Hiring and the Dynamics of the Gender Gap

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Abstract

We investigate how the same hiring opportunity leads to different labor market outcomes for male and female full-time workers. To study firms' wage-setting behavior following exogenous vacancies, we analyze the wages of new hires after sudden worker deaths between 1981 and 2016. Using administrative data from Germany, we apply a novel technique to identify external replacement workers, and we use machine learning to compare replacements hired for comparable positions by similar firms. We find that female replacement workers' starting wages are, on average, 10 log points lower than those of replacing men of the same productivity. Differences in labor supply, within-firm adjustments, or outside options do not explain this gap; instead, we attribute it to gender differences in bargaining. We conclude that a significant portion of the gender wage gap emerges within firms at the hiring stage.

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1 Introduction

The gender gap in wages remains a pervasive feature of labor markets worldwide. Across all OECD countries in 2021, women working in full-time jobs earned 12% less than men (OECD, 2023). In the past, the gender wage gap has often been attributed to gender differences in educational attainment (e.g., Blau and Kahn 1992). However, given substantial progress in closing or even reversing the gender gap in educational attainment (Goldin et al., 2006), a pure human capital perspective cannot explain the remaining gap. Why, then, are women still paid less?

Existing research has identified a host of alternative explanations for gender disparities in labor markets.[1] One aspect, however, has received relatively little attention: firms' wage-setting practices during the hiring process. In frictional labor markets, firms' wage-setting power may lead to equally productive men and women encountering disparities in job opportunities and bargaining prospects, e.g., because women place a higher value on geographic proximity (Robinson, 1933; Manning, 2011).[2] Firm-specific hiring and compensation practices may therefore be key to understanding why the gender wage gap persists. However, investigating such patterns empirically is challenging when men and women sort into different jobs and firms (Blau, 1977; Groshen, 1991; Petersen and Morgan, 1995; Bayard et al., 2003; Card et al., 2016; Lochner and Merkl, 2022).

In this paper, we address this challenge by focusing on gender gaps arising from firm responses to *exogenous* vacancies of existing workers. At the core of the paper, we propose a novel method to identify replacements for workers who died unexpectedly, making it possible for the first time to study worker-to-worker transitions across the same position within a firm in German administrative data. We complement this analysis with a machine learning approach that enables us to control for a firm's ex-ante probability of hiring a female worker, based on a comprehensive set of firm-level and local labor market characteristics. Using this method, we first ask how the same hiring opportunity that arises within firms may lead to differences in wage and career outcomes for new hires, depending on their gender. In a next step, we control for replacement workers' pre-hire wages as a proxy for their productivity, to investigate whether gender differences at the hiring stage exist even for equally productive men and women. Finally, we combine several additional datasets to determine the role of working hours, within-firm adjustments, outside options, and amenities. Taken together, our analysis provides important evidence on the mechanisms behind the role of firms in the gender wage gap.

Our study leverages detailed matched employer–employee data from Germany spanning four

[1] These include, for example, the child penalty (Kleven et al., 2019, 2024); gender-specific sorting across firms, occupations and industries (Card et al., 2016; Blau and Kahn, 2017), including differences in how men and women value flexible work arrangements (Goldin, 2014; Mas and Pallais, 2017; Bolotnyy and Emanuel, 2022); gender differences in job search (Le Barbanchon et al., 2021; Cortés et al., 2023) and outside options (Caldwell and Danieli, 2024); behavioral differences (Niederle and Vesterlund, 2007; Flory et al., 2015), including gender differences in the wages candidates ask for at the hiring stage (Roussille, 2024); and gender norms (Charles et al., 2022; Boelmann et al., 2024).

[2] Policy-makers place increasing emphasis on the role of firms in addressing the gender wage gap. In the United States, Title VII of the Civil Rights Act mandates that companies are barred from engaging in discriminatory practices against women and other protected groups concerning hiring, layoffs, and promotions. Similarly, since 2017, firms in Germany with more than 200 employees are required, upon request, to disclose the average salary of colleagues of the opposite gender if they perform work of equivalent value to that of the inquiring employee (Brütt and Yuan, 2022). Such policies have been mostly ineffective in lowering gender gaps (Gulyas et al., 2023) or have had the unintended consequence of lowering average firm wages (Cullen, 2024).

