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JEL Classification: J0

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The Gender Gap in Earnings Losses after Job Displacement*

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August 2021

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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., 2020). 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. Furthermore, many papers have 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 response to a job loss of their own differs from men (a few exceptions are Maxwell and D'Amico, 1986; Crossley et al., 1994; Kunze and Troske, 2015; Meekes and Hassink, 2020). 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 distinguish the role of gender from these confounding job characteristics, we focus our analysis on a set of men and women who are displaced from very similar jobs (along observable dimensions). We show that when comparing men and women displaced from similar jobs and with similar pre-displacement earnings, women experience

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

about 35% larger earnings losses than men, what we call the 'gender gap in earnings losses'. Furthermore, while there is some recovery in earnings losses for both genders relative to non-displaced workers, this recovery is markedly slower for displaced women, so that the gender gap in earnings losses between men and women grows substantially with time since job loss.

In a second step, we investigate the main drivers that underly 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, while in the longer term, daily wages become a more important factor, as they show no recovery as time passes. Furthermore, the gender gap is apparent 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. 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.[2] 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 are around 15 log points lower.

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 seem not to be driving the gender gap in wage losses. One factor that does turn out to be important is establishment pay premia, estimated using the two-way fixed effects model of Abowd et al. (1999) (AKM).[3] We find that in the long run (5 years post displacement), women are employed at establishments paying slightly lower wage premia than men (9 log point loss for women vs. 7 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 fall down the job-ladder (with little sign of climbing back up), women fall further and recover more slowly.[4]

[2]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, 2021).

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

[4]This is in line with the results in Card et al. (2016) that the distribution of men and women across

In a fourth 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 self-reported job search preferences (from the UI system), we show that displaced women are substantially more likely to look for part-time instead of full-time employment and have a more narrow geographic scope. This suggests that at least some of the differences in outcomes are likely due to differences in labor supply.

In a final step, we turn to the household level to better understand the experience of men and women after job loss and how this is shaped by factors such as the added worker effect or the presence of children in the household. Since the household dimension is key for understanding possible mechanisms, we focus our entire analysis 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 first show that there is no added worker effect in our context. In fact the opposite: both for men and women, a job loss is associated with small earnings declines of their partner in the following years. We then investigate how recovery paths vary by 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. Thus parenthood sharply widens the gender gap in earnings losses, as well as wage and employment losses.

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. Jacobson et al., 1993; Crossley et al., 1994; Hijzen et al., 2010; Kunze and Troske, 2015), 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 attempt to account for such pre-displacement differences and to focus on a set of similar men and women in the comparison. A recent example in this spirit is Meekes and Hassink (2020) which studies post-displacement labor market outcomes for men and women in the Netherlands. The paper focuses on job flexibility as an outcome, but also reports estimates for employment and wages. However, the job characteristics of of displaced men and women in the paper look very different from each other. Certainly, these broad comparisons of displaced men and women are interesting in their own right, and likely the right estimates for quantifying differences in the cost of job

establishments with different wage premia plays an important role in explaining the gender wage gap.

loss for example for purposes of policy advice. However, they complicate the interpretation since it remains unclear whether differences are due to different characteristics of jobs that men and women hold vs. gender per se (be it due to differences in labor supply decisions or differences in labor demand, e.g. because of discrimination). By comparing men and women displaced from very similar jobs, we can zoom in on differences that are more directly tied to gender and we can show that even men and women who have had very similar labor market experiences so far and made similar choices can be very differently affected by shocks.

Our paper is also different from these previous papers on the gender gap, in that 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 premia) and their ability to explain the gender gap in earnings and wage losses. Finally, an important difference is the ability to investigate the household dimension in some detail in the same context, such as the added worker effect and the role of children.

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., 2020) 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. (2020). 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. (2020) focus on earnings losses over the business cycle, we use this design to estimate the gender gap in losses and 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.[5] We created a dataset of matched married couples for each year from 2001 to 2014, building on Goldschmidt et al. (2017). The linkage relies on the fact that most married couples in Germany share a last name (at least in part in the case of hyphenated names). Thus men and women who live at the same address with the same last name and within a certain age distance have a high likelihood of being married to each other. 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 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. Similarly, Meekes and Hassink (2020) find that women search longer for jobs after displacement and seek out jobs with shorter commuting times and more hours flexibility. In line with this, we show that after job displacement, women are more likely to take up part-time or marginal employment instead of a full-time job. This pattern is particularly striking for mothers with children below the age of 4, suggesting that part of it is due to women trying to reconcile career and family life.[6]

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). While we cannot observe home production in our data, we show that the gender gap in earnings losses is particularly high for mothers with young children. It is moreover larger for women in married couples as opposed to non-married women, suggesting

[5]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.

[6]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.

that their incentives for labor market re-integration differ. Similarly, we add to the added worker effect literature (e.g. Lundberg, 1985, Halla et al., 2020), by investigating whether partners of the displaced workers respond to the displacement by increasing their own labor supply. Finally, we 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. Additionally, Kleven et al. (2021) document a similar-sized child penalty for mothers of adopted and biological children, which the authors view as evidence against a biological source of the child penalty. 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 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: mothers experience much larger earnings, wage, and employment losses.[7] This finding 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.

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 Diff-in-Diff 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 investigate gender differences in post-displacement job characteristics and analyze to what extent these differences are driving the large wage losses of women. In Section 5 we then turn to the household level, showing gender differences in the effects of job loss on partner's labor supply decisions and in how the presence of young children affects labor market outcomes. Section 6 discusses these results and concludes.

[7] 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.

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[8]. 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).[9]

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.[10] We combine this with a sample of couples where no partner experienced a 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.[11] 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.

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

[9]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 olde"st child in a household.

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

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

2.2 Measuring Job Displacement

In our definition of job displacement, we follow Schmieder et al. (2020). 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. (2020), 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.[12] 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 establishments 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. (2020) 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. For each baseline year c we consider all workers that satisfy the following

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

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.[13] 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 $t = c$ and $t = c + 1$ if she fulfills the following two conditions: First, she leaves the establishment between $t = c$ and $t = c+1$ and is not employed at the year c establishment in any of the following 10 years. Second, the establishment she works at has a mass layoff between year $t = c$ and $t = c+1$. We exclude potential comparison workers who move establishments between $t = c$ and $t = c + 1$. Note, however, that control workers can be displaced in future years.

