

The Gender Wage Gap Revisited:

Evidence from Worker Deaths*

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Abstract

We propose a novel strategy to estimate the gender wage gap for workers who succeed each other in the same job position: Using a large administrative data set spanning more than 40 years, we identify unexpected worker deaths. We then determine the replacement worker for each open position, and compute the wage gap between each deceased-replacement worker pair. Most previous studies estimate gender wage gaps within the same occupation in a firm, omitting the possibility of within-team wage differences, e.g. resulting from hierarchical levels. In our setting, we improve on this by comparing workers doing exactly the same type of job. We find that even when holding the job position constant, a substantial gender wage gap emerges: While men replacing deceased women earn slightly higher wages than their predecessors, women replacing deceased men face a wage discount of 31 log points. In addition, replacing women's wages grow much more slowly over time. Controlling for replacing workers' prior employment histories only explains about one quarter of the gender wage gap.

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1 Introduction

Despite considerable progress with respect to women’s labor force participation in the past decades, the gender wage gap is persisting not only over time but also across countries (Olivetti and Petrongolo (2008)). In the US in 2020, women’s earnings were only 84% of men’s, and women would need to work an additional 42 days per year to catch up (Pew-Research-Center (2021)). In Germany, the gap was similar yet slightly larger, with women receiving just 82% of men’s earnings in 2020 (Destatis (2021)). Altogether, this evidence opens up one central question of gender economics: Why do women (still) earn less than men?

Previous research has shown that observational differences between men and women can explain a substantial part of the gender wage gap, and that sorting into different occupations or firms plays a particular important role (e.g., Card et al. (2016); Macpherson and Hirsch (1995)). Studies on the gender wage gap therefore typically control for occupations, industries, and all sorts of individual characteristics such as age and education. Yet even after controlling for such potential confounders, an unexplained part of the gender wage gap remains (e.g., Blau and Kahn (2017); Bertrand et al. (2010)). The most demanding specifications control for occupation times establishment fixed effects, thus essentially comparing workers within the same team inside the same establishment. However, even within a team there are often hierarchies with very different types of positions. Thus, the standard way of estimating gender wage gaps may miss out on important within-team differences in wages.

In this paper, we innovate on existing approaches and suggest a new empirical strategy to compare women and men working in exactly the same job position. For this purpose, we identify exogenous worker deaths in 1980-2015 using German administrative employer-employee data (following Jaeger and Heining (2019)), where an establishment unexpectedly loses a prime age worker and has to find a replacement. For each deceased worker, we then identify their successor, using detailed 5-digit occupation codes and precise information on new hires in treated establishments following the death event. We consider individuals who worked full-time at the time of death, and replacement workers who started in full-time work when

they were hired. We then compute the wage gap between deceased and replacement workers. We distinguish between four types of transition: male-male, male-female, female-male, and female-female.

Instead of focusing on worker deaths, we could also compute wage gaps for any transition event where a worker leaves an establishment. However, the reasons why workers leave establishments are often endogenous: Workers may leave because they have a better offer somewhere else or because the establishment did not extend their contract due to, e.g., a bad match. In particular, women might be more likely to leave work for family reasons, and this could influence the replacement worker gap. Another advantage of identifying sudden worker deaths is that we can be much more precise in identifying the correct replacement worker, since hiring needs cannot be anticipated in this case.

Assuming that most deceased and replacement workers work in exactly the same position within a team, inside the same establishment, one would expect them to earn about the same wages (at least after some adjustments in the long term). In the absence of gender-specific reservation wages, gender-specific negotiation behavior, or gender discrimination, one would expect the wage gap across transition groups to be the same. In fact, however, we show that when men replace deceased women, they earn higher wages than their predecessors. The opposite is true for women who replace deceased men.

Consistent with the concepts of asymmetric information and establishment-specific human capital, most replacement workers earn lower full-time wages in the year of being hired compared to deceased workers' last recorded wages. For same-sex deceased-replacement pairs, this hiring penalty amounts to about 12 log points. However, for opposite-sex deceased-replacement workers, the pattern strikingly differs: Men following deceased women earn about 3 log points more than their predecessors. In contrast, women following deceased men have a staggering 31 log points lower full-time entry wages. Overall, this implies a gender wage gap of 15 to 19 log points.

We implement a reweighting strategy to address the concern that job positions vary across

transition groups. For example, deceased men replaced by men work in different occupations than deceased men replaced by women: They are much more likely to work in simple manual tasks (32% vs. 7.1%), and less likely to work in qualified commercial and administrative tasks (8% vs. 40%). Relative to female-female transition pairs, deceased women replaced by men are more likely to be engineers (1.1% vs. 0.2%), and managers (2.7% vs. 0.13%). To ensure that our results are not driven by these differences, we apply a reweighting approach (following DiNardo et al. (1996) and Illing et al. (2021)) to make job types of the male-female (female-male) transition group comparable to male-male (female-female) jobs. Even after reweighting, our main pattern that replacing women face substantially larger wage discounts does not change. If anything, it somewhat increases the gender component of the hiring wage gap (from 19 to 23 log points).

One explanation for the gender component in the hiring wage gap could be that employers are more concerned about asymmetric information when hiring women, for example because they worry about women carrying out additional (non-paid) care work. Thus, women's entry wages may be lower but their wages may also grow more quickly over time. We therefore investigate wage trajectories of deceased workers before death, and of replacement workers after replacement. Again, a clear trend emerges: Men's wages grow quickly, eventually reaching the level of their deceased predecessors. While women's wages also grow, women following men do not reach the level of their predecessors at least 5 years after replacement.

We explore three potential mechanisms behind the gender component of the hiring wage gap. First, we show that controlling for replacing workers' prior employment histories (e.g., work experience, full-time job, and previous wage) can explain about one quarter of the hiring wage penalty's gender component. This suggests that replacing women careers differ from those of men, perhaps because they have more fragmented worker biographies due to child care duties. Yet such gender-specific differences in the observable characteristics of replacement workers are only a small piece in the puzzle.

Second, we show that for replacement workers in each transition group, full-time wages

in their new job slightly increase relative to full-time wages in the year before replacement. Thus, for all types of replacing workers, switching jobs pays off, but we find that this is less so for women than for men. Overall, this suggests as in [Jäger et al. \(2021\)](#) that workers use their prior wages as an anchor for their reservation wages. Women may ask for lower wages per se, especially if they do not know what their predecessors earned. In addition, it may be that women put more emphasis on flexibility rather than wages in the negotiation process ([Le Barbanchon et al. \(2021\)](#)).

Last, we show that women are more likely to switch to part-time or marginal employment over time. While upon entering an establishment, our restrictions require replacing workers to work full-time, women start to substantially increase their days worked in more flexible jobs in the year following their hire. If we investigate the wages from all types of employment, rather than only full-time wages, we find that women's wages hardly grow over time. One reason why women do not catch up with men over time is thus their tendency to sort into more flexible employment contracts (consistent with the findings in [Goldin \(2014\)](#)).

We conduct an extensive set of robustness checks. We show that the gender gap is robust to using a stricter definition of replacing workers, and to restricting our sample to small establishments (where the potential error in identifying replacements is smaller). Our results moreover also hold for a balanced sample of workers. The gap does not change if we exclude workers in the construction sector or managers from our sample. Another potential worry is that our results are driven by mothers. Previous research has emphasized the importance of child penalties in explaining the gender wage gap (e.g., [Angelov et al. \(2016\)](#); [Kleven et al. \(2019b\)](#)). Indeed, employers may fear that mothers are less productive ([Xiao \(2021\)](#); [Kleven et al. \(2019a\)](#); [Gallen \(2018\)](#)). However, the main pattern holds even if we exclude all women who ever become mothers from our analysis sample.

We contribute to the existing literature on gender wage gaps by proposing a novel empirical strategy to estimate gender gaps for workers in exactly the same job position. In particular, we make two contributions to the existing literature: First, this is the first study using exogenous

worker deaths to identify four types of deceased-replacement worker transition groups: Male-male, male-female, female-female, and female-male. While previous studies control at most for firm-times-occupation specific differences, we fix job positions within a team. We show that even when holding the position constant, women face substantial discounts in wages. Our identification of replacement workers can also be applied to different settings, e.g. to investigate migrant-native wage gaps.

Second, our study quantifies the gender wage gap at the hiring stage and dynamically in the subsequent years. Most of the existing literature estimates gender wage gaps for men and women at different stages of seniority in an establishment. By exploiting worker deaths, we can pin down which part of the gender wage gap is due to gender-specific wages upon hiring. We show that the gender wage gap manifests itself upon establishment entry, and hardly closes over time.

This paper proceeds as follows: In Section 2 we first describe the data, our identification of worker deaths, and our identification of replacement workers. In Section 3, we then continue to describe our empirical strategies, which include the computation of a “hiring wage gap”, an event study specification, and the reweighting approach. In Section 4, we present our main results. Section 5 discusses channels, and Section 6 lists our robustness checks. Section 7 concludes.

2 Data

2.1 German Administrative Data

For our empirical investigation we use a sample of linked employer-employee biographies from the universe of German social security records in 1975-2019. We combine the *Integrated Employment Biographies (IEB), Version 15*, and the *Establishment History Panel (BHP)* databases provided by the Institute for Employment Research (IAB). This data covers the universe of German workers subject to social security (i.e., excluding civil servants and self-employed workers), corresponding to roughly 80% of the German workforce. It moreover

provides detailed information on all establishments in Germany.

The main advantage of the data for our study is that we observe all entries and exits of workers in all establishments, the exact dates of those events, and the workers' exact death date. In addition, we directly observe the reason why an employment contract ended (including e.g., "end of employment", "education", and "death"), as well as the exact date when it ended. We use this information to identify deceased workers.

The data moreover contain a rich set of individual and establishment characteristics such as wages, occupations, and education. The German social security system collects this data directly from employers, and it is therefore highly reliable. Both the universal coverage as well as the precise reporting make this data attractive for our analysis. A caveat of the data is that it records the daily, rather than the hourly wage. For this reason our main analysis focuses on full-time wages but we present the results for the full wage measure (combining full-time and part-time wages) in the Appendix.

Based on the code provided by [Dauth and Eppelsheimer \(2020\)](#), we construct a worker-level panel. We moreover correct implausible education entries following [Fitzenberger et al. \(2006\)](#).

2.2 Identifying Worker Deaths

In the spirit of [Jaeger and Heining \(2019\)](#), we focus on establishments that experience an exogenous worker exit due to the sudden death of an employee. To ensure that we identify unexpected deaths, we closely follow [Jaeger and Heining \(2019\)](#) and consider only deceased workers who, at the time of death, fulfill the following restrictions: They i) are at most 65 years old, ii) worked full-time, and iii) did not have any sick leave that exceeded 6 weeks in the 5 years preceding their death. To limit measurement error to a minimum, we do not consider deceased workers with another spell starting at least a month after the identified death date. In addition, we only consider establishments that we observe for up to 5 years ($k = d + 5$) after the death event. Last, we drop establishments with multiple sudden deaths in the same

year.

Instead of focusing on sudden worker deaths, we could also follow a “naive” approach and consider any exiting worker event. However, in this case, the exiting worker could be either positively selected (e.g., if they were leaving for better outside options), or negatively selected (e.g., if they were fired due to low performance). In particular, women might be more likely to leave work for family reasons. All of this could potentially influence the replacement worker gap, such that gender differences may arise due to a different selection of exiting workers. Focusing on sudden worker deaths, in contrast, helps us control for such endogeneity in leaving an establishment.

Another advantage of identifying sudden worker deaths is that in this setting, hiring cannot be anticipated. This means that the replacing employee can start working only after the death of their predecessor. It is thus easier to identify the correct replacement worker in the data.

2.3 Identifying Replacements

The administrative employment records do not contain information on who is replacing whom, so that we need to approximate replacements using occupation, type of contract, and hiring time. We focus on external hires (e.g., new establishment entrants) and consider only establishments with less than 150 employees. This ensures that there are not too many coworkers with the same occupation code, reducing the scope for measurement error. Figure A6, Panels (a) and (b) show that our main results do not change if we apply even stricter establishment size restrictions (50 and 35 employees, respectively).