decades. We start by identifying about 209,500 prime-age full-time workers who died unexpectedly. These departures result in unanticipated hiring shocks that circumvent the endogeneity of worker exits. We then focus on events with external replacements for the unforeseen vacancies. For this purpose, we determine a set of rules to identify external replacement workers. In particular, motivated by the empirical pattern that excess new hires occur during the first six months of the death event, we define a replacement worker as the first new full-time hire of the same 3-digit occupation as the deceased worker within this time period.[3]

The focus on unforeseen worker deaths is crucial for our identification strategy. It ensures that the outgoing worker is neither positively selected (e.g., leaving for better outside options), nor negatively selected (e.g., fired due to low performance). In particular, in cases of anticipated hiring, women might be more likely to leave work for family reasons. All of this could potentially influence the wage gap between outgoing and replacement worker, 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.

In addition to focusing on exogenous vacancies, we would ideally like to randomize the gender of the replacement worker. Whether a firm hires a man or a woman is, however, an active choice influenced by various factors, such as the gender distribution of job applicants or the firm's willingness to hire a worker of the same or a different gender. To rule out that firm differences drive the gender hiring opportunity gap, we therefore need to compare male and female hires with the same ex-ante probability of being hired.

For this purpose, we employ a random forest approach to predict whether the replacement hire will be a woman. We base our prediction on a comprehensive set of approximately 600 variables, including firm and labor market characteristics in the three years prior to the sudden death.[4] All of our regression specifications control for this predicted ex-ante probability of hiring a female worker; our underlying identifying assumption is that conditional on the predicted probability, the actual realization of the gender of the new hire is as good as random. We support this assumption by showing that key firm characteristics measured two years before the death event are very similar by replacement worker gender.

We term the wage gap that results from this combination of exogenous vacancies and the same ex-ante hiring probability the *gender hiring opportunity gap*. Our baseline estimate for the gender hiring opportunity gap reveals a large gender difference, with women earning 18 log points lower starting wages. However, one additional confounder that we need to control for is differences in replacement workers' productivity. Replacing women's productivity may differ systematically from replacing men's; in particular, women may have less work experience or occupational tenure, resulting in lower productivity. To investigate whether this is the case, our most comprehensive specification compares hiring wages of male and female replacement workers with the same starting productivity, proxied by

[3] Section 2.1 and Appendix A.3 describe our definition of sudden deaths and excess hiring in detail.

[4] See Appendix Table A10 for an overview on the top 10 predictors.

the pre-hire wage at their previous firm.[5] Controlling for replacement worker productivity decreases the gap to 10 log points for the full sample, or 6 log points in the past decade.[6] Taken together, this shows that firms do, on average, hire less productive women; however, firms also compensate workers with similar productivity differently based on their gender.

Leveraging our rich data, we conduct various additional analyses to confirm that we are indeed comparing equally productive workers. We merge data on working hours to parts of our analysis sample to show that male and female replacements do not differ in their labor supply. We moreover show that there is no change in incumbent (and total) coworkers' wage bill depending on the gender of the replacement, as might be the case if replacing women were less productive. Leveraging the Orbis-ADIAB business database (Antoni et al., 2018) for parts of our sample, we find no evidence that firms expand their capital differently when hiring a female worker. Additionally, there is no significant decrease in output, as proxied by firm sales.

In addition to studying the wage gap at the hiring stage, our rich data allows us to follow replacement workers' careers over time. We find that in the four years following replacement, the gender gap is far from closing; instead, it increases to a staggering 21 log points by year five after the initial replacement spell, even for replacement workers with the same productivity. Part of this is driven by women switching to part-time employment.

A large gap of 9.4 log points persists even when we condition on highly attached replacement worker who remain in full-time positions up to four years after the hiring spell, without closing over time. The fact that the gap is so similar for the highly attached sample of workers suggests that firms base their pay decisions on group identity (Altonji and Blank, 1999; Fang and Moro, 2011). Employer learning models propose that firms may learn about worker productivity over time leading to a narrowing of the gap (Farber and Gibbons, 1996; Altonji and Pierret, 2001); the persistent gap even for highly attached workers suggests that this is not the case in our setting. Instead, our results underscore the importance of path dependency, where a lower starting wage acts as a negative signal of productivity to both current and future employers (Barron et al., 1993; Bernhardt, 1995; Tô, 2018), potentially resulting in reduced on-the-job training.

