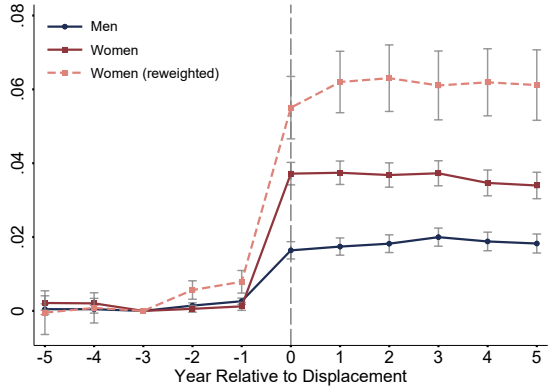
(f) Day Worked in Mini-job

Notes: This figure shows how labor market characteristics before and after displacement differ for men and women. Panels (a)-(f) show eventstudy coefficients for log wage, log wage from fulltime job, employment, days worked, days worked in fulltime job, and days worked in minijob. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

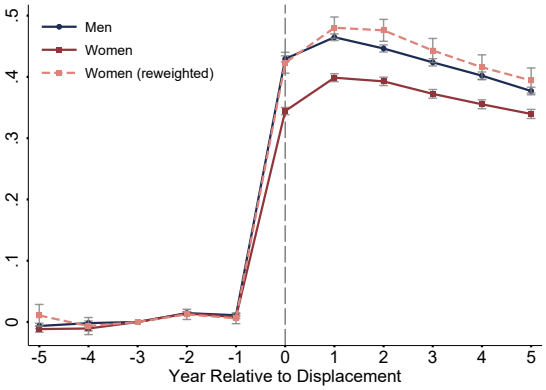
Figure 4: Changes in Job Characteristics after Displacement



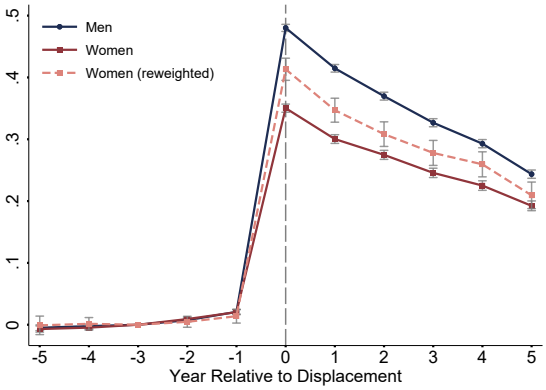
(a) Log Size of Establishment



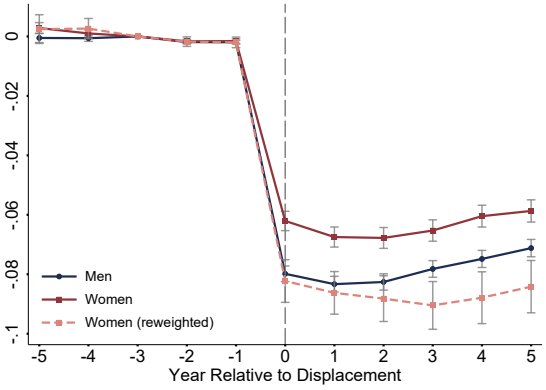
(b) Share of Females in Establishment



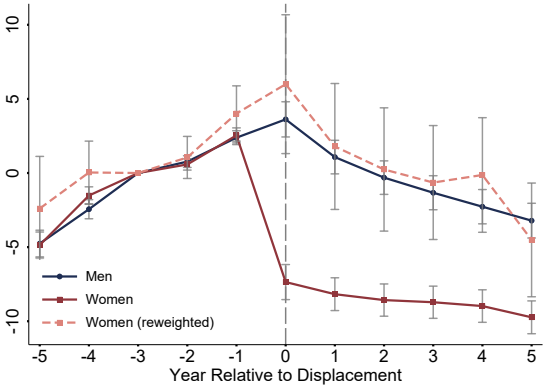
(c) Industry Different from Industry at t=c-1



(d) Occupation Different from Occupation at t=c-1



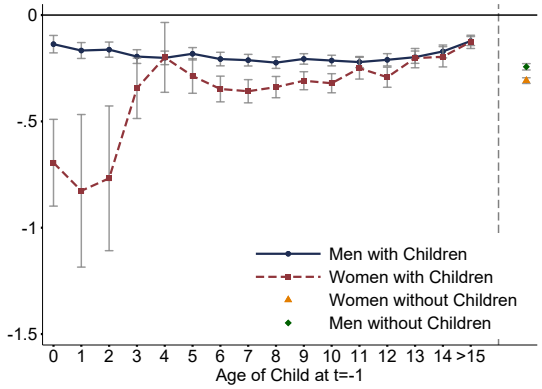
(e) Establishment Effect



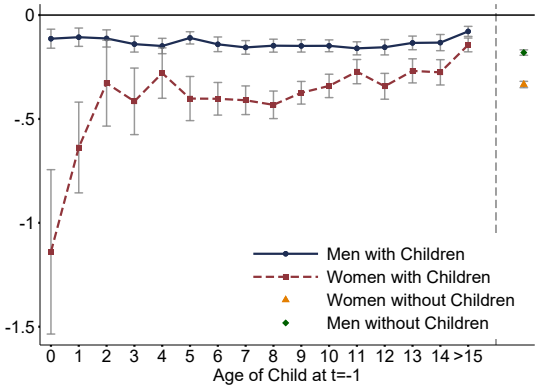
(f) Commuting Distance

Notes: This figure shows how job characteristics for men and women evolve before and after displacement. Panels (a)-(f) show event study coefficients for log establishment size, share of female workers in establishment (leave-one-out mean), industry switches (2-digits), occupation switches (3-digits), AKM establishment effects, and commuting distance (in km). The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Commuting distance is measured on the municipality level, and is recorded on December 31 each year. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

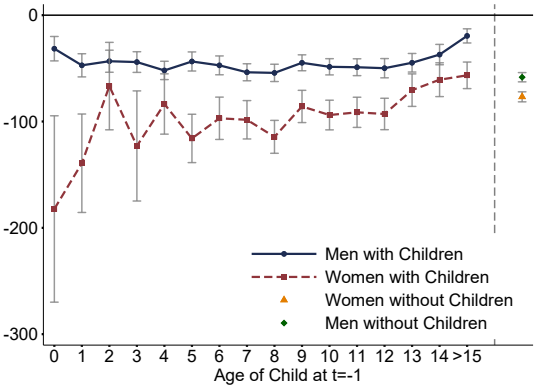
Figure 5: The Gender Gap and Children



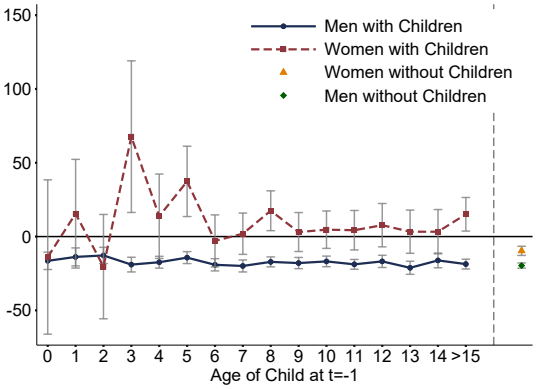
(a) Earnings Relative to t=c-2



(b) Log Wage



(c) Days Worked Fulltime



(d) Days Worked Parttime

Notes: This figure shows how labor market outcomes before and after displacement differ for men and women by age of first child at time of displacement. All outcomes variables are the respective difference-in-difference estimate. Panels (a)-(d) show eventstudy coefficients for earnings relative to t=c-2, log wage, days worked in fulltime job, and days worked in parttime job. The dark blue line corresponds to men with children, the dashed red line corresponds to women with children. The green diamond and orange triangle report coefficients for men without children and women without children, correspondingly. All regressions control for individual and establishment characteristics. Individual characteristics are a worker's log wage in t=c-3 and t=c-4, fulltime employment in t=c-3, and age, years of education, tenure, and location in East or West Germany in t=c-1. Establishment characteristics are 1-digit industry dummies and log establishment size in t=c-1. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the displacement establishment level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

Online Appendix

A Data

A.1 Identifying Couples

Goldschmidt et al. (2017) (henceforth: GKS) developed a method to identify likely married, mixed-sex couples in German administrative data. The procedure relies on identifying likely married couples by selecting pairs of individuals that a) share the same last name, b) live at the exact same address, c) there are exactly two persons with the same last name at a given location. In addition, it restricts to mixed-sex name-pairs with an absolute age difference of less than 15 years. GKS provide evidence that this procedure is effective in identifying couples, with an estimated rate of false positives of less than 5%. At the same time, not all couples can be identified with this method. As a direct result of the data restrictions, only mixed-sex couples sharing a last name and an age difference of less than 15 years are selected.[35]

An additional restriction is that to be identified as a couple, both individuals of that couple have to appear in the administrative data at the same time. This requires that each of the individuals of a couple have to be in either dependent, social security liable employment (including marginal employment) or a recorded unemployment spell (including any UI, UI-II receipt, registered unemployment, or registered job search status). The procedure thus selects more conservative and older (but not yet retired) couples with some (but potentially weak) attachment to the labor force. In this paper we rely on a recent data update of GKS for the years 2001-2014 (Bächmann et al. (2021)). This yields a yearly panel dataset of more than 8 million couples for the years 2001-2014.

A.2 Main Analysis Sample

Sample Construction

We construct a sample of workers laid off in 2002 through 2012 from the Integrated Employment Biographies (IEB) provided by the IAB. We start with the universe of all social security liable employment in the IEB and subsequently add the following restrictions to arrive at our baseline sample of laid off workers.

[35] This restriction aims at reducing measurement error as age differences of more than 15 years might also stem from parent-child links and same-sex pairs might importantly reflect borther-sister pairs.

- Mass layoff or plant closure: We define an individual as being laid off during a mass layoff if they fulfill the following conditions:
  - They leave the establishment between June 30 in $t = c - 1$ and June 30 in $t = c$, where $c \in \{2002..., 2012\}$ and do not return to the establishment in the 5 subsequent years.
  - The displacing establishment exhibits low employment fluctuations in the two years before the layoff, i.e., the workforce did not increase by more than 30% in at least one of the two years preceding the layoff.
  - The workforce of the displacing establishment declines by at least 30% between $t = c - 1$ and $t = c$.
  - The employment outflows at that establishment between $t = c - 1$ and $t = c$ are "dispersed". I.e., following Hethey-Maier and Schmieder (2013), we require that no more than 30% of the outflow go to one particular establishment to exclude mergers, takeovers, or changes in employer identification numbers.
  - The establishment empoyed at least 30 individuals in the year prior to layoff $t = c - 1$.
- Married couples: We restrict our baseline sample to married couples. This requires that the individual has to be observed as being in a couple (as defined in A.1) in one of the five years prior to layoff.
- Age and tenure: To ensure that workers in our baseline sample are highly attached to the labor force, we consider only workers aged 24-50 (at $t = c - 1$), workers with at least two years of tenure (at $t = c - 1$), and workers who were not in marginal employment in the four years preceding displacement.

Comparison to Schmieder, von Wachter, and Heining (2020)

Our sample construction closely follows Schmieder et al. (forthcoming) (henceforth SvWH). As in SvWH, we consider only workers aged 24-50 in $t = c - 1$. However, our baseline restrictions are less strict when it comes to tenure, full-time employment, and establishment size. This is because otherwise, we would exclude many women from our sample. In particular, we deviate form SvWH in the following ways:

- While SvWH restrict their baseline sample to workers with three years of tenure in in $t = c - 1$, we relax this restriction to two years.
- In contrast to SvWH, we allow for part-time employment of workers before displacement.
- We consider establishments with a workforce of at least 30 employees in $t = c - 1$, and thus allow for slightly smaller establishments (at least 50 employees in SvWH).

Another important difference is that for our main analysis, we focus on individuals who were part of a couple in at least one of the five years before displacement. In addition, while SvWH focus on West Germany only, we consider (non-)displaced workers both in East and West Germany.

A.3 Job Search and Job Preferences Data: ASU and SMS

(X)ASU

The (X)ASU (or *Jobseeker History Panel*) is an administrative dataset provided by the IAB (see Antoni et al. (2019) for an overview on individual-level data at the IAB).[36] It contains information on individuals who are registered as unemployed and stems from the Federal Employment Agency's (BA) job placement software "VerBIS". Everyone who receives unemployment benefits is part of this databse. It is possible to link job seekers from this database to the employment data via a unique person ID.

Caseworkers collect the information on job preferences during the first consultation with the job seeker and enter it into the software. For example, the caseworker asks the job seeker whether they are looking for a i) full-time job, ii) part-time job, or iii) either and then adds this information to the job seeker's profile in the BA system. In another question, job seekers have to indicate whether they are looking for i) a permanent contract, ii) a fixed-term contract, or iii) any contract.

For the scope of geographic search, the job seeker has to indicate whether they would be willing to accept a job anywhere in Germany or whether they are limited in their regional scope of search. Job seekers can also indicate in which regions (out of the 16 German federal state or out of the 155 job agency regions) they would preferably accept a job in (though this information is, unfortunately, not part of the data). As soon as the job seeker indicates

[36] Note that we use "ASU" version V06.11.00 and "XASU" version V02.03.00-201904.

that they would also be willing to accept offers non-prefered regions (on a federal, state, or job agency level), the caseworker classifies them as searching with "broader geographic scope". Note that the information on the geographic scope of search is only available for spells starting before July 2006.

Table 4, Columns (1) vs. (2), shows how our baseline sample of displaced workers (Column (1)) differs form individuals who appear in the (X)ASU data (Column (2)). Column (2) shows that individuals in the (X)ASU are somewhat negatively selected: They have lower earnings (31,000 vs. 33,000, t=c-2), work fewer full-time days (290 vs. 293, t=c-1), and spent slightly less time in education (11.1 vs. 11.3 years). Individuals in the (X)ASU data are also 4 percentage points less likely to be female. This could be either because women find new jobs more quickly, or because they are more likely to completely drop out of the workforce after job displacement.

SMS

The SMS-data constitutes a novel, high frequency data set on job search effort and has been collected by DellaVigna et al. (2022) to describe within-individual job search effort overt the unemployment spell and around benefit exhaustion. The targeting sample consists of a random sample of individual UI recipients between age 25 and 55, with stratifications by eligibility duration and current unemployment durations (see DellaVigna et al. 2022 for details). The survey was conducted between 2018 and 2019 and contains information on search effort, target wage, life-satisfaction and job-found information. A question on search effort was asked twice a week, while each of the other questions was asked effectively every third week (each week, one of the additional questions was asked on a rotating basis).

B Additional Analysis: The Added Worker Effect

A long-standing hypothesis in labor economics is that married women increase their labor supply in response to their husbands' unemployment (e.g. Cain, 1966, Lundberg, 1985). Our newly created link of married couples allows us for the first time to study this effect in German administrative data. As a departure from the long-standing focus of this literature on the labor force participation of wives only, we look at labor supply responses of both husbands and wives of displaced workers. This allows us to examine whether there are gender differences in spousal labor supply which could either mitigate or amplify the individual-level gender gap

in the costs of job loss.

Our main results are shown in Figure 7 and Table 18. Panel (a) of Figure 7 reports the impact of job loss on the partner's earnings relative to t=c-2 by gender of the displaced worker.[37] The blue line shows that if a man loses his job there is a small decline in the wife's earnings in the order of about 2% of the displaced workers' earnings. There is also a negative effect on the days worked on the wives of displaced men (Panel (b)), which fall by around 18 days. For women, the unweighted pattern is stronger in that it appears that husbands of displaced women do have a sizable negative earnings shock in the subsequent years of around 4-5%. Similarly, days worked and even more so days worked full-time (Panel (c)) decline for the partners of displaced women. While reweighting women to men makes these estimates noisier, the basic pattern is similar.

These graphical results are confirmed by regression estimates in Table 18. Column (1) Panel A shows that the added worker effect is negative for men and women. When a man loses his job, his wife's earnings decline in the following years by about 2% of earnings of the job loser at baseline. On the flip side, if a woman loses her job, her husband's earnings decline by an additional 4.5 percentage points. The gender gap is similar when using either reweighting or regression adjustment to hold other characteristics constant (Panels B and C), though somewhat noisy in the first case. Column (2) shows that the negative added worker effect does not operate through log wages, which are unchanged, but instead through days worked: both partners of men and women work fewer days and partners of female job losers lose more days working full-time.

To examine gender differences in individual and spousal responses jointly, we look at earnings at the household level. In Figure 7 (d), we show the effect of displacement on household income relative to $t = c - 1$. Given that partner's earnings only mildly respond to job displacement, the picture on the household level is very similar to the individual level. Women's job loss leads to smaller household earnings losses in the overall sample than when men lose their job. However, once we reweight the sample so that we compare similar men and women, the losses are significantly larger if women lose their job.

Table 18 Column (5) confirms that the gender gap persists on the household level when

[37] Our outcome variable is the change in earnings divided by the earnings of the jobloser in the baseline year ($t = c - 1$) : $\frac{\Delta y_{partner}}{y_{jobloser,t=c-1}}$. Scaling by the earnings of the jobloser, rather than the earnings of the parter at baseline, has the advantage that $y_{jobloser,t=c-1}$ is always a positive and reasonably large number, while $y_{partner,t=c-1}$ can be small or zero which would lead to relative wage changes that go to infinity creating huge outliers.

looking at relative household earnings (i.e. relative to household earnings in $t = c - 1$): after controlling for observable characteristics, a household where the female worker is laid off experiences a significant 3.5% higher earnings loss than a household where a man loses his job (Panel B). The fact that the gender gap for household earnings is positive in the unweighted sample (Panel A) is consistent with the smaller absolute earnings losses of women in conjunction with the fact that men tend to contribute a higher share of total household income in our data (see Table 1 in the paper).

Why do we observe a negative added worker effect for both male and female job losers? One caveat is that we can only identify married couples where both partners are in the social security data, either by working a social security liable job or by receiving UI benefits. In particular, we miss couples where one spouse is not in the labor force at all or is self-employed. It may well be the case that spouses who are not working or self-employed are the most likely to respond by increasing their labor supply, which would lead us to underestimate the added worker effect in the overall population.

Within our sample, we can get at the role of opportunities to increase labor supply by comparing job losers where the partner is working full-time or part-time. In Panels D and E we split our sample by whether or not the partner is working full-time or part-time prior to displacement.[38] The results partially confirm the importance of the partner's opportunity to increase labor supply. Among full-time working partners of displaced men, the added worker effect is clearly negative: about a 4% loss in earnings and a decrease of about 16 days of full-time work (and 19 days in days worked overall). The pattern for women is very similar for days worked but earnings losses are even larger. On the other hand when looking at partners who are working part-time or are unemployed the added worker effect is less negative. Earnings decrease only by about 1.3% for partners of male displaced workers and are unchanged for

[38] When splitting the sample a technical issue arises: In our matching procedure to generate a suitable control group we do not match on characteristics of the partner. This means that within the matched displaced/non-displaced pairs the full-time status of the partner is often different. If we then condition only on the partner of the displaced worker to be working full-time, the control group will include workers working full-time or part-time leading to very different pre-trends and a bias from regression to the mean. For this reason, rather than estimating Equation (7), we instead estimate the effect in first differences:

$$\Delta_d y_{ic} = \beta \, Female_{ic} * Displaced_{ic} + \delta \, Female_{ic} + X_{ic}\theta + \varepsilon_{ic} \tag{10}$$

and then apply baseline restrictions to both displaced and non-displaced workers.

This is identical to estimating Equation (7) in the full sample but avoids the regression to the mean bias in split sample regressions. Since non-displaced workers are treated as distinct observations, the number of observations is twice as large as in the previous analysis.

partners of female displaced workers. Similarly partner days worked decline somewhat for men but remain the same for women.

A plausible reason for observing a **negative** added worker effect is likely that there are correlated shocks on the household level (Huber and Winkler (2019)). Spouses tend to work in similar regions, firms, and industries. Thus, if one spouse is displaced, the other spouse might also face a negative labor demand shock in the form of job loss or cuts in hours. Table 18, Panels F and G split the sample by whether or not both partners work in the same or different industry at baseline. Looking at the differences for men (mean of dependent variable), the earnings losses of the partner are almost 10 times larger when both partners work in the same industry (10.4% vs 1.2%). Similarly, losses in days worked (58.6 vs. 12.4 days) and days worked full-time (27.7 vs. 2.0 days) are much larger if both work in the same industry. The gender gap estimates in Panel G and F, suggest even larger negative effects for partners of displaced women when both partners work in the same industry. Similarly, Appendix Table 18 shows that partners' earnings and employment losses are also much larger when both partners work in the same establishment (while same occupations are less predictive). Our results point thus to an important role of correlated demand shocks negatively affecting earnings of both spouses.

Our finding that spousal labor supply responses are negative and not able to mitigate the costs of job loss is somewhat in contrast to Halla et al. (2020) who study the added worker effect in the Austrian context. Halla et al. (2020) find a slightly positive employment response of married women to the job loss of their husbands. A key data difference is that they have access to the marriage and divorce register, and thus can include couples where the wife is not working prior to the displacement event of the husband. In fact, when they restrict the sample to women who were employed at baseline they also find a clear negative added worker effect (see Halla et al., 2020, Table 3).

C Appendix Tables and Figures

Table 1: Summary Statistics for Displaced Workers and Matched Controls in t=c-1

	(1) Non-Displaced Women	(2) Displaced Women	(3) Non-Displaced Men	(4) Displaced Men
Panel A: Individual Characteristics				
Years of education	11.4	11.4	11.3	11.3
	[1.5]	[1.5]	[1.6]	[1.6]
Potential experience	22.4	22.8	21.8	21.9
	[6.2]	[6.1]	[6.2]	[6.2]
Tenure with current employer	7.5	7.5	7.7	7.7
	[4.1]	[4.1]	[4.4]	[4.5]
Log wage in t=c-2	4.2	4.2	4.5	4.5
	[0.485]	[0.471]	[0.360]	[0.356]
Earnings in t=c-1	26999.8	26623.3	37167.9	36677.8
	[12004.7]	[11881.2]	[12715.9]	[12881.5]
Total yearly income	25675.6	24451.5	35585.8	33729.2
	[11834.4]	[11831.6]	[13077.3]	[13388.0]
Days Worked in Year	363.2	343.0	363.1	343.2
	[14.0]	[48.2]	[13.2]	[46.7]
Days Worked in Fulltime Job	239.4	226.9	356.3	335.5
	[172.2]	[162.0]	[50.3]	[64.4]
Couple	1	1	1	1
	[0]	[0]	[0]	[0]
Panel B: Establishment Characteristics				
Firmsize	572.4	513.1	277.4	281.3
	[1177.0]	[867.8]	[714.4]	[616.4]
Share female workers	0.602	0.616	0.287	0.279
	[0.240]	[0.239]	[0.212]	[0.212]
Share fulltime workers	0.636	0.649	0.806	0.829
	[0.269]	[0.278]	[0.183]	[0.180]
Number of Observations	31806	31806	48849	48849

Notes: Characteristics of displaced and non-displaced workers in year prior to displacement year. Workers satisfy the following baseline restrictions: The individual is aged 24 to 50, has at least two years of tenure, she was not in marginal employment in the four years preceding displacement, and she works in an establishment which has at least 30 employees. Each displaced worker is assigned a non-displaced worker via 1:1 propensity score matching within gender, year and industry cells. Non-displaced workers come from a random sample of couples who satisfy the same baseline restrictions. Standard deviations in brackets.