In our main analysis, we define a new hire to be the replacement of a deceased worker if they fulfill the following conditions: They are i) the first hire after the death event with the same 5-digit occupation code as the deceased worker, ii) working full-time, and iii) hired in the first 180 days after the worker’s death. As an additional restriction, we only consider new hires if no more than four new full-time employees with the same 5-digit occupation code were hired in the first 180 days after the death event, and if the second hire with the same 5-digit

occupation code was hired more than 4 weeks after the first.¹ With this definition, we identify 48,667 deceased-worker-replacement pairs.² On average, establishments take 66 days to hire a new worker, and we identify replacement workers for 27% of deceased workers in our sample.

Once we have identified all replacement workers, we classify our data into four groups of deceased-replacement worker pairs: 1) male-male, 2) male-female, 3) female-male, and 4) female-female transitions.

We then define individual cut-off dates for each deceased/replacement worker. For deceased workers, the cut-off date is the end of their last spell which was terminated due to death. For example, if the last spell of a deceased worker ended on May 22, 2014, then this will be his/her cut-off date, where $k = r$. We will define all previous years relative to this cut-off date. E.g., May 22, 2013, would correspond to $k = r - 1$, and so on. Similarly, if a replacement worker is hired on June 22, 2013, then this will be his/her cut-off date, where $k = d$. June 22, 2014, would then correspond to $k = d + 1$, and June 22, 2015, would correspond to $k = d + 2$.

3 Estimation Strategy

3.1 The Concept

Figure 1 introduces the concept behind the gender gap in hiring wages. Imagine that a male worker is replaced by another man. In that case, both workers' wage trajectories may evolve in a similar way as depicted in Figure 1, Panel (a), increasing with tenure. Upon being hired, the replacement worker earns somewhat less than his predecessor. This wage penalty can be due to, e.g., seniority wages, asymmetric information, or firm-specific human capital. With tenure at the new firm, the replacement worker's wage increases, eventually reaching the level of his predecessor.

Let's then imagine a second case, where a male worker is replaced by a woman Figure 1

¹The code is based on the 2010 classification of occupations (KldB 2010). To give one example for how detailed the 5-digit code is, it includes several classifications for chefs: Chef (without specialization, helper tasks); chef (without specialization, qualified tasks); chef for starters, cold dishes, or dessert (qualified); chef for barbecue, roast, or fish; chef (other qualified task); supervising chef; monitoring chef.

²Figure A5 replicates our main results with an alternative replacement worker restriction.

Panel (b), dashed green line). In that case, the overall picture may look similar: The male worker earns a wage that is increasing in tenure. The female worker then faces a wage penalty compared to her predecessor. Over time, her wages grow.

The question we are asking in this paper is the following: Is there a gender component in the hiring wage penalty? To be more precise: If the same male worker was replaced by a man and a woman alike, would their wages differ?

Since we cannot observe the same male worker in the event where he is replaced by a man *and* in the event where he is replaced by a woman simulatenously, we need to apply econometrics to make deceased workers as comparable as possible (see Figure 1, Panel (c)). For this purpose we use a reweighting algorithm based on deceased worker characteristics, which we explain in more detail in Section 3.4.

Note that the gender component in hiring wages can have multiple explanations. For example, replacing women may systematically differ from replacing men in terms of their labor market experience. Another part of the gender component may be gender-specific differences in reservations wages. We explore some of the underlying mechanisms in Section 5.

3.2 The Hiring Gender Wage Gap

We start our analysis by computing the “hiring wage gap” between deceased and replacement workers. For this purpose, we first compute the wage difference between each deceased worker (at the time of death) and their identified replacement worker (upon being hired), within each worker pair:

$$\log(wage_{GAP}) = \log(wage_{r,k=r}) - \log(wage_{d,k=d}) \tag{1}$$

We then estimate cross-sectional regressions, where we regress this wage difference on dummies for transition type and an extensive set of control variables:

$$\log(wage_{GAP}) = \sum_{g=2}^4 I(g_i = g) + X'_d \gamma + \gamma_m + \pi_t \tag{2}$$

where $\sum_{g=2}^4 I(g_i = g)$ corresponds to dummies for the transition groups “male-female”, “female-male”, and “female-female”, and we omit “male-male” as the reference category. We then control for the calendar month of death γ_m , year fixed effects π_t , and deceased worker level controls $X_d'\gamma$, all measured in $k = d - 4$, four years before death. These are: Age, education, experience (all measured in years), a dummy for full-time employment, 5-digit occupation dummies, and 3-digit industry dummies.

3.3 The Dynamic Gender Wage Gap

In order to observe how wages evolve dynamically, we next complement the cross-sectional analysis with an event study regression model. We estimate one regression, including all transition groups simultaneously, with transition group 1 being “male-male”, and groups 2, 3, and 4 being “male-female”, “female-male”, and “female-female”, respectively. We regress the $\log(wage)$ of deceased-replacement worker pair p on dummies for year since death and a number of control variables:

$$\log(wage_p) = \beta_1^k \times \sum_{k=d-4, k \neq d-1}^{r+5} I(k_i = k) \times I(g_i = 1) + \beta_g^k \times \sum_{k=d-4}^{r+5} \sum_{g=2}^4 I(k_i = k) \times I(g_i = g) + X_d'\gamma + \gamma_m + \pi_t + \varepsilon_p \quad (3)$$

The first part of Equation 3 corresponds to the interaction between a dummy for group 1 (male-male transitions) and dummies for year $k = d - n$ before death, and $k = r + n$ after death, excluding the observation a year before death. The second part of Equation 3 corresponds to the time-group interactions for the other three transitions groups (male-female, female-male, and female-female). We estimate all coefficients relative to year $k = d - 1$ for transition group 1, i.e., relative to wages of deceased male workers followed by a male replacement, in the year before their death. We control for the calendar month of death γ_m and year fixed effects π_t . We also add a number of controls at the deceased worker level $X_d'\gamma$, all measured in $k = d - 4$: Age, education, experience (all measured in years), a dummy for full-time employment, 5-digit occupation dummies, and 3-digit industry dummies.

3.4 Making Transition Groups Comparable: Reweighting

To ensure that we compare similar jobs not only within, but also across transition groups, we implement a reweighting strategy that allows us to compare deceased-replacement worker pairs with observationally similar deceased workers. While we are confident that our identification of deceased-replacement worker pairs enables us to compare workers on the same job position *within* transition group, jobs may systematically differ across transition groups and this may bias our results. For example, deceased men replaced by male workers might work in different occupations than deceased men replaced by female workers. For an extreme case example, imagine that deceased men replaced by men all worked in engineering jobs, where - due to skilled worker shortages - workers' bargaining power in wage negotiations is high. In contrast, deceased men followed by women might all work in educational jobs, and in these jobs, on-the-job experience may be a strong predictor of wages, explaining why newly hired women's wages are so low.

To give an idea of differences across transition groups, Table 1 reports average wage and employment (Panel A), individual characteristics (Panel B), and 1-digit occupations (Panel C) for deceased workers by transition group in the year before death ($k = d - 1$). Male deceased workers (Columns (1) and (2)) clearly differ from female deceased workers (Columns (3) and (4)): They earn higher daily wages (98 Euro vs. 77 Euro), are somewhat older (46 vs. 43 years), and have more work experience (15 vs. 13.5 years). Moreover, men are more likely to work in simple, manual tasks and in engineering jobs.

Yet, differences do not only exist across gender, but also within gender, in particular in terms of the occupational distribution. For example, 32% of deceased men who are replaced by a man work in simple, manual tasks, while this share is only 7.1% for men replaced by women. In turn, men replaced by women are substantially more likely to work in qualified commercial and administrative tasks (40% vs 8%). For deceased women, the occupational distribution is somewhat more similar, but there are also notable differences: 1.1% of women

replaced by a man are engineers, whereas this share is only .2% for women replaced by women. 2.7% of women replaced by men are managers, and only .13% of women replaced by women.

To control for these differences, we implement a reweighting strategy following DiNardo et al. (1996), applied in a similar context by Illing et al. (2021). The idea behind this approach is to artificially make the distribution of characteristics in one group (e.g., male-female pairs) comparable to another group (e.g., male-male pairs). To implement this strategy empirically, we first estimate probit regressions of the following form:

$$Pr(group_i = 1 | X_{i,k=d,k=d-4}) = \varphi [X'_{i,k=d,k=d-4} \beta] \quad (4)$$

where $group_i$ is what we call the “baseline group” for worker i , e.g. deceased men followed by men. We regress a dummy for this group on a rich set of deceased workers’ control variables. These are: Age, years of education, years of experience, a dummy for full-time employment, tenure in years, 1-digit industry dummies, and 1-digit occupation dummies (all measured in $d=4$), and a dummy for wage decile (measured in $k=d$). We then use the estimated propensity scores to compute the weights, where

$$\omega_p = \frac{\hat{p}_s}{1 - \hat{p}_s}.$$

Weights ω_p are assigned at the deceased-replacement-pair level. For workers in the baseline group, $\omega_p = 1$. We compute two sets of weights, with two different baseline groups:

- Baseline group 1 consists of deceased workers in the male-male transition group. We reweight workers in the male-female transition group to match their distribution of observable characteristics.
- Baseline group 2 consists of deceased workers in the female-female transition group. We reweight workers in the female-male transition group to match their distribution of observable characteristics.

Thus, we use baseline groups 1 and 2 in order to make deceased individuals of the same gender

comparable across transition group, allowing for observational differences between deceased women and men.

4 The Gender Wage Gap Revisited

4.1 The Hiring Gender Wage Gap

We start our analysis by exploring the “hiring wage gap” by transition group, i.e., the differences between deceased workers’ wages at the time of their death ($k = d$) and replacement workers’ entry wages ($k = r$). For this purpose, we first compute this gap for each deceased-replacement worker pair, and then estimate the simple cross-sectional regression model described in Section 3.2. Table 2, Panel A, presents the regression results for our main outcome variable, full-time log wages.³ In Column (1), we report the mean difference in the outcome variable for male-male pairs, which serves as the base category for the coefficients on the three remaining transition groups in Columns (2)-(4). Table 2, Panel A, has three key messages:

1. Entry wages of men replacing men are, on average, 12 log points lower than the wages of their predecessors. This pattern is consistent with asymmetric information upon hiring, and with the accumulation of firm-specific human capital over time. The same pattern holds for women replacing women (Column (3)).
2. Men following women (Column (2)) earn slightly higher wages than their female predecessors.
3. Women following men face the largest wage discount, with a total gap of 31 log points. Compared to men replacing men, women replacing men earn an additional 19 log points less (the “gender component” of the hiring wage penalty). Compared to the entry wage gap in the other transition groups, this number is striking, yet it is well in the range of conventional estimations of the explained gender wage gap in Germany: Depending on

³For a version of this table with weights, see Appendix Table A2.

sample, time range, and empirical approach, they are ranging from about 12 to 25 log points (e.g., Gallego-Granados et al. (2015); Antonczyk et al. (2010)).

In Panel B of Table 2, we present coefficients for overall number of days worked in a given year, by employment type. Reassuringly, we see that across transition groups, there is virtually no difference in employment types. Women replacing men are somewhat more likely to work in a minijob in the year of replacement but the coefficient is very small (1.7 days per year, Column (4)).

Differences in yearly earnings, which we document in Panel C, are therefore entirely due to differences in wages: For women replacing deceased men, full-time earnings per year are about 1872 Euro lower than their predecessors', corresponding to about 8% of their total full-time earnings in the year before replacement. While these women seem to make up for this somewhat by increasing their part-time earnings by about 55 Euro, this does not at all compensate for the relatively lower earnings. Women replacing women also face an earnings discount, but it is only about one third the size. In contrast, men replacing women manage to substantially increase their yearly earnings: Their yearly full-time earnings increase by about 1141 Euro relative to their predecessors.

4.2 The Dynamic Gender Wage Gap

We have documented that women replacing deceased men earn substantially lower wages upon entry into the establishment, while men replacing deceased women earn slightly higher wages than their predecessors. One reason for this could be that when establishments hire women, they worry more about asymmetric information. For example, they may be afraid that women will have more sick days per year, because they are the ones who will stay at home to care for a sick child. Establishments may also worry that women, in particular mothers, are less productive (Xiao (2021); Kleven et al. (2019a); Gallen (2018)). As time passes and establishments update their information on their new hires, however, they may correct for their initial beliefs, and women's wages could thus grow at a faster pace than men's.