We explore two potential explanations for the gender hiring opportunity gap: outside options and non-wage amenities. As in Caldwell and Danieli (2024), male replacement workers may have better outside options and therefore negotiate higher starting wages. We investigate this using a comprehensive measure for outside options that combines information on labor market thickness on the 2-digit and commuting zone level with data on gender-specific transition patterns across 2-digit occupations. The coefficient for this outside options indicator, reflecting outside options during replacements' last spell at the previous job, does not differ by replacement worker gender. We analyze

[5] We acknowledge that pre-hire wages are an imperfect proxy for workers' true productivity. However, if women were indeed paid below their productivity level, as our analysis suggests, we would underestimate the true gender wage gap. Furthermore, as shown in Appendix Table A7, our results are robust to a range of alternative productivity proxies, including experience, skills, tenure, and predicted pre-hire wages based on a sample of male workers.

[6] Our baseline analysis focuses on all death events in the sample, ranging from 1981-2016. In a heterogeneity analysis, we show that the gender gap has decreased substantially over time, from 16 log points in the 1980s to 12 log points in the 1990s, 8.5 log points in the 2000s, and 6 log points from 2010-2016. This hiring wage gap is comparable to the adjusted gender wage gap in a sample of full-time workers in Germany across all career stages (see Figure A1).

two additional proxies for outside options that measure the quality of the replacements' previous employer. Neither provides evidence that women work for lower-quality firms; if anything, women come from slightly better firms. We conclude that outside options do not affect replacement women's bargaining power differently.

Consistent with evidence in Le Barbanchon et al. (2021) and Mas and Pallais (2017), women may value non-wage amenities such as more flexible or regular work schedules more. We start by investigating whether women switch jobs to reduce their daily commutes. This is not the case; both women and men increase their commutes by approximately 4 km relative to the commuting distance in their last job, without gender difference. We moreover show that women do not sort into systematically different firms with lower gender wage gaps. This suggests that women do not move to firms that offer amenities they are likely to value more. One limitation of our study is the lack of detailed information on workers' contracts, including potential gender differences in contract-specific, non-wage amenities such as job flexibility. However, non-mothers are less likely to exhibit differing preferences for specific job types, yet we still observe a significant gender gap among childless female replacement workers across all age groups.

Finally, our data, covering several decades, regions, and firms, enables us to study detailed heterogeneity. When plotting wage gaps by replacement workers' age and mother status we find a particularly large gap for women with children in their 30s which suggests a motherhood penalty à la Kleven et al. (2019). Consistent with stylized facts presented by Arellano-Bover et al. (2024), we find that the gender gap decreases for younger cohorts, and disappears for workers born from 1990. This is not driven by a relative increase in women's wages; instead, men from more recent cohorts earn increasingly lower real wages compared to their predecessors. We also show that the type of firm matters: the gap is marginally smaller in firms with more female bosses, again driven in part by a relative decrease in replacing men's wages. In line with this, the gap is smaller in more family-friendly firms with lower gender wage gaps. Consistent with results in Boelmann et al. (2024) that gender norms are important, we moreover find that women working in East Germany (data available from 1992) face a 27% smaller gap.

Nevertheless, no sample split fully eliminates the gender hiring opportunity gap, and for most sample splits, it does not fall below 5 log points. There is one single exception: Analyzing the gap by 1-digit occupation and industry reveals a substantially reduced gap in sectors with limited scope for wage bargaining, such as public administration and education. We interpret this as additional evidence for a significant bargaining component of the gender hiring opportunity gap.

This paper contributes to the vast literature in economics on gender gaps in the labor market. While job mobility plays an essential role in facilitating fast wage growth for male workers (Topel and Ward, 1992), the case is much less clear for female workers (Loprest, 1992; Hospido, 2009; Del Bono and Vuri, 2011; Barth et al., 2021). The empirical strategy we employ in this paper helps isolate the component that arises from men and women moving to the same hiring opportunities. In the language of Card et al. (2016), it speaks to the "bargaining" component of the gender gap, when men and women get different shares of firms' surplus, instead of the "sorting" component, when women work at lower-paying firms. What is termed the "bargaining" component could include factors from the firms' side including discrimination or factors from the workers' side including preferences and negotiation (Babcock and Laschever, 2003; Roussille, 2024; Goldin, 2014). Our results are consistent with facts documented by Caldwell et al. (2024) for the German labor market, in particular, the lower propensity of women to negotiate their wages at the start of an employment spell, even conditional on outside options.