Table 2: Summary Statistics for Displaced Women and Matched Controls with Information on Spouses in t=c-1

	(1) Non-Displaced Women	(2) Displaced Women	(3) Non-Displaced Women Husband Info	(4) Displaced Women Husband Info
Panel A: Individual Characteristics				
Years of education	11.4	11.4	11.6	11.5
	[1.5]	[1.5]	[1.7]	[1.6]
Potential experience	22.4	22.8	22.1	22.6
	[6.2]	[6.1]	[6.9]	[7.0]
Tenure with current employer	7.5	7.5	5.7	5.6
	[4.1]	[4.1]	[5.6]	[5.6]
Real daily wage in t=c-2	4.2	4.2	4.5	4.5
	[0.485]	[0.471]	[0.582]	[0.585]
Total yearly earnings in t=c-1	26999.8	26623.3	19204.8	18934.5
	[12004.7]	[11881.2]	[20368.5]	[20229.2]
Total yearly income	25675.6	24451.5	26653.3	25978.4
	[11834.4]	[11831.6]	[18391.6]	[18116.1]
Days per year working	363.2	343.0	277.7	274.8
	[14.0]	[48.2]	[147.6]	[148.1]
Days per year working fulltime	239.4	226.9	262.6	260.2
	[172.2]	[162.0]	[156.7]	[156.6]
Couple	1	1	1	1
	[0]	[0]	[0]	[0]
Panel B: Establishment Characteristics				
Firmsize	572.4	513.1	923.9	965.1
	[1177.0]	[867.8]	[3855.4]	[4080.4]
Share female workers	0.602	0.616	0.287	0.290
	[0.240]	[0.239]	[0.225]	[0.229]
Share fulltime workers	0.636	0.649	0.793	0.794
	[0.269]	[0.278]	[0.205]	[0.205]
Number of Observations	31806	31806	31806	31806

Notes: Characteristics of displaced and non-displaced women in year prior to displacement year. Workers satisfy the following baseline restrictions: The individual is aged 24 to 50, has at least two years of tenure, she was not in marginal employment in the four years preceding displacement, and she works in an establishment which has at least 30 employees. Each displaced woman is assigned a non-displaced woman via 1:1 propensity score matching within year and industry cells. Non-displaced women come from a random sample of couples who satisfy the same baseline restrictions. Corresponding characteristics of husbands in Columns (3) and (4). Standard deviations in brackets.

Table 3: Summary Statistics for Displaced Men and Matched Controls with Information on Spouses in t=c-1

	(1) Non-Displaced Men	(2) Displaced Men	(3) Non-Displaced Men Men Wife Info	(4) Displaced Men Men Wife Info
Panel A: Individual Characteristics				
Years of education	11.3	11.3	11.1	11.1
	[1.6]	[1.6]	[1.4]	[1.4]
Potential experience	21.8	21.9	17.8	17.8
	[6.2]	[6.2]	[6.6]	[6.6]
Tenure with current employer	7.7	7.7	4.3	4.2
	[4.4]	[4.5]	[4.7]	[4.6]
Real daily wage in t=c-2	4.5	4.5	3.5	3.5
	[0.360]	[0.356]	[0.976]	[0.985]
Total yearly earnings in t=c-1	37167.9	36677.8	8848.8	8903.2
	[12715.9]	[12881.5]	[12715.9]	[12881.5]
Total yearly income	35585.8	33729.2	12957.2	12925.9
	[13077.3]	[13388.0]	[13204.9]	[13297.4]
Days per year working	363.1	343.2	258.5	254.7
	[13.2]	[46.7]	[154.9]	[155.7]
Days per year working fulltime	356.3	335.5	107.1	108.0
	[50.3]	[64.4]	[161.3]	[160.8]
Couple	1	1	1	1
	[0]	[0]	[0]	[0]
Panel B: Establishment Characteristics				
Firmsize	277.4	281.3	409.5	417.2
	[714.4]	[616.4]	[1477.5]	[1461.2]
Share female workers	0.287	0.279	0.683	0.689
	[0.212]	[0.212]	[0.250]	[0.246]
Share fulltime workers	0.806	0.829	0.511	0.512
	[0.183]	[0.180]	[0.301]	[0.304]
Number of Observations	48849	48849	48849	48849

Notes: Characteristics of displaced and non-displaced men in year prior to displacement year. Workers satisfy the following baseline restrictions: The individual is aged 24 to 50, has at least two years of tenure, she was not in marginal employment in the four years preceding displacement, and she works in an establishment which has at least 30 employees. Each displaced man is assigned a non-displaced man via 1:1 propensity score matching within year and industry cells. Non-displaced men come from a random sample of couples who satisfy the same baseline restrictions. Corresponding characteristics of wifes in Columns (3) and (4). Standard deviations in brackets.

Table 4: Summary Statistics for Displaced Workers in ASU Sample in t=c-1

	(1) All	(2) All in ASU	(3) All with Child	(4) All w/o Child
Panel A: Individual Characteristics				
Log Wage in t=c-2*	4.40	4.35	4.40	4.33
	[0.444]	[0.431]	[0.441]	[0.426]
Earnings in t=c-1	32712.9	30761.5	32414.6	30104.6
	[13427.9]	[12689.0]	[13316.0]	[12370.1]
Days per Year Working Fulltime	292.7	290.1	288.3	290.8
	[125.2]	[119.4]	[122.8]	[118.0]
Days per Year Working Parttime	50.2	43.3	46.5	42.1
	[120.1]	[110.5]	[113.9]	[109.1]
Female	0.394	0.358	0.263	0.395
	[0.489]	[0.479]	[0.440]	[0.489]
Years of Education*	11.3	11.1	11.1	11.1
	[1.53]	[1.28]	[1.31]	[1.27]
Tenure*	7.67	7.97	7.93	7.99
	[4.31]	[4.46]	[4.37]	[4.49]
Age*	41.3	41.4	39.2	42.2
	[5.91]	[5.94]	[5.11]	[6.03]
Commuting Distance	35.4	27.1	26.5	27.3
	[82.4]	[70.8]	[68.4]	[71.7]
Has child under 7	0.085	0.080	0.281	0
	[0.278]	[0.271]	[0.450]	[0]
Has child aged 7 or older	0.233	0.237	0.719	0.045
	[0.422]	[0.425]	[0.450]	[0.208]
Panel B: Establishment Characteristics				
Log Firmsize*	4.94	4.57	4.59	4.57
	[1.23]	[0.876]	[0.884]	[0.873]
AKM Estab FE, 2003-2010	-0.222	-0.215	-0.187	-0.227
	[0.229]	[0.233]	[0.215]	[0.238]
Panel C: Household Characteristics				
Total Yearly Household Earnings	50176.3	45946.0	46419.3	45757.8
	[22208.4]	[20950.8]	[19169.9]	[21615.1]
Total Yearly Earnings - Partner	18915.1	17539.5	16218.5	18064.5
	[17708.0]	[17147.5]	[16177.4]	[17490.6]
Share of Household Income	68.1	68.3	70.0	67.6
	[25.6]	[26.2]	[25.1]	[26.6]
Same Establishment as Spouse	0.048	0.040	0.037	0.041
	[0.213]	[0.196]	[0.189]	[0.199]
Same Industry as Spouse	0.084	0.070	0.072	0.070
	[0.278]	[0.255]	[0.258]	[0.254]
Number of Individuals	80655	52929	15052	37877

Notes: This table summarizes characteristics of displaced workers in the ASU sample. Column (1) shows characteristics of all displaced workers. Column (2) shows all displaced workers who appear in the ASU sample. Column (3) shows all displaced workers in the ASU sample whose first child is aged 15 or younger in the year before displacement. Column (4) shows all displaced workers in the ASU sample without a child aged 15 or younger in the year before displacement. Variables with * are used in reweighting. Standard deviations in brackets.

Table 5: Summary Statistics for Nonemployed Workers in SMS Data

	(1) All	(2) All Non-Emp.	(3) All Non-Emp. with Child	(4) All Non-Emp. w/o Child
Panel A: Individual Characteristics				
Monthly Gross Earnings (Pre-UI)	1788.2	1789.2	1711.2	1821.0
	[1672.7]	[1671.0]	[1621.0]	[1690.0]
Log-Monthly Gross Earnings (Pre-UI)	7.51	7.50	7.41	7.54
	[0.724]	[0.724]	[0.715]	[0.725]
Indicator for Female	0.475	0.474	0.549	0.447
	[0.499]	[0.499]	[0.498]	[0.497]
Education years	9.93	9.93	9.90	9.94
	[1.23]	[1.23]	[1.22]	[1.23]
Indicator for Female	0.475	0.474	0.549	0.447
	[0.499]	[0.499]	[0.498]	[0.497]
Education years	9.93	9.93	9.90	9.94
	[1.23]	[1.23]	[1.22]	[1.23]
Pre-UI Tenure in Years	2.09	2.09	1.78	2.21
	[2.57]	[2.56]	[2.16]	[2.70]
Pre-UI Fulltime = 1	0.548	0.549	0.465	0.584
	[0.498]	[0.498]	[0.499]	[0.493]
Age in Years	43.2	43.2	41.3	43.9
	[8.01]	[8.01]	[7.16]	[8.22]
Has child under 7	0.116	0.116	0.443	0
	[0.320]	[0.321]	[0.497]	[0]
Has child aged 7 or older	0.207	0.208	0.557	0.084
	[0.405]	[0.406]	[0.497]	[0.277]
Panel B: Unemployment Characteristics				
Eligibility Duration in Months at UI-Start	10.1	10.1	9.49	10.4
	[3.16]	[3.16]	[2.78]	[3.25]
Nonemployment Duration at date of contact	6.69	6.70	6.48	6.77
	[3.39]	[3.38]	[3.23]	[3.44]
Months since UI exhaustion	-2.85	-2.88	-2.41	-3.05
	[3.71]	[3.71]	[3.42]	[3.79]
Total Nonempoyment Duration in Months	14.0	14.0	13.5	14.2
	[11.0]	[11.0]	[8.92]	[11.7]
Panel C: Household Characteristics				
Indicator for Married	0.429	0.429	0.637	0.341
	[0.495]	[0.495]	[0.481]	[0.474]
Number of Obs.	222844	217199	57050	160149

Notes: This table summarizes characteristics of the SMS data. Column (1) shows characteristics of all workers. Column (2) shows all nonemployed workers. Column (3) shows all nonemployed workers whose first child is aged 15 or younger at time of UI entry. Column (4) shows all nonemployed workers whose first child is older than 15 or without children at time of UI entry. Standard deviations in brackets.

Table 6: Industry Distribution for Displaced Workers and Matched Controls in t=c-1

	(1) All Workers Women	(2) Baseline Sample Women	(3) Reweighted Women	(4) All Workers Men	(5) Baseline Sample Men
Agriculture	0.0074	0.0020	0.00097	0.012	0.0015
	[0.086]	[0.045]	[0.031]	[0.108]	[0.039]
Mining, Energy	0.0050	0	0	0.017	0
	[0.070]	[0]	[0]	[0.131]	[0]
Food Manufacturing	0.027	0.050	0.028	0.022	0.039
	[0.162]	[0.218]	[0.166]	[0.148]	[0.194]
Consumption Goods	0.031	0.086	0.069	0.038	0.084
	[0.174]	[0.281]	[0.253]	[0.192]	[0.278]
Production Goods	0.023	0.038	0.083	0.069	0.096
	[0.151]	[0.191]	[0.276]	[0.253]	[0.294]
Investment Goods	0.046	0.073	0.138	0.166	0.171
	[0.210]	[0.260]	[0.345]	[0.372]	[0.377]
Construction	0.016	0	0	0.075	0
	[0.124]	[0]	[0]	[0.263]	[0]
Retail	0.180	0.215	0.123	0.136	0.148
	[0.384]	[0.411]	[0.329]	[0.343]	[0.355]
Traffic, Telecommunication	0.035	0.043	0.102	0.077	0.088
	[0.184]	[0.203]	[0.302]	[0.267]	[0.284]
Credit, Insurance	0.038	0.023	0.013	0.028	0.015
	[0.190]	[0.150]	[0.114]	[0.164]	[0.122]
Restaurants	0.055	0.019	0.0088	0.032	0.0082
	[0.228]	[0.137]	[0.094]	[0.176]	[0.090]
Education	0.052	0.126	0.025	0.026	0.026
	[0.221]	[0.332]	[0.155]	[0.160]	[0.160]
Health	0.191	0.060	0.012	0.045	0.012
	[0.393]	[0.238]	[0.108]	[0.207]	[0.109]
Commercial Services	0.150	0.151	0.337	0.169	0.251
	[0.358]	[0.358]	[0.473]	[0.374]	[0.434]
Other Services	0.053	0.024	0.032	0.035	0.029
	[0.223]	[0.154]	[0.176]	[0.184]	[0.169]
Non-Profit	0.024	0.025	0.015	0.013	0.015
	[0.153]	[0.155]	[0.123]	[0.113]	[0.121]
Public Administration	0.067	0.064	0.014	0.040	0.014
	[0.250]	[0.245]	[0.116]	[0.197]	[0.119]
Number of Observations	3939514	31806	31806	4178728	48849

This table summarizes the industry distribution of different samples of (displaced) men and women. Columns (1) and (4) show characteristics of a random sample of workers in Germany 2003-2012. Columns (2) and (5) represent all displaced workers in the couple dataset fulfilling our baseline restrictions. We measure characteristics in t=c. We exclude individuals working in the construction and mining sectors. Column (3) contains women in the couple dataset reweighted to men. Variables with * are used in reweighting. Standard deviations in brackets.

Table 7: Reweighting Variables by Gender - DFL Reweighted

	Female	Male	P-Value
Log Wage in t=c-2	4.598	4.543	8.71e-25
Log Wage in t=c-3	4.578	4.528	7.02e-21
Fulltime Employment in t=c-2	0.982	0.983	0.173
Years of Education	11.38	11.34	0.127
Tenure (yrs)	7.325	7.745	2.81e-13
Age (yrs)	40.39	40.99	3.11e-10
East Germany	0.226	0.210	0.00395
Baseline Log Firmsize	4.700	4.773	0.000000102
Agriculture	0.000966	0.00149	0.0342
Mining Energy	0	0	.
Food Manufacturing	0.0284	0.0391	6.32e-12
Consumption Goods	0.0685	0.0845	5.98e-10
Production Goods	0.0829	0.0959	0.00178
Investment Goods	0.138	0.171	2.52e-12
Construction	0	0	.
Retail	0.123	0.148	8.90e-13
Traffic Telecommunication	0.102	0.0884	0.0150
Credit Insurance	0.0131	0.0152	0.0265
Restaurants	0.00884	0.00823	0.450
Education	0.0247	0.0264	0.0810
Health	0.0119	0.0120	0.928
Commercial Services	0.337	0.251	2.19e-28
Other Services	0.0321	0.0294	0.264
Non-Profit	0.0154	0.0149	0.692
Public Administration	0.0136	0.0142	0.391
Number of Observations	31806	48849	0

Notes: Table shows the differences in reweighting variables for displaced women and displaced men in t=c-1. Women are reweighted to men. The last column shows the P-Value of an F-Test for equality of means.

Table 8: The Impact of Individual Control and Reweighting Variables on the Gender Gap in Earnings

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS
Panel A: Unadjusted Gender Gap									
Female	0.014	0.021	0.017	0.0037	-0.0030	-0.0072	-0.028	-0.051	-0.077
	(0.012)	(0.012)	(0.011)	(0.016)	(0.017)	(0.013)	(0.014)*	(0.011)**	(0.0072)**
Age in t=c-1		-0.0094	-0.0078	-0.0078	-0.0075	-0.0077	-0.0080	-0.0080	-0.0080
		(0.00063)**	(0.00078)**	(0.00080)**	(0.00078)**	(0.00072)**	(0.00071)**	(0.00078)**	(0.00075)**
Years of education in t=c-1		0.016	0.017	0.019	0.020	0.018	0.015	0.013	0.013
		(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.0076)
Tenure in t=c			-0.012	-0.012	-0.011	-0.011	-0.011	-0.0099	-0.0081
			(0.0016)**	(0.0017)**	(0.0017)**	(0.0015)**	(0.0015)**	(0.0016)**	(0.0011)**
Log wage in t=c-3				-0.037	0.17	0.17	0.19	0.17	0.15
				(0.016)*	(0.021)**	(0.022)**	(0.022)**	(0.022)**	(0.021)**
Log wage in t=c-4					-0.22	-0.22	-0.20	-0.21	-0.22
					(0.022)**	(0.022)**	(0.022)**	(0.022)**	(0.020)**
Working in East Germany in t=c-1						0.041	0.050	0.029	-0.014
						(0.024)	(0.024)*	(0.023)	(0.013)
Fulltime Employed in t=c-3							-0.100	-0.088	-0.075
							(0.013)**	(0.015)**	(0.015)**
Log(Firmsize) in t=c-1								0.043	0.029
								(0.011)**	(0.0082)**
Observations	80655	80655	80655	80655	80655	80655	80655	80655	80655
R^2	0.000	0.012	0.022	0.022	0.026	0.027	0.030	0.039	0.054
Mean of dep. var	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25
Industry Dummies	No	No	No	No	No	No	No	No	Yes

Notes: Each column in each panel returns the coefficients from a OLS regression. Controls correspond to PS matching variables: age, edyrs, tenure, log wage in t=c-3, log wage in t=c-4, working in East Germany, logfirmsize, fulltime employment in t=c-1, 1-digit industries. Standard Errors clustered on displacement establishment level (constant within matched worker pairs). * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 9: Explaining the Gender Gap in Wage Losses After Displacement: Reweighting with Separate Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Panel A: All Workers: Log Wage									
Female	-0.13	-0.11	-0.13	-0.11	-0.13	-0.12	-0.12	-0.096	-0.095
	(0.013)**	(0.012)**	(0.013)**	(0.013)**	(0.013)**	(0.012)**	(0.012)**	(0.011)**	(0.011)**
Parttime Job		-0.18						-0.17	-0.17
		(0.020)**						(0.018)**	(0.018)**
Minijob		-0.82						-0.70	-0.69
		(0.029)**						(0.026)**	(0.026)**
Industry Change			-0.14					-0.090	-0.084
			(0.011)**					(0.010)**	(0.0098)**
Occ. Change			-0.13					-0.082	-0.077
			(0.0096)**					(0.0084)**	(0.0081)**
Log Estab Size				0.059				0.036	0.032
				(0.0040)**				(0.0032)**	(0.0035)**
Estab Share Women				-0.41				-0.22	-0.20
				(0.034)**				(0.027)**	(0.027)**
Commut. Distance					-0.000011			-0.000069	-0.000064
					(0.000070)			(0.000060)	(0.000061)
AKM Estab FE						1.06	1	0.83	1
						(0.064)**		(0.057)**	
Observations	73598	73598	73598	73598	73598	73598	73598	73598	73598
R^2	0.010	0.140	0.043	0.083	0.034	0.157	0.038	0.319	0.219
Mean Dep. Var Men	-.201	-.201	-.201	-.201	-.201	-.201	-.201	-.201	
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	
Panel B: Full-time Workers: Full-time Log Wage									
Female	-0.039	-0.039	-0.038	-0.035	-0.039	-0.032	-0.030	-0.030	-0.028
	(0.0084)**	(0.0084)**	(0.0084)**	(0.0085)**	(0.0084)**	(0.0075)**	(0.0075)**	(0.0076)**	(0.0076)**
Industry Change			-0.053					-0.031	-0.021
			(0.0068)**					(0.0067)**	(0.0062)**
Occ. Change			-0.022					-0.0096	-0.0019
			(0.0059)**					(0.0054)	(0.0050)
Log Estab Size				0.025				0.012	0.0053
				(0.0023)**				(0.0018)**	(0.0027)*
Estab Share Women				-0.14				-0.056	-0.024
				(0.018)**				(0.016)**	(0.015)
Commut. Distance					0.000066			0.000054	0.000066
					(0.000043)			(0.000040)	(0.000041)
AKM Estab FE						0.74	1	0.70	1
						(0.055)**		(0.055)**	
Observations	52996	52996	52996	52996	52996	52996	52996	52996	52996
R^2	0.003	0.003	0.014	0.030	0.004	0.220	0.011	0.228	0.015
Mean Dep. Var Men	-.094	-.094	-.094	-.094	-.094	-.094	-.094	-.094	
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	

Notes: This table shows to what extent changes in contract type, industry, occupation, and establishment characteristics can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. We reweight women to men using individual and establishment characteristics pre displacement. In Panel A, the outcome variable is log wages. In Panel B, the outcome variable is full-time log wages. In both panels, we control for the same set of difference-in-differences estimates as depicted in the table. Columns (2)-(6) control for various difference-in-differences terms. Column (7) controls for all difference-in-differences terms at once. In columns (6) and (8), the coefficient on the establishment effect is forced to be equal to 1. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 10: Explaining the Gender Gap in Wage Losses After Displacement: Reg. Adjustment Instead of Weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Workers: Log Wage								
Female	-0.17	-0.16	-0.15	-0.17	-0.15	-0.15	-0.13	-0.13
	(0.0098)**	(0.0095)**	(0.0095)**	(0.0097)**	(0.0090)**	(0.0087)**	(0.0084)**	(0.0082)**
Industry Change		-0.10					-0.082	-0.079
		(0.0056)**					(0.0047)**	(0.0046)**
Occ. Change		-0.11					-0.091	-0.086
		(0.0053)**					(0.0045)**	(0.0045)**
Log Estab Size			0.066				0.046	0.041
			(0.0027)**				(0.0025)**	(0.0021)**
Estab Share Women			-0.31				-0.23	-0.22
			(0.018)**				(0.016)**	(0.016)**
Commute Distance				0.00010			-0.000013	-0.000015
				(0.000031)**			(0.000030)	(0.000031)
AKM Estab FE					0.93	1	0.80	1
					(0.043)**		(0.038)**	
Observations	73598	73598	73598	73598	73598	73598	73598	73598
R^2	0.058	0.082	0.125	0.085	0.177	0.063	0.247	0.138
Mean Dep. Var Men	-.201	-.201	-.201	-.201	-.201	-.201	-.201	-.201
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Panel B: Full-time Workers: Full-time Log Wage								
Female	-0.045	-0.045	-0.040	-0.044	-0.030	-0.023	-0.028	-0.022
	(0.0052)**	(0.0052)**	(0.0052)**	(0.0053)**	(0.0049)**	(0.0048)**	(0.0048)**	(0.0048)**
Industry Change		-0.033					-0.022	-0.016
		(0.0031)**					(0.0033)**	(0.0033)**
Occ. Change		-0.021					-0.011	-0.0029
		(0.0027)**					(0.0025)**	(0.0023)
Log Estab Size			0.028				0.014	0.0063
			(0.0013)**				(0.0017)**	(0.0011)**
Estab Share Women			-0.10				-0.043	-0.010
			(0.0092)**				(0.0085)**	(0.0081)
Commute Distance				0.00015			0.000100	0.000094
				(0.000023)**			(0.000021)**	(0.000025)**
AKM Estab FE					0.67	1	0.64	1
					(0.043)**		(0.043)**	
Observations	52996	52996	52996	52996	52996	52996	52996	52996
R^2	0.068	0.073	0.095	0.070	0.252	0.037	0.261	0.040
Mean Dep. Var Men	-.094	-.094	-.094	-.094	-.094	-.094	-.094	-.094
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)