In a next step, we therefore show evidence on how the wage trajectories of deceased workers and their replacements evolve over time. Figure 2 plots event study coefficients by transition group where the dependant variable is log full-time wages.⁴ In the four years leading up to death ($k = d - 4$ to $k = d - 1$) and at the time of death ($k = d$) we plot deceased workers' wage trajectories; in the entry year ($k = r$) and the five years following replacement ($k = r + 1$ to $k = r + 5$) we plot replacement workers' wages. Note that $k = d$ refers to the time of death, and $k = r$ refers to the time of replacement. This might be in the same or in subsequent years, depending on what time of the year the death happened, and how long it took the establishment to hire a replacement worker.

From Figure 2, Panel (a), a number of interesting facts stand out. First, male deceased workers earn substantially higher wages than female deceased workers. Within the group of men, deceased men replaced by women (dashed red line) have somewhat lower wages than deceased men replaced by men (blue solid line). In turn, deceased women replaced by men (dotted green line) have higher wages than deceased women replaced by women (dashed-dotted orange line).

Comparing replacement workers' wages to deceased workers' wages within transition group yields essentially the same picture as the cross-sectional analysis from Section 4.1: For same-sex transition groups, replacement workers' entry wages are 10 to 15 percent lower than deceased workers' wages in the year of death. They then start growing in the years after replacement, surpassing their predecessors' wage after five years. This pattern is consistent with asymmetric information upon hiring, and with the accumulation of firm-specific human capital over time.

Yet for opposite-sex transition groups, the pattern strikingly differs: For male workers replacing deceased female workers, there is no wage difference in the year of replacement. Male workers replacing deceased women, on average, earn the same wage in the year of

⁴It is important to be aware that since Figure 2 is showing full-time wages only, the sample composition may change over time. This may be gender-specific: Women could be more likely to switch to part-time jobs over time. We explore these employment patterns in more detail in Section 5.3. Figure A7 presents the results for overall log wages (full-time + part-time) where women's wage growth over time is much slower.

replacement. Five years after replacement, their wages have grown by about 20 log points, and have reached the level of wages in the male-male transition group. In contrast, women replacing deceased men earn about 30 log points less than their predecessors immediately in the year after replacement, and catch up only slightly over time, without reaching the level of their predecessors.

The patterns depicted in Figure 1 could be driven by systematic differences across transition groups: Job positions of male-male (female-female) transition pairs may systematically differ from male-female (female-male) transition pairs. To account for this, we next apply the reweighting approach discussed in Section 3.4 to i) reweight deceased men replaced by women to match the characteristics of deceased men replaced by men, and ii) reweight deceased women replaced by men to match the characteristics of deceased women replaced by women. Figure 2, Panel (b), shows that this technique helps to make the wage trajectories of deceased workers very similar within the two groups, while the main pattern for replacement workers (who are weighted using the pair-wise weight) does not change. If anything, the pattern becomes even more pronounced, with men replacing deceased women earning about 7 log points higher wages already in the year of replacement. Thus, it is unlikely that our findings are driven by different job characteristics across transition groups.

5 Mechanisms

The gender component of the hiring wage gap may consist of different parts. In this section, we explore two of them: 1) Differences in replacement worker characteristics, and 2) the role of replacement workers' prior wages. We then ask why replacing women do not catch up with men over time, and to what extent this is driven by differences in employment patterns (e.g. sorting into part-time jobs over time).

5.1 Can Replacement Workers' Work Histories Explain the Gap?

Replacing women may differ from replacing men in terms of observable characteristics, and this may explain part of why they earn lower wages upon being hired. For example, replacing women may have lower labor market experience, they may be more likely to transition from non-employment, and they may be more likely to switch industries.

Table 3 explores to what extent such gender-specific differences in work histories can explain the gender gap in hiring. We estimate 2 separate regressions, where the coefficient on “female” in Panel A shows how the entry wage gap $\log(wage_{GAP})$ differs when a woman follows a deceased man, relative to $\log(wage_{GAP})$ when a man follows a man. In Panel B, the coefficient on “male” shows how the entry wage gap $\log(wage_{GAP})$ differs when a man follows a deceased women, relative to when a woman follows a woman. We use weights for deceased worker characteristics in all regressions.

Columns (2)-(6) consecutively introduce replacement worker controls, and Column (7) reports coefficients from regressions with all controls at once. Overall, replacement worker controls explain a quarter of the male-female gap (14% of the female-male gap). In the specification with all controls, the male-female and female-male gaps are exactly symmetric: Women following deceased men earn 18 log points lower wages than replacing men, while men following deceased women earn 18 log points higher wages than replacing women.

Panel A, Column (2), shows that adding a dummy for “transition from non-employment” only slightly lowers the gender gap. Occupational tenure, experience, and education (Column (3)) together decrease the gap by 3 log points. Adding a dummy for whether a worker switched from another full-time job also has some explanatory power, reducing the gap by 3 log points (Column (4)). Prior wages have the highest explanatory power (4 log points decrease, Column (5)), while the coefficients on industry or occupation switches are insignificant at the 10% level (Column (6)). Overall, gender-specific differences of replacement workers do play a role for the gender hiring gap but they are not the end of the story.

5.2 The Role of Prior Wages for the Entry Wage Gap

One argument which is often made in the literature analyzing gender wage gaps is that women negotiate less, are less optimistic, or have lower reservation wages than men (Cortés et al. (2021); Biasi and Sarsons (2020); Exley and Kessler (2019); Croson and Gneezy (2009)). In this section, we thus evaluate the role of replacing workers' wages in the year *before* they are hired.

The idea behind this is simple: Replacing workers usually have limited or no information on their predecessor's wage. Instead, what may determine their reservation wage, or their bargaining power in wage negotiations, is their own prior wage (Jäger et al. (2021)). Thus, if replacing women's wages were already lower before they applied for the new position, they i) would likely have lower reservation wages, and ii) would have lower bargaining power if employers asked them for their current/previous wage in the negotiation process.

To test this hypothesis, we proceed as follows: First, we compute the wage difference between a replacement workers' wage in their new job (in $k = r$) minus their wage in their previous job (in $k = r - 1$).⁵ We then regress this difference on dummies for transition group, a set of control variables for calendar year, month of death, and replacement worker characteristics in the year before replacement.⁶

Table 4, Panel A, reports the mean difference for the base category - men replacing men (Column (1)) - and the corresponding regression coefficients for men replacing women (Column (2)), women replacing women (Column (3)), and women replacing men (Column (4)). Indeed, all groups of replacing workers benefit from the job switch in terms of higher full-time log wages: Men replacing men increase their wages by, on average, 3 log points. For men replacing women, and women replacing women, the wage increase is similar. For women replacing men, wages increase only by roughly one half of this amount, or 1.6 log points.⁷

⁵The approach is similar to our computation of the hiring wage gap, except that we focus on replacement workers, only.

⁶The exact list of controls is: Age, years of education, years of experience, a full-time dummy, 3-digit industry dummies, and 5-digit occupation dummies.

⁷Note that if we reweight transition groups, this difference for women replacing men vanishes (see Figure

Combined with the results from Table 3, this set of results implies that replacing women earned lower wages than replacing men before replacement. This may very well shape their negotiation behavior: Women might simply not know that they could have asked for higher wages.

Overall, this is suggestive for workers using their prior wages as an anchor for their reservation wages, or for their demands in wage negotiations, putting women at a clear disadvantage. Compared to the other transition groups, women replacing deceased men seem to have either had lower reservation wages, or they were less successful in wage bargaining.

Panel B of Table 4 shows that women were somewhat more likely than men to expand their employment following replacement, and that this was mainly due to an increase in part-time employment (about 6 additional days per year). This suggests that women were somewhat more likely to be unemployed or out of work before the replacement.

Table 4, Panel C, shows that all four transition groups gained in terms of higher yearly full-time earnings (around 3,000 Euro compared to their full-time earnings in the year before replacement), with men replacing men gaining most.

5.3 The Role of Employment for Women’s Slower Wage Growth

The event study graphs show that in the 5 years after replacement, women never catch up with men’s wages. One explanation for this pattern comes to mind immediately: Women may sort into different employment contracts than men. If replacing women, in the long run, were more likely to work in low-wage part-time jobs or marginal employment⁸, then this could explain why they do not catch up in terms of wage growth. There are several reasons why women might sort into employment contracts with reduced working hours: For example, women in Germany typically perform more unpaid care work than men (e.g., [Jessen et al. \(2021\)](#)),

A3). This suggests that the difference is driven by systematic differences in job positions of male-male vs. male-female transition groups, rather than the gender of the replacement worker.

⁸In the German context, marginal employment comes in the shape of “minijobs”. These are special employment contracts which are exempt from payroll and income taxes, and subject to an income threshold (since 2013, this threshold is 450 Euro per month). For more information, see for example [Gudgeon and Trenkle \(2019\)](#).

essentially forcing them to reduce their working hours. Moreover, the German tax system incentivizes secondary wage earners within married couples to reduce their employment to a minimum.⁹

In Figure 3, we therefore plot employment trajectories for the four transition groups, showing days worked for deceased and replacement workers over time. Figure 3, Panel (a), shows that the four groups follow very similar employment trajectories in terms of overall days worked per year: Deceased workers in all transition groups work about the same amount of days in the years before they die. In the year of their death, there is a sharp drop of about 60 days less (relative to deceased men replaced by men in $k = d - 1$). This drop is mechanical, since most of the deceased workers die before the end of a calendar year, thus automatically reducing the amount of days they can spend at work.

Once we split employment by type of contract in Panels (b)-(d) of Figure 3, the expected pattern emerges: Women are more likely to start working in part-time or marginal employment. While this also holds for deceased women to some extent, the pattern is much stronger for replacing women. Given our restrictions on replacing workers, who have to work full-time when they are hired, there are no differences in days worked by employment contract in $k = r$. However, starting in the year after replacement, women are much more likely to switch to more flexible employment contracts. In year 5 after replacement, they work about 100 fewer days in full-time employment per year compared to the baseline (about -50 days for male workers), 40 more days in part-time employment (5-10 days for male workers), and about 17 days more in a minijob (about 5 days for male workers).

Figure 3 thus holds suggestive evidence for the reason for women’s stagnating wages: Flexible employment contracts limit their long-run wage growth potential. This pattern can be due both to labor supply (i.e. women voluntarily reducing their working hours) or due to labor demand (i.e. employers offering different types of contracts to women).

⁹In Germany, earnings of married partners are added up and then taxed jointly, implying that the average marginal tax rate on the secondary wage earner’s income (typically the wife) is higher (e.g., [Bick et al. \(2019\)](#)).

5.4 Other Heterogeneity

5.4.1 The Gender Wage Gap Over Time

In Figure A2, we plot wage gaps by decade. Consistent with previous literature on the gender wage gap (e.g., Blau and Kahn (2017)), we find that the gap becomes somewhat weaker over time. This observation is also consistent with changing gender norms, and more favourable child care policies (e.g., an increase in public child care provision in Germany in the 2000s).

5.4.2 East and West Germany

Figure A3 shows how the pattern differs for event establishments in East vs. West Germany. While the overall pattern holds regardless of geographic origin, the wage gap is somewhat lower in East Germany, perhaps reflecting differences in gender norms stemming from East Germany's communist past.

6 Robustness

In the following, we briefly discuss several sets of robustness checks.

Different Definition of Replacing Workers We first show that our results hold for a stricter definition of replacing workers. In this definition, replacement workers are i) the only new full-time hire with the same 5-digit occupation code hired in the first 100 days after death and ii) there was no other new full-time hire in the first 100 days with the same 3-digit occupation code. Figure A5 shows that this definition produces essentially the same results.

Smaller Establishments Similarly, we might be worried that we pick up spurious replacements in larger establishments. We thus estimate separate regressions where instead of allowing for establishment sizes up to 150 employees, we restrict the sample to i) establishments with less than 50 employees in the year before death and ii) establishments with less

than 35 employees in the year before death. Figure A6 shows that the hiring gender wage gap persists.

Full-time and Part-time Wages So far, we have focused on *full-time* log wages as main outcome variable, because we measure daily instead of hourly wages in the German social-security data. However, one might be worried that focusing on full-time wages leads to changes in the composition of workers over time. In particular, we have shown in Section 5.3 that women sort into more flexible employment contracts. We therefore replicate our main results for all wages (i.e., including wages from part-time work or minijobs) instead of only full-time wages. Figure A7 presents the results: Replacing women’s wage growth is now much smaller, or even stagnating.