In the Card et al. (2016) analysis, the two components are captured in a Kitagawa-Blinder-Oaxaca decomposition of the gender-specific firm fixed effects in a Abowd et al. (1999) model. We find large gender differences that may not be captured in a firm-worker fixed effect framework when the gender hiring opportunity gap for equally productive workers translates into differences in individual fixed effects rather than differential firm fixed effects over time. We thus emphasize the fact that equally productive men and women can be given different opportunities and women may work in jobs below their productivity levels.

Comparing the prospects of men and women in the labor market is challenging empirically when gender is not randomized, with few exceptions such as blind auditioning as in Goldin and Rouse (2000). Past work that documents differences in hiring prospects often utilizes an audit study or correspondence study approach with its own limitations (Azmat and Petrongolo, 2014). We join the small set of studies using quasi-experimental variation to understand gender disparities in the labor market, including Roussille (2024) and Mocanu (2024) on hiring settings, and Illing et al. (2024), which focuses on the flip side when workers experience job losses.

Using unexpected departures of workers allows us to focus on exogenous hiring opportunities from the firm's perspective, which also sets us apart from other papers that also leverage death as a source of variation (Jones and Olken, 2005; Isen, 2013; Bennedsen et al., 2020; Jäger et al., 2024). While these papers often compare the treatment group with death events to a matched control group without, a unique aspect of our work is using the event to study gender disparities and compare departing with replacement workers.

A methodological contribution of our paper is that we are, to the best of our knowledge, the first to identify external replacements for workers who suddenly die. This provides a unique opportunity to compare workers in the same job position. While an identifier linking job positions sometimes exists in survey or private firm data, such an identifier is absent in administrative datasets. Our technique to link job positions can also help to study wage gaps in other contexts, such as migrant-native wage disparities.

The remainder of the paper is organized as follows: Section 2 describes the data and our identification of sudden deaths and replacement workers. Section 3 proceeds with outlining our empirical strategy. In Section 4 we quantify the gender hiring opportunity gap and describe our results on heterogeneity. We discuss the mechanisms in Section 5, and our robustness checks in Section 6. Section 7 concludes.

2 German Administrative Data

We draw our sample from the universe of linked employer–employee German social security records from 1975 to 2021. We combine the *Integrated Employment Biographies (IEB), Version 16.1* and the *Establishment History Panel (BHP), Version 7519, 2* 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 firms in Germany[7].

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 dates. In addition, we directly observe the reason why an employment contract ended (including exit due to death), as well as the exact date when it ended. The data moreover contain a rich set of characteristics such as wages, detailed occupation codes[8], and education. From the linked data, we create firm-level characteristics such as workforce composition, average wage level or the firm gender wage gap.[9] 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; we moreover merge additional information on weekly hours worked to parts of our baseline sample. We impute information on mothers using the algorithm provided by Müller et al. (2017).

2.1 Unexpected Death as Exogenous Hiring Shock

We follow Jäger et al. (2024) and use sudden worker deaths as exogenous shocks to hiring (see Appendix A.1 for details on how we define sudden worker deaths in the data). This has two key advantages: First, we keep the reason for worker exit constant. Second, hiring cannot be anticipated. This means that the replacing employee can start working only after the death of their predecessor which is a key condition for our definition of replacement workers. Note that we restrict the event sample to firms with max. 3-150 full-time and 300 total employees in the calendar year preceding the death event. We only consider deaths from 1981-2016.

Exits Panels (a) and (b) of Figure 1 plot the monthly exits of full-time workers in our sample. Panel (a) shows a strong hiring spike in the month of the identified death event, both for all workers and for workers in the same 3-digit or 5-digit occupation. We also compute a measure of excess exits compared to 24 months earlier, in order to control for potential seasonality in exits. Figure 1, Panel (b), shows that the number of excess exits is exactly one, confirming that the unexpected death is an

[7] In this paper, we use the terms "firm" and "establishment" interchangeably. The German admin data collects firm information on the *establishment* level, where one establishment is located at one specific workplace, and several establishments can be part of one firm.

[8] For most of our analysis, we use the first three digits of the *Klassifikation der Berufe (KldB) 2010*. See Paulus et al. (2013) for an overview.