Notes: This table shows to what extent changes in industry, occupation, and establishment characteristics can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. We control for individual and establishment characteristics pre displacement. In panel (A), the outcome variable is log wages. In panel (B), the outcome variable is full-time log wages. In both panels, we control for the same set of difference-in-differences estimates as depicted in the table. Columns (2)-(6) control for various difference-in-differences terms. Column (8) controls for all difference-in-differences terms at once. In columns (6) and (8), the coefficient on the establishment effect is forced to be equal to 1. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 11: Explaining the Gender Gap in Wage Losses After Displacement: Wage Premia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All Workers: Log Wage							
Female	-0.13	-0.12	-0.12	-0.10	-0.12	-0.12	-0.14
	(0.013)**	(0.012)**	(0.012)**	(0.012)**	(0.013)**	(0.013)**	(0.013)**
AKM Estab FE		1.06	1				
		(0.064)**					
AKM Estab FE - Gender				0.92	1		
				(0.078)**			
AKM Estab FE Kmeans						0.78	1
						(0.091)**	
Observations	73598	73598	73598	73598	73598	73598	73598
R^2	0.010	0.157	0.038	0.148	0.035	0.056	0.027
Mean Dep. Var Men	-.201	-.201	-.201	-.201	-.201	-.201	-.201
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Panel B: Fulltime Workers: Full-time Log Wage							
Female	-0.039	-0.032	-0.030	-0.024	-0.022	-0.038	-0.039
	(0.0084)**	(0.0075)**	(0.0075)**	(0.0080)**	(0.010)*	(0.0080)**	(0.0082)**
AKM Estab FE		0.74	1				
		(0.055)**					
AKM Estab FE - Gender				0.70	1		
				(0.063)**			
AKM Estab FE Kmeans						0.65	1
						(0.078)**	
Observations	52996	52996	52996	52996	52996	52996	52996
R^2	0.003	0.220	0.011	0.222	0.009	0.096	0.005
Mean Dep. Var Men	-.094	-.094	-.094	-.094	-.094	-.094	-.094
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)

Notes: This table shows to what extent changes in different wage premia measured by AKM-style establishment FE can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. We reweight women to men using individual and establishment characteristics pre displacement. In panel (A), the outcome variable is log wages. In panel (B), the outcome variable is full-time log wages. In both panels, we control for the same set of difference-in-differences estimates as depicted in the table. In columns (3), (5), and (7), the coefficient on the establishment effect is forced to be equal to 1. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 12: Explaining the Gender Gap in Wage Losses After Displacement: Estab. Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All Workers: Log Wage							
Female	-0.13	-0.14	-0.13	-0.13	-0.14	-0.13	-0.14
	(0.013)**	(0.013)**	(0.013)**	(0.013)**	(0.013)**	(0.013)**	(0.012)**
Turnover Rate		-0.24					-0.23
		(0.031)**					(0.033)**
Separation Rate		-0.20					-0.20
		(0.049)**					(0.048)**
Firm Age in t=c			-0.0013				0.00030
			(0.00068)				(0.00068)
New Estab				-0.024			0.0056
				(0.016)			(0.015)
Business Service Estab					-0.23		-0.22
					(0.020)**		(0.027)**
Temp Work						-0.13	0.25
						(0.021)**	(0.033)**
Observations	73598	73598	73598	73598	73598	73598	73598
R^2	0.010	0.065	0.010	0.019	0.027	0.020	0.071
Mean Dep. Var Men	-.201	-.201	-.201	-.201	-.201	-.201	-.201
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Panel B: Fulltime Workers: Fulltime Log Wage							
Female	-0.039	-0.046	-0.042	-0.039	-0.044	-0.040	-0.049
	(0.0084)**	(0.0081)**	(0.0083)**	(0.0084)**	(0.0084)**	(0.0084)**	(0.0080)**
Turnover Rate		-0.18					-0.15
		(0.016)**					(0.016)**
Separation Rate		-0.038					-0.044
		(0.025)					(0.025)
Firm Age in t=c			-0.0012				-0.00053
			(0.00038)**				(0.00035)
New Estab				-0.015			0.0036
				(0.0085)			(0.0074)
Business Service Estab					-0.18		-0.10
					(0.013)**		(0.017)**
Temp Work						-0.24	-0.048
						(0.015)**	(0.021)*
Observations	52996	52996	52996	52996	52996	52996	52996
R^2	0.003	0.060	0.004	0.003	0.024	0.021	0.069
Mean Dep. Var Men	-.094	-.094	-.094	-.094	-.094	-.094	-.094
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)

Notes: This table shows to what extent firms' turnover and separation rates, switches to new establishments (younger than 6 years), displacement establishment's age, switches to business service establishments, and switches to temp work can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. We reweight women to men using individual and establishment characteristics pre displacement. In Panel A, the outcome variable is log wages. In Panel B, the outcome variable is full-time log wages. In both panels, we control for the same set of difference-in-differences estimates as depicted in the table. Columns (2)-(6) control for various difference-in-differences terms. Column (7) controls for all difference-in-differences terms at once. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 13: The Gender Gap in Job Search Preferences: Adding Job Search Info

	(1) Mean Outcome Men		(2) Unadjusted Gender Gap		(3) Composition Adjusted Gender Gap Regression-Adj.		(4) Composition Adjusted Gender Gap Reweighted		(5) Number of Observations	(6) Data Source
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.		
Panel A: All										
Has Job Search Spell	0.696	[0.0096]	**-0.101**	[0.022]	**-0.020**	[0.0060]	**-0.032**	[0.0098]	80,655	ASU
Seeking full-time job	0.979	[0.0016]	**-0.314**	[0.0061]	**-0.136**	[0.0054]	**-0.113**	[0.0060]	45,087	ASU
Seeking any (full- or parttime) employment	0.018	[0.0015]	**0.093**	[0.0041]	**0.058**	[0.0045]	**0.047**	[0.0041]	45,087	ASU
Broad geographic search	0.439	[0.0051]	**-0.040**	[0.0073]	**-0.024**	[0.0085]	-0.019	[0.012]	31,349	ASU
Permanent contract	0.745	[0.0075]	**-0.035**	[0.0091]	**0.020**	[0.0094]	-0.0066	[0.010]	45,131	ASU
Any (fixed or permanent) Contract	0.255	[0.0075]	**0.035**	[0.0091]	**-0.020**	[0.0094]	0.0066	[0.010]	45,131	ASU
Minutes job search	94.0	[1.62]	**-18.0**	[2.09]	**-7.05**	[2.21]	**-9.18**	[2.68]	116,159	SMS
Target wage ratio	1.17	[0.016]	**0.077**	[0.023]	**-0.097**	[0.022]	**-0.054**	[0.027]	5,541	SMS
Log-Target wage ratio	0.075	[0.012]	**0.053**	[0.018]	**-0.084**	[0.017]	**-0.054**	[0.024]	5,541	SMS
Log Target Wage	7.90	[0.013]	**-0.315**	[0.019]	**-0.172**	[0.018]	**-0.172**	[0.026]	8,533	SMS
Life Satisfaction (Scale 1-5)	2.99	[0.022]	**0.117**	[0.031]	**0.148**	[0.035]	**0.154**	[0.039]	14,158	SMS
Panel B: Age Youngest Child ≤ 15										
Has Job Search Spell	0.675	[0.0089]	**-0.070**	[0.020]	-0.0065	[0.011]	0.016	[0.019]	22,966	ASU
Seeking full-time job	0.981	[0.0019]	**-0.550**	[0.011]	**-0.323**	[0.013]	**-0.272**	[0.020]	12,735	ASU
Seeking any (full- or parttime) employment	0.016	[0.0018]	**0.091**	[0.0063]	**0.068**	[0.0087]	**0.065**	[0.0099]	12,735	ASU
Broad geographic search	0.446	[0.0073]	**-0.050**	[0.013]	-0.032	[0.018]	**-0.069**	[0.028]	8,884	ASU
Permanent contract	0.759	[0.0083]	**-0.081**	[0.013]	-0.028	[0.016]	**-0.095**	[0.023]	12,731	ASU
Any (fixed or permanent) Contract	0.241	[0.0083]	**0.081**	[0.013]	0.028	[0.016]	**0.095**	[0.023]	12,731	ASU
Minutes job search	91.5	[3.37]	**-22.2**	[3.94]	-3.15	[3.93]	-8.28	[6.00]	30,581	SMS
Target wage ratio	1.20	[0.031]	**0.132**	[0.044]	**-0.118**	[0.047]	**-0.168**	[0.074]	1,607	SMS
Log-Target wage ratio	0.098	[0.024]	**0.087**	[0.034]	**-0.108**	[0.034]	**-0.169**	[0.067]	1,607	SMS
Log Target Wage	7.96	[0.028]	**-0.447**	[0.038]	**-0.209**	[0.035]	-0.136	[0.089]	2,200	SMS
Life Satisfaction (Scale 1-5)	3.08	[0.050]	**0.142**	[0.062]	**0.197**	[0.072]	**0.191**	[0.094]	3,663	SMS
Panel C: Age Youngest Child > 15/No Children										
Has Job Search Spell	0.706	[0.011]	**-0.114**	[0.023]	**-0.024**	[0.0062]	**-0.046**	[0.011]	57,689	ASU
Seeking full-time job	0.978	[0.0019]	**-0.252**	[0.0061]	**-0.103**	[0.0055]	**-0.085**	[0.0057]	32,352	ASU
Seeking any (full- or parttime) employment	0.019	[0.0018]	**0.093**	[0.0044]	**0.056**	[0.0049]	**0.043**	[0.0043]	32,352	ASU
Broad geographic search	0.435	[0.0056]	**-0.036**	[0.0080]	**-0.021**	[0.0092]	-0.0093	[0.013]	22,465	ASU
Permanent contract	0.738	[0.0078]	**-0.020**	[0.0095]	**0.030**	[0.0098]	0.013	[0.011]	32,400	ASU
Any (fixed or permanent) Contract	0.262	[0.0078]	**0.020**	[0.0095]	**-0.030**	[0.0098]	-0.013	[0.011]	32,400	ASU
Minutes job search	94.7	[1.84]	**-15.8**	[2.49]	**-7.64**	[2.63]	**-8.89**	[3.00]	85,578	SMS
Target wage ratio	1.16	[0.018]	0.046	[0.027]	**-0.087**	[0.024]	-0.032	[0.028]	3,934	SMS
Log-Target wage ratio	0.068	[0.014]	0.032	[0.021]	**-0.071**	[0.019]	-0.029	[0.024]	3,934	SMS
Log Target Wage	7.89	[0.014]	**-0.267**	[0.022]	**-0.149**	[0.021]	**-0.157**	[0.027]	6,333	SMS
Life Satisfaction (Scale 1-5)	2.96	[0.025]	**0.093**	[0.036]	**0.127**	[0.040]	**0.147**	[0.043]	10,495	SMS

Notes: Each row represents a separate regression of the outcome variable on a constant and a dummy for female for a sample of displaced workers, only. In Panels B and C we restrict the sample to individuals with young children $\leq$ the age of 15 and above the age of 15 respectively. Data source ASU refers to the job-search preference data collected by the caseworkers at the local UI agency and is based on the subset of about 70% workers of the baseline job-loss sample for whom this information is available. SMS refers to the high-frequency job-search data among unemployed workers between 2017 and 2019 as collected and described in DellaVigna et al. 2022, with number of observations referring to the person $\times$ survey-date level. The first column shows the constant, representing the mean effect for men. The second column the coefficient on a female dummy without any controls. The third column the coefficient on the female dummy controlling for all covariates. The fourth column uses reweighting. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Coefficients in bold are statistically significant at the 5%-level.

Table 14: Explaining the Gender Gap in Wage Losses After Displacement: Job Search Info

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Workers: Log Wage						
Female	-0.13	-0.19	-0.18	-0.19	-0.19	-0.18
	(0.013)**	(0.016)**	(0.017)**	(0.016)**	(0.016)**	(0.017)**
Fulltime Employment			-0.18			-0.10
			(0.019)**			(0.080)
Parttime Employment			-0.41			-0.34
			(0.046)**			(0.091)**
Any Employment			-0.24			-0.18
			(0.040)**			(0.086)*
Permanent Contract				-0.19		0.036
				(0.021)**		(0.096)
Any Contract				-0.16		-0.041
				(0.021)**		(0.080)
All Regions					-0.084	-0.10
					(0.020)**	(0.035)**
Narrow Regions					-0.13	-0.15
					(0.019)**	(0.035)**
Observations	73598	47319	47319	47319	47319	47319
R^2	0.010	0.017	0.029	0.026	0.023	0.031
Mean Dep. Var Men	-.201	-.289	-.289	-.289	-.289	-.289
	(.003)	(.004)	(.004)	(.004)	(.004)	(.004)
Panel B: Fulltime Workers: Fulltime Log Wage						
Female	-0.039	-0.070	-0.063	-0.070	-0.069	-0.062
	(0.0084)**	(0.010)**	(0.010)**	(0.010)**	(0.010)**	(0.010)**
Fulltime Employment			-0.084			-0.080
			(0.013)**			(0.033)*
Parttime Employment			-0.24			-0.23
			(0.063)**			(0.069)**
Any Employment			-0.14			-0.14
			(0.023)**			(0.038)**
Permanent Contract				-0.088		0.033
				(0.013)**		(0.036)
Any Contract				-0.076		0.0078
				(0.014)**		(0.033)
All Regions					-0.033	-0.031
					(0.011)**	(0.022)
Narrow Regions					-0.055	-0.051
					(0.011)**	(0.022)*
Observations	52996	34325	34325	34325	34325	34325
R^2	0.003	0.009	0.019	0.016	0.013	0.020
Mean Dep. Var Men	-.094	-.143	-.143	-.143	-.143	-.143
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)

Notes: This table shows to what extent job search characteristics can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. We reweight women to men using individual and establishment characteristics pre displacement. In Panel A, the outcome variable is log wages. In Panel B, the outcome variable is fulltime log wages. In both panels, we control for the same set of job search characteristics as depicted in the table. In Columns (2)-(6), we restrict the sample to individuals with at least one job search spell. For each job search characteristic, the omitted category is "missing information". We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 15: Kitagawa-Oaxaca-Blinder Decomposition with Full Sample

	Log Wage		Log Full-time Wage	
	(1)	(2)	(3)	(4)
Panel A: Endowments				
overall				
difference	-0.13	100.0	-0.039	100.0
	(0.016)**	(11.8)**	(0.014)**	(35.4)**
endowments				
Parttime - Diff-Diff	-0.0084	6.31		
	(0.0012)**	(0.90)**		
Minijobs - Diff-Diff	-0.0079	5.91		
	(0.0024)**	(1.81)**		
Industry Change	-0.0033	2.49	-0.0011	2.86
	(0.00083)**	(0.62)**	(0.00040)**	(1.02)**
Occ. Change	0.0028	-2.12	0.00059	-1.51
	(0.00081)**	(0.61)**	(0.00021)**	(0.53)**
Log Establishment Size	-0.0013	0.96	0.000018	-0.045
	(0.0012)	(0.93)	(0.00040)	(1.03)
Estab Share Women	-0.0089	6.71	-0.0012	3.18
	(0.0012)**	(0.94)**	(0.00032)**	(0.81)**
Commute Distance	-0.0000017	0.0013	0.000028	-0.072
	(0.000016)	(0.012)	(0.00015)	(0.39)
AKM Estab FE	-0.0066	4.94	-0.0072	18.2
	(0.0039)	(2.90)	(0.0035)*	(9.01)*
Observations	73598	73598	52996	52996
Total	-.035	26.258	-.009	22.492
Panel B: Coefficients				
overall				
difference	-0.13	100.0	-0.039	100.0
	(0.016)**	(11.8)**	(0.014)**	(35.4)**
coefficients				
Parttime - Diff-Diff	0.0022	-1.67		
	(0.0013)	(0.97)		
Minijobs - Diff-Diff	-0.0080	6.05		
	(0.0021)**	(1.58)**		
Industry Change	-0.021	15.8	-0.0083	21.2
	(0.014)	(10.4)	(0.015)	(37.7)
Occ. Change	-0.014	10.5	-0.00034	0.87
	(0.0074)	(5.56)	(0.0074)	(18.8)
Log Establishment Size	-0.0058	4.38	-0.0044	11.3
	(0.0056)	(4.24)	(0.0047)	(12.1)
Estab Share Women	-0.0013	0.94	-0.0014	3.58
	(0.0034)	(2.59)	(0.0024)	(6.18)
Commute Distance	-0.00035	0.26	-0.000052	0.13
	(0.00045)	(0.34)	(0.00054)	(1.37)
AKM Estab FE	0.0032	-2.44	-0.0080	20.5
	(0.0044)	(3.32)	(0.0057)	(14.7)
Observations	73598	73598	52996	52996
Total	-.098	73.742	-.03	77.508

Notes: This table uses a Kitagawa-Oaxaca-Blinder decomposition to show to what extent changes in contract type, industry, occupation, and establishment characteristics can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. In all columns, we reweight women to men using individual and establishment characteristics pre displacement. Panel A shows the explained part, or endowment effects. Panel B shows the unexplained part, or coefficient effects. Columns (1) and (2) report coefficients for log wages as outcome variable. In columns (3) and (4), the outcome variable is log wages from full-time employment. Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Standard errors (in brackets) are clustered at the dispalcement establishment level (constant within matched worker pairs). * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 16: Kitagawa-Oaxaca-Blinder Decomposition for Couples without Children pre Displacement

	Log Wage		Log Full-time Wage	
	(1)	(2)	(3)	(4)
Panel A: Endowments				
overall				
difference	-0.10	100.0	-0.025	100.0
	(0.018)**	(17.5)**	(0.014)	(55.1)
endowments				
Parttime - Diff-Diff	-0.0072	7.14		
	(0.0013)**	(1.25)**		
Minijobs - Diff-Diff	-0.0068	6.76		
	(0.0032)*	(3.15)*		
Industry Change	-0.0039	3.88	-0.0012	4.67
	(0.0010)**	(1.00)**	(0.00045)**	(1.77)**
Occ. Change	0.0025	-2.52	0.00057	-2.23
	(0.00093)**	(0.92)**	(0.00024)*	(0.93)*
Log Establishment Size	-0.00046	0.45	0.00011	-0.44
	(0.0014)	(1.38)	(0.00036)	(1.40)
Estab Share Women	-0.011	11.3	-0.0016	6.33
	(0.0016)**	(1.58)**	(0.00038)**	(1.52)**
Commute Distance	0.0000082	-0.0081	-0.000097	0.38
	(0.000037)	(0.036)	(0.00021)	(0.84)
AKM Estab FE	-0.0021	2.09	-0.0039	15.3
	(0.0042)	(4.12)	(0.0038)	(15.1)
Observations	49904	49904	35549	35549
Total	-.029	28.746	-.006	23.574
Panel B: Coefficients				
overall				
difference	-0.10	100.0	-0.025	100.0
	(0.018)**	(17.5)**	(0.014)	(55.1)
coefficients				
Parttime - Diff-Diff	0.0018	-1.81		
	(0.0013)	(1.32)		
Minijobs - Diff-Diff	-0.0063	6.23		
	(0.0022)**	(2.18)**		
Industry Change	-0.027	26.8	-0.012	47.8
	(0.015)	(15.3)	(0.015)	(58.2)
Occ. Change	-0.011	10.5	-0.00095	3.72
	(0.0085)	(8.47)	(0.0079)	(31.2)
Log Establishment Size	-0.0067	6.69	-0.0062	24.4
	(0.0064)	(6.30)	(0.0050)	(19.7)
Estab Share Women	0.0011	-1.04	-0.0017	6.71
	(0.0040)	(3.98)	(0.0025)	(9.85)
Commute Distance	-0.00020	0.20	-0.000014	0.055
	(0.00038)	(0.38)	(0.00032)	(1.27)
AKM Estab FE	0.0066	-6.59	-0.0060	23.7
	(0.0047)	(4.62)	(0.0061)	(23.8)
Observations	49904	49904	35549	35549
Total	-.072	71.254	-.019	76.426

Notes: This table uses a Kitagawa-Oaxaca-Blinder decomposition to show to what extent changes in contract type, industry, occupation, and establishment characteristics can explain the effect of being female on wages after displacement. We restrict the sample to couples without children in the year before displacement. All outcome variables are based on the individual difference-in-differences estimate. In all columns, we reweight women to men using individual and establishment characteristics pre displacement. Panel A shows the explained part, or endowment effects. Panel B shows the unexplained part, or coefficient effects. Columns (1) and (2) report coefficients for log wages as outcome variable. In columns (3) and (4), the outcome variable is log wages from full-time employment. Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Standard errors (in brackets) are clustered at the dispalcement establishment level (constant within matched worker pairs). * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 17: Kitagawa-Oaxaca-Blinder Decomposition for Couples with Children pre Displacement

	Log Wage		Log Full-time Wage	
	(1)	(2)	(3)	(4)
Panel A: Endowments				
overall				
difference	-0.22	100.0	-0.079	100.0
	(0.027)**	(12.6)**	(0.037)*	(46.8)*
endowments				
Parttime - Diff-Diff	-0.014	6.26		
	(0.0031)**	(1.42)**		
Minijobs - Diff-Diff	-0.0086	3.93		
	(0.0035)*	(1.61)*		
Industry Change	-0.0021	0.95	-0.0013	1.70
	(0.0011)	(0.52)	(0.00071)	(0.90)
Occ. Change	0.0046	-2.09	0.00084	-1.07
	(0.0015)**	(0.68)**	(0.00046)	(0.58)
Log Establishment Size	-0.00081	0.37	0.00095	-1.21
	(0.0023)	(1.07)	(0.0012)	(1.49)
Estab Share Women	-0.0035	1.60	-0.00030	0.38
	(0.0013)**	(0.58)**	(0.00039)	(0.50)
Commute Distance	0.00017	-0.080	0.00034	-0.43
	(0.00023)	(0.10)	(0.00029)	(0.37)
AKM Estab FE	-0.016	7.35	-0.014	18.3
	(0.0071)*	(3.26)*	(0.0073)*	(9.24)*
Observations	23694	23694	17447	17447
Total	-.044	20.176	-.014	17.866
Panel B: Coefficients				
overall				
difference	-0.22	100.0	-0.079	100.0
	(0.027)**	(12.6)**	(0.037)*	(46.8)*
coefficients				
Parttime - Diff-Diff	0.0041	-1.88		
	(0.0033)	(1.49)		
Minijobs - Diff-Diff	-0.011	5.10		
	(0.0044)*	(2.00)*		
Industry Change	0.018	-8.34	0.018	-23.4
	(0.023)	(10.4)	(0.039)	(49.6)
Occ. Change	-0.028	12.8	0.0019	-2.45
	(0.011)*	(5.13)*	(0.014)	(18.1)
Log Establishment Size	-0.0030	1.39	-0.0017	2.15
	(0.010)	(4.72)	(0.011)	(13.5)
Estab Share Women	-0.0026	1.20	0.00032	-0.40
	(0.0043)	(1.95)	(0.0036)	(4.55)
Commute Distance	-0.0015	0.67	-0.0013	1.70
	(0.0017)	(0.80)	(0.0044)	(5.58)
AKM Estab FE	-0.010	4.65	-0.015	18.6
	(0.010)	(4.78)	(0.015)	(19.7)
Observations	23694	23694	17447	17447
Total	-.174	79.824	-.065	82.134