Our baseline restrictions ensure that displaced and non-displaced workers are somewhat 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 $t = c - 2$ and $t = c - 3$, full-time employment status in $t = c - 2$, and age, years of education, tenure, and log establishment size in $t = c$. 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.

[13] 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).

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 premia (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:

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

The composition adjusted gender gap thus amounts to a test for the hypothesis that earnings losses are independent of gender, conditioning on the covariates: $\Delta \perp D| X$.[14] 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 $t = c - 2$ and $t = c - 3$, full-time employment in $t = c - 2$, and age, years of education, tenure, log establishment size, 1-digit industry dummies, and location in East or West Germany in $t = c$. We obtain the predicted propensity score from this regression $\hat{p}$ and use $\hat{\phi}(x) = \frac{\hat{p}}{1-\hat{p}}$ to reweight women in our sample to match their male counterparts.[15]

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 4). 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 premia.

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

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

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 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:

$$y_{itc} = \sum_{k=-5}^{5} \delta_k \times I(t = c + 1 + k) \times \text{Disp}_i + \sum_{k=-5}^{5} \gamma_k \times I(t = c + 1 + k) + \pi_t + \alpha_i + X_{it}\beta + \varepsilon_{itc} \quad (5)$$

where y_{itc} denotes the outcome (e.g., log earnings) for worker i at time t, in "cohort" (baseline year) 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 $k = c - 2$ from the regression.

Like Schmieder et al. (2020) we control for "year relative to baseline year" fixed effects (coefficients γ_k).[16] 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 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

[16] 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. (2020), Online Appendix.

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, 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 is the first year after displacement and -1 is the baseline year c. 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 $t = c$, the baseline year, which is not surprising given the matching algorithm. In year $t = c$ a small gap opens up driven by the fact that displacement occurs at some point between June 30 of $t = c$ and $t = c+1$. In the displacement year $t = c+1$, 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 $t = c - 1$, that is the year before the baseline year, we denote this as $\tilde{y}_{i,t} \equiv \frac{y_{i,t}}{y_{i,-2}}$. This outcome variable has the distinct advantage that it allows for expressing 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 very 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. (2020) 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 6 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.[17] 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.

[17] 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.

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.[18] 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 is 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.

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. Figure 4 shows how the nature of jobs change after displacement. Several recent papers have shown that job losers tend to move to lower paying firms 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

[18] 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 (2021); Tazhitdinova (2020)).

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 premia, and is consistent with the evidence from Card et al. (2016) that women tend to be concentrated in low-paying establishments.[19] 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 period was estimated by Bellmann et al. (2020)[20] 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. (2020) 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

[19] 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.

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

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. (2020), 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. 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.[21] Column (1) reproduces the benchmark results from Table 2 Column (4) for the two outcomes.

We first include indicators for changing industry and occupation in Column (2). While both are associated with large drops in log daily wages and full-time wages, the coefficient on female remains unchanged, which is not surprising given that the incidence of occupation change and industry change is so similar for both groups (Figure 4). Column (3) includes the change in establishment size and shows that larger establishments pay higher wages (elasticity of 0.06 or 0.03 for full-time workers). We also include the share of women working in an establishment as an explanatory variable, since women are often concentrated in low-wage establishments. While this is strongly negatively correlated with overall log wages and full-time wages, only a small share of the gender gap is explained by the size and gender composition of the post-displacement establishment.

Based on Le Barbanchon et al. (2020), 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, but we also see no evidence for this in Column (4). Commuting distance is not clearly related to wages and the gender gap is unchanged when controlling for it.

In Columns (5) and (6), we turn to the AKM establishment effect. The establishment

[21] Appendix Table 7 shows the same table using regression adjustment instead of weights.

effect does explain a substantial part of the gender gap in wage losses, especially for full-time workers where the gap is reduced from 3.9 to 3.2 log points (or around 20%) in Column (6). The coefficient on the establishment effect is 0.74 in Column (5). 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. (2020) show that using a two sample IV leads to a coefficient close to 1 in this type of regression. If we simply impose that the establishment effect has a coefficient of 1, we find that about a quarter of the gender gap is explained by changes in the establishment effects (Column 6).[22]

Finally, we put in all job characteristics jointly in Columns (7) and (8). For overall wages, job characteristics explain roughly a quarter of the gender gap, while for full-time wages they explain about 30%.

4.3 Labor Supply or Labor Demand? Gender Differences in Job Preferences 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. While we cannot fully disentangle these two channels, we can shed some light on this by comparing self- reported job preferences in our sample, which we obtained from the UI system. 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

[22] Appendix Table 8 shows results using establishment effects estimated from AKM models estimated separately by gender and using the Kmeans hybrid approach proposed in Schmieder et al. (2020). 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, perhaps because a lot of within group variation is lost.

mass-layoff and we have valid information on job preferences for about 45,000 individuals in our sample.[23] Table 4 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 B 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, the gender gap shrinks but women are still about 11-13 percentage points less likely to exclusively look for a full-time job, despite the fact that in this reweighted sample almost everyone was working full-time before. Women are also much more likely to be searching only for part-time jobs or for either type of employment, with the differences persisting even after controlling for observables.

Panel C looks at whether workers are only interested in permanent (as opposed to temporary) contracts, which are typically viewed as better. In the unaddjusted comparison women are also more open to looking at any (including temporary) contract, but the differences are small after adjusting for characteristics. Finally, Panel D: shows that women (before and after reweighting) are less likely to say that they have a very broad geographic scope of job search, though consistent with the previous evidence on commuting the effect is not large.

Overall, this is some evidence that women have systematically different labor supply than men, in particular in their willingness to work part-time as opposed to full-time.[24]

4.4 Robustness of Main Results

Table 5 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 12.[25]

Sample Construction:

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

[24] Appendix Table 11 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, though a relatively small part. It is probably not surprising that stated job search preferences are a noisy measure of differences in labor supply and this analysis thus can only provide a lower bound for the importance of the labor supply channel.