[9] In addition, we use the data's unique firm identifiers to enrich it with AKM firm FE provided by the IAB (Lochner et al., 2023). We moreover impute missing education information following Fitzenberger et al. (2006). We deflate wages using the consumer price index provided by the German Statistical Office, with base year 2010.

exogenous hiring shock.

Entries Panels (c) and (d) of Figure 1 plot the number of monthly entries of full-time workers in our sample, confirming that firms did not anticipate the worker's death. While monthly entries do not show any pre-trends in the months leading up to the death event, entries increase right afterward and stay elevated for about six months (see Panel c). The same pattern is visible in Panel (d), which plots excess entries compared to 24 months earlier. Excess hiring hovers around zero and peaks in month 1 after the death event at about 0.14 workers if we consider all workers, and at about 0.1 workers if considering new entries of full-time workers in the same 3-digit or 5-digit occupation, respectively. We find that excess hiring is 62% (56%) concentrated in the same 3-digit (5-digit) occupation as the departing worker. Roughly 30% or 68,459 of sudden deaths are followed by excess, and thus external, hiring.

Replacement Workers These patterns motivate our definition of replacement workers. We define replacement workers in excess hiring firms as (i) the first full-time hire in (ii) the same 3-digit occupation as the deceased worker in (iii) the first 6 months after the death event. Once we have identified all replacement workers, we classify our data into four groups of deceased-replacement worker pairs: (1) male-male, (2) opposite sex, and (3) female-female transitions.

2.2 Construction of Panel Data

Sample Selection From the full population of worker biographies, we draw two separate samples. For each sudden death event in our sample, we first classify whether they were followed by excess hiring, or not. For events with excess hiring, we then draw all workers employed at the respective firms in the 12 calendar years around the death event. For events without excess hiring, we draw all workers employed at the respective firms in the 4 calendar years leading up to the death event.

Firm Panel We start by constructing a firm panel of excess and non-excess hiring firms for our machine learning exercise. This panel collects firm characteristics in the 3 years preceding sudden worker death. The cut-off date is the date of death, i.e., we record the status quo in the 3 calendar years before the year of death, at the day and month of the death. We compute precise information on the firm's workforce composition and its wage bill, where the wage bill is the sum of all employees' daily wages, multiplied by days worked at the firm per year. See Appendix B.1 for a detailed list of the firm variables that enter the machine learning.

For excess hiring firms, we construct an additional firm panel that contains the wage bill of all workers, incumbents, and new hires in the years around the death event, again using the death date as the cut-off date. We define incumbent workers as any firm employee whose work spell at event firm j overlaps with the date of death; we define new hires as any firm employee who worked at firm

j in t but not in $t-1$. We distinguish between (i) all workers, and (ii) coworkers, where coworkers work in the same 3-digit occupation as the deceased/replacement worker.

Deceased-Replacement Panel Finally, we construct a yearly panel of deceased-replacement workers in excess hiring firms, our baseline sample. This data set includes a unique pair id linking each deceased-replacement pair, and a unique event id for each firm × death event.[10] Since we observe daily instead of hourly wages, we consider only deceased-replacement pairs where both workers worked in a full-time contract at the time of death and at the time of hiring, respectively.

To reduce noise and to reduce bias from firms that were hiring many workers in the same 3-digit occupation closely before the death event, we further drop the following events: events where firms ever hired more than 150 new workers in any month in the 3 years before or 1 year after the death; events where firms hired 10 or more full-time workers in the same 3-digit occupation as the deceased worker, 1 year before the death. We moreover restrict the sample to deceased-replacement pairs where deceased workers earned wages above 0 in their last working spell.[11]

For spells leading up to and including the death event ($d-4$ to d), the cut-off date is the date of death. For spells following replacement workers' starting date at the treated firm, the cut-off date is the date of the hiring spell (r to $r+4$). For example, if the last spell of a deceased worker ended on May 15, 2014, then this will be his/her cut-off date, where $t = d$. We will define all previous years relative to this cut-off date. E.g., May 15, 2013, would correspond to $t = d-1$, and so on. Similarly, if a replacement worker is hired on June 22, 2014, then this will be his/her cut-off date, where $t = r$. June 22, 2015, would then correspond to $t = r+1$, and June 22, 2016, would correspond to $t = r+2$.