Notes: This table uses a Kitagawa-Oaxaca-Blinder decomposition to show to what extent changes in contract type, industry, occupation, and establishment characteristics can explain the effect of being female on wages after displacement. We restrict the sample to couples with children in the year before displacement. All outcome variables are based on the individual difference-in-differences estimate. In all columns, we reweight women to men using individual and establishment characteristics pre displacement. Panel A shows the explained part, or endowment effects. Panel B shows the unexplained part, or coefficient effects. Columns (1) and (2) report coefficients for log wages as outcome variable. In columns (3) and (4), the outcome variable is log wages from full-time employment. Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Standard errors (in brackets) are clustered at the dispalcement establishment level (constant within matched worker pairs). * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 18: Household Outcomes and Added Worker Effect

	(1) Partner Earn. Rel. To Job Loser's in t=c-1	(2) Partner Log Wage	(3) Partner Days Worked	(4) Partner Days Worked Fulltime	(5) Household Earnings Rel. To t=c-1
Panel A: Unadjusted Gender Gap					
Female*Displaced	-0.045	-0.018	3.28	-8.07	0.045
	(0.0087)**	(0.0071)*	(1.89)	(1.68)**	(0.0098)**
Observations	161310	93392	161310	161310	161310
Mean Dep. Var Men	-.02	.005	-15.949	-4.124	-.224
	(.003)	(.006)	(1.843)	(.982)	(.007)
Panel B: Adjusted Gender Gap, Reweighted					
Female*Displaced	-0.019	0.0016	8.85	-2.63	-0.025
	(0.033)	(0.013)	(3.47)*	(3.36)	(0.025)
Observations	161310	93392	161310	161310	161310
Mean Dep. Var Men	-.02	.005	-15.949	-4.124	-.224
	(.003)	(.006)	(1.843)	(.982)	(.007)
Panel C: Regression Adjusted Gender Gap					
Female*Displaced	-0.042	-0.018	4.20	-7.55	0.048
	(0.0088)**	(0.0071)*	(1.93)*	(1.71)**	(0.0100)**
Observations	161310	93392	161310	161310	161310
Mean Dep. Var Men	-.02	.005	-15.949	-4.124	-.224
	(.003)	(.006)	(1.843)	(.982)	(.007)
Panel D: Regression Adjusted Gender Gap If Partner Is Full-time Worker					
Female*Displaced	-0.045	-0.012	3.61	-0.54	0.027
	(0.011)**	(0.0082)	(2.52)	(2.63)	(0.0097)**
Observations	75097	54759	75097	75097	75097
Mean Dep. Var Men	-.039	-.006	-18.771	-15.778	-.189
	(.007)	(.008)	(2.123)	(2.164)	(.008)
Panel E: Regression Adjusted Gender Gap If Partner Is Part-time Worker or Unemployed					
Female*Displaced	0.016	0.030	13.9	2.60	0.033
	(0.013)	(0.029)	(2.87)**	(2.28)	(0.013)*
Observations	86213	38633	86213	86213	86213
Mean Dep. Var Men	-.013	.012	-15.138	.245	-.24
	(.004)	(.008)	(1.372)	(.789)	(.004)
Panel F: Regression Adj. Gender Gap, Partners Working in Different Industries					
Female*Displaced	-0.032	-0.017	4.44	-5.88	0.054
	(0.0091)**	(0.0074)*	(1.97)*	(1.77)**	(0.0099)**
Observations	147305	83540	147305	147305	147305
Mean Dep. Var Men	-.012	.015	-12.16	-1.983	-.22
	(.005)	(.005)	(1.241)	(1.028)	(.004)
Panel G: Regression Adj. Gender Gap, Partners Working in Same Industry					
Female*Displaced	-0.11	0.0091	12.4	-16.6	-0.00018
	(0.030)**	(0.022)	(7.21)	(6.19)**	(0.024)
Observations	14005	9852	14005	14005	14005
Mean Dep. Var Men	-.104	-.094	-58.603	-27.715	-.263
	(.017)	(.015)	(4.17)	(3.872)	(.013)

Notes: This table shows household outcomes after displacement from regressions based on the full sample of workers (displaced and non-displaced workers). All outcome variables are based on the individual first differences estimate. Panel A shows the raw gender gap without controls. Panel B shows the adjusted gender gap using reweighting. Panel C shows the regression adjusted gender gap. Panel D shows the gender gap adjusting if the partner is a full-time worker in t=c-1. Panel E shows the gender gap adjusting if the partner is not a full-time worker (e.g., part-time employed or unemployed) in t=c-1. Panel F shows the regression adjusted gender gap for couples where both partners worked in different 2-digit industries in the year before displacement. Panel G shows the regression adjusted gender gap for couples where both partners worked in the same 2-digit industry in the year before displacement. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 19: The Gender Gap in Earnings Losses - Robustness Checks: More Outcomes

	(1) Baseline	(2) 10 Years Post Displ.	(3) Shorter Tenure Restr.	(4) Mahalanobis And Exact Matching	(5) Reweight. With Occupations	(6) Displ. Estab. FE	(7) Matching Without Wages	(8) Reweight. Men to Women	(9) Non Couples	(10) Couples + Non-Couples
Panel A: Days Worked										
Female	-7.05	-2.17	-12.5	-3.36	-10.4	-5.85	-6.36	5.76	3.08	-3.46
	(2.13)**	(2.63)	(2.05)**	(2.15)	(5.48)	(1.93)**	(2.20)**	(3.51)	(3.50)	(3.45)
Observations	80655	55107	93755	80707	80423	77144	80706	78695	16422	96158
R^2	0.001	0.000	0.002	0.000	0.002	0.330	0.001	0.000	0.000	0.000
Mean Dep. Var Men	-67.66	-49.787	-69.259	-67.125	-67.66	-67.66	-67.588	-67.676	-81.858	-78.058
	(.585)	(.751)	(.553)	(.582)	(.585)	(.585)	(.586)	(.586)	(1.376)	(.567)
Panel B: Days Worked Parttime										
Female	11.3	25.6	12.6	2.08	12.0	9.34	6.27	22.5	7.64	10.5
	(1.66)**	(2.59)**	(1.58)**	(1.45)	(2.97)**	(1.56)**	(1.83)**	(4.37)**	(2.28)**	(2.28)**
Observations	80655	55107	93755	80707	80423	77144	80706	78695	16422	96158
R^2	0.003	0.012	0.003	0.000	0.003	0.300	0.001	0.005	0.001	0.002
Mean Dep. Var Men	-.154	1.18	.03	-.297	-.154	-.154	-.127	.04	-1.736	-1.682
	(.559)	(.702)	(.522)	(.523)	(.559)	(.559)	(.555)	(.547)	(1.145)	(.497)
Panel C: Days Worked in Mini-job										
Female	4.88	2.77	3.31	7.75	4.85	7.81	3.16	12.8	2.69	0.16
	(1.51)**	(1.95)	(1.41)*	(1.31)**	(4.13)	(1.59)**	(1.59)*	(2.59)**	(2.18)	(2.03)
Observations	80655	55107	93755	80707	80423	77144	80706	78695	16422	96158
R^2	0.001	0.000	0.000	0.002	0.001	0.252	0.000	0.004	0.000	0.000
Mean Dep. Var Men	1.086	1.202	1.123	.838	1.086	1.086	1.428	1.071	2.352	2.032
	(.448)	(.516)	(.419)	(.448)	(.448)	(.448)	(.446)	(.445)	(.914)	(.393)
Panel D: Log(Earnings)										
Female	-0.13	-0.13	-0.18	-0.13	-0.20	-0.16	-0.13	-0.13	-0.036	-0.044
	(0.017)**	(0.021)**	(0.017)**	(0.016)**	(0.045)**	(0.016)**	(0.016)**	(0.024)**	(0.022)	(0.020)*
Observations	76321	52601	88465	76361	76090	72813	76363	74435	15279	90732
R^2	0.005	0.004	0.009	0.005	0.011	0.349	0.005	0.005	0.000	0.001
Mean Dep. Var Men	-.41	-.319	-.419	-.392	-.405	-.41	-.4	-.406	-.456	-.443
	(.004)	(.005)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.01)	(.004)

Notes: Each column in this table represents a different robustness check. All specifications are estimated using weights. Column (1) reports the baseline coefficients. Column (2) reports results for a longer post-displacement time window (10 years). Column (3) reports results for shorter tenure workers (1 year at time of displacement). Column (5) reports results when reweighting with 1-digit occupations in addition to industries and individual characteristics. Column (4) reports results when using Mahalanobis matching in combination with exact matching of pre-displacement earnings deciles. Column (6) reports regression coefficients controlling for pre-displacement establishment fixed effects. Column (7) reports regression coefficients for a sample of treated and control workers, where the propensity score matching did not include log wages. Column (8) reports results when reweighting men to women. Trimmed at 99%. Column (9) reports regression coefficients for a dataset of non-couples. Column (10) reports regression coefficients for a combined dataset of couples and non-couples in our sample. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 20: The Gender Gap in Earnings Losses - Robustness Checks without Controls

	(1) Baseline	(2) 10 Years Post Displ.	(3) Shorter Tenure Restr.	(4) Mahalanobis And Exact Matching	(5) Displ. Estab. FE	(6) Matching Without Wages	(7) Non Couples	(8) Couples + Non-Couples
Panel A: Earnings Rel. to t=c-2								
Female	0.014	0.019	-0.0040	-0.0012	-0.049	0.010	0.044	0.036
	(0.012)	(0.016)	(0.012)	(0.012)	(0.0062)**	(0.012)	(0.012)**	(0.011)**
Observations	80655	55107	93756	80707	77144	80706	16424	96159
R^2	0.000	0.000	0.000	0.000	0.262	0.000	0.001	0.001
Mean Dep. Var Men	-.258	-.203	-.268	-.245	-.258	-.258	-.297	-.287
	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)	(.006)	(.002)
Panel B: Log Wages								
Female	-0.066	-0.063	-0.082	-0.077	-0.14	-0.070	-0.032	-0.039
	(0.013)**	(0.018)**	(0.014)**	(0.013)**	(0.0094)**	(0.013)**	(0.013)*	(0.012)**
Observations	73598	51670	85093	73626	70058	73634	14553	87343
R^2	0.003	0.002	0.004	0.004	0.246	0.003	0.001	0.001
Mean Dep. Var Men	-.201	-.187	-.205	-.188	-.201	-.201	-.201	-.203
	(.003)	(.004)	(.003)	(.003)	(.003)	(.003)	(.007)	(.003)
Panel C: Log Fulltime Wages								
Female	0.013	0.017	0.010	-0.00035	-0.037	0.014	0.00032	0.0053
	(0.0085)	(0.011)	(0.0092)	(0.0072)	(0.0055)**	(0.0083)	(0.0088)	(0.0078)
Observations	52996	39002	60891	56077	49526	53169	10946	63191
R^2	0.000	0.000	0.000	0.000	0.271	0.000	0.000	0.000
Mean Dep. Var Men	-.094	-.091	-.094	-.084	-.094	-.093	-.086	-.09
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
Panel D: Days Worked Fulltime								
Female	31.4	23.7	27.6	33.1	11.1	30.8	32.7	32.2
	(3.24)**	(3.79)**	(2.98)**	(2.99)**	(2.18)**	(3.13)**	(3.65)**	(3.19)**
Observations	80655	55107	93756	80707	77144	80706	16424	96159
R^2	0.008	0.004	0.006	0.010	0.252	0.008	0.008	0.008
Mean Dep. Var Men	-75.47	-56.298	-77.46	-74.628	-75.47	-75.8	-88.476	-84.705
	(.766)	(.976)	(.717)	(.727)	(.766)	(.763)	(1.706)	(.716)

Notes: Each column in this table represents a different robustness check. Specifications are estimated without weights. Column (1) reports the baseline coefficients. Column (2) reports results for a longer post-displacement time window (10 years). Column (3) reports results for shorter tenure workers (1 year at time of displacement). Column (4) reports results when using Mahalanobis matching in combination with exact matching of pre-displacement earnings deciles. Column (5) reports regression coefficients controlling for pre-displacement establishment fixed effects. Column (6) reports regression coefficients for a sample of treated and control workers, where the propensity score matching did not include log wages. Column (7) reports regression coefficients for a dataset of non-couples. Column (8) reports regression coefficients for a combined dataset of couples and non-couples in our sample. We cluster standard errors at the displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 21: The Gender Gap in Earnings Losses - Robustness Checks with Reg. Adjustment

	(1) Baseline	(2) 10 Years Post Displ.	(3) Shorter Tenure Restr.	(4) Mahalanobis And Exact Matching	(5) Displ. Estab. FE	(6) Matching Without Wages	(7) Non Couples	(8) Couples + Non-Couples
Panel A: Earnings Rel. to t=c-2								
Female	-0.077	-0.075	-0.093	-0.085	-0.076	-0.082	-0.00037	-0.022
	(0.0072)**	(0.0095)**	(0.0086)**	(0.0072)**	(0.0070)**	(0.0074)**	(0.012)	(0.0097)*
Observations	80655	55107	93756	80707	77144	80706	16424	96159
R^2	0.054	0.055	0.045	0.041	0.281	0.056	0.048	0.048
Mean Dep. Var Men	-.258	-.203	-.268	-.245	-.258	-.258	-.297	-.287
	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)	(.006)	(.002)
Panel B: Log Wages								
Female	-0.17	-0.16	-0.18	-0.18	-0.15	-0.17	-0.077	-0.099
	(0.0098)**	(0.013)**	(0.011)**	(0.0095)**	(0.011)**	(0.0099)**	(0.014)**	(0.011)**
Observations	73598	51670	85093	73626	70058	73634	14553	87343
R^2	0.058	0.062	0.053	0.051	0.262	0.059	0.050	0.051
Mean Dep. Var Men	-.201	-.187	-.205	-.188	-.201	-.201	-.201	-.203
	(.003)	(.004)	(.003)	(.003)	(.003)	(.003)	(.007)	(.003)
Panel C: Log Fulltime Wages								
Female	-0.045	-0.043	-0.042	-0.062	-0.053	-0.044	-0.025	-0.031
	(0.0052)**	(0.0068)**	(0.0058)**	(0.0047)**	(0.0058)**	(0.0053)**	(0.0087)**	(0.0070)**
Observations	52996	39002	60891	56077	49526	53169	10946	63191
R^2	0.068	0.062	0.063	0.065	0.296	0.067	0.068	0.067
Mean Dep. Var Men	-.094	-.091	-.094	-.084	-.094	-.093	-.086	-.09
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
Panel D: Days Worked Fulltime								
Female	-24.9	-33.7	-29.2	-10.1	-18.8	-23.6	-3.63	-9.72
	(2.51)**	(2.92)**	(2.52)**	(2.39)**	(2.30)**	(2.43)**	(3.38)	(2.82)**
Observations	80655	55107	93756	80707	77144	80706	16424	96159
R^2	0.150	0.141	0.143	0.094	0.332	0.148	0.136	0.140
Mean Dep. Var Men	-75.47	-56.298	-77.46	-74.628	-75.47	-75.8	-88.476	-84.705
	(.766)	(.976)	(.717)	(.727)	(.766)	(.763)	(1.706)	(.716)

Notes: Each column in this table represents a different robustness check. Specifications are estimated without weights. Column (1) reports the baseline coefficients. Column (2) reports results for a longer post-displacement time window (10 years). Column (3) reports results for shorter tenure workers (1 year at time of displacement). Column (4) reports results when using Mahalanobis matching in combination with exact matching of pre-displacement earnings deciles. Column (5) reports regression coefficients controlling for pre-displacement establishment fixed effects. Column (6) reports regression coefficients for a sample of treated and control workers, where the propensity score matching did not include log wages. Column (7) reports regression coefficients for a dataset of non-couples. Column (8) reports regression coefficients for a combined dataset of couples and non-couples in our sample. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 22: The Gender Gap in Earnings Losses - Varying Estimation Samples

	(1) Baseline	(2) West Germany	(3) East Germany	(4) Complete Closures	(5) Mass Layoffs	(6) Stricter Baseline Restrictions
Panel A: Earnings Rel. to t=c-2						
Female	-0.092	-0.10	-0.052	-0.092	-0.092	-0.22
	$(0.012)^{**}$	$(0.019)^{**}$	$(0.014)^{**}$	$(0.016)^{**}$	$(0.017)^{**}$	$(0.071)^{**}$
Observations	80655	58373	22280	24819	55836	35473
R^2	0.007	0.007	0.003	0.008	0.006	0.012
Mean Dep. Var Men	-.258	-.259	-.257	-.262	-.257	-.277
	(.002)	(.003)	(.005)	(.004)	(.004)	(.003)
Panel B: Log Wages						
Female	-0.13	-0.11	-0.17	-0.17	-0.12	-0.16
	$(0.013)^{**}$	$(0.015)^{**}$	$(0.026)^{**}$	$(0.021)^{**}$	$(0.017)^{**}$	$(0.042)^{**}$
Observations	73598	53292	20304	23007	50591	32229
R^2	0.010	0.007	0.017	0.016	0.007	0.012
Mean Dep. Var Men	-.201	-.206	-.183	-.213	-.195	-.213
	(.003)	(.003)	(.006)	(.005)	(.005)	(.004)
Panel C: Log Fulltime Wages						
Female	-0.039	-0.034	-0.056	-0.060	-0.031	-0.069
	$(0.0084)^{**}$	$(0.011)^{**}$	$(0.013)^{**}$	$(0.015)^{**}$	$(0.010)^{**}$	$(0.023)^{**}$
Observations	52996	38692	14303	16975	36021	28518
R^2	0.003	0.002	0.007	0.007	0.002	0.009
Mean Dep. Var Men	-.094	-.097	-.083	-.108	-.084	-.1
	(.002)	(.002)	(.003)	(.003)	(.003)	(.002)
Panel D: Days Worked Fulltime						
Female	-23.1	-21.9	-24.0	-25.9	-21.7	-27.3
	$(2.84)^{**}$	$(3.57)^{**}$	$(4.26)^{**}$	$(4.99)^{**}$	$(3.52)^{**}$	$(7.85)^{**}$
Observations	80655	58373	22280	24819	55836	35473
R^2	0.005	0.004	0.005	0.006	0.004	0.007
Mean Dep. Var Men	-75.47	-75.15	-76.682	-72.364	-77	-80.036
	(.766)	(.851)	(1.721)	(1.295)	(1.295)	(.947)

Notes: Each column in this table represents a different robustness check. All specifications are estimated using weights. Column (1) reports the baseline coefficients. Column (2) reports results workers working in West Germany in t=c-1. Column (3) reports results workers working in East Germany in t=c.-1 Column (4) reports results for workers displaced from a complete establishment closure, only. Column (5) reports results for workers displaced from a mass-layoff, excluding workers displaced from a complete establishment closure. Column (6) reports results for workers applying the same baseline restrictions as in Schmieder et al. (2020). These are: the worker is between age 24 and 50, works full-time at a West German establishment with at least 50 employees, and has at least 3 years of tenure. For Columns (2) and (3), we reweight women in West (East) Germany to men in West (East) Germany. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 23: Household Outcomes and Added Worker Effect: Alternative Sample Splits

	(1) Partner Earn. Rel. To Job Loser's in t=c-1	(2) Partner Log Wage	(3) Partner Days Worked	(4) Partner Days Worked Fulltime	(5) Household Earnings Rel. To t=c-1
Panel A: Unadjusted Gender Gap					
Female*Displaced	-0.045	-0.018	3.28	-8.07	0.045
	(0.0087)**	(0.0071)*	(1.89)	(1.68)**	(0.0098)**
Observations	161310	93392	161310	161310	161310
Mean Dep. Var Men	-.02	.005	-15.949	-4.124	-.224
	(.003)	(.006)	(1.843)	(.982)	(.007)
Panel B: Adjusted Gender Gap, Reweighted					
Female*Displaced	-0.019	0.0016	8.85	-2.63	-0.025
	(0.033)	(0.013)	(3.47)*	(3.36)	(0.025)
Observations	161310	93392	161310	161310	161310
Mean Dep. Var Men	-.02	.005	-15.949	-4.124	-.224
	(.003)	(.006)	(1.843)	(.982)	(.007)
Panel C: Regression Adj. Gender Gap, Partners Working in Different Establishments					
Female*Displaced	-0.030	-0.018	5.08	-5.82	0.057
	(0.0089)**	(0.0072)*	(1.96)**	(1.69)**	(0.0098)**
Observations	153294	87808	153294	153294	153294
Mean Dep. Var Men	-.013	.014	-13.02	-2.093	-.221
	(.005)	(.005)	(1.217)	(1.011)	(.004)
Panel D: Regression Adj. Gender Gap, Partners Working in Same Establishment					
Female*Displaced	-0.20	0.048	8.35	-22.3	-0.068
	(0.039)**	(0.030)	(7.66)	(7.67)**	(0.025)**
Observations	8016	5584	8016	8016	8016
Mean Dep. Var Men	-.152	-.18	-77.538	-45.456	-.282
	(.022)	(.02)	(5.686)	(5.368)	(.017)
Panel E: Regression Adj. Gender Gap, Partners Working in Different Occupations					
Female*Displaced	-0.044	-0.018	4.22	-7.88	0.048
	(0.0088)**	(0.0073)*	(1.99)*	(1.71)**	(0.010)**
Observations	152065	86636	152065	152065	152065
Mean Dep. Var Men	-.017	.009	-15.346	-3.345	-.225
	(.005)	(.005)	(1.223)	(1.015)	(.004)
Panel F: Regression Adj. Gender Gap, Partners Working in Same Occupation					
Female*Displaced	-0.012	0.0089	7.22	1.32	0.039
	(0.042)	(0.025)	(7.62)	(7.33)	(0.024)
Observations	9245	6756	9245	9245	9245
Mean Dep. Var Men	-.064	.034	-26.104	-17.597	-.197
	(.025)	(.012)	(5.247)	(4.939)	(.016)

Notes: This table shows household outcomes after displacement from regressions based on the full sample of workers (displaced and non-displaced workers). All outcome variables are based on the individual first differences estimate. Panel A shows the raw gender gap without controls. Panel B shows the adjusted gender gap using reweighting. Panel C shows the regression adjusted gender gap for couples where both partners worked in different establishments in t=c-1. Panel D shows the regression adjusted gender gap for couples where both partners worked in the same establishment in t=c-1. Panel E shows the regression adjusted gender gap for couples where both partners worked in different 3-digit occupations in t=c-1. Panel F shows the regression adjusted gender gap for couples where both partners worked in the same 3-digit occupation in t=c-1. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

Table 24: Top 10 2-Digit Industries in the Five Years Before Displacement

(1) Men			(2) Women			(3) Women - Reweighted		
Industry	Code	Percent	Industry	Code	Percent	Industry	Code	Percent
Wholesale Trade	46	8.0	Retail	47	14.6	Retail	47	6.9
Property Development	41	7.1	Education	85	12.4	Infrastructure Operations	52	4.9
Metal Equipment	25	5.2	Administration	84	6.3	Wholesale Trade	46	4.9
Manufacturing of Machines	28	5.2	Wholesale Trade	46	6.2	Cleaning Services	81	4.7
Infrastructure Operations	52	5.1	Meat Production	10	4.6	Management, Consulting	70	4.3
Retail	47	4.3	Cleaning Services	81	3.9	IT Services	62	4.2
Labor Recruitment	78	3.8	Associations	94	2.4	Manufacturing	26	3.6
Meat Production	10	3.3	Health Care	86	2.3	Metal Equipment	25	3.3
Synthetic Products	22	2.8	Infrastructure Operations	52	2.2	Property Development	41	3.0
Education	85	2.6	Social Services	88	2.0	Labor Recruitment	78	2.9

Notes: Table reports top 10 2-digit source industry codes by gender. We define source industry as a worker's most frequent industry in the five years before displacement.