[25] We also reproduce this Table without controls and with regression adjustment instead of reweighting in Appendix Tables 13 and 14.

While our baseline specification estimates the cost of job loss over a 5-year-horizon after displacement, Table 5 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 15 Column (6) that imposing the stricter restrictions (3 years tenure, baseline establishment size larger than 50) from Schmieder et al. (2020) 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 5 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 17 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 5 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 5 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 5 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 5 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.[26]

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 15, 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 15 show, the gender gap is remarkably stable for these two groups of workers.

5 Displacement in the Household Context: The Added Worker Effect and the Role of Children

5.1 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).

[26]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.

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 5 and Table 6. Panel (a) of Figure 5 reports the impact of job loss on the partner's earnings relative to t=c-1 by gender of the displaced worker.[27] 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 6. 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 5 (d), we show the effect of displacement on household income relative to $t = c - 1$. Given that partner's earnings only mildly respond

[27] Our outcome variable is the change in earnings divided by the earnings of the jobloser in the baseline year $(t = -2)$: $\frac{\Delta y_{partner}}{y_{jobloser,t=-2}}$. Scaling by the earnings of the jobloser, rather than the earnings of the parter at baseline, has the advantage that $y_{jobloser,t=-2}$ is always a positive and reasonably large number, while $y_{partner,t=-2}$ can be small or zero which would lead to relative wage changes that go to infinity creating huge outliers.

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 6 Column (5) confirms that the gender gap persists on the household level when 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).

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.[28] 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

[28] 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:

$$\Delta_d y_{ic} = \beta \, Female_{ic} * Displaced_{ic} + \delta \, Female_{ic} + X_{ic}\theta + \varepsilon_{ic} \tag{9}$$

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.

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 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 6, 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 16 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).

5.2 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):

$$\Delta_{dd} y_{ic} = \sum_{a} (\alpha_a + \beta_a \, Female_i) \, I_{KidAge_i=a} + X_i \theta + \varepsilon_{ic} \tag{10}$$

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.[29]

Figure 6 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-1. For men and women without young children, the results are similar as the results in Section 3.3: women have significantly larger earnings losses than men when holding pre-displacement characteristics constant. A striking 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

[29] 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.

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 children.

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.

Table 7 shows comparable results from a regression model, where we estimate Equation (8) but include dummies for children under 7 and over 6, 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 6.7 percentage points, somewhat less than the overall gender gap. The coefficient on the dummy for young child (0.064) and its interaction with a female dummy (-0.13) show that the presence of young children substantially reduces the earnings losses for men, but sharply increase earnings losses for women. Older children seem to have a slight positive effect on earnings losses (i.e. reducing the losses) both for men and women.

The remaining Columns of Table 7, as well as the other panels of Figure 6, 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 smaller probability of working part-time. For women, the effects are reversed with much larger losses in days worked and wages, and a higher propensity to work part-time or mini-jobs. Women also move to smaller and lower-paying employers if they have young children.

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

5.3 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, if gender identity norms, as in Bertrand et al. (2015), that make it undesirable for either or both partners if the wife makes more money than the husband are important, then the pre-displacement within household income distribution may be an important determinant for post-displacement outcomes.

In Table 7 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 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 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).

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 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 may seem 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 much harder for them to find any or at least a full-time job. We provided suggestive evidence based on stated job preferences 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-2*	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	.	52662.4	66600.9	.	48557.5
		[24048.2]	[27799.8]		[20764.6]
Total Yearly Earnings - Partner	.	27063.1	29824.6	.	13609.9
		[19233.8]	[21146.6]		[14335.4]
Share of Household Income	.	55.5	60.7	.	76.3
		[27.1]	[24.2]		[20.8]
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. 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. Variables with * are used in reweighting. 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-1	-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)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Workers: Log Wage								
Female	-0.13	-0.13	-0.11	-0.13	-0.12	-0.12	-0.11	-0.11
	(0.013)**	(0.013)**	(0.013)**	(0.013)**	(0.012)**	(0.012)**	(0.012)**	(0.012)**
Industry Change		-0.14					-0.10	-0.10
		(0.011)**					(0.011)**	(0.010)**
Occ. Change		-0.13					-0.095	-0.092
		(0.0096)**					(0.0089)**	(0.0086)**
Log Estab Size			0.059				0.042	0.039
			(0.0040)**				(0.0035)**	(0.0038)**
Estab Share Women			-0.41				-0.28	-0.27
			(0.034)**				(0.030)**	(0.029)**
Commute Distance				-0.000011			-0.000052	-0.000049
				(0.000070)			(0.000064)	(0.000065)
AKM Estab FE					1.06	1	0.90	1
					(0.064)**		(0.061)**	
Observations	147196	147196	147196	147196	147196	147196	147196	147196
R^2	0.010	0.043	0.083	0.034	0.157	0.038	0.227	0.117
Mean Dep. Var Men	-.201	-.201	-.201	-.201	-.201	-.201	-.201	-.201
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Panel B: Full-time Workers: Full-time Log Wage								
Female	-0.039	-0.038	-0.035	-0.039	-0.032	-0.030	-0.030	-0.028
	(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)
Commute 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	105992	105992	105992	105992	105992	105992	105992	105992
R^2	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
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)

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 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 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 4: Gender Differences in Job Search Preferences 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
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Any Job Search History?									
Has Job Search Spell	0.696	[0.0096]	**-0.101**	[0.022]	**-0.020**	[0.0060]	**-0.032**	[0.0098]	80,655
Panel B: Preferred Type of Employment									
Full-time Employment	0.979	[0.0016]	**-0.314**	[0.0061]	**-0.136**	[0.0054]	**-0.113**	[0.0060]	45,087
Part-time Employment	0.0028	[0.00032]	**0.221**	[0.0050]	**0.079**	[0.0034]	**0.066**	[0.0045]	45,087
Part-time or Full-time	0.018	[0.0015]	**0.093**	[0.0041]	**0.058**	[0.0045]	**0.047**	[0.0041]	45,087
Panel C: Preferred Type of Contract									
Permanent Contract	0.745	[0.0075]	**-0.035**	[0.0091]	**0.020**	[0.0094]	-0.0066	[0.010]	45,131
Any Contract	0.255	[0.0075]	**0.035**	[0.0091]	**-0.020**	[0.0094]	0.0066	[0.010]	45,131
Panel D: Geographic Scope of Job Search									
Broad	0.439	[0.0051]	**-0.040**	[0.0073]	**-0.024**	[0.0085]	-0.019	[0.012]	31,349
Narrow	0.561	[0.0051]	**0.040**	[0.0073]	**0.024**	[0.0085]	0.019	[0.012]	31,349