Results for Balanced Sample of Workers Next, we carry out our main analyses for a balanced sample of workers only. This means that we only consider deceased-replacement worker pairs where workers are observable in the social-security data for the full observation period around death/replacement. Figure A8 shows that this does not change results.

Gender Wage Gap by Industry/Occupation We may be worried that our results are driven by particular industries. For example, the construction sector has relatively few female employees, and wage discounts for women may be particularly large. Similarly, the main pattern could be driven by workers in managing occupations. Reassuringly, however, Figure A9, Panels (a) and (b), shows that our results do not change if we omit these groups from the regression sample.

Excluding Mothers Another potential explanation for the pattern that we see is that the wage differences reflect a child penalty for women (e.g., Kleven et al. (2019b,a)). For example, women replacing deceased workers may often return from maternity leave. If they have young children, they may be more likely than men to sort into part-time employment, or leave the labor force completely. Likewise, employers may expect women with young children to be less

productive, in turn offering them lower wages. Figure A10 thus shows the unweighted wage gaps for a sample of women who never become mothers in our observation period. While this somewhat decreases the wage gap for male-female transition pairs, and leads to female replacements displaying somewhat higher wage growth over time, it does not change the main pattern.

7 Conclusion

In this paper, we use a novel empirical strategy to revisit the gender wage gap. By focusing on exogenous worker deaths and identifying replacements for deceased workers, we innovate on existing research and compute wage gaps for workers of opposite gender in exactly the same job position. Thus, we severely reduce the scope for differences in position and wage structure within the same team (e.g., when only controlling for establishment times occupation fixed effects) to confound our estimates of the gender wage gap. We distinguish between four types of transitions: Male-male, male-female, female-female, and female-male.

We show that most replacement workers earn lower full-time wages in the year of their hire compared to deceased workers' last recorded wages. For same-sex deceased-replacement pairs, this gap is about 12 log points. However, for opposite-sex deceased-replacement workers, the pattern strikingly differs: Men following deceased women earn about 3 log points more than their predecessors. In contrast, women following deceased men have a staggering 31 log points lower full-time entry wages, implying a gender component of 19 log points.

This pattern is stable to controlling for differences in the respective job positions across transition groups. Differences in the characteristics of replacing workers explain about one quarter of the gap. Women's more fragmented labor market trajectories are thus partly responsible for their lower wages but a significant amount of the gap is due to other factors. One of these are prior wages: All replacing workers somewhat increase their wages relative to their previous employment spell. This suggests that when they negotiate wages for a new job, workers take their previous/current wage as an anchor, and this puts women at a disadvantage.

In addition, women are much more likely to switch to more flexible employment contracts over time. Thus, while men's overall wages (full-time and part-time) grow fast over time, women's overall wages stagnate. Differential sorting into flexible employment contracts is one reason why women do not catch up with men's wages over time.

References

- Angelov, Nikolay, Per Johansson, and Erica Lindahl, "Parenthood and the gender gap in pay," *Journal of Labor Economics*, 34 (3), (2016), 545–579.
- Antonczyk, Dirk, Bernd Fitzenberger, and Katrin Sommerfeld, "Rising wage inequality, the decline of collective bargaining, and the gender wage gap," *Labour economics*, 17 (5), (2010), 835–847.
- Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet, "Gender differences in job search: Trading off commute against wage," *The Quarterly Journal of Economics*, 136 (1), (2021), 381–426.
- Bertrand, Marianne, Claudia Goldin, and Lawrence F Katz, "Dynamics of the gender gap for young professionals in the financial and corporate sectors," *American economic journal: applied economics*, 2 (3), (2010), 228–55.
- Biasi, Barbara and Heather Sarsons, "Flexible wages, bargaining, and the gender gap," Technical Report, National Bureau of Economic Research (2020).
- Bick, Alexander, Bettina Brüggemann, Nicola Fuchs-Schündeln, and Hannah Paule-Paludkiewicz, "Long-term changes in married couples' labor supply and taxes: Evidence from the US and Europe since the 1980s," *Journal of International Economics*, 118 (2019), 44–62.
- Blau, Francine D and Lawrence M Kahn, "The gender wage gap: Extent, trends, and explanations," *Journal of Economic Literature*, 55 (3), (2017), 789–865.
- Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women," *The Quarterly Journal of Economics*, 131 (2), (2016), 633–686.
- Cortés, Patricia, Jessica Pan, Laura Pilossoph, and Basit Zafar, "Gender differences in job search and the earnings gap: Evidence from business majors," Technical Report, National Bureau of Economic Research (2021).
- Croson, Rachel and Uri Gneezy, "Gender differences in preferences," *Journal of Economic literature*, 47 (2), (2009), 448–74.
- Dauth, Wolfgang and Johann Eppelsheimer, "Preparing the Sample of Integrated Labour Market Biographies (SIAB) for Scientific Analysis: A Guide," *Journal for Labour Market Research*, 54 (1), (2020), 1-14.
- Destatis, "Gender Pay Gap 2020: Frauen verdienen 18M€ weniger," Technical Report, German Federal Statistical Office (2021).
- DiNardo, John, Nicole Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, 64 (5), (1996), 1001-1044.

- Exley, Christine L and Judd B Kessler, “The gender gap in self-promotion,” Technical Report, National Bureau of Economic Research (2019).
- Fitzenberger, Bernd, Aderonke Osikominu, Robert Völter et al., “Imputation Rules to Improve the Education Variable in the IAB Employment Subsample,” *Schmollers Jahrbuch: Journal of Applied Social Science Studies/Zeitschrift für Wirtschafts-und Sozialwissenschaften*, 126 (3), (2006), 405–436.
- Gallego-Granados, Patricia, Johannes Geyer et al., “Distributional and Behavioral Effects of the Gender Wage Gap,” Technical Report, DIW Berlin, German Institute for Economic Research (2015).
- Gallen, Yana, “Motherhood and the gender productivity gap,” *Becker Friedman Institute for Research in Economics Working Paper*, (2018-41), (2018).
- Goldin, Claudia, “A grand gender convergence: Its last chapter,” *American Economic Review*, 104 (4), (2014), 1091–1119.
- Gudgeon, Matthew and Simon Trenkle, “The Speed of Earnings Responses to Taxation and the Role of Firm Labor Demand,” *Mimeo*, (2019).
- Illing, Hannah, Johannes F Schmieder, and Simon Trenkle, “The Gender Gap in Earnings Losses after Job Displacement,” Technical Report w29251, National Bureau of Economic Research (2021).
- Jaeger, Simon and Joerg Heining, “How substitutable are workers? Evidence from worker deaths,” *mimeo*, (2019).
- Jäger, Simon, Christopher Roth, U Cologne, Nina Roussille, and Benjamin Schoefer, “Worker Beliefs About Rents and Outside Options,” Technical Report, Working Paper (2021).
- Jessen, Jonas, C Katharina Spiess, Sevrin Waights, and Katharina Wrohlich, “Sharing the Caring? The Gender Division of Care Work during the COVID-19 Pandemic in Germany,” (2021).
- Kleven, Henrik, Camille Landais, and Jakob Egholt Søggaard, “Children and gender inequality: Evidence from Denmark,” *American Economic Journal: Applied Economics*, 11 (4), (2019), 181–209.
- , —, Johanna Posch, Andreas Steinhauer, and Josef Zweimüller, “Child penalties across countries: Evidence and explanations,” in “AEA Papers and Proceedings,” Vol. 109 (2019), pp. 122–26.
- Macpherson, David A and Barry T Hirsch, “Wages and gender composition: why do women’s jobs pay less?,” *Journal of Labor Economics*, 13 (3), (1995), 426–471.
- Olivetti, Claudia and Barbara Petrongolo, “Unequal pay or unequal employment? A cross-country analysis of gender gaps,” *Journal of Labor Economics*, 26 (4), (2008), 621–654.
- Pew-Research-Center, “Gender pay gap in U.S. held steady in 2020,” (2021).

Xiao, Pengpeng, "Wage and employment discrimination by gender in labor market equilibrium," (2021).

Table 1: Summary Table of Deceased Workers in the Year Before Death

	(1)	(2)	(3)	(4)
	Male-Male	Male-Female	Female-Male	Female-Female
Panel A: Wage and Employment				
Daily Wage in EUR	94.6	101.7	81.8	73.6
	[222.2]	[60.5]	[40.2]	[39.3]
Full-time Employed	1	1	1	1
	[0]	[0]	[0]	[0]
Panel B: Individual Characteristics				
Age	45.3	46.8	43.9	42.7
	[11.2]	[10.9]	[11.6]	[12.0]
Tenure (Yrs)	8.15	8.91	8.02	7.78
	[6.48]	[6.83]	[6.13]	[6.17]
Experience (Yrs)	14.6	15.5	13.9	13.1
	[7.77]	[7.96]	[7.65]	[7.39]
Education (Yrs)	11.9	12.3	12.0	11.8
	[1.33]	[1.78]	[1.76]	[1.33]
Panel C: 1-digit Occupations				
Agriculture, gardening, work with animals	0.023	0.024	0.017	0.011
	[0.15]	[0.15]	[0.13]	[0.10]
Simple, manual tasks	0.19	0.071	0.11	0.069
	[0.39]	[0.26]	[0.32]	[0.25]
Qualified, manual tasks	0.32	0.083	0.090	0.038
	[0.47]	[0.28]	[0.29]	[0.19]
Technician	0.036	0.051	0.033	0.022
	[0.19]	[0.22]	[0.18]	[0.15]
Engineer	0.018	0.017	0.011	0.0021
	[0.13]	[0.13]	[0.10]	[0.046]
Simple services	0.24	0.093	0.11	0.11
	[0.43]	[0.29]	[0.31]	[0.31]
Qualified services	0.013	0.041	0.029	0.10
	[0.11]	[0.20]	[0.17]	[0.30]
Semi-professions	0.012	0.084	0.081	0.11
	[0.11]	[0.28]	[0.27]	[0.31]
Professions	0.0041	0.018	0.022	0.011
	[0.064]	[0.13]	[0.15]	[0.10]
Simple commercial and administrative tasks	0.044	0.083	0.094	0.19
	[0.21]	[0.28]	[0.29]	[0.39]
Qualified commercial and administrative tasks	0.079	0.40	0.38	0.33
	[0.27]	[0.49]	[0.48]	[0.47]
Manager	0.023	0.029	0.027	0.013
	[0.15]	[0.17]	[0.16]	[0.11]
Number of Individuals	36485	4458	1565	6159

This table presents characteristics of deceased workers in the year before death. Each column corresponds to a different transition group: Column (1) shows characteristics of deceased men replaced by men, Column (2) shows characteristics of deceased men replaced by women, Column (3) shows characteristics of deceased women replaced by men, and Column (4) shows characteristics of deceased women replaced by women. Standard deviations in brackets.

Table 2: The Gender Gap in Wages and Employment - Deceased vs. Replacement Workers

	(1) Mean FD Male-Male		(2) Coefficient Female-Male		(3) Coefficient Female-Female		(4) Coefficient Male-Female		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages									
Full-time Log Wage	-0.12	[0.0020]	0.15	[0.014]	-0.011	[0.0091]	-0.19	[0.0087]	40,712
Panel B: Employment									
Total Days Worked per Year	1.93	[0.25]	0.98	[1.44]	-0.081	[0.93]	-0.40	[0.83]	40,720
Full-Time Days Worked per Year	1.65	[0.26]	1.32	[1.51]	-0.73	[0.98]	-1.39	[0.88]	40,720
Part-Time Days Worked per Year	0.30	[0.050]	-0.043	[0.60]	0.56	[0.31]	0.62	[0.32]	40,720
Days Worked in Minijob per Year	0.81	[0.099]	-0.26	[0.72]	0.55	[0.41]	1.70	[0.47]	40,720
Panel C: Earnings									
Total Yearly Earnings	-266.6	[32.9]	1415.9	[230.3]	-272.2	[122.3]	-1519.4	[129.5]	40,720
Total Yearly Full-Time Earnings	-282.1	[33.1]	1422.9	[230.7]	-302.4	[123.1]	-1589.6	[130.7]	40,720
Total Yearly Part-Time Earnings	5.87	[1.38]	-2.30	[19.2]	27.4	[12.3]	49.4	[22.7]	40,720

Notes: Each row represents a separate regression of the gap in the outcome variable (e.g., log wage of replacement worker 1 year after replacement - log wage of deceased worker in year of death) on dummies for the transition type and deceased worker controls. The first column shows the mean in the gap for a given outcome for male-male transitions. The second column shows the coefficient on female-male transitions, i.e. the extent to which their effect differs from male-male transitions. The third column shows the coefficient on female-female replacements, and the fourth column shows the coefficient on male-female replacements. Controls include the calendar year, the month of death, and the following controls: Age, years of education, years of experience, a full-time dummy, 3-digit industry dummies, and 5-digit occupation dummies (all measured for deceased workers in $k=d-4$). We restrict the sample to worker pairs observed at least 8 out of 11 periods. We cluster standard errors at the replacement worker level. Deaths occur in 1980-2014, and our sample spans 1980-2015. Coefficients in bold are statistically significant at the 5%-level.