Table 25: Top 10 2-Digit Industries in the Five Years After Displacement

(1) Men			(2) Women			(3) Women - Reweighted		
Industry	Code	Percent	Industry	Code	Percent	Industry	Code	Percent
Wholesale Trade	46	7.9	Retail	47	15.4	Retail	47	8.9
Metal Equipment Productin	25	5.5	Education	85	12.8	Wholesale Trade	46	5.9
Manufacturing of Machines	28	5.4	Administration	84	6.1	Cleaning Services	81	5.2
Infrastructure Operations	52	5.0	Wholesale Trade	46	5.2	Management, Consulting	70	3.7
Retail	47	4.3	Cleaning Services	81	4.5	Infrastructure Operations	52	3.6
Labor Recruitment	78	4.2	Meat Production	10	3.9	IT Services	62	3.4
Property Development	41	3.9	Nursing	87	3.3	Education	85	3.4
Passenger Transport	49	3.3	Health Care	86	3.1	Metal Equipment	25	3.1
Meat Production	10	2.9	Social Services	88	2.3	Labor Recruitment	78	3.1
Cleaning Services	81	2.7	Food Service Industry	56	2.2	Architecture	71	2.8

Notes: Table reports top 10 2-digit destination industry codes by gender. We define destination industry as a worker's most frequent industry in the five years after displacement.

Table 26: Top 10 3-Digit Occupations in the Five Years Before Displacement

(1) Men			(2) Women			(3) Women - Reweighted		
Occupation	Code	Percent	Occupation	Code	Percent	Occupation	Code	Percent
Qualified Office Employee	781	7.3	Qualified Office Employee	781	27.1	Qualified Office Employee	781	30.6
Trucker	714	6.5	Salesperson	682	11.6	Salesperson	682	5.0
Warehouseman	744	3.9	Cleaner	933	4.3	Cleaner	933	3.9
Data Processing Expert	774	3.0	Nursery Worker	864	2.8	Accountant	772	2.8
Bricklayer	441	2.8	Despatcher	522	2.3	Purchasing Agent	681	2.6
Helper	531	2.8	Purchasing Agent	681	2.2	Data Processing Expert	774	2.5
Technician	628	2.4	Warehouseman	744	2.1	Stenographer	782	2.5
Stockman	741	2.4	Helper	531	1.9	Manager	751	2.2
Salesperson	682	2.3	Chef	411	1.6	Warehouseman	744	1.9
Electrician	311	2.1	Secondary School Teacher	873	1.6	Despatcher	522	1.8

Notes: Table reports top 10 3-digit source occupation codes by gender. We define source occupation as a worker's most frequent occupation in the five years before displacement.

Table 27: Top 10 3-Digit Occupations in the Five Years After Displacement

(1) Men			(2) Women			(3) Women - Reweighted		
Occupation	Code	Percent	Occupation	Code	Percent	Occupation	Code	Percent
Trucker	714	7.4	Qualified Office Employee	781	25.1	Qualified Office Employee	781	27.8
Qualified Office Employee	781	6.4	Salesperson	682	12.1	Salesperson	682	6.0
Warehouseman	744	4.1	Cleaner	933	5.5	Cleaner	933	4.9
Data Processing Expert	774	3.0	Nursery Worker	864	3.2	Accountant	772	3.5
Manager	751	2.9	Warehouseman	744	2.3	Purchasing Agent	681	2.9
Stockman	741	2.6	Purchasing Agent	681	2.3	Manager	751	2.6
Bricklayer	441	2.4	Social Worker	861	2.1	Warehouseman	744	2.3
Salesperson	682	2.3	Chef	411	1.9	Data Processing Expert	774	2.0
Electrician	311	2.2	Accountant	772	1.8	Stenographer	782	1.6
Technician	628	2.1	Despatcher	522	1.6	Helper	531	1.4

Notes: Table reports top 10 3-digit destination occupation codes by gender. We define destination occupation as a worker's most frequent occupation in the five years after displacement.

Table 28: 2-digit Industry Switches - Women

	Destination Industries										
	Retail	Edu-cation	Admin-istration	Whole-sale Trade	Maint. Services	Nursing	Temp Work	Food Prod.	Food Services	Medical Care	All
Retail	2914	32	44	193	69	60	72	169	70	54	4706
Education	8	3111	113	4	4	65	12	1	13	17	3990
Administration	61	569	1123	5	4	12	6	2	4	22	2058
Wholesale Trade	350	20	38	366	55	24	63	76	45	31	1988
Food Production	407	5	7	79	53	32	61	410	46	17	1535
Maintenance Services	25	8	17	7	566	56	22	12	49	27	1011
Clothing Manufacturing	81	7	10	62	24	45	19	23	23	18	805
Nursing	7	317	24	2	2	96	5	4	7	28	797
Logistics	89	9	4	44	22	15	47	16	14	17	784
Production of Electronics	86	11	13	47	19	17	48	14	24	17	726

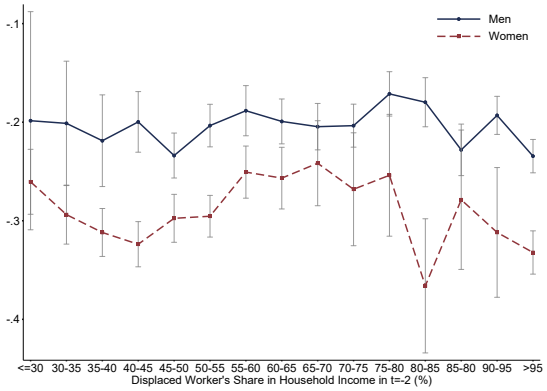
Notes: This table shows the number of women in the 10 most common origin 2-digit industries (rows) switching to the 10 most common destination industries (columns). The last column shows the total number of women in a given origin 2-digit industry.

Table 29: 2-digit Industry Switches - Men

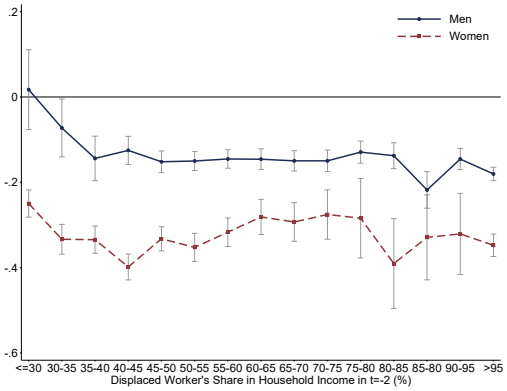
	Destination Industries										
	Whole-sale Trade	Temp Work	Metal Pro-cessing	Logistics	Retail Trade	Machine Prod.	Building Instal-lation	Con-struc-tion	Transport	Edu-cation	All
Construction	99	78	71	59	50	24	613	1414	73	20	4407
Wholesale Trade	1139	135	86	261	255	113	85	15	117	17	3824
Logistics	191	127	33	908	75	30	36	7	382	6	2488
Machine Production	179	119	327	16	56	679	73	6	20	14	2383
Metal Processing	132	142	650	35	56	203	118	21	34	12	2381
Retail Trade	223	60	30	70	910	28	77	8	33	20	2206
Temp Work	66	687	98	66	20	94	96	9	29	4	1875
Food Production	149	100	37	71	82	38	40	4	60	2	1786
Production of Electronics	128	67	92	32	67	138	25	4	17	20	1673
Plastics Production	73	106	113	41	26	62	54	7	27	10	1469

Notes: This table shows the number of men in the 10 most common origin 2-digit industries (rows) switching to the 10 most common destination industries (columns). The last column shows the total number of men in a given origin 2-digit industry.

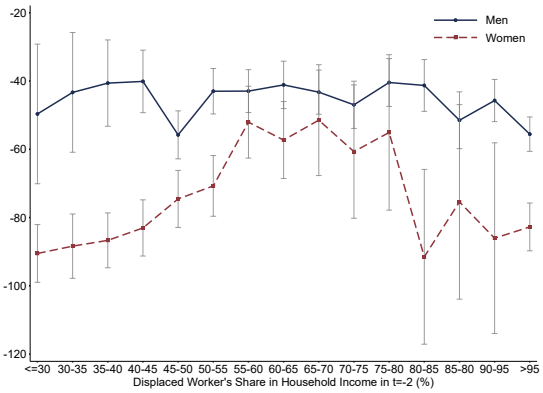
Figure 1: Costs of Job Loss by Displaced Worker's Share in Household Income in t=c-1



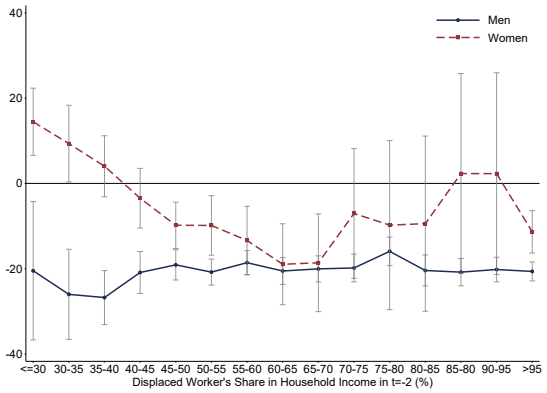
(a) Earnings Relative to t=c-2



(b) Log Wage



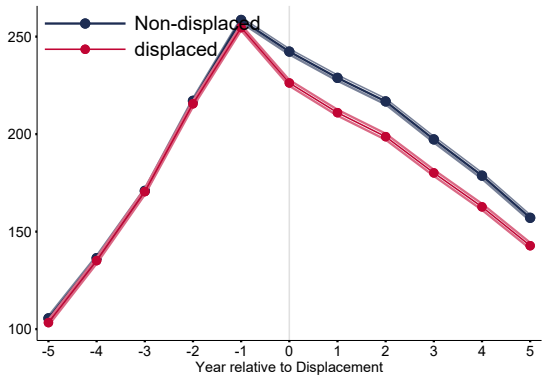
(c) Days Worked Fulltime



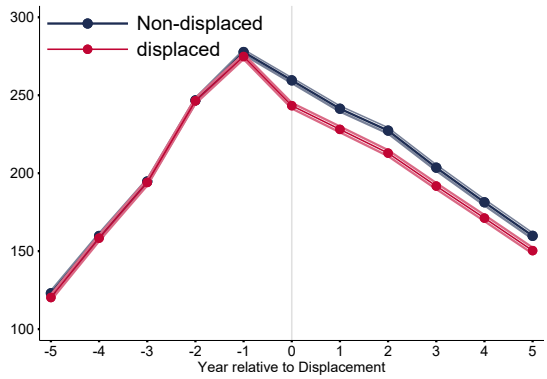
(d) Days Worked Parttime

Notes: This figure shows how labor market outcomes before and after displacement differ for men and women by their share in household income in t=c-1. All outcomes variables are the respective difference-in-difference estimate. Panels (a)-(d) show eventstudy coefficients for earnings relative to t=c-2, log wage, days worked in fulltime job, and days worked in parttime job. The dark blue line corresponds to men, the dashed red line corresponds to women. All regressions control for individual and establishment characteristics. Individual characteristics are a worker's log wage in t=c-3 and t=c-4, fulltime employment in t=c-3, and age, years of education, tenure, and location in East or West Germany in t=c-1. Establishment characteristics are 1-digit industry dummies and log establishment size in t=c-1. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the displacement establishment level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

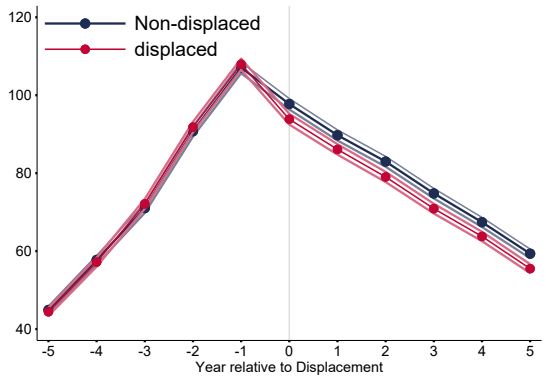
Figure 2: Partner Outcomes before and after Displacement without Controlling for Pre-Displacement Characteristics



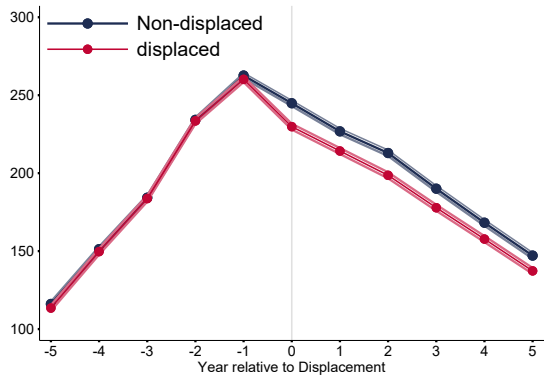
(a) Partner Days Worked - Men



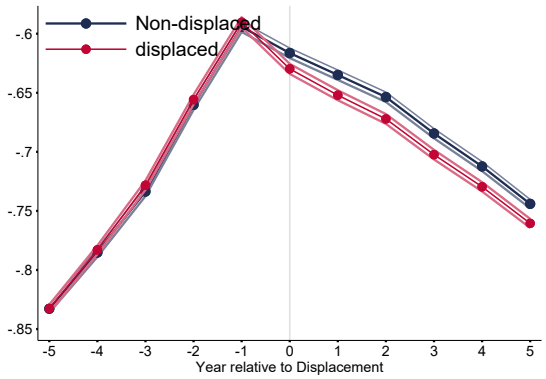
(b) Partner Days Worked - Women



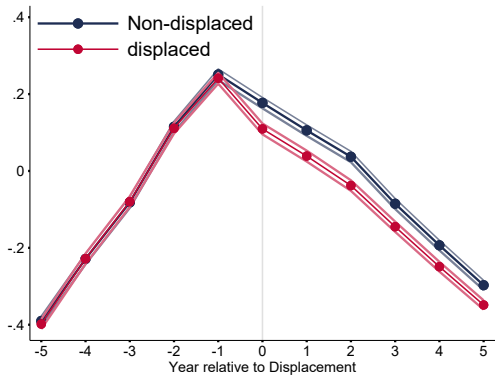
(c) Partner Days Worked Fulltime - Men



(d) Partner Days Worked Fulltime - Women



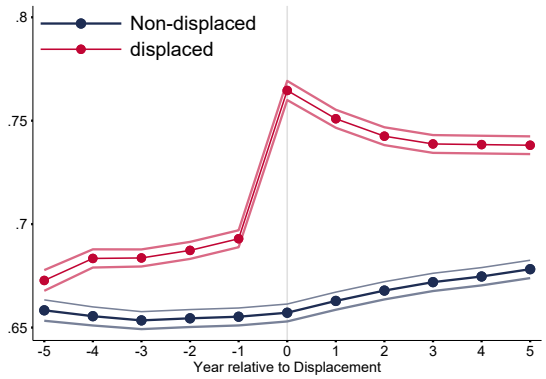
(e) Earnings Rel. To (Non-)Displaced Partner in t=c-2 - Men



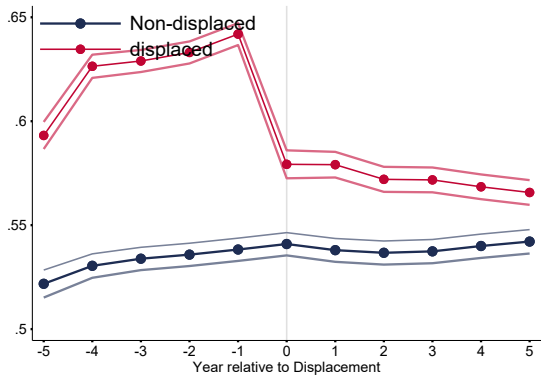
(f) Earnings Rel. To (Non-)Displaced Partner in t=c-2 - Women

Notes: This figure shows parnters' outcomes without controls for displaced and non-displaced men and women. Panels (a) and (b) show (non-)displaced workers' partners days worked, Panels (c) and (d) show (non-)displaced workers' partners days worked in fulltime employment, Panels (e) and (f) show partners earnings relative to (non-)displaced workers' earnings in t=c-2. The red line corresponds to workers who are displaced from year t=c-1 to t=c, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group.

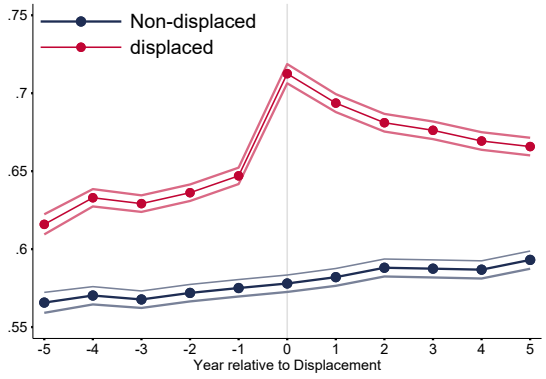
Figure 3: Commuting Outcomes before and after Displacement without Controlling for Pre-Displacement Characteristics



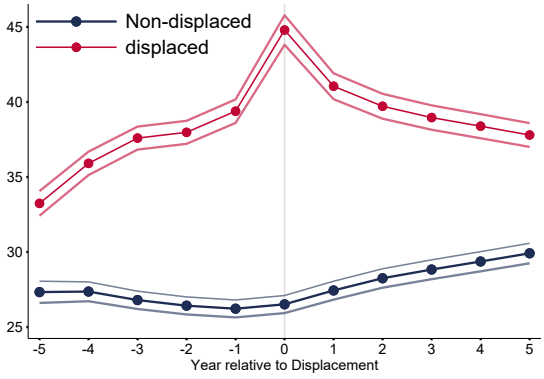
(a) Propensity to Commute - Men



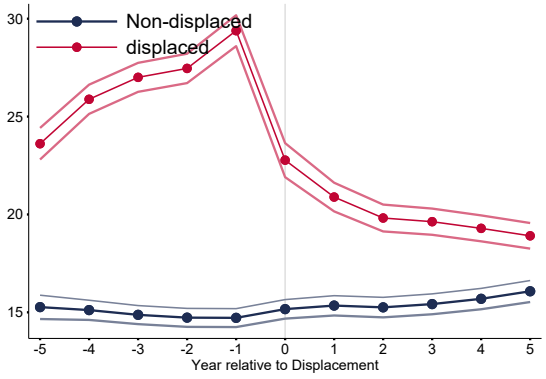
(b) Propensity to Commute - Women



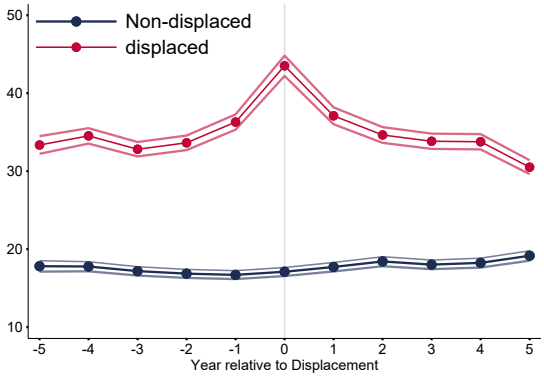
(c) Propensity to Commute - Women Reweighted



(d) Commuting Distance (km) - Men



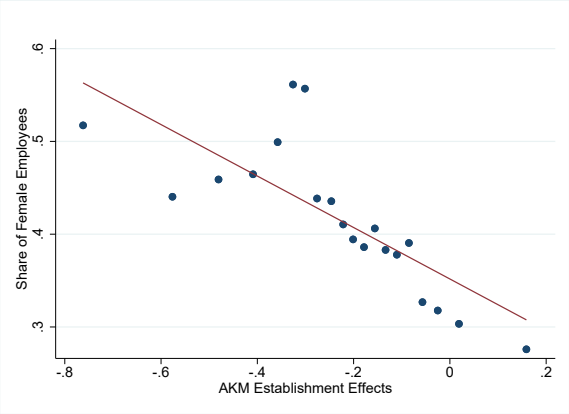
(e) Commuting Distance (km) - Women



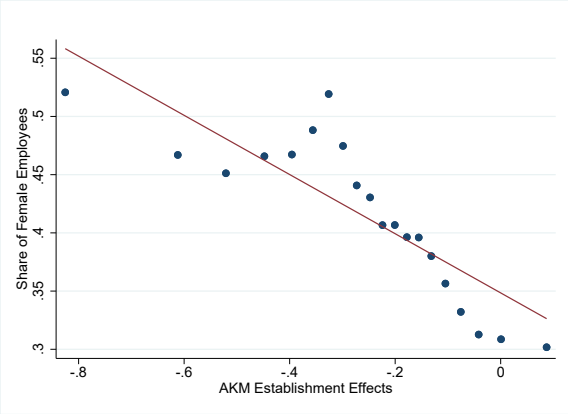
(f) Commuting Distance (km) - Women Reweighted

Notes: The figures show commuting outcomes without controls for displaced and non-displaced men and women. All commuting outcomes are defined on the municipality level. Panels (a), (b), and (c) show the propensity to commute for displaced and non-displaced men (a), women (b), and reweighted women (c). Panels (d), (e), and (f) show commuting distance between workplace municipality and residence municipality (in km) for displaced and non-displaced men (d), women (e), and reweighted women (f). The red line corresponds to workers who are displaced from year t=c-1 to t=c, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group.