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, C, and D we restrict the sample to individuals with any job search history and with non-missing search information in the corresponding variable. 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 5: 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) 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: Earnings Rel. to t=c-1										
Female	-0.092	-0.093	-0.11	-0.093	-0.12	-0.086	-0.087	-0.068	-0.017	-0.048
	$(0.012)^{**}$	$(0.018)^{**}$	$(0.014)^{**}$	$(0.012)^{**}$	$(0.025)^{**}$	$(0.0089)^{**}$	$(0.012)^{**}$	$(0.020)^{**}$	(0.013)	$(0.013)^{**}$
Observations	80655	55107	93755	80707	80423	77144	80706	78695	16422	96158
R^2	0.007	0.006	0.008	0.007	0.013	0.352	0.006	0.003	0.000	0.002
Mean Dep. Var Men	-.258	-.203	-.268	-.245	-.258	-.258	-.258	-.259	-.297	-.287
	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.006)	(.002)
Panel B: Log Wages										
Female	-0.13	-0.14	-0.16	-0.15	-0.22	-0.16	-0.13	-0.16	-0.079	-0.075
	$(0.013)^{**}$	$(0.017)^{**}$	$(0.013)^{**}$	$(0.013)^{**}$	$(0.036)^{**}$	$(0.013)^{**}$	$(0.013)^{**}$	$(0.017)^{**}$	$(0.016)^{**}$	$(0.015)^{**}$
Observations	73598	51670	85092	73626	73369	70058	73634	71758	14551	87342
R^2	0.010	0.009	0.013	0.013	0.025	0.347	0.009	0.014	0.004	0.003
Mean Dep. Var Men	-.201	-.187	-.205	-.188	-.201	-.201	-.201	-.202	-.201	-.203
	(.003)	(.004)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.007)	(.003)
Panel C: Log Fulltime Wages										
Female	-0.039	-0.046	-0.052	-0.067	-0.090	-0.061	-0.051	-0.045	-0.039	-0.044
	$(0.0084)^{**}$	$(0.012)^{**}$	$(0.0079)^{**}$	$(0.0077)^{**}$	$(0.027)^{**}$	$(0.0074)^{**}$	$(0.0086)^{**}$	$(0.0099)^{**}$	$(0.011)^{**}$	$(0.012)^{**}$
Observations	52996	39002	60891	56077	52939	49526	53169	52938	10944	63191
R^2	0.003	0.003	0.005	0.009	0.015	0.360	0.005	0.004	0.003	0.003
Mean Dep. Var Men	-.094	-.091	-.094	-.084	-.094	-.094		-.094	-.086	-.09
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
Panel D: Days Worked Fulltime										
Female	-23.1	-32.5	-30.4	-10.1	-31.9	-22.3	-17.4	-25.4	-6.68	-14.4
	$(2.84)^{**}$	$(3.73)^{**}$	$(2.73)^{**}$	$(2.74)^{**}$	$(6.66)^{**}$	$(2.87)^{**}$	$(2.86)^{**}$	$(4.64)^{**}$	(4.20)	$(4.07)^{**}$
Observations	80655	55107	93755	80707	80423	77144	80706	78695	16422	96158
R^2	0.005	0.009	0.008	0.001	0.009	0.335	0.003	0.004	0.000	0.002
Mean Dep. Var Men	-75.47	-56.298	-77.46	-74.628	-75.471	-75.47	-75.8	-75.664	-88.476	-84.705
	(.766)	(.976)	(.717)	(.727)	(.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 when reweighting with 1-digit occupations in addition to industries and individual characteristics. 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 6: 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)

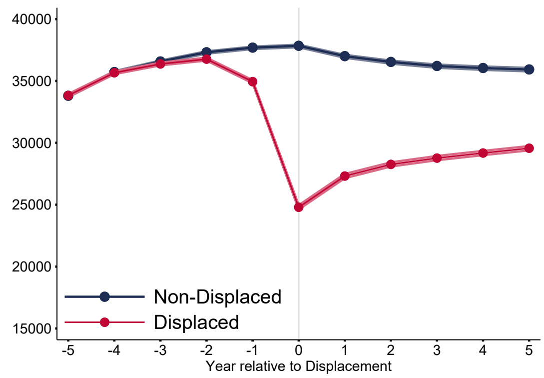
Notes: This table shows household outcomes after displacement from regressions based on the full sample of workers (displaced and non-displaced workers). All outcome variables are based on the individual first differences estimate. Panel A shows the raw gender gap without controls. Panel B shows the 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. 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. 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 7: Labor Market Outcomes for Couples with Children