Table 3: The Gender Gap in Wages and Replacement Worker Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Male-male vs. male-female							
Female	-0.24 (0.015)**	-0.23 (0.014)**	-0.21 (0.014)**	-0.21 (0.013)**	-0.20 (0.014)**	-0.23 (0.014)**	-0.18 (0.013)**
From Non-Employment		-0.10 (0.016)**					-0.021 (0.17)
Occupational Tenure (yrs)			0.0050 (0.0013)**				0.0014 (0.0013)
Experience (yrs)			0.0065 (0.0011)**				0.0059 (0.0011)**
Education (yrs)			0.030 (0.0045)**				0.023 (0.0053)**
Full-time job (yrs)				0.15 (0.046)**			0.098 (0.043)*
Log Wage					0.089 (0.0089)**		0.049 (0.010)**
Changed 5-Digit Occupation						-0.019 (0.013)	-0.030 (0.013)*
Changed 3-Digit Industry						-0.011 (0.012)	-0.044 (0.012)**
Observations	34503	34503	34503	34503	34503	34503	34503
R^2	0.186	0.194	0.218	0.206	0.213	0.187	0.231
Mean Gap Same-Sex Transition	-.119 (.003)	-.119 (.003)	-.119 (.003)	-.119 (.003)	-.119 (.003)	-.119 (.003)	-.119 (.003)
Panel B: Female-female vs. female-male							
Male	0.21 (0.020)**	0.21 (0.019)**	0.20 (0.019)**	0.20 (0.019)**	0.18 (0.019)**	0.21 (0.019)**	0.18 (0.018)**
From Non-Employment		-0.12 (0.020)**					0 (.)
Occupational Tenure (yrs)			0.0061 (0.0021)**				0.0024 (0.0021)
Experience (yrs)			0.014 (0.0018)**				0.012 (0.0018)**
Education (yrs)			0.022 (0.0056)**				0.0090 (0.0054)
Full-time job (yrs)				0.10 (0.022)**			0.032 (0.023)
Log Wage					0.13 (0.014)**		0.078 (0.015)**
Changed 5-Digit Occupation						0.0052 (0.022)	-0.00084 (0.021)
Changed 3-Digit Industry						-0.0026 (0.020)	-0.052 (0.021)*
Observations	6100	6100	6100	6100	6100	6100	6100
R^2	0.173	0.183	0.223	0.200	0.216	0.173	0.238
Mean Gap Same-Sex Transition	-.137 (.007)	-.137 (.007)	-.137 (.007)	-.137 (.007)	-.137 (.007)	-.137 (.007)	-.137 (.007)

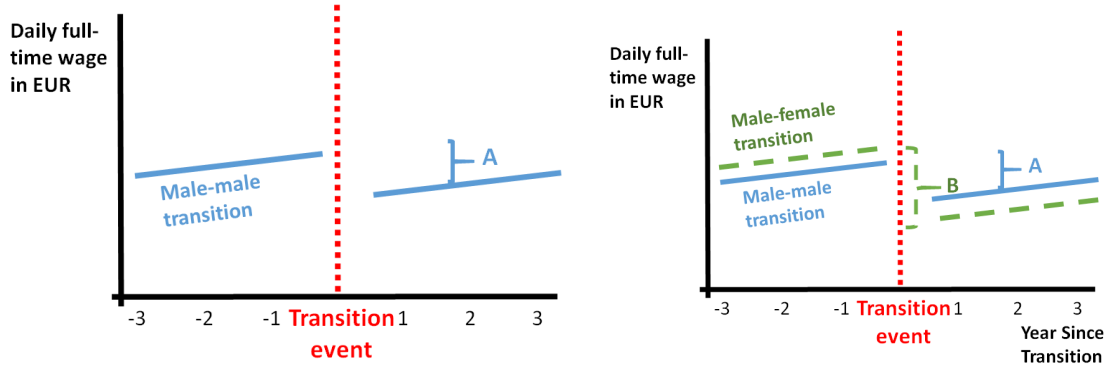
Notes: This table explores to what extent replacement worker characteristics determine the wage gap between deceased and replacement workers. The outcome variable in both panels is the difference in full-time log wages between the deceased worker in their last spell before death and their replacement workers' hiring spell. In Panel A, the baseline category is male-male transitions, and the coefficient on Female indicates how the wage gap differs for male-female transitions. In Panel B, the baseline category is female-female transitions, and the coefficient on Male indicates how the wage gap differs for female-male transitions. We reweight male (female) deceased workers followed by female (male) workers to male (female) deceased workers followed by male (female) workers based on individual characteristics, 1-digit industries, and 1-digit occupations (in $d=-4$). Column (1) adds a dummy for whether the replacement worker was non-employed (unemployed or not in social-security records) in the year before being hired. Column (2) adds a dummy for whether the replacement worker switched 5-digit occupation from $r=-1$ to r . Column (3) adds a dummy for whether the replacement worker switched 3-digit industry from $r=-1$ to r . Column (4) adds the change of the AKM establishment fixed effect for replacement workers between $r=-1$ and r . Column (5) adds the change of the share of female coworkers for replacement workers between $r=-1$ and r . Column (6) adds all replacement worker controls simultaneously. We cluster standard errors at the deceased worker level (constant within deceased-replacement worker pairs). * and ** correspond to 5 and 1 percent significance levels, respectively.

Table 4: The Gap in Wages and Employment - Replacement Workers Post vs. Pre Hiring

	(1) Mean FD Male-Male		(2) Coefficient Female-Male		(3) Coefficient Female-Female		(4) Coefficient Male-Female		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages									
Log Wage	0.0064	[0.0020]	-0.016	[0.012]	-0.019	[0.0098]	-0.0097	[0.0083]	26,069
Full-time Log Wage	0.030	[0.0013]	0.00030	[0.0065]	-0.0068	[0.0071]	-0.014	[0.0066]	25,476
Panel B: Employment									
Total Days Worked per Year	28.4	[0.63]	-2.17	[3.57]	7.81	[2.50]	4.37	[2.54]	27,877
Full-Time Days Worked per Year	30.9	[0.66]	-3.63	[3.82]	1.80	[2.92]	-0.34	[2.97]	27,877
Part-Time Days Worked per Year	-0.26	[0.18]	0.63	[1.49]	6.02	[1.70]	5.85	[1.61]	27,877
Days Worked in Minijob per Year	-0.056	[0.24]	-0.57	[1.49]	-0.13	[1.21]	-0.85	[1.31]	27,877
Panel C: Earnings									
Total Yearly Earnings	3427.0	[61.1]	-452.7	[330.5]	-297.8	[229.9]	54.1	[259.5]	27,877
Total Yearly Full-Time Earnings	3483.3	[62.3]	-452.4	[341.5]	-717.3	[249.0]	-316.6	[280.6]	27,877
Total Yearly Part-Time Earnings	-11.3	[9.28]	8.67	[86.6]	378.7	[101.3]	390.2	[103.6]	27,877

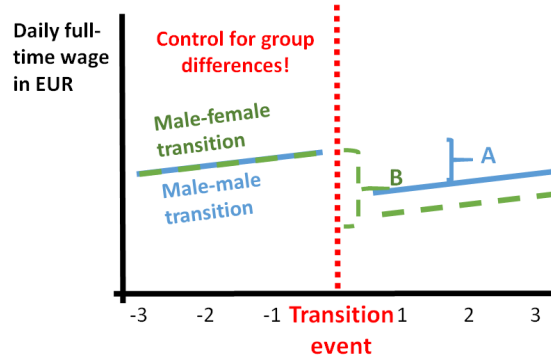
Notes: Each row represents a separate regression of the gap in the outcome variable (e.g., log wage of replacement worker 1 year after replacement - log wage of replacement worker in entry spell) on dummies for the transition type and deceased worker controls. The first column shows the mean of the difference for men replacing men. The second column shows the coefficient on women replacing men, i.e. the extent to which their effect differs from men replacing men. The third column shows the coefficient on women replacing women, and the fourth column shows the coefficient on men replacing women. Controls include the calendar year, the month of death, and the following controls: Age, years of education, years of experience, a full-time dummy, 3-digit industry dummies, and 5-digit occupation dummies (all measured for replacement workers in $k=r-1$). We restrict the sample to replacement workers observed at least 8 out of 11 periods. We cluster standard errors at the replacement worker level. Deaths occur in 1980-2014, and our sample spans 1980-2015. Coefficients in bold are statistically significant at the 5%-level.

Figure 1: The Idea of the Hiring Gender Wage Gap



(a) Male-male Transition

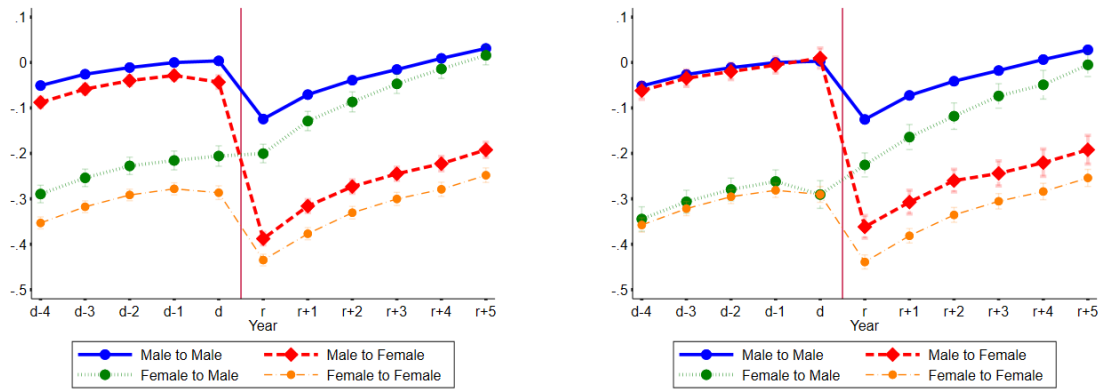
(b) Male-female Transition



(c) The Hiring Gender Wage Gap

Notes: This figure conceptualizes the transition gender wage gap. In Panel (a), the blue line shows hypothetical wage trajectories of a male-male transition pair (solid blue line). In Panel (b), we add hypothetical wage trajectories of male-female transition pairs (dashed green line). Panel (c) visualizes the gender component of the hiring wage gap after controlling for differences in type of jobs.