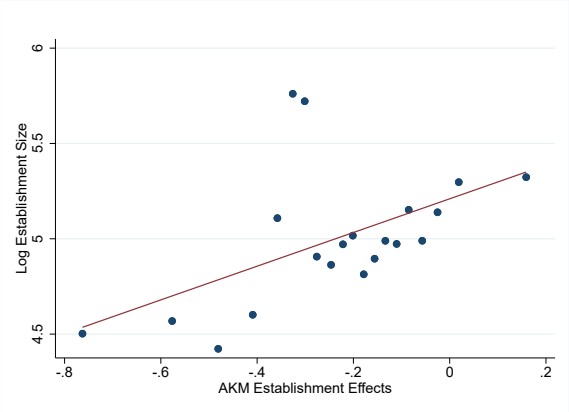
Figure 4: Binscatter Plots



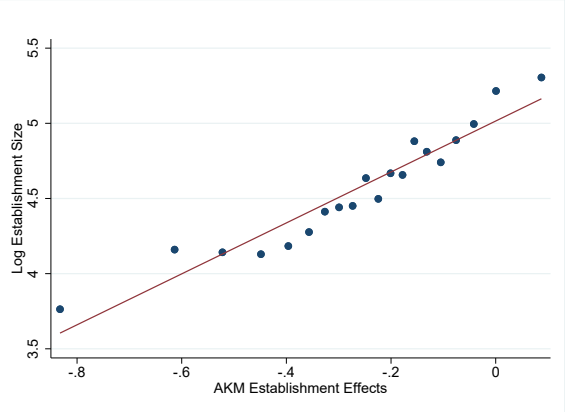
(a) Binscatter Plot of AKM Effects vs. Share of Female Employees Pre Displ.



(b) Binscatter Plot of AKM Effects vs. Share of Female Employees Post Displ.



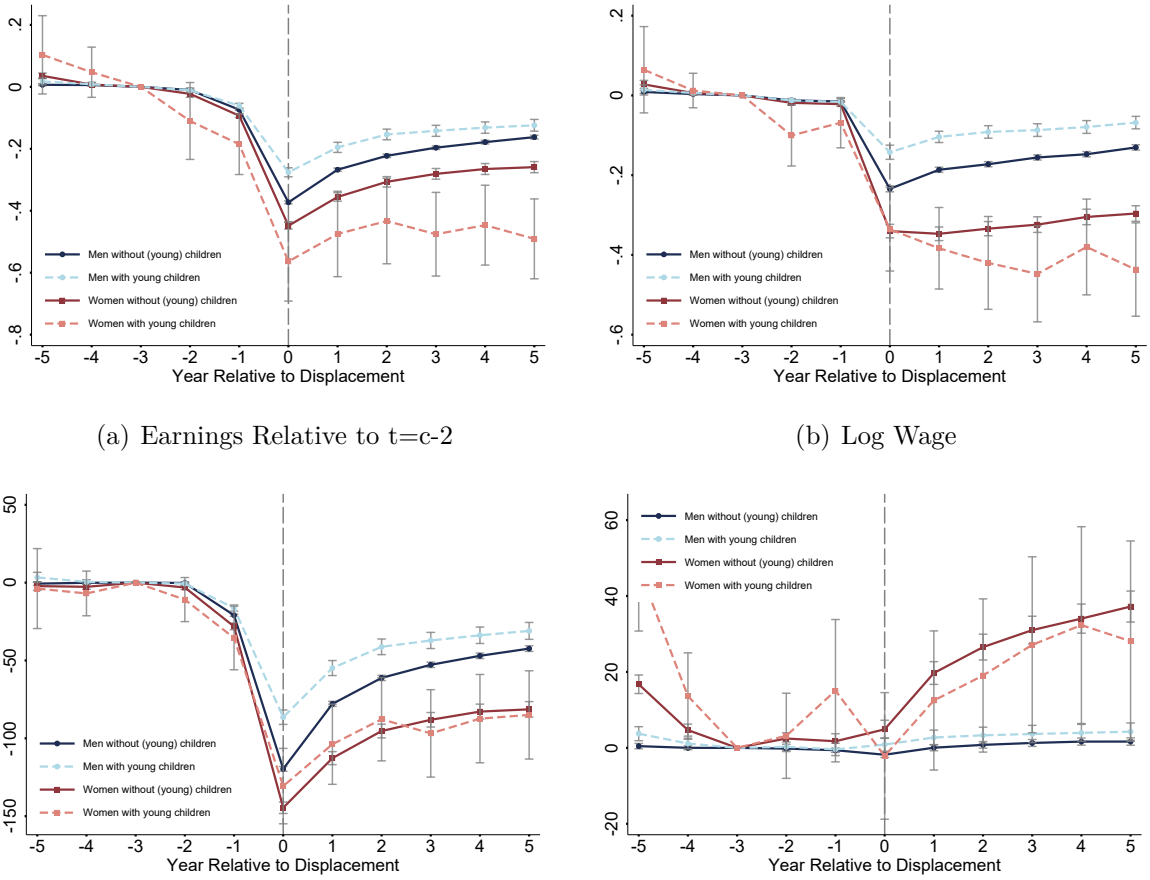
(c) Binscatter Plot of AKM Effects vs. Establishment Size Pre Displ.



(d) Binscatter Plot of AKM Effects vs. Establishment Size Post Displ.

Notes: This figure shows different binscatter plots for AKM establishment effects vs. the share of female employees in an establishment (Panels A-B), and AKM establishment effects vs. establishment size (Panels C-D).

Figure 5: The Gender Gap and Children



(a) Earnings Relative to t=c-2

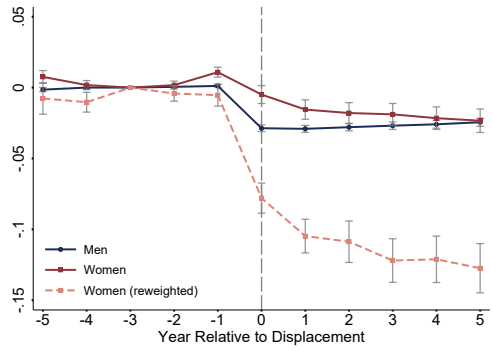
(b) Log Wage

(c) Days Worked Fulltime

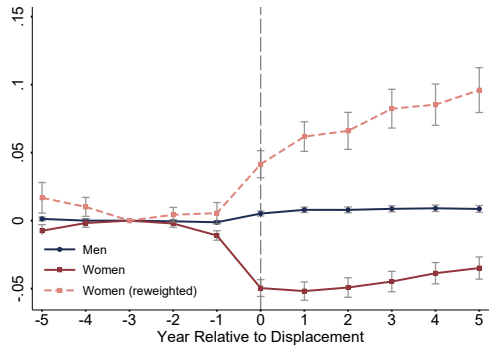
(d) Days Worked Parttime

Notes: This figure shows how labor market outcomes before and after displacement differ for men and women with older and younger children. Panels (a)-(d) show eventstudy coefficients for earnings relative to t=c-2, log wage, days worked in fulltime employment, and days worked in parttime employment. The four lines correspond to four event study regressions: Men with no children or children older than 6 only, women with no children and children older than 6 only, men with children younger than 7, women with children younger than 7. In reweighting, men with no or older children are the baseline group, to which we reweight the other three groups using individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Commuting distance is measured on the municipality level, and is recorded on December 31 each year. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

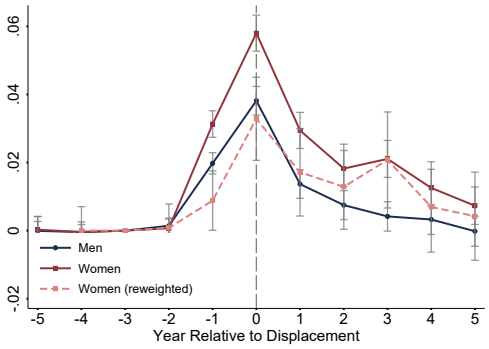
Figure 6: The Gender Gap in Earnings Losses - Additional Outcomes



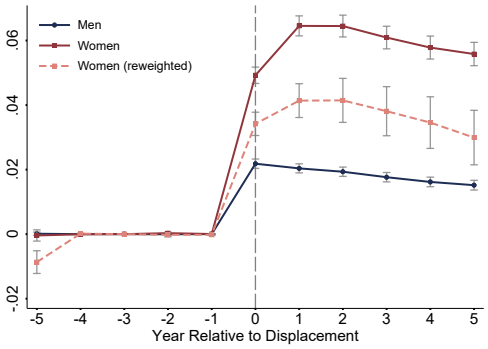
(a) Fulltime Employment Conditional on Working



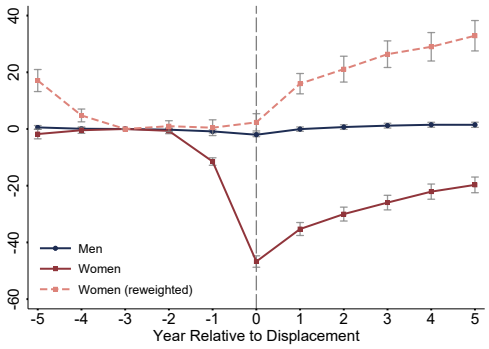
(b) Parttime Employment Conditional on Working



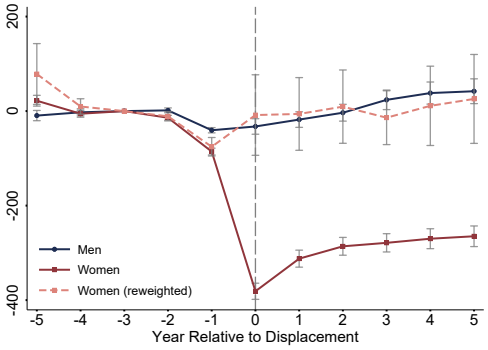
(c) At Least 1 Mini-job Conditional on Working



(d) Only Mini-job Conditional on Working



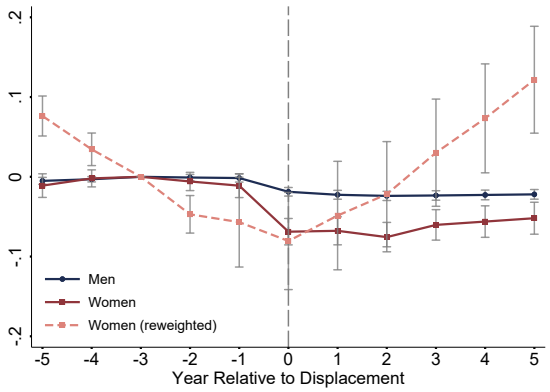
(e) Days Worked in Parttime Employment



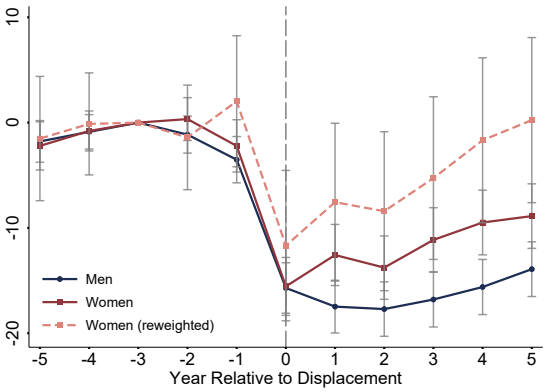
(f) Establishment Size

Notes: This figure shows how fulltime employment, parttime employment, marginal employment (all conditional on working), days worked in parttime employment, and establishment size evolve differently for non-displaced workers compared to displaced workers. Panels (a)-(d) show eventstudy coefficients for the propensity to be fulltime employed, parttime employed, employed in at least 1 mini-job, and only employed in mini-jobs, all conditional on working. Panels (e)-(f) show event study coefficients for the number of days worked in parttime employment per year, and establishment size. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

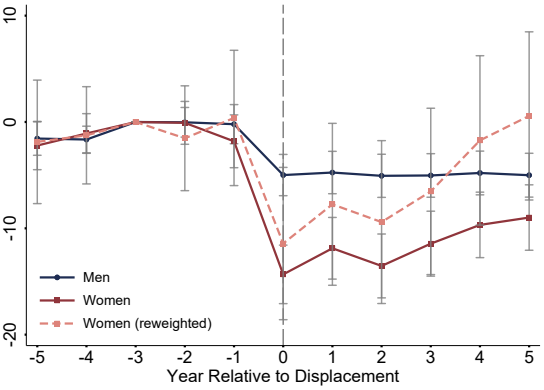
Figure 7: Job Loss on the Household Level - The Added Worker Effect



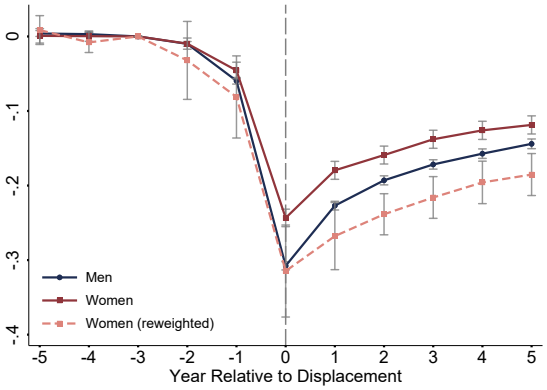
(a) Partner's Earnings Relative to Job Loser's in t=c-2



(b) Partner's Days Worked per Year



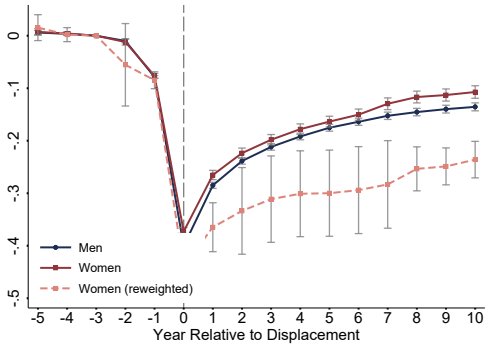
(c) Partner's Days Worked Fulltime per Year



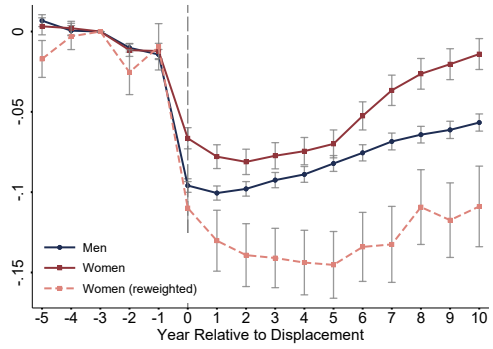
(d) Household Earnings Relative to t=c-2

Notes: This figure shows how partner and household outcomes evolve differently for non-displaced workers compared to displaced workers. Panels (a)-(d) show eventstudy coefficients for partner's earnings relative to the earnings of the job loser in t=c-2, partner's days worked per year, partner's days worked fulltime per year, and household earnings relative to t=c-2. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

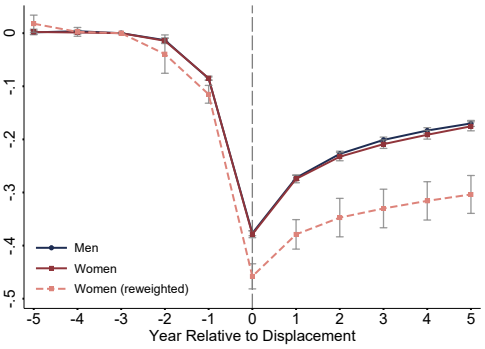
Figure 8: Robustness Checks: Longer Time Window, Shorter Tenure, Mahalanobis Matching



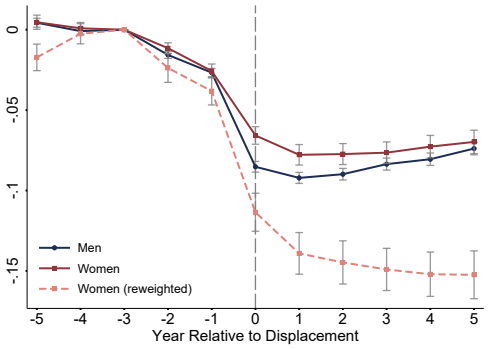
(a) Earnings Relative to t=c-2 - 10 Years Post Displ.



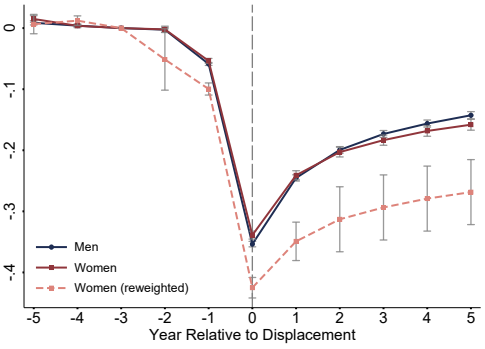
(b) Log Wage Fulltime - 10 Years Post Displ.



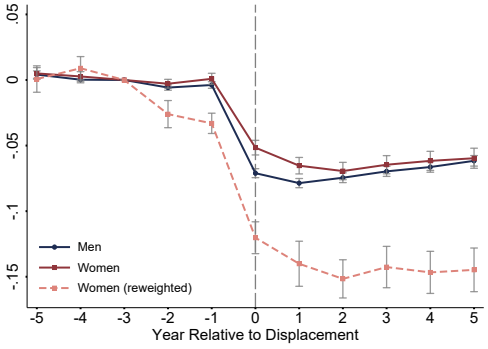
(c) Earnings Relative to t=c-2 - Shorter Tenure Restr.



(d) Log Wage Fulltime - Shorter Tenure Restr.



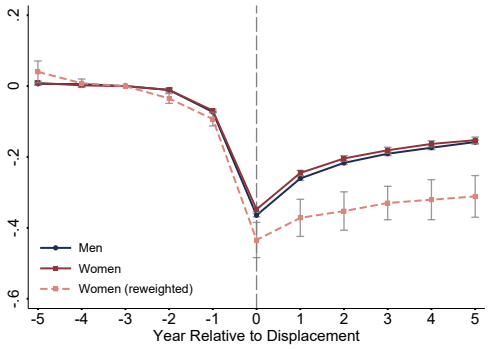
(e) Earnings Relative to t=c-2 - Mahalanobis Matching



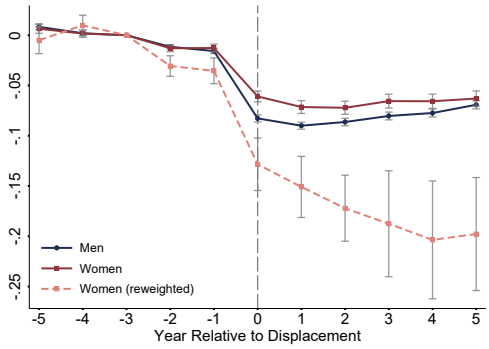
(f) Log Wage Fulltime - Mahalanobis Matching

Notes: This figure shows how earnings relative to t=c-2 and fulltime log wages differ for men and women before and after displacement for different robustness specifications. Panels (a)-(b) show event study coefficients for a sample of workers which are observable up to 10 years after job loss. Panels (c)-(d) show event study coefficients for a sample of workers with at least 1 year of tenure in t=c-1. Panels (e)-(f) show event study coefficients for a sample of workers matched via Mahalanobis in combination with exact matching of pre-displacement earnings deciles. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

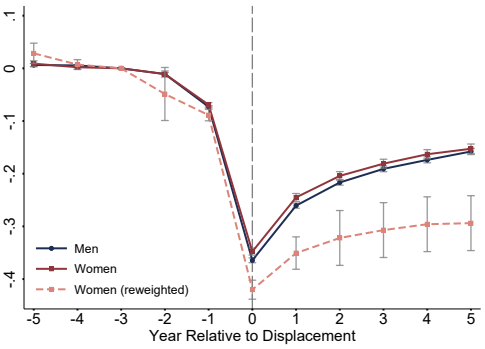
Figure 9: Robustness Checks: Occupational Reweighting, Displ. Estab. Fixed Effects, Matching without Wages



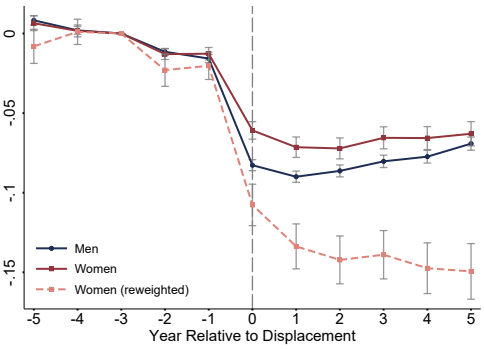
(a) Earnings Relative to t=c-2 - Reweighting with Occupations



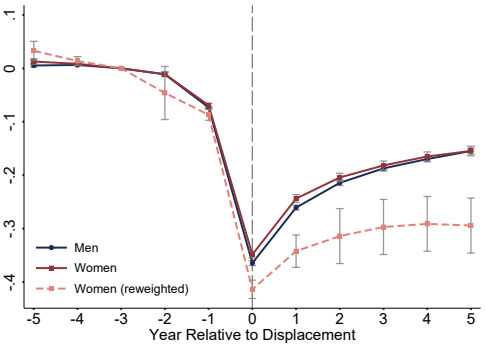
(b) Log Wage Fulltime - Reweighting with Occupations



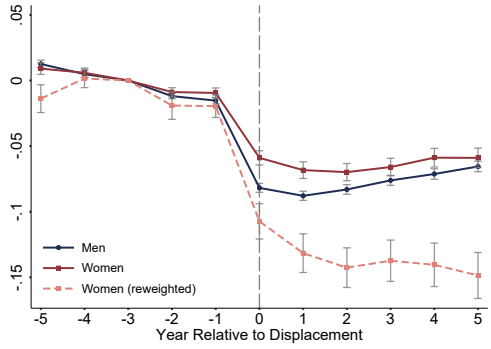
(c) Earnings Relative to t=c-2 - Adding Displ. Estab. Effects



(d) Log Wage Fulltime - Adding Displ. Estab. Effects



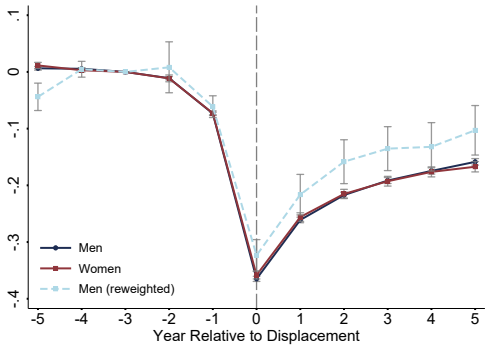
(e) Earnings Relative to t=c-2 - Matching Without Wages