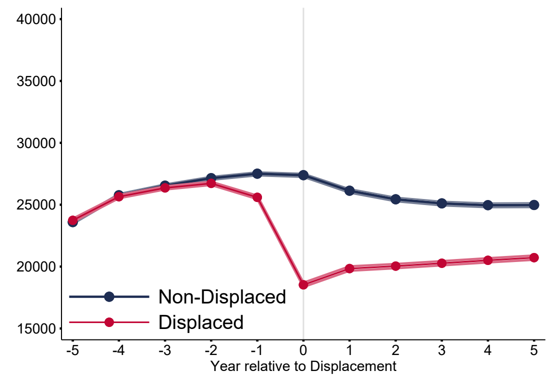
	(1) Earnings Rel. To t=c-1	(2) Log Wage	(3) Log Wage Fulltime	(4) Days Worked	(5) Days Worked Fulltime	(6) Days Worked Parttime	(7) Days Worked In Minijob	(8) Commuting Distance	(9) Log Estab Size	(10) Estab FE	(11) Partner's Earn. Rel. to Job Loser's
Panel A: Regression Adjusted Gender Wage Gap - Adding Family Controls											
Female	-0.067	-0.15	-0.041	0.48	-18.6	9.92	10.2	-1.02	-0.039	-0.015	-0.029
	(0.0082)**	(0.011)**	(0.0056)**	(1.93)	(2.78)**	(1.58)**	(1.18)**	(1.54)	(0.025)	(0.0048)**	(0.011)**
Child<= 6 yrs	0.064	0.058	0.031	16.0	14.5	3.33	-2.58	-0.62	0.092	0.025	0.020
	(0.0078)**	(0.0086)**	(0.0050)**	(2.10)**	(2.26)**	(1.04)**	(1.33)	(1.58)	(0.026)**	(0.0040)**	(0.0085)*
Female*Young Child	-0.13	-0.13	-0.067	-14.9	-39.5	19.1	3.82	-6.25	-0.21	-0.058	0.063
	(0.028)**	(0.028)**	(0.024)**	(5.58)**	(6.33)**	(6.08)**	(3.43)	(3.34)	(0.069)**	(0.010)**	(0.050)
Child> 6 yrs	0.049	0.044	0.016	15.9	15.0	1.47	-0.38	-2.27	0.035	0.022	0.056
	(0.0059)**	(0.0068)**	(0.0037)**	(1.59)**	(1.80)**	(0.76)	(1.07)	(1.25)	(0.020)	(0.0034)**	(0.0054)**
Female*Old Child	0.014	0.0024	0.013	-4.03	-19.1	16.2	-0.12	3.12	-0.068	-0.021	-0.098
	(0.011)	(0.013)	(0.012)	(2.82)	(3.73)**	(3.07)**	(1.97)	(1.87)	(0.035)	(0.0058)**	(0.021)**
Observations	80655	73598	52996	80655	80655	80655	80655	73027	72811	63452	80655
R^2	0.056	0.059	0.069	0.032	0.151	0.211	0.012	0.038	0.218	0.072	0.002
Mean Dep. Var Men	-.258	-.201	-.094	-67.66	-75.471	-.154	1.086	2.59	-.74	-.086	-.02
	(.002)	(.003)	(.002)	(.585)	(.766)	(.56)	(.448)	(.442)	(.009)	(.001)	(.004)
Panel B: Regression Adjusted Gender Wage Gap - Adding Household Income Controls											
Female	-0.083	-0.17	-0.047	-5.37	-25.7	11.2	10.4	-0.37	-0.077	-0.025	-0.039
	(0.0072)**	(0.0099)**	(0.0054)**	(1.73)**	(2.55)**	(1.52)**	(1.09)**	(1.50)	(0.024)**	(0.0045)**	(0.011)**
Earn. Share in HH Inc.	-0.069	-0.084	-0.028	-16.9	-25.6	1.36	10.3	2.31	-0.24	-0.012	0.067
	(0.012)**	(0.015)**	(0.0083)**	(3.15)**	(3.74)**	(1.80)	(2.08)**	(3.00)	(0.044)**	(0.0086)	(0.018)**
Female*Earn. Share	0.033	0.085	0.011	-1.99	33.1	-20.6	-19.3	-2.17	0.27	0.0021	-0.0025
	(0.018)	(0.021)**	(0.016)	(4.08)	(5.27)**	(4.03)**	(3.12)**	(3.47)	(0.059)**	(0.0096)	(0.039)
Observations	80655	73598	52996	80655	80655	80655	80655	73027	72811	63452	80655
R^2	0.054	0.058	0.068	0.030	0.150	0.210	0.013	0.038	0.218	0.071	0.002
Mean Dep. Var Men	-.258	-.201	-.094	-67.66	-75.471	-.154	1.086	2.59	-.74	-.086	-.02
	(.002)	(.003)	(.002)	(.585)	(.766)	(.56)	(.448)	(.442)	(.009)	(.001)	(.004)

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/older than 7. In Germany, children enter school aged 6-7. Panel B adds shows the regression adjusted gender gap controlling for the job loser's earnings share in household income measured in t=c. 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.

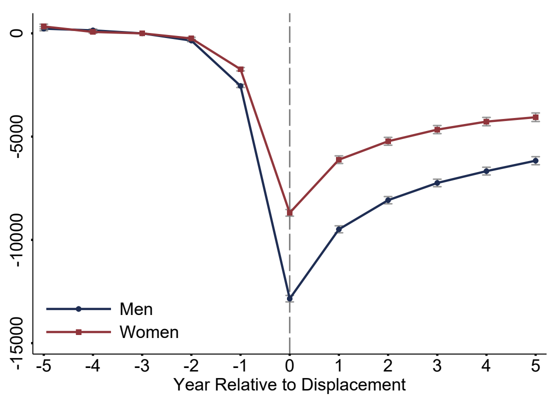
Figure 1: The Gender Gap in Earnings Losses after Displacement without Controlling for Pre-Displacement Characteristics



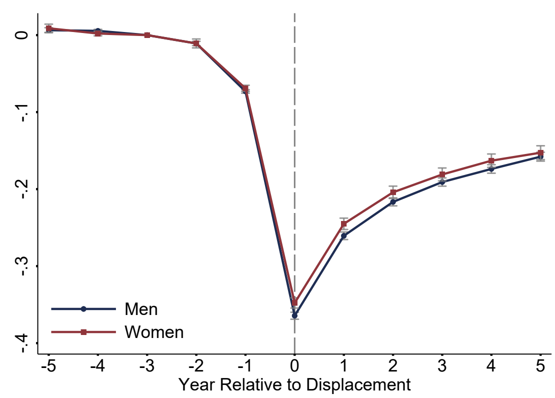
(a) Total Earnings in Year - Men



(b) Total Earnings in Year - Women



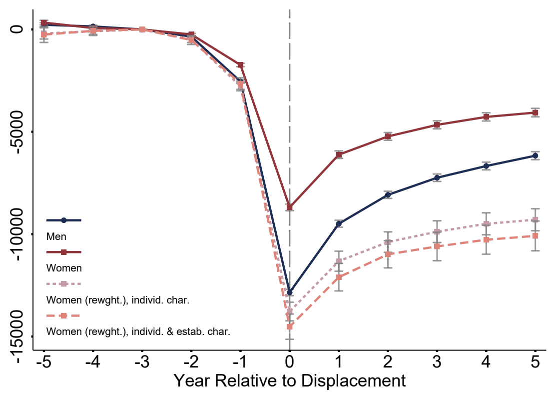
(c) Total Earnings in Year - Men and Women