Figure 2: The Gender Wage Gap Over Time

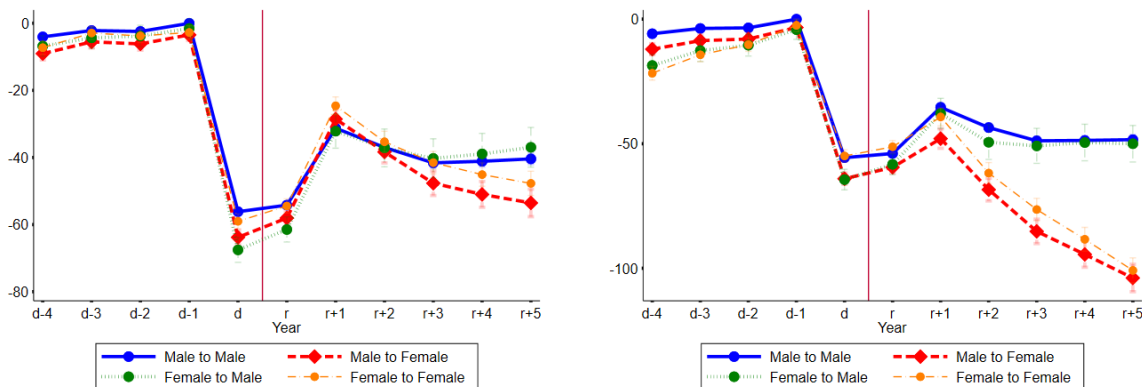


(a) Event Study Coefficients - Unweighted

(b) Event Study Coefficients - Reweighted

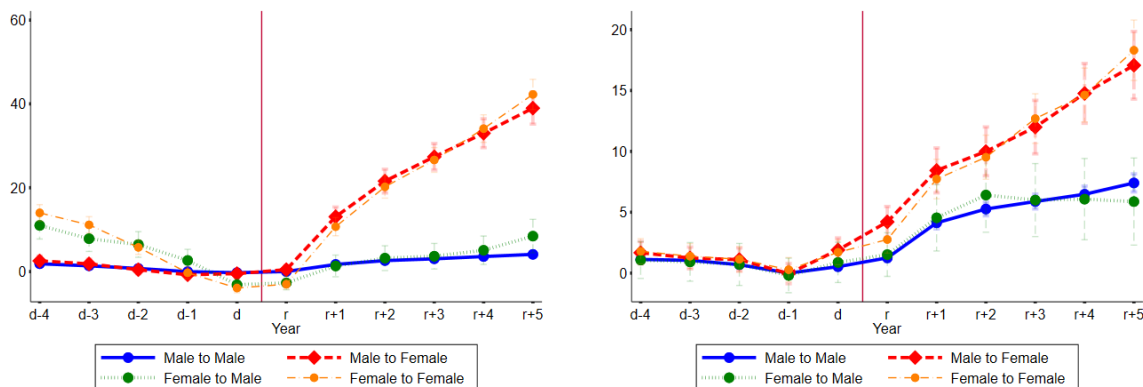
Notes: This figure presents unweighted (Panel (a)) and weighted (Panel (b)) event study coefficients for the log full-time wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5). The 4 lines plot the coefficients for the 4 transition groups: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). We reweight workers using the following controls: age, years of education, years of experience, fulltime dummy, years of tenure, 1-digit industry dummies, and 1-digit occupation dummies (all measured in d-4), and wage deciles (measured in d). We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure 3: The Employment Gap Over Time



(a) Days Worked

(b) Days Worked in Full-time Job



(c) Days Worked in Part-time Job

(d) Days Worked in Minijob

Notes: This figure presents (unweighted) event study coefficients for the employment trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5). The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). Panel (a) presents all days worked per year, Panel (b) presents days worked in full-time employment per year, Panel (c) presents days worked in part-time employment per year, and Panel (d) presents days worked in a minijob per year. All regressions control for calendar year, month of death, and the following control variables (all measured for deceased workers in d-4): age, years of education, years of experience, fulltime dummy, 5-digit occupation, 3-digit industry. We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Table A1: Summary Table of Deceased Workers in the Year Before Death - Weighted

	(1) Male-Male	(2) Male-Female	(3) Female-Male	(4) Female-Female
Panel A: Wage and Employment				
Wage in EUR	94.6	95.7	75.0	73.6
	[222.2]	[57.3]	[34.3]	[39.3]
Full-time Employment	1	1	1	1
	[0]	[0]	[0]	[0]
Panel B: Individual Characteristics				
Age	45.3	46.4	44.9	42.7
	[11.2]	[10.7]	[10.7]	[12.0]
Tenure (Yrs)	8.15	8.28	8.34	7.78
	[6.48]	[6.55]	[6.14]	[6.17]
Experience (Yrs)	14.6	15.3	14.1	13.1
	[7.77]	[7.84]	[7.24]	[7.39]
Education (Yrs)	11.9	11.9	11.8	11.8
	[1.33]	[1.45]	[1.54]	[1.33]
Panel C: 1-digit Occupations				
Agriculture, gardening, work with animals	0.023	0.030	0.012	0.011
	[0.15]	[0.17]	[0.11]	[0.10]
Simple, manual tasks	0.19	0.16	0.076	0.069
	[0.39]	[0.37]	[0.27]	[0.25]
Qualified, manual tasks	0.32	0.24	0.048	0.038
	[0.47]	[0.43]	[0.21]	[0.19]
Technician	0.036	0.036	0.026	0.022
	[0.19]	[0.19]	[0.16]	[0.15]
Engineer	0.018	0.017	0.0040	0.0021
	[0.13]	[0.13]	[0.063]	[0.046]
Simple services	0.24	0.20	0.10	0.11
	[0.43]	[0.40]	[0.30]	[0.31]
Qualified services	0.013	0.021	0.075	0.10
	[0.11]	[0.14]	[0.26]	[0.30]
Semi-professions	0.012	0.026	0.11	0.11
	[0.11]	[0.16]	[0.31]	[0.31]
Professions	0.0041	0.0063	0.014	0.011
	[0.064]	[0.079]	[0.12]	[0.10]
Simple commercial and administrative tasks	0.044	0.070	0.15	0.19
	[0.21]	[0.25]	[0.36]	[0.39]
Qualified commercial and administrative tasks	0.079	0.17	0.37	0.33
	[0.27]	[0.37]	[0.48]	[0.47]
Manager	0.023	0.022	0.017	0.013
	[0.15]	[0.15]	[0.13]	[0.11]
Number of Individuals	36485	4458	1565	6159

This table presents characteristics of deceased workers in the year before death. We reweight deceased men (women) replaced by women (men) to deceased men (women) replaced by men (women). Each column corresponds to a different transition group: Column (1) shows characteristics of deceased men replaced by men, Column (2) shows characteristics of deceased men replaced by women, Column (3) shows characteristics of deceased women replaced by men, and Column (4) shows characteristics of deceased women replaced by women. Reweighting characteristics are: age, years of education, years of experience, fulltime dummy, years of tenure, 1-digit industry dummies, and 1-digit occupation dummies (all measured in d-4), and wage deciles (measured in d). Standard deviations in brackets.

Table A2: The Gender Gap in Wages and Employment - Reweighting Transition Groups

	(1)		(2)		(3)		(4)		(5)
	Mean FD		Coefficient		Coefficient		Coefficient		Number of
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages									
Log Wage	-0.12	[0.0020]	0.20	[0.019]	-0.0021	[0.014]	-0.23	[0.015]	40,610
Full-time Log Wage	-0.12	[0.0020]	0.20	[0.019]	-0.0030	[0.014]	-0.23	[0.015]	40,603
Panel B: Employment									
Total Days Worked per Year	1.93	[0.25]	1.09	[1.67]	0.79	[1.15]	0.65	[1.04]	40,610
Full-Time Days Worked per Year	1.65	[0.26]	2.06	[1.95]	-0.75	[1.54]	-0.57	[1.14]	40,610
Part-Time Days Worked per Year	0.30	[0.050]	-0.69	[1.07]	1.64	[1.05]	1.16	[0.75]	40,610
Days Worked in Minijob per Year	0.81	[0.099]	-0.39	[0.72]	0.16	[0.58]	1.81	[0.86]	40,610
Panel C: Earnings									
Total Yearly Earnings	-266.6	[32.9]	1597.8	[264.1]	-152.2	[171.4]	-1373.3	[163.7]	40,610
Total Yearly Full-Time Earnings	-282.1	[33.1]	1628.5	[269.6]	-230.5	[180.4]	-1464.3	[167.7]	40,610
Total Yearly Part-Time Earnings	5.87	[1.38]	-19.8	[42.7]	84.9	[45.5]	76.6	[37.4]	40,610

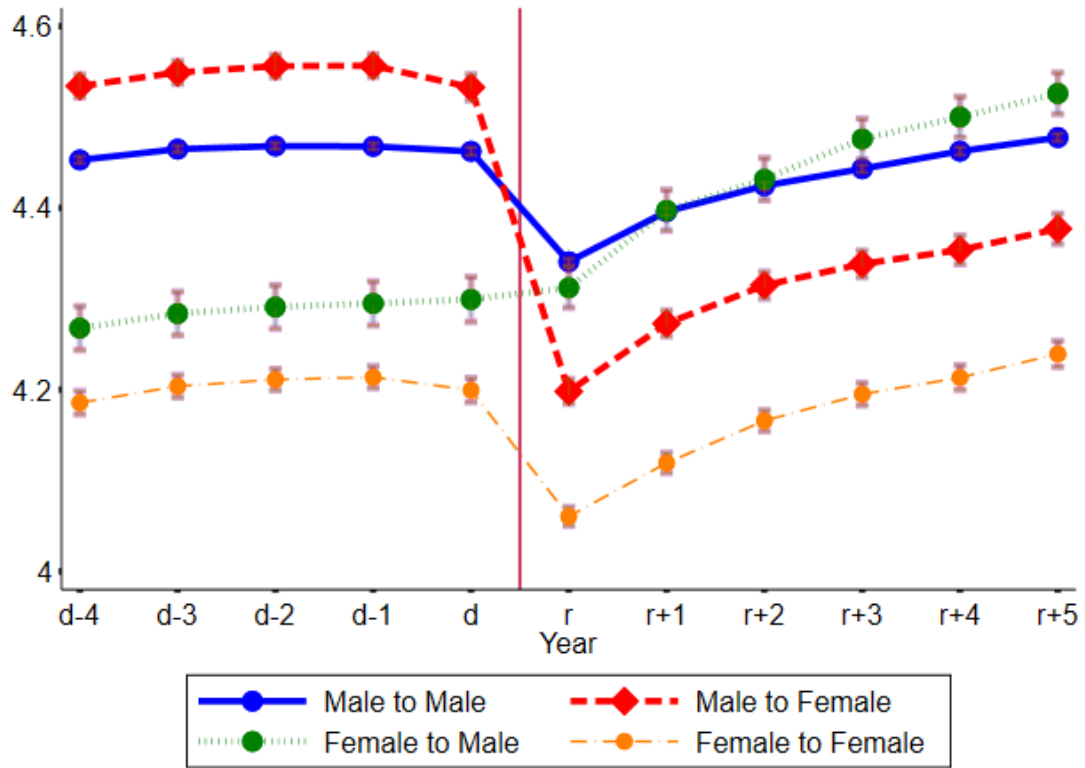
Notes: Each row represents a separate regression of the gap in the outcome variable (e.g., log wage of replacement worker 1 year after replacement - log wage of deceased worker in year of death) on dummies for the transition type and deceased worker controls. We use weights to reweight deceased men (women) followed by deceased women (men) to deceased men (women) followed by men (women). The first column shows the mean in the gap for a given outcome for male-male transitions. The second column shows the coefficient on female-male transitions, i.e. the extent to which their effect differs from male-male transitions. The third column shows the coefficient on female-female replacements, and the fourth column shows the coefficient on male-female replacements. Controls include the calendar year, the month of death, and the following controls: Age, years of education, years of experience, a full-time dummy, 3-digit industry dummies, and 5-digit occupation dummies (all measured for deceased workers in $k=d-4$). We restrict the sample to worker pairs observed at least 8 out of 11 periods. We cluster standard errors at the replacement worker level. Deaths occur in 1980-2014, and our sample spans 1980-2015. Coefficients in bold are statistically significant at the 5%-level.

Table A3: Replacement Workers Post vs. Pre Hiring - Reweighting Transition Groups

	(1) Mean FD Male-Male		(2) Coefficient Female-Male		(3) Coefficient Female-Female		(4) Coefficient Male-Female		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages									
Log Wage	0.0064	[0.0020]	-0.020	[0.014]	-0.0060	[0.015]	-0.0077	[0.013]	25,820
Full-time Log Wage	0.030	[0.0013]	-0.012	[0.0092]	-0.00052	[0.013]	-0.017	[0.012]	25,243
Panel B: Employment									
Total Days Worked per Year	28.4	[0.63]	-1.03	[4.96]	9.61	[3.18]	6.34	[3.65]	27,609
Full-Time Days Worked per Year	30.9	[0.66]	-1.54	[5.18]	3.56	[3.87]	2.38	[4.04]	27,609
Part-Time Days Worked per Year	-0.26	[0.18]	-0.54	[1.85]	5.61	[2.25]	3.87	[1.49]	27,609
Days Worked in Minijob per Year	-0.056	[0.24]	-1.18	[1.84]	1.81	[1.85]	4.29	[2.18]	27,609
Panel C: Earnings									
Total Yearly Earnings	3427.0	[61.1]	-183.9	[451.2]	140.8	[290.1]	82.3	[319.5]	27,609
Total Yearly Full-Time Earnings	3483.3	[62.3]	-151.6	[461.1]	-236.7	[312.3]	-217.3	[327.3]	27,609
Total Yearly Part-Time Earnings	-11.3	[9.28]	-27.0	[89.1]	322.1	[111.7]	276.4	[77.8]	27,609

Notes: Each row represents a separate regression of the gap in the outcome variable (e.g., log wage of replacement worker 1 year after replacement - log wage of replacement worker in entry spell) on dummies for the transition type and deceased worker controls. We reweight male (female) deceased workers followed by female (male) workers to male (female) deceased workers based on individual characteristics, 1-digit industries, and 1-digit occupations (in $d=-4$). The first column shows the mean of the difference for men replacing men. The second column shows the coefficient on women replacing men, i.e. the extent to which their effect differs from men replacing men. The third column shows the coefficient on women replacing women, and the fourth column shows the coefficient on men replacing women. We restrict the sample to replacement workers observed at least 8 out of 11 periods. We cluster standard errors at the replacement worker level. Deaths occur in 1980-2014, and our sample spans 1980-2015. Coefficients in bold are statistically significant at the 5%-level.