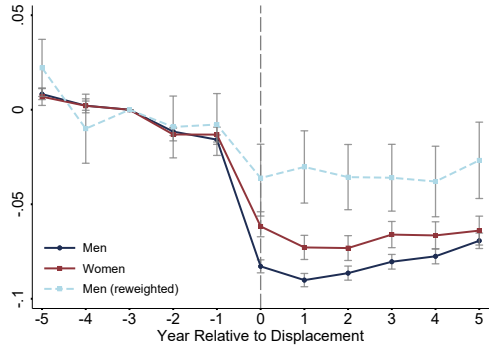
(f) Log Wage Fulltime - Matching Without Wages

Notes: This figure shows how earnings relative to t=c-2 and fulltime log wages differ for men and women before and after displacement for different robustness specifications. Panels (a)-(b) show event study coefficients for our baseline sample of workers, where we add 1-digit occupations as controls to our reweighting algorithm. Panels (c)-(d) show event study coefficients for our baseline sample of workers, where we add displacement establishment fixed effects to the regression specifications. Panels (e)-(f) show event study coefficients for a sample of workers matched using our baseline propensity score matching algorithm but without matching on pre-displacement wages. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

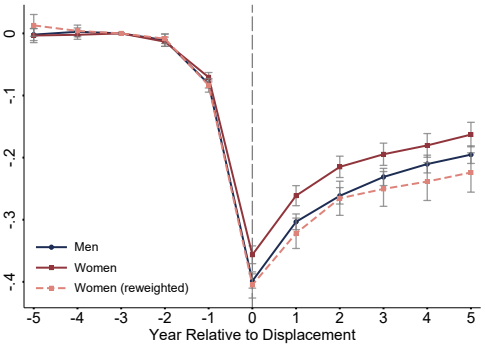
Figure 10: Robustness Checks: Reweighting Men to Women, Non-Couples, Couples and Non-Couples



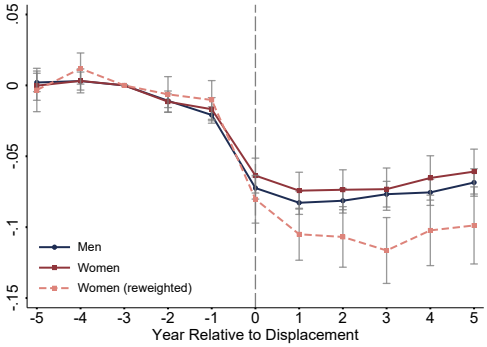
(a) Earnings Relative to t=c-2 - Reweighting Men to Women



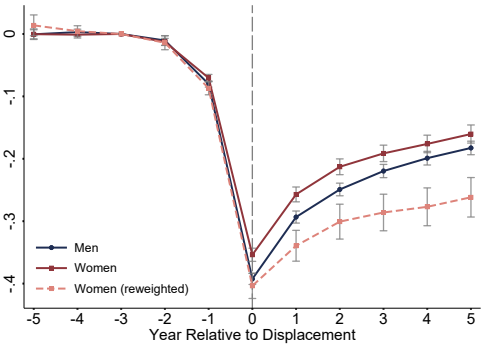
(b) Log Wage Fulltime - Reweighting Men to Women



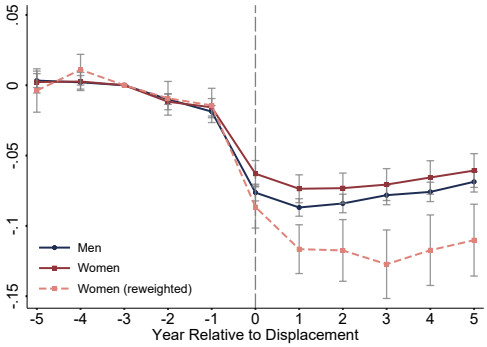
(c) Earnings Relative to t=c-2 - Non-Couples Only



(d) Log Wage Fulltime - Non-Couples Only



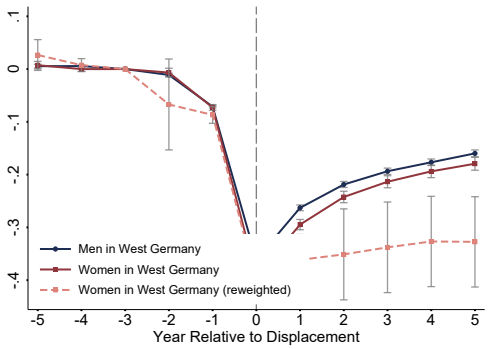
(e) Earnings Relative to t=c-2 - Couples + Non-Non-Couples



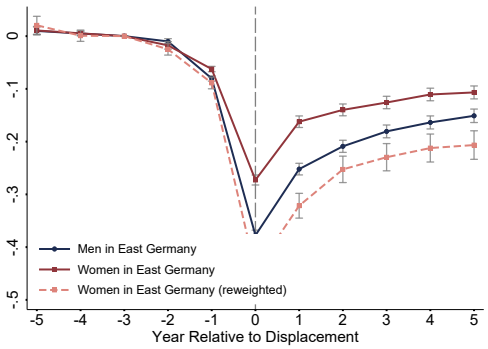
(f) Log Wage Fulltime - Couples + Non-Couples

Notes: This figure shows how earnings relative to t=c-2 and fulltime log wages differ for men and women before and after displacement for different robustness specifications. Panels (a)-(b) show event study coefficients for our baseline sample of workers, where we reweight men to women with respect to individual characteristics and 1-digit industries. Panels (c)-(d) show event study coefficients for a sample of workers not identified in the couple data. Panels E-F show eventstudy coefficients for a combined sample of workers in the couple data and not in the couple data. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

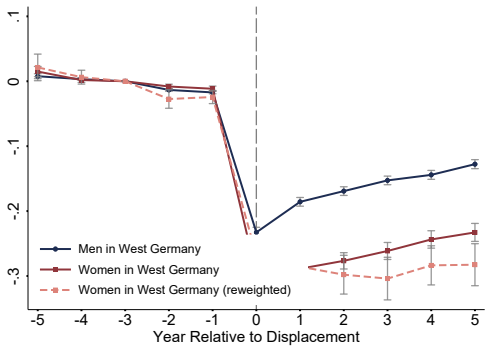
Figure 11: Earnings and Wage Losses - East vs. West Germany



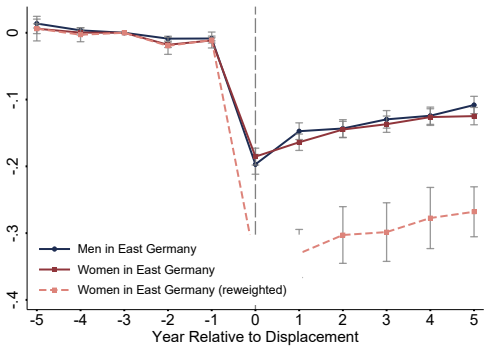
(a) Earnings Rel. To t=c-2 - West Germany



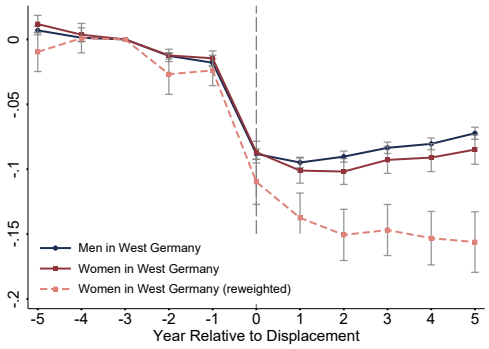
(b) Earnings Rel. To t=c-2 - East Germany



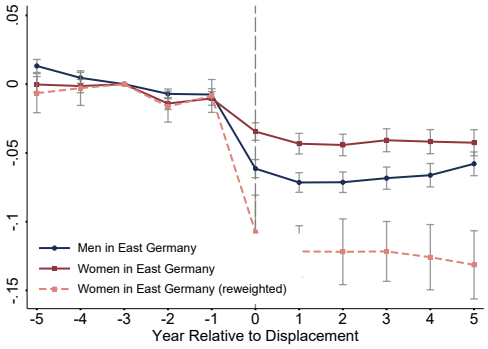
(c) Log Wage - West Germany



(d) Log Wage - East Germany



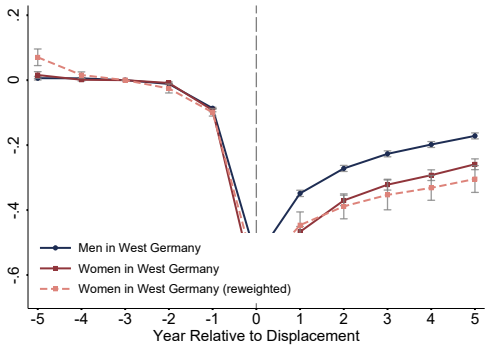
(e) Log Wage Full-time Job - West Germany



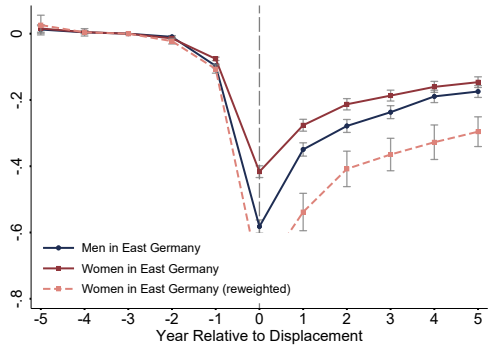
(f) Log Wage Full-time Job - East Germany

Notes: This figure shows how labor market characteristics before and after displacement differ for men and women working in West and East Germany in t=c-1, respectively. Panels (a), (c), and (e) show event study coefficients for earnings relative to earnings in t=c-2, log wages, and log wages in fulltime job for West Germany. Panels (b), (d), and (f) show eventstudy coefficients for earnings relative to earnings in t=c-2, log wages, and log wages in fulltime job for East Germany. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. Women in West (East) Germany are reweighted to men in West (East) Germany. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

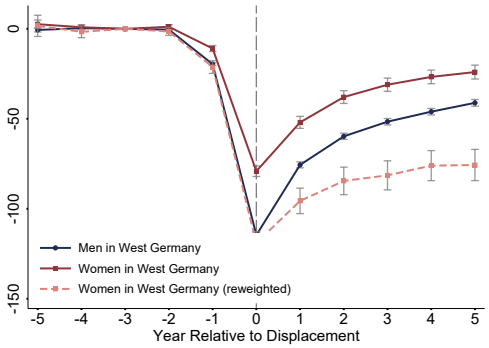
Figure 12: Log Earnings and Days Worked - East vs. West Germany



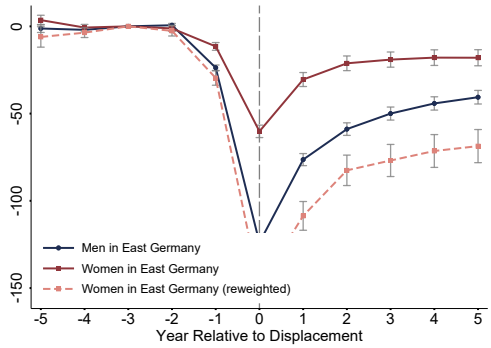
(a) Log Earnings - West Germany



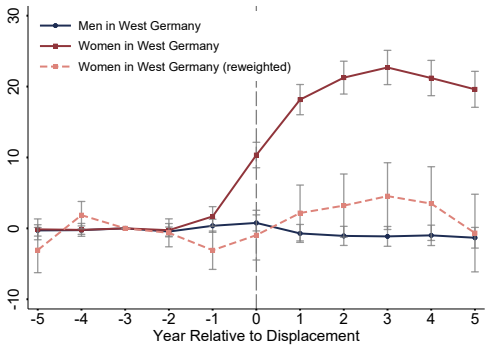
(b) Log Earnings - East Germany



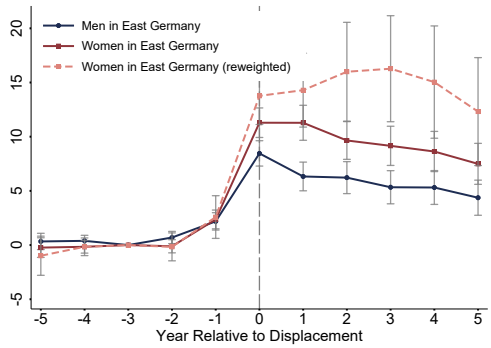
(c) Days Worked in Full-time Job - West Germany



(d) Days Worked in Full-time Job - East Germany



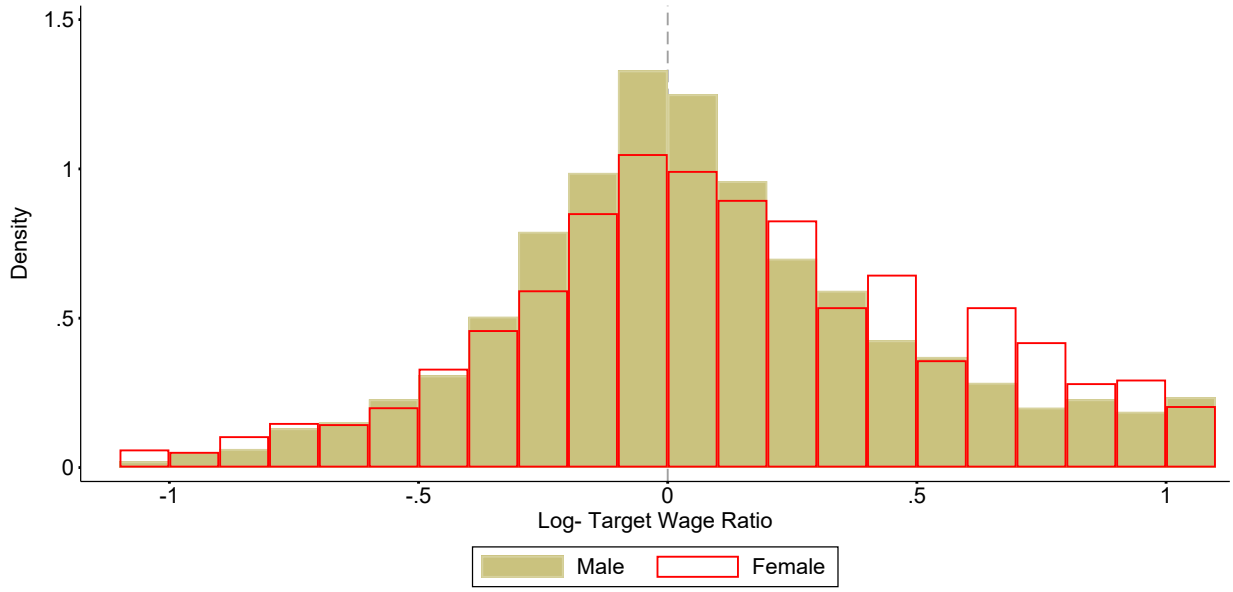
(e) Days Worked in Minijob - West Germany



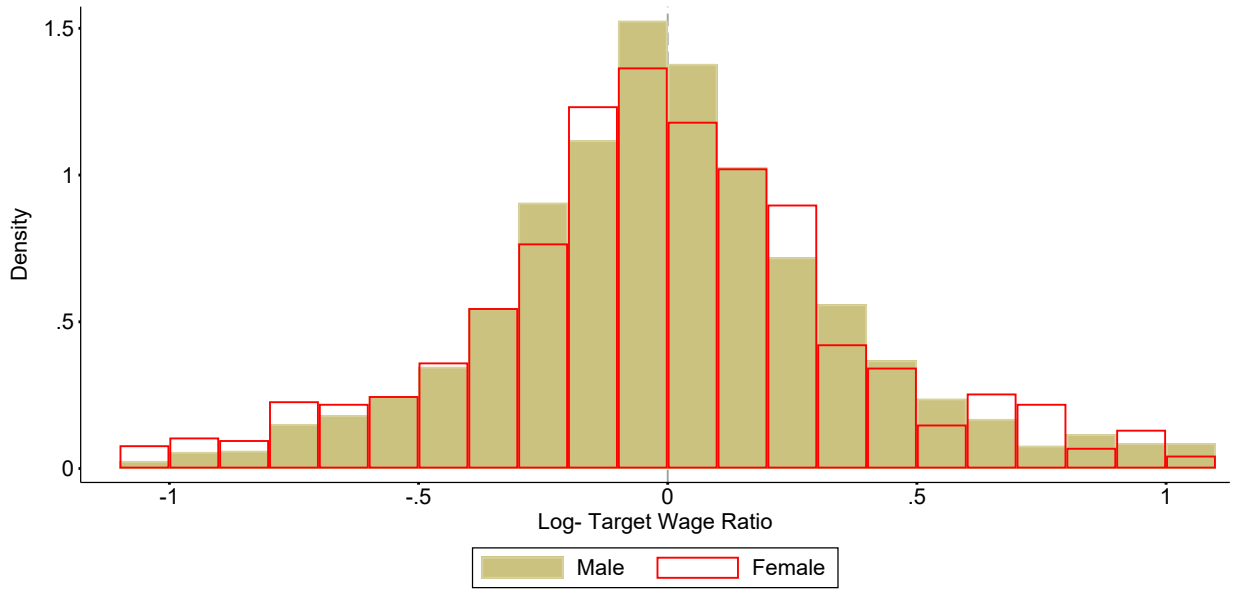
(f) Days Worked in Minijob - East Germany

Notes: This figure shows how labor market characteristics before and after displacement differ for men and women working in West and East Germany in t=c-1, respectively. Panels (a), (c), and (e) show eventstudy coefficients for log earnings, days worked in full-time job and days worked in minijob for West Germany. Panels (b), (d), and (f) show eventstudy coefficients for log earnings, days worked in fulltime job and days worked in minijob for East Germany. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. Women in West (East) Germany are reweighted to men in West (East) Germany. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

Figure 13: Log Target Wage Ratio



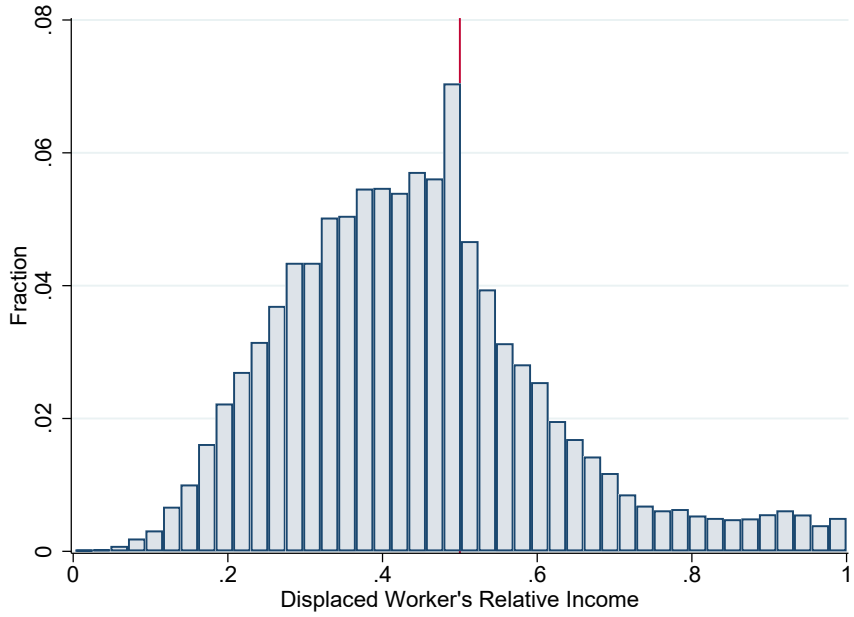
(a) Log Target Wage Ratio - All Nonemployed



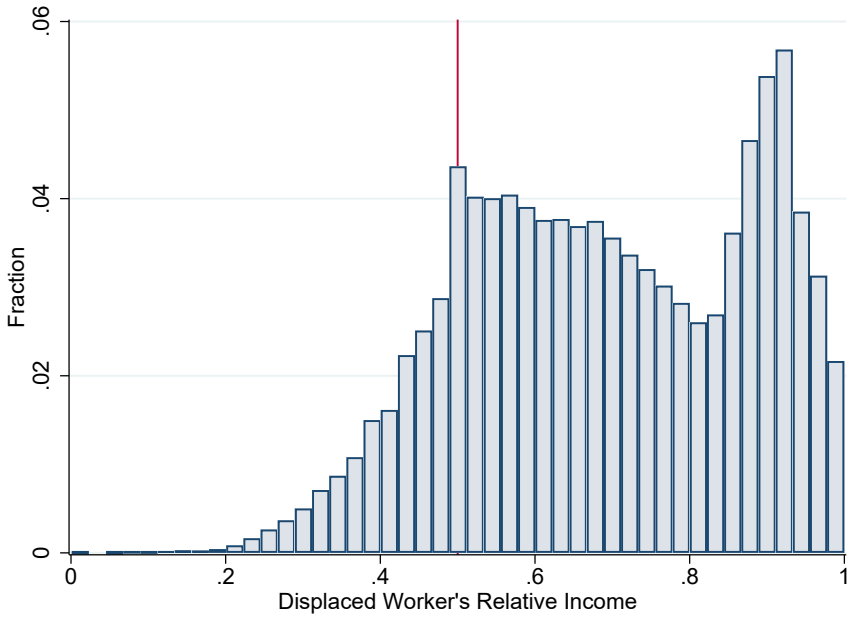
(b) Log Target Wage Ratio - Nonemployed w/ Fulltime Job Pre UI

Notes: This figure shows histograms of the log-target wage ratio, defined as the log of the ratio of monthly target wage (the monthly gross wage of the job last applied to) and the monthly gross wage pre unemployment separate by males and females. Panel (A) includes all observations during nonemployment, panel B restricts further to individuals with a fulltime-job pre unemployment.

Figure 14: Distribution of Share in Household Income by Gender



(a) Distribution of Displaced Wifes' Share in Household Income - t=c-1



(b) Distribution of Displaced Husbands' Share in Household Income - t=c-1

Notes: This figure shows the distribution of displaced wifes' (Panel (a)) and husbands' (Panel (b)) share in household income in the year before displacement (t=c-1). We set the share equal to zero if the partner is not working.