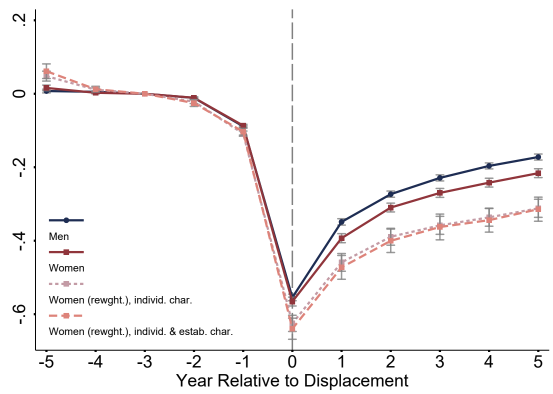
(d) Earnings Relative to t=c-1 - Men and Women

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 to t=c+1 (corresponding to year -1 and year 0 since displacement), 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-1 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.

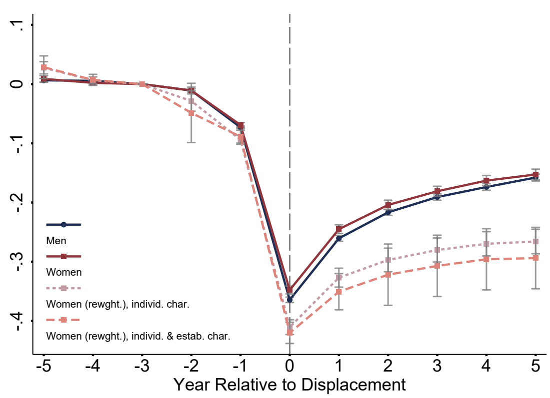
Figure 2: The Gender Gap in Earnings Losses after Displacement, Controlling for Pre-Displacement Job and Worker Characteristics



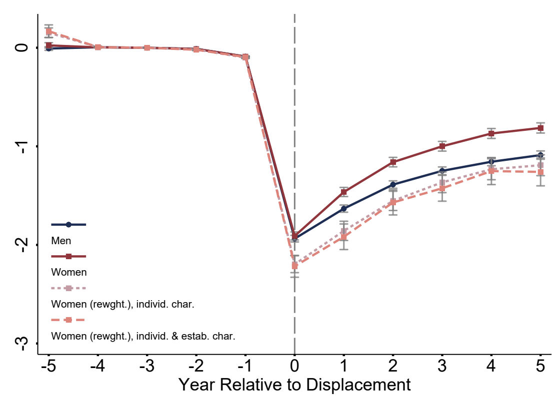
(a) Total Earnings



(b) Log Earnings



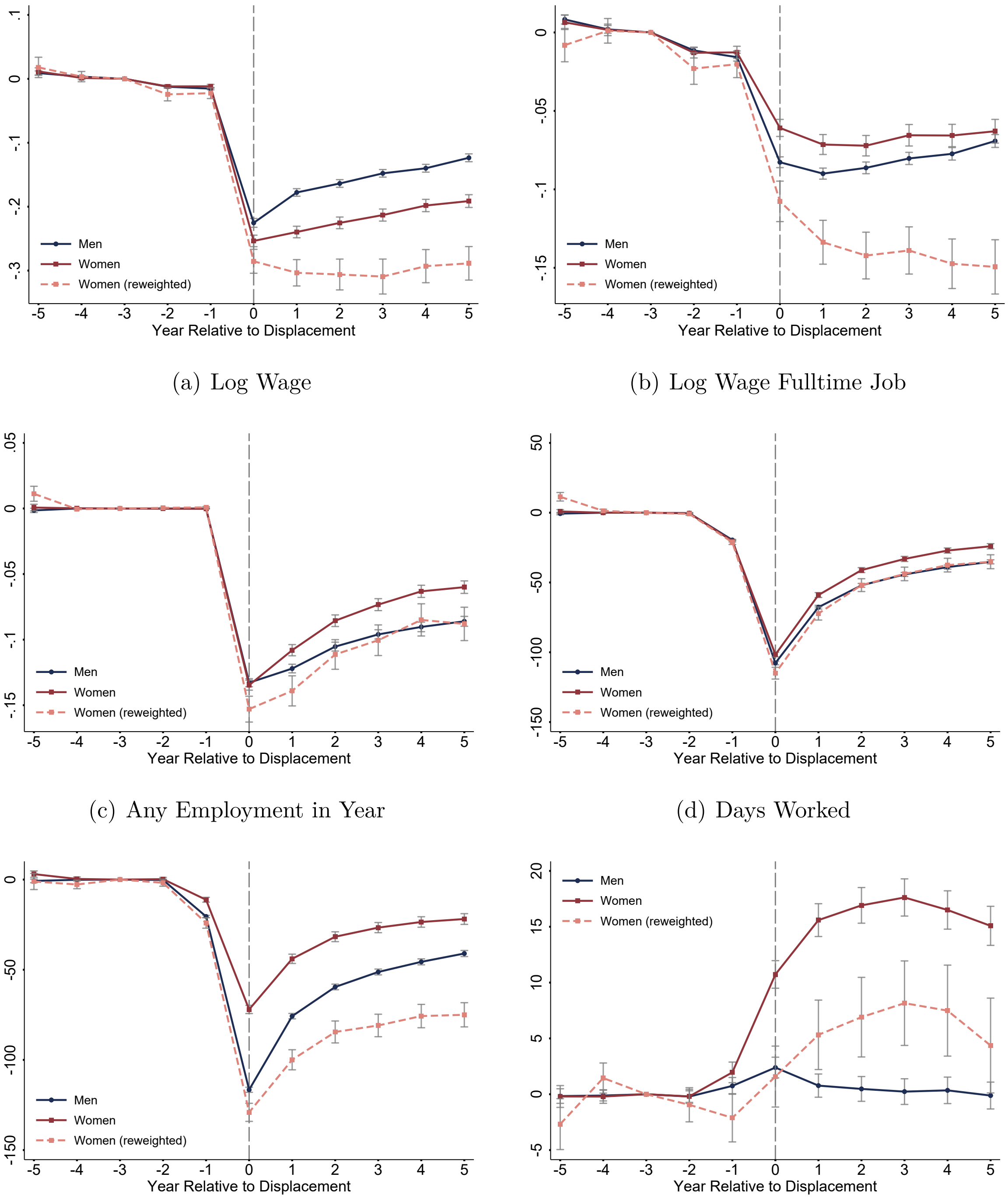
(c) Earnings Relative to t=c-1



(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-1, 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-2 and t=c-3, fulltime employment in t=c-2, and age, years of education, tenure, and location in East or West Germany in t=c. 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