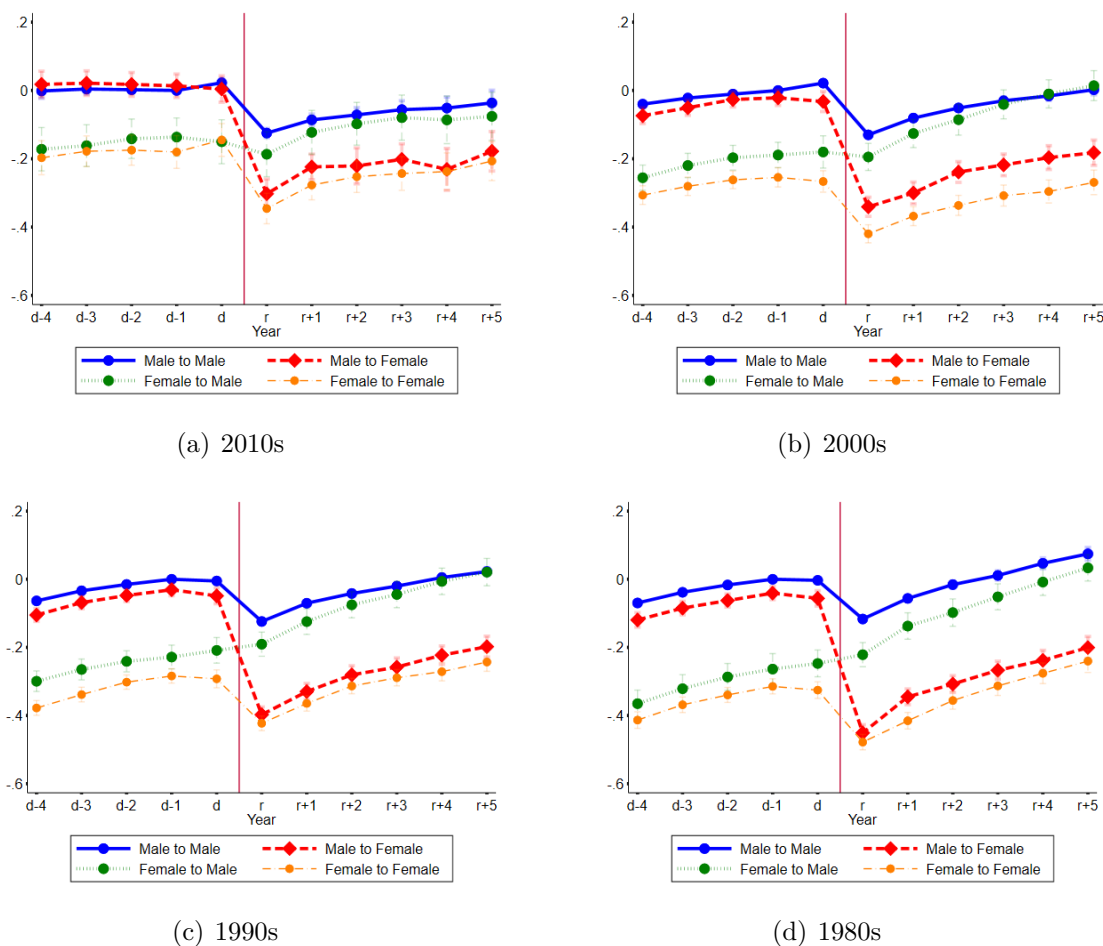
Figure A1: The Gender Wage Gap Over Time - Raw Means



(a) Gender Wage Gap - Raw Means

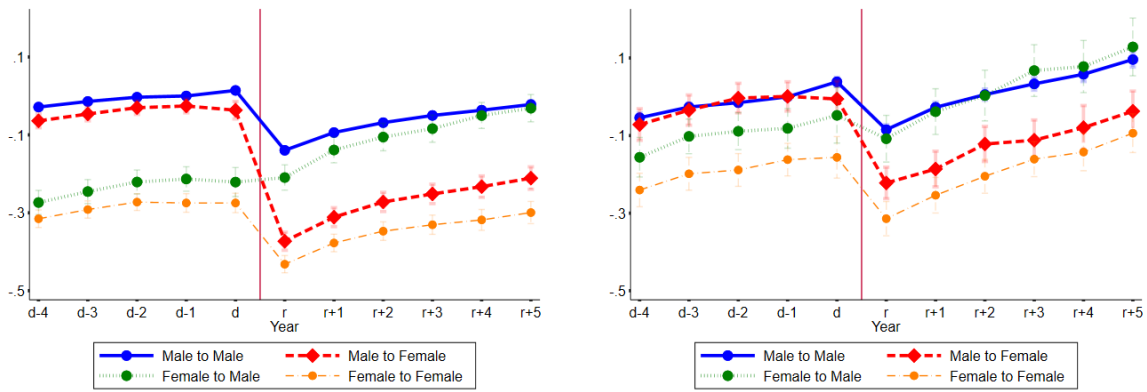
Notes: This figure presents mean log full-time wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5). The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). We restrict the sample to worker pairs observed at least 8 out of 11 periods. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A2: The Gender Wage Gap by Decade



Notes: This figure presents (unweighted) event study coefficients for the log wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5) by decade. The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). Panel (a) plots coefficients for deaths occurring in the 2010s, Panel (b) plots coefficients for deaths occurring in the 2000s, Panel (c) plots coefficients for deaths occurring in the 1990s, and Panel (d) plots coefficients for deaths occurring in the 1980s. We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A3: The Gender Wage Gap in West vs. East Germany

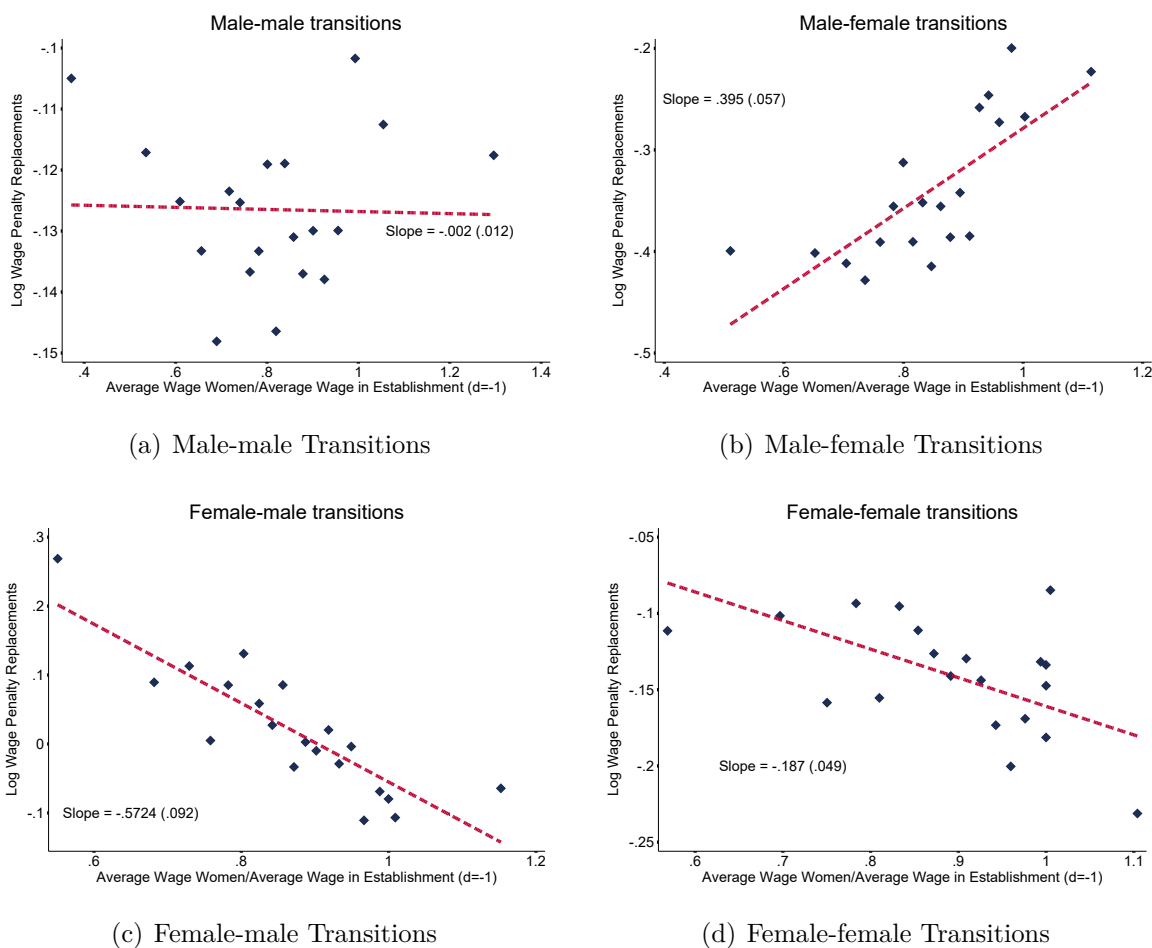


(a) Gender Wage Gap - West Germany

(b) Gender Wage Gap - East Germany

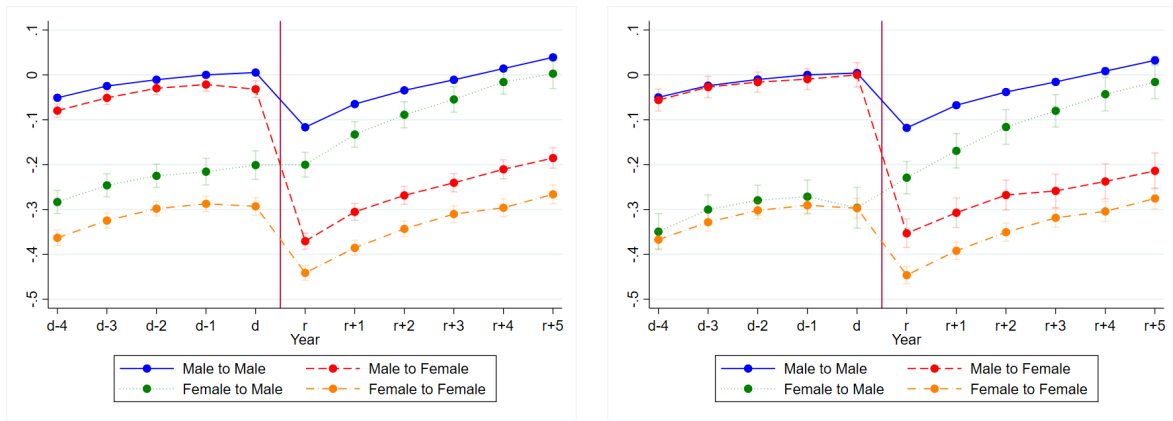
Notes: Notes: This figure presents (unweighted) event study coefficients for the log wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5) by region of origin. The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). In Panel (a) we restrict the sample to deaths occurring in West Germany, while Panel (b) shows event study coefficients for deaths occurring in East Germany. We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A4: Hiring Penalty vs. Relative Wage of Women in Establishment in $d=-1$