Table D1: The Gender Gap in Earnings Losses and Other Characteristics After Displacement

	(1) Mean Change in Outcome Variable for Men		(2) Unadjusted Gender Gap		(3) Composition Adjusted Gender Gap Regression-Adj.		(4) Composition Adjusted Gender Gap Reweighted		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Earnings, Wages, and Employment									
Total Yearly Earnings	-10177.2	[247.1]	**3051.6**	[339.6]	130.2	[273.2]	**-2257.8**	[507.7]	96,158
Earnings in t=c-2 - Diff-Diff	-0.287	[0.0063]	**0.036**	[0.011]	**-0.022**	[0.0097]	**-0.048**	[0.013]	96,158
Log Earnings - Diff-Diff	-0.443	[0.0096]	0.0079	[0.018]	**-0.070**	[0.015]	**-0.044**	[0.020]	90,732
Sinh(Earnings)	-1.83	[0.051]	**0.272**	[0.075]	0.049	[0.062]	**-0.249**	[0.099]	96,158
Log Wage Loss	-0.203	[0.0061]	**-0.039**	[0.012]	**-0.099**	[0.011]	**-0.075**	[0.015]	87,342
Fulltime Log Wage - Diff-Diff	-0.090	[0.0033]	0.0053	[0.0078]	**-0.031**	[0.0070]	**-0.044**	[0.012]	63,191
Days Worked	-78.1	[1.71]	**12.4**	[2.86]	**4.41**	[2.24]	-3.46	[3.45]	96,158
Days Worked Fulltime - Diff-Diff	-84.7	[1.90]	**32.2**	[3.19]	**-9.72**	[2.82]	**-14.4**	[4.07]	96,158
Days Worked Parttime - Diff-Diff	-1.68	[0.637]	**-26.6**	[1.89]	**8.75**	[1.76]	**10.5**	[2.28]	96,158
Days Worked in Minijob - Diff-Diff	2.03	[0.671]	**8.05**	[1.22]	**6.83**	[1.44]	0.163	[2.03]	96,158
Panel B: Job Characteristics									
Commuting Distance	1.65	[1.60]	**-6.15**	[1.81]	0.662	[2.00]	0.466	[3.62]	86,502
Log Establishment Size - Diff-Diff	-0.752	[0.028]	**-0.484**	[0.065]	**-0.123**	[0.030]	-0.073	[0.048]	86,318
Industry Change	0.440	[0.0064]	-0.021	[0.014]	**0.029**	[0.0099]	0.017	[0.013]	87,320
Occ. Change	0.280	[0.0060]	**-0.050**	[0.010]	-0.0074	[0.0092]	-0.018	[0.013]	87,254
Estab Share Women	0.0064	[0.0025]	**0.031**	[0.0037]	**0.054**	[0.0041]	**0.059**	[0.0059]	85,877
Temp Work	0.040	[0.0020]	**-0.020**	[0.0026]	**-0.017**	[0.0032]	**-0.016**	[0.0037]	86,318
Business Service Estab	0.069	[0.0028]	**-0.030**	[0.0038]	**-0.033**	[0.0044]	**-0.036**	[0.0049]	86,318
New Estab	0.200	[0.0064]	**0.061**	[0.015]	0.0056	[0.0086]	0.0087	[0.011]	86,318
AKM Estab FE	-0.062	[0.0055]	0.0063	[0.0055]	**-0.013**	[0.0043]	-0.0030	[0.0056]	96,158

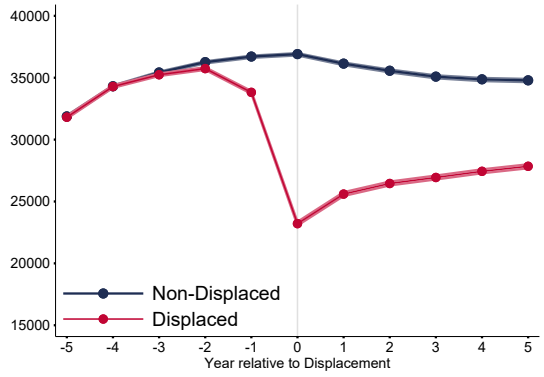
Notes: Regression results for a sample of couples and non-couples. Each row represents a separate regression of the mean change in the outcome variable over a five year period after job loss on a constant and a dummy for female. The first column shows the constant, representing the mean effect for men. The second column the coefficient on a female dummy without any controls. The third column the coefficient on the female dummy controlling for all covariates. The fourth column uses reweighting. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. Coefficients in bold are statistically significant at 5%-level.

Table D2: Explaining the Gender Gap in Wage Losses After Displacement

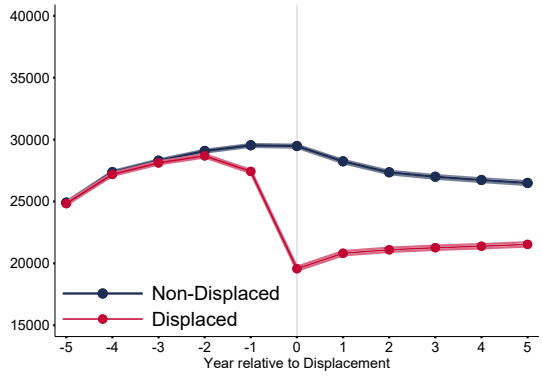
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All Workers: Log Wage									
Female	-0.075	-0.076	-0.045	-0.080	-0.049	-0.071	-0.071	-0.043	-0.044
	(0.015)**	(0.015)**	(0.014)**	(0.015)**	(0.013)**	(0.014)**	(0.013)**	(0.011)**	(0.011)**
Industry Change		-0.095						-0.039	-0.033
		(0.013)**						(0.011)**	(0.010)**
Occ. Change		-0.15						-0.076	-0.073
		(0.014)**						(0.010)**	(0.010)**
Log Establishment Size - Diff-Diff			0.057					0.034	0.029
			(0.0063)**					(0.0048)**	(0.0048)**
Estab Share Women			-0.43					-0.19	-0.17
			(0.045)**					(0.034)**	(0.034)**
Commuting Distance				-0.00012				-0.000098	-0.000093
				(0.000083)				(0.000066)	(0.000065)
Fulltime - Diff-Diff					0.69			0.58	0.56
					(0.025)**			(0.021)**	(0.020)**
AKM Estab FE						1.09	1	0.80	1
						(0.064)**		(0.052)**	
Observations	87342	87342	87342	87342	87342	87342	87342	87342	87342
R^2	0.003	0.032	0.070	0.023	0.231	0.181	0.039	0.378	0.266
Mean Dep. Var Men	-.202	-.202	-.202	-.202	-.202	-.202	-.202	-.202	-.202
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Panel B: Fulltime Workers: Fulltime Log Wage									
Female	-0.044	-0.044	-0.034	-0.044	-0.049	-0.044	-0.043	-0.044	-0.045
	(0.012)**	(0.012)**	(0.011)**	(0.012)**	(0.012)**	(0.012)**	(0.012)**	(0.011)**	(0.011)**
Industry Change		-0.042						-0.017	-0.0082
		(0.010)**						(0.0088)	(0.0086)
Occ. Change		-0.022						-0.0041	0.00084
		(0.012)						(0.0094)	(0.0095)
Log Establishment Size - Diff-Diff			0.025					0.0089	0.00087
			(0.0035)**					(0.0028)**	(0.0034)
Estab Share Women			-0.15					-0.052	-0.012
			(0.038)**					(0.032)	(0.032)
Commuting Distance				-0.000087				-0.000076	-0.000068
				(0.000094)				(0.000080)	(0.000083)
Fulltime - Diff-Diff					0.33			0.24	0.20
					(0.029)**			(0.026)**	(0.025)**
AKM Estab FE						0.73	1	0.66	1
						(0.049)**		(0.048)**	
Observations	63191	63191	63191	63191	63191	63191	63191	63191	63191
R^2	0.003	0.009	0.031	0.004	0.082	0.225	0.035	0.270	0.070
Mean Dep. Var Men	-.093	-.093	-.093	-.093	-.093	-.093	-.093	-.093	-.093
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)

Notes: Regression results for a sample of couples and non-couples. This table shows to what extent changes in industry, occupation, and establishment characteristics can explain the effect of being female on wages after displacement. All outcome variables are based on the individual difference-in-differences estimate. We reweight women to men using individual and establishment characteristics pre displacement. In panel (A), the outcome variable is log wages. In panel (B), the outcome variable is fulltime log wages. In both panels, we control for the same set of difference-in-differences estimates as depicted in the table. Columns (2)-(7) control for various difference-in-differences terms. Column (8) controls for all difference-in-differences terms at once. In columns (7) and (9), the coefficient on the establishment effect is forced to be equal to 1. We cluster standard errors at displacement establishment level (constant within matched worker pairs). Workers in our sample are displaced in 2002-2012, and they are observed from 1996-2017. * and ** correspond to 5 and 1 percent signficance levels, respectively.

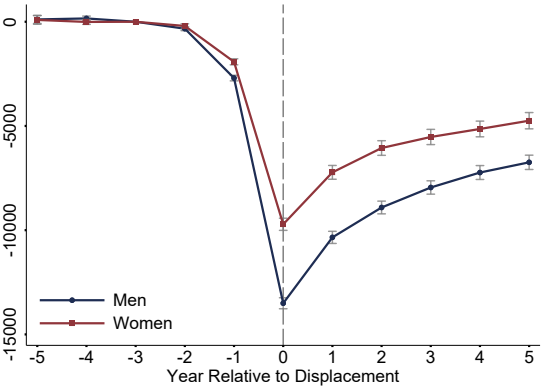
Figure D1: The Gender Gap in Earnings Losses after Displacement without Controlling for Pre-Displacement Characteristics



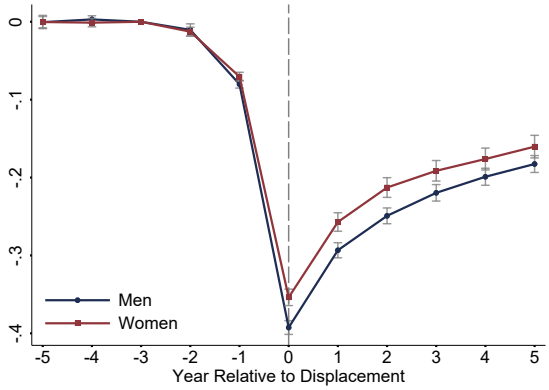
(a) Total Earnings in Year - Men



(b) Total Earnings in Year - Women



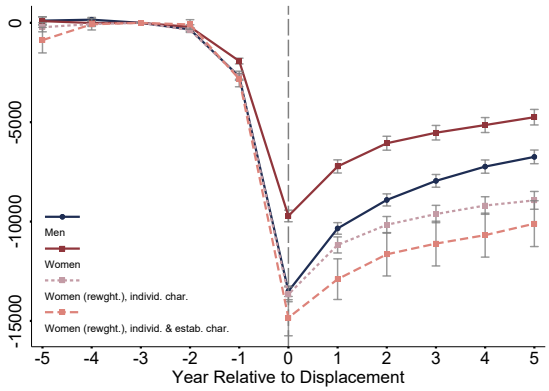
(c) Total Earnings in Year - Men and Women



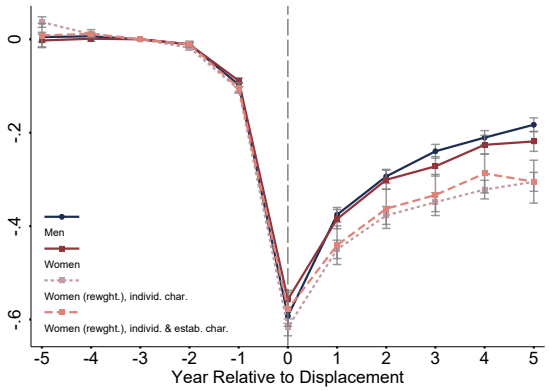
(d) Earnings Relative to t=c-2 - Men and Women

Notes: The figures show earnings losses for displaced and non-displaced workers for a combined sample of couples and non-couples. Panels (a) and (b) show total yearly earnings for displaced and non-displaced men (a) and women (b). The red line corresponds to workers who are displaced from year t=c-1 to t=c, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group. Panels C and D show event study coefficients, controlling for person FE, year FE, years since separation, and age polynomials. Panel (c) shows event study coefficients for total yearly earnings as outcome. Panel (d) shows event study coefficients for earnings relative to t=c-2 as outcome. The red line corresponds to women, the blue line corresponds to men. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

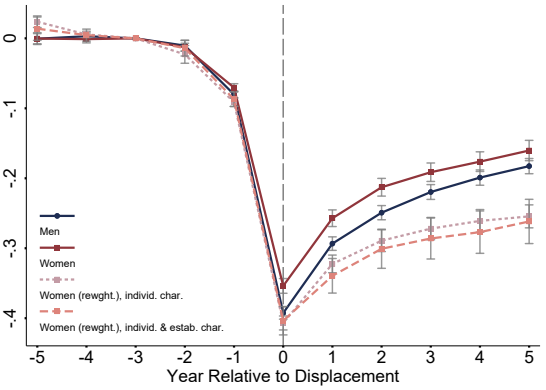
Figure D2: The Gender Gap in Earnings Losses after Displacement, Controlling for Pre-Displacement Job and Worker Characteristics



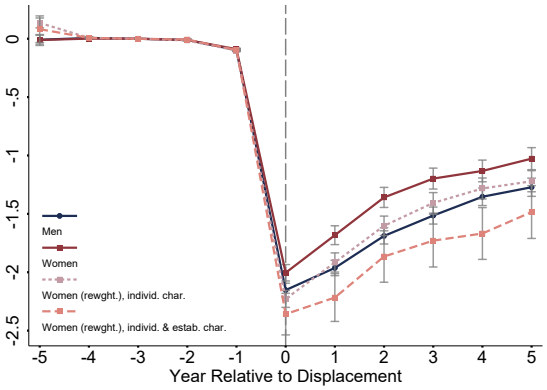
(a) Total Earnings



(b) Log Earnings



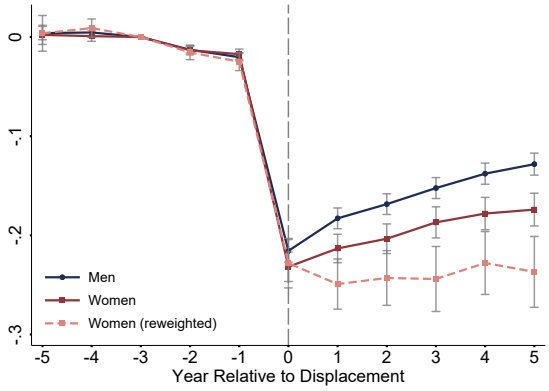
(c) Earnings Relative to t=c-2



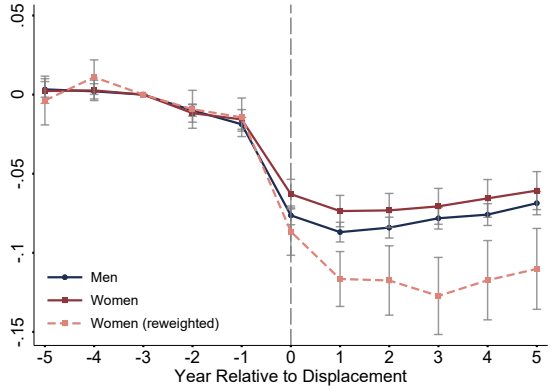
(d) Inverse Hyperbolic Sine Earnings

Notes: This figure shows how earnings losses from displacement differ for men and women. Combined sample of couples and non-couples. Panels (a)-(d) show eventstudy coefficients for total yearly earnings, log earnings, earnings relative to t=c-2, and inverse hyperbolic sine earnings. The four lines correspond to four event study regressions: Men only, women only, women reweighted with individual characteristics, and women reweighted with individual characteristics and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

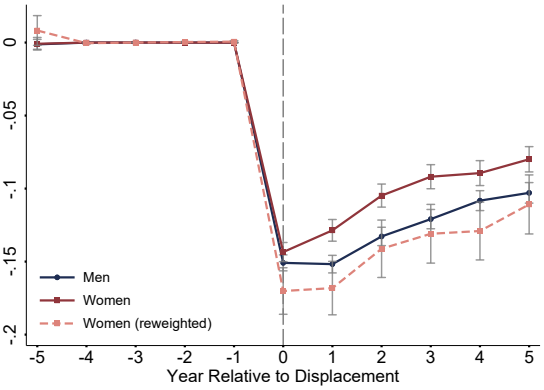
Figure D3: The Gender Gap in Wage and Employment Losses after Displacement



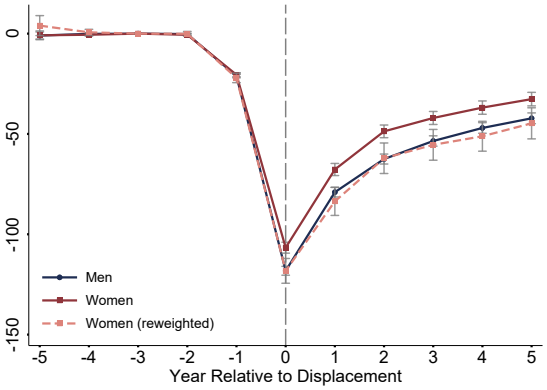
(a) Log Wage



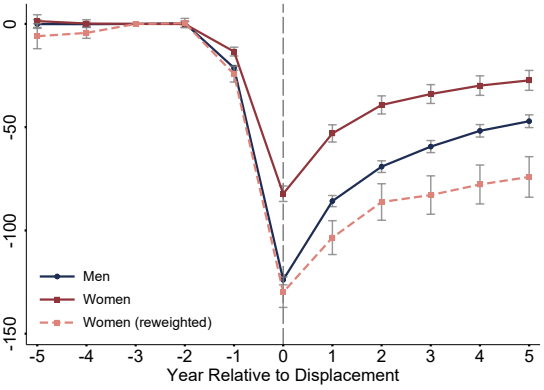
(b) Log Wage Fulltime



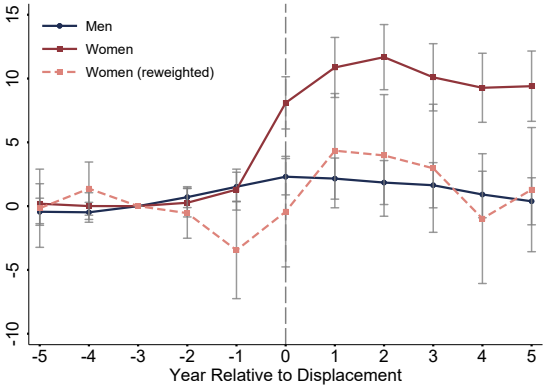
(c) Any Employment in Year



(d) Days Worked



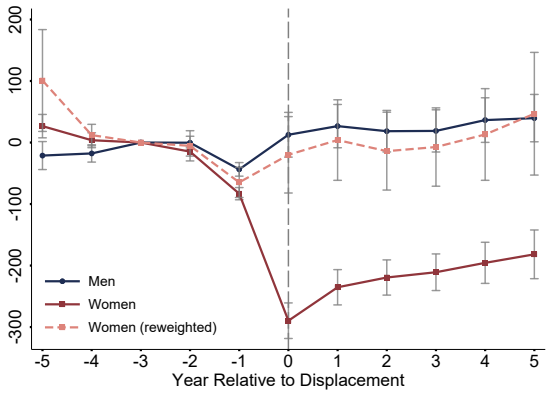
(e) Days Worked Fulltime



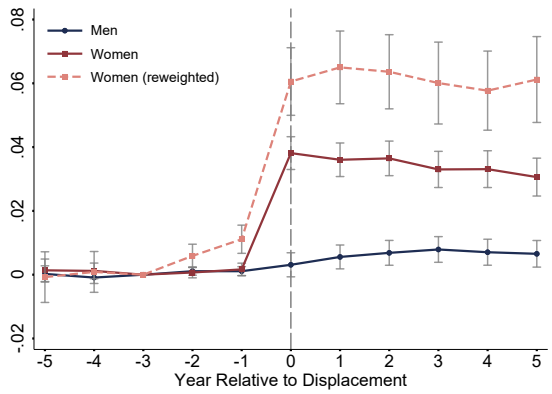
(f) Day Worked in Mini-job

Notes: This figure shows how labor market characteristics before and after displacement differ for men and women. Combined sample of couples and non-couples. Panels (a)-(f) show event study coefficients for log wage, log wage from fulltime job, employment, days worked, days worked in fulltime job, and days worked in minijob. The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Workers are displaced in 2002-2012, and they are observed from 1997-2017.

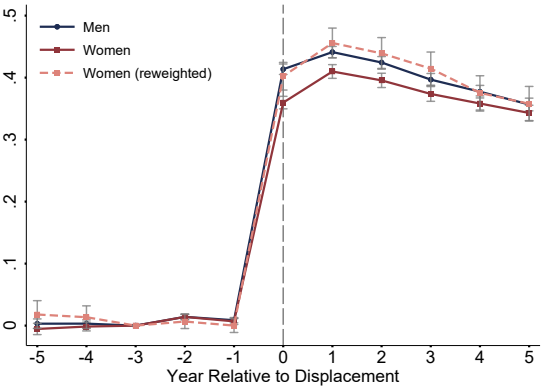
Figure D4: Changes in Job Characteristics after Displacement



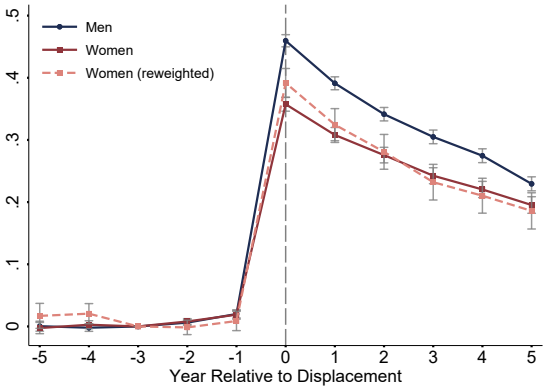
(a) Size of Establishment



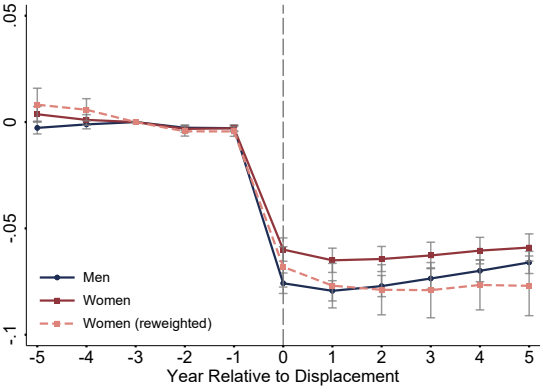
(b) Share of Females in Establishment



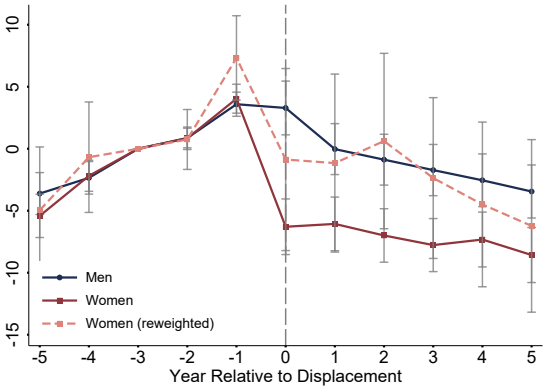
(c) Industry Different from Industry at t=c-1



(d) Occupation Different from Occupation at t=c-1



(e) Establishment Effect



(f) Commuting Distance

Notes: This figure shows how job characteristics for men and women evolve before and after displacement. Combined sample of couples and non-couples. Panels (a)-(f) show eventstudy coefficients for establishment size, share of female workers in establishment (leave-one-out mean), industry switches (2-digits), occupation switches (3-digits), AKM establishment effects, and commuting distance (in km). The three lines correspond to three event study regressions: Men only, women only, and women reweighted with individual and establishment characteristics. All regressions include controls for person FE, year FE, years since separation, and age polynomials. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Commuting distance is measured on the municipality level, and is recorded on December 31 each year. Workers are displaced in 2002-2012, and they are observed from 1997-2017.