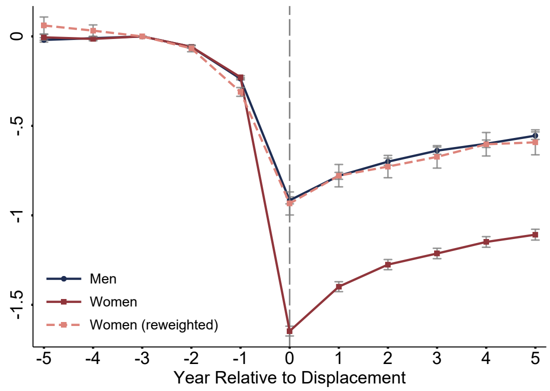
(d) Days Worked

(e) Days Worked Fulltime

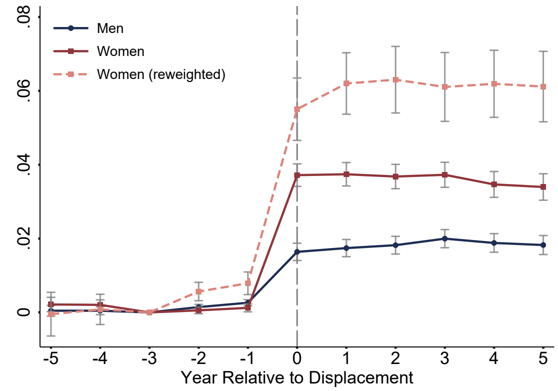
(f) Day Worked in Mini-job

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.

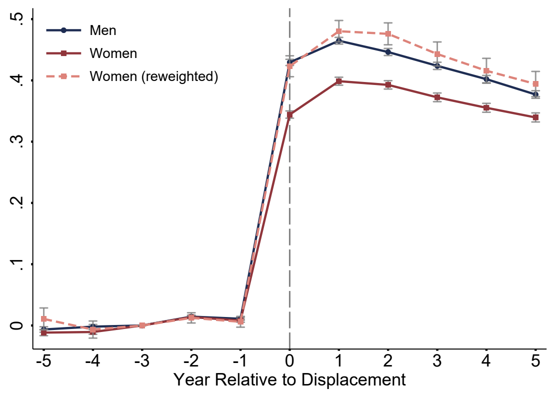
Figure 4: Changes in Job Characteristics after Displacement



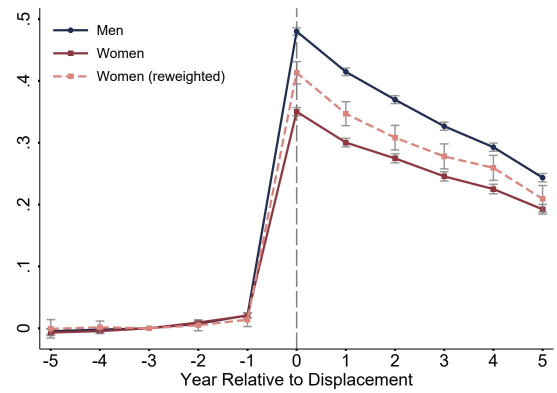
(a) Log Size of Establishment



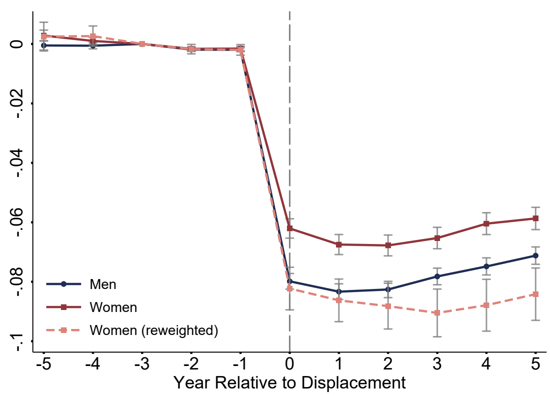
(b) Share of Females in Establishment



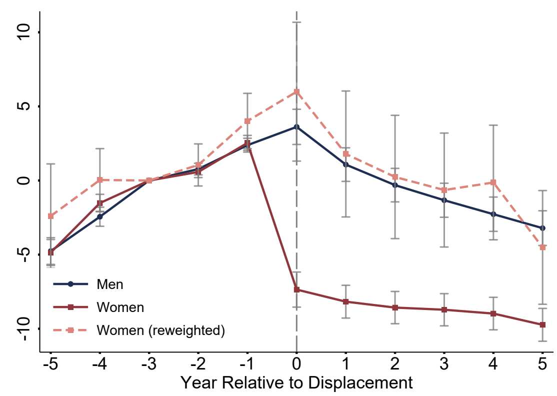
(c) Industry Different from Industry at t=c