Notes: This figure plots the relative wage of female employees in an establishment in the year before death(x-axis) against the wage gap between deceased workers' last wage and replacement workers' hiring wage. Panel (a) restricts the sample to male-male transitions, Panel (b) restricts the sample to male-female transitions, Panel (c) restricts the sample to female-male transitions, and Panel (d) restricts the sample to female-female transitions. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A5: Robustness Check: The Gender Wage Gap with Alternative Replacement Definition

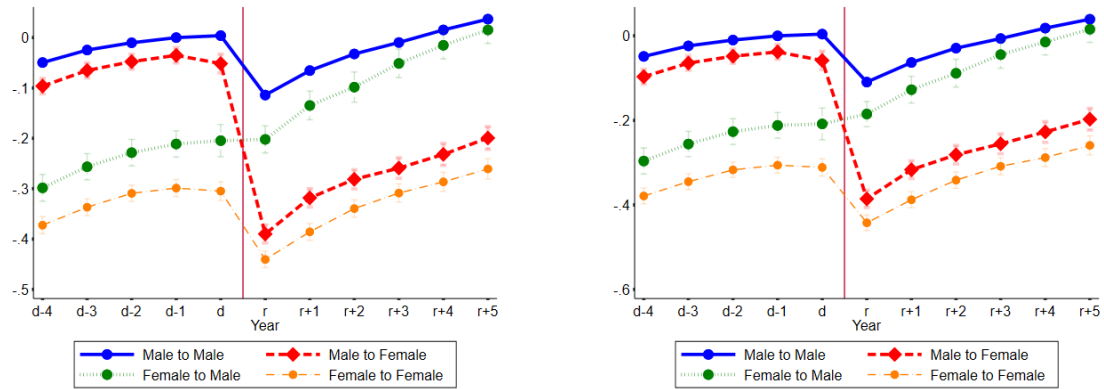


(a) Event Study Coefficients - Unweighted

(b) Event Study Coefficients - Reweighted

Notes: This figure presents event study coefficients for the log wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5) for an alternative definition of replacement workers. In this definition, replacement workers are i) the only new full-time hire with same 5-digit occupation code hired in the first 100 days after death and ii) there was no other new full-time hire in first 100 days has the same 3-digit occupation code. The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). In Panel (a) we do not use any weights. In Panel (b), we reweight deceased men (women) replaced by a male (female) worker to deceased men (women) replaced by a female (male) worker. We reweight workers using the following characteristics: age, years of education, years of experience, fulltime dummy, years of tenure, 1-digit industry dummies, and 1-digit occupation dummies (all measured in d-4), and wage deciles (measured in d). All regressions control for calendar year, month of death, and the following control variables (all measured for deceased workers in d-4): age, years of education, years of experience, fulltime dummy, 3-digit occupation, 3-digit industry. We restrict the sample to worker pairs observed at least 8 out of 11 periods. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A6: Robustness Check: Smaller Establishments

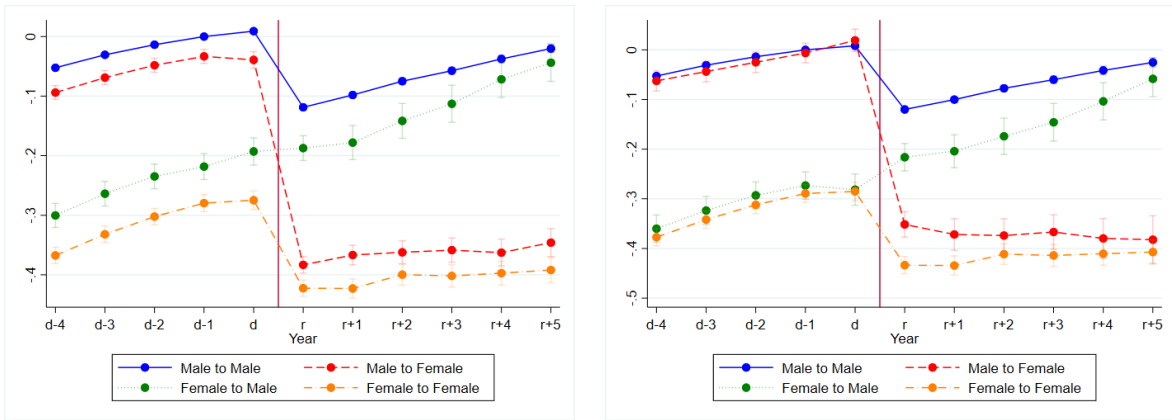


(a) Establishments with < 50 Employees

(b) Establishments with < 35 Employees

Notes: This figure presents (unweighted) event study coefficients for the log wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5). We restrict the sample to establishments with less than 50 employees at d=-1 (Panel (a)), and establishments with less than 35 employees at d=-1 (Panel (b)). The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

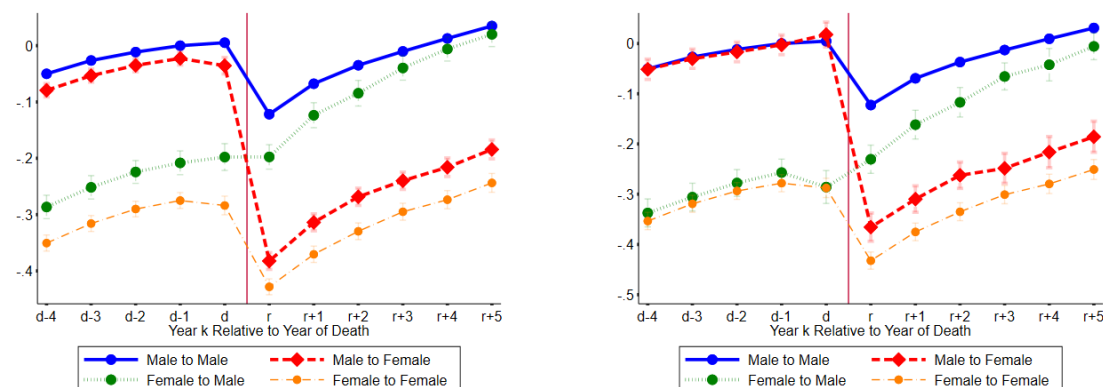
Figure A7: Robustness Check: Showing All Wages Instead of Full-time Wages



(a) Event Study Coefficients Log Wages - Un-weighted (b) Event Study Coefficients Log Wages - Reweighted

Notes: This figure presents unweighted (Panel (a)) and weighted (Panel (b)) event study coefficients for the log wage trajectories (rather than full-time wage trajectories) of deceased workers (d-4 to d), and replacement workers (r to r+5). The 4 lines plot the coefficients for the 4 transition groups: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). We reweight workers using the following controls: age, years of education, years of experience, fulltime dummy, years of tenure, 1-digit industry dummies, and 1-digit occupation dummies (all measured in d-4), and wage deciles (measured in d). We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A8: Robustness Check: The Gender Wage Gap for a Balanced Panel of Workers

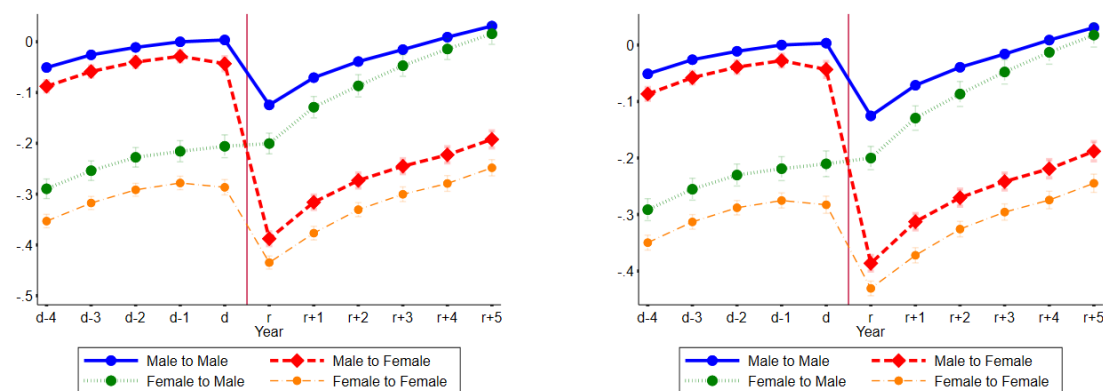


(a) Balanced Panel of Workers

(b) Balanced Panel, Reweighting Within Gender

Notes: Notes: This figure presents event study coefficients for the log wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5) for a balanced sample of workers. The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). In Panel (a) we do not use any weights. In Panel (b), we reweight deceased men (women) replaced by a male (female) worker to deceased men (women) replaced by a female (male) worker. We reweight workers using the following characteristics: age, years of education, years of experience, fulltime dummy, years of tenure, 1-digit industry dummies, and 1-digit occupation dummies (all measured in d-4), and wage deciles (measured in d). All regressions control for calendar year, month of death, and the following control variables (all measured for deceased workers in d-4): age, years of education, years of experience, fulltime dummy, 3-digit occupation, 3-digit industry. We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A9: Robustness Check: The Gender Wage Gap and Industries/Occupations

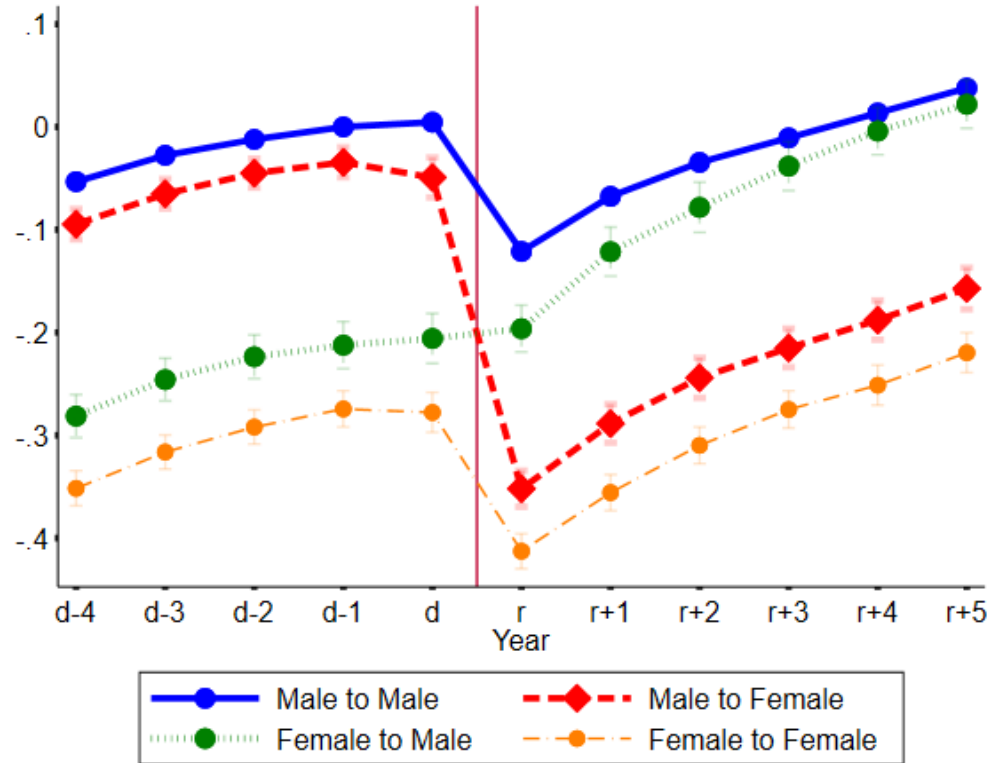


(a) Excluding Construction

(b) Excluding Managers

Notes: Notes: This figure presents (unweighted) event study coefficients for the log wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5). The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). In Panel (a) we exclude transition pairs working in the construction sector. In Panel (b), we exclude transition pairs working as managers. All regressions control for calendar year, month of death, and the following control variables (all measured for deceased workers in d-4): age, years of education, years of experience, fulltime dummy, 3-digit occupation, 3-digit industry. We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.

Figure A10: Robustness Check: Excluding Mothers



(a) Gender Wage Gap - Excluding Mothers

Notes: This figure presents (unweighted) event study coefficients for the log wage trajectories of deceased workers (d-4 to d), and replacement workers (r to r+5). We drop all women who ever become mothers in 1975-2019 from our sample. The four lines plot the coefficients from our main event study regression: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dashed-dotted line). We restrict the sample to worker pairs observed at least 8 out of 11 periods. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the deceased worker level. Deaths occur in 1980-2015, and our sample spans 1975-2019.