(d) Occupation Different from Occupation at t=c



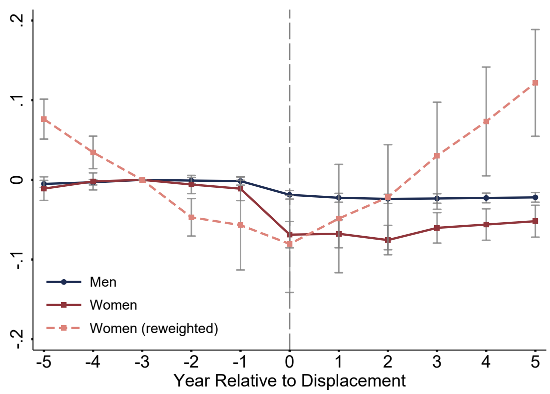
(e) Establishment Effect



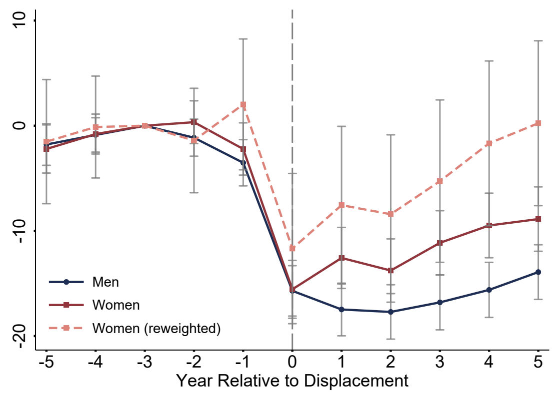
(f) Commuting Distance

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.

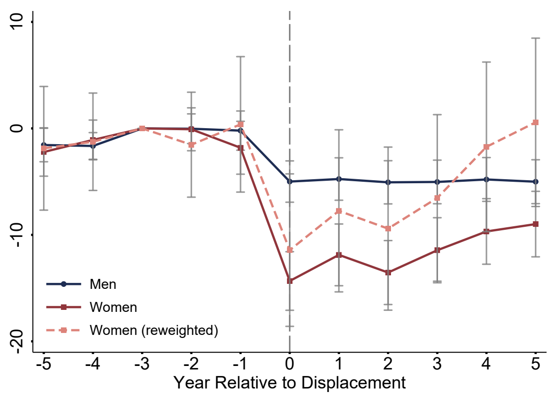
Figure 5: Job Loss on the Household Level - The Added Worker Effect



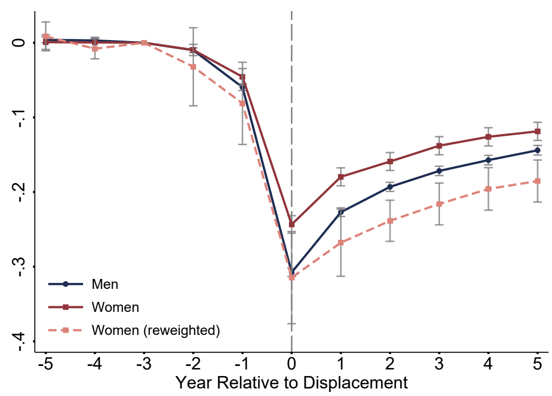
(a) Partner's Earnings Relative to Job Loser's in t=c-1



(b) Partner's Days Worked per Year



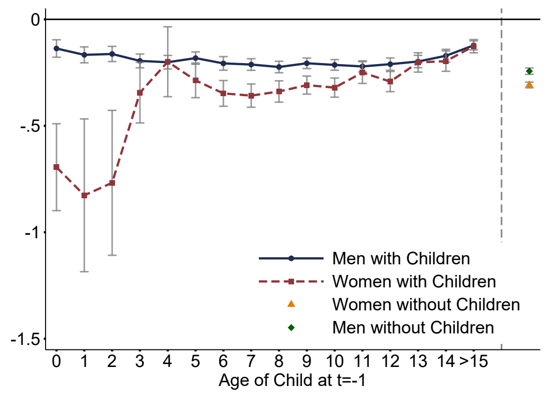
(c) Partner's Days Worked Fulltime per Year



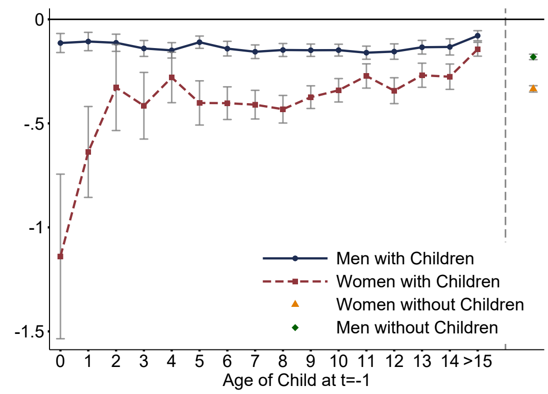
(d) Household Earnings Relative to t=c-1

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-1, partner's days worked per year, partner's days worked fulltime per year, and household earnings relative to t=c-1. 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.

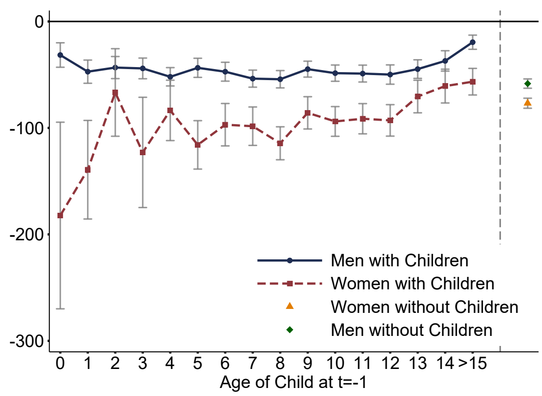
Figure 6: The Gender Gap and Children



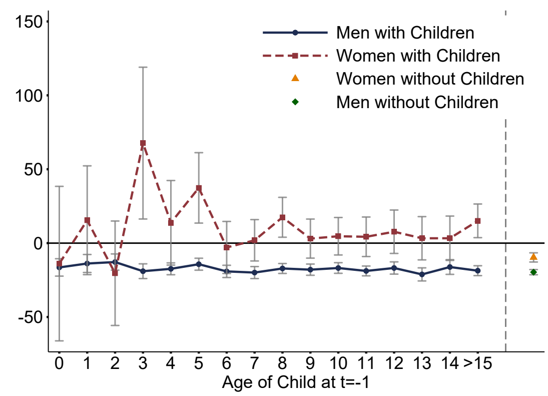
(a) Earnings Relative to t=c-1



(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-1, 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-2 and t=c-3, fulltime employment in t=c-2, and age, years of education, tenure, and location in East or West Germany in t=c. Establishment characteristics are 1-digit industry dummies and log establishment size in t=c. 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.