We moreover collect information on a set of replacement workers' characteristics at the cut-off date in their previous job before starting to work at the treated firm, which we refer to as $r-1$.[12] To ensure better comparability of replacement workers, in our baseline analysis, we restrict the deceased-replacement panel to replacement workers whose employment contract in $r-1$ was a full-time job. In addition, we drop women whose last employment spell ended in maternity leave. This leaves us with 43,068 deceased-replacement worker pairs; our baseline model is identified for 42,837 pairs. We replicate the main results of the paper for the full sample without conditioning on full-time employment for replacement workers in $r-1$ in Appendix E.

Summary statistics of deceased and replacement workers in Table 1 show that deceased workers earn higher wages than replacements, likely due to their higher age, occupational and firm tenure, and labor market experience. While demographics such as tenure and education are comparable across transition pairs, male-male and opposite-sex transition pairs earn substantially higher wages than female-female pairs. See Appendix Section A.1 for a more detailed discussion of Table 1, including

[10]Firms can enter the data with several events if sudden deaths happen in different calendar years. During our sample period, firms are subject to between 1 and 10 sudden worker deaths; for excess hiring firms, this reduces to between 1 and 7 events.

[11]In less than 2% of our baseline events, the deceased workers' final full-time employment spell records 0 wages. This is likely due to measurement error, for example, because the firm misreports the true wage or because the worker died already earlier. To reduce measurement error to a minimum, we therefore exclude these events.

[12]Note that due to our sample selection that limits worker biographies to the 12 calendar years around a death event, we can only consider previous jobs that started at least 6 years prior to the death event.

sorting across 1-digit occupations and industries. To account for potential differences in the positions that are replaced by male vs. female workers, our baseline analysis controls for deciles of the firm-specific ex-ante probability of hiring a woman, predicted using the machine learning exercise detailed in Section 3.1.

3 Empirical Strategy

This section describes our empirical strategy. It starts with details on our machine learning exercise to predict excess hiring and female replacement, followed by a description of our event study style regression analysis. We moreover outline our analysis of first differences to, amongst others, compare transition pairs and firm outcomes between d and r.

3.1 Machine Learning Algorithm

We start with a machine learning exercise, using the full set of firms with sudden worker deaths. Our aim is to (i) understand how firms with excess hiring differ from firms without excess hiring, and ii) predict the probability that the replacement worker is female versus male. For these two classification exercises, we use the "Ranger" algorithm which is a machine learning algorithm used for classification and regression tasks.[13] Ranger is an ensemble learning algorithm that builds an ensemble of decision trees. It is based on the Random Forest concept, which combines multiple decision trees to make predictions. The Ranger algorithm utilizes multi-threading and parallel processing, making it suitable for handling large datasets and complex problems. Its speed and efficiency make it a good choice for our task, involving about 190,000 observations and approximately 600 variables covering firm characteristics and labor market conditions in the three years leading to the death event.

The task is evaluated using 5-fold cross-validation. The predicting variables include characteristics such as the gender share in the establishment by full-time status and occupation, the gender, wage, and tenure of the deceased worker, detailed occupation and industry classifications, the size of the establishment, different measures of establishment wages, and local labor market thickness. See Appendix B.1 for a list of all variables.

Predicting Excess Hiring To understand whether excess hiring firms differ from firms without excess hiring, we first differentiate between establishments with and without excess hiring in the 180 days since the death event, compared to the year before. We use an ROC (Receiver Operating Characteristic) curve to evaluate the performance of our two binary classification models. An ROC curve plots the true positive rate (sensitivity) against the false positive rate (1 - specificity) across different classification thresholds to assess how well a model correctly classifies positive instances while mini-

[13] We use the R package "ranger" together with the "mlr3" package that provides a framework for machine learning.

mizing false positives.[14] The area under the curve (AUC) quantifies the overall ability of the model to distinguish between the positive and negative classes.[15]

Panel (a) of Figure A4 shows the model's ROC curve which lies above the 45-degree line, indicating that the probability of being able to distinguish the two groups is 77% (AUC = 0.77). This implies that firms with and without a replacement worker are relatively similar observably, yet with non-negligible differences. Panel A of Table A10 lists the top 10 predictors. They exclusively include the pre-event workforce composition at the firm (in particular, the share of (full-time) workers in the same 3-digit occupation as the deceased worker) and the wage bill of all workers at the hiring firm in $d-3$ to $d-1$. This is in line with Table A3 showing that firms with excess hiring are a bit larger, have slightly fewer high-skilled workers, and pay lower wages than non-excess hiring firms. It is not surprising that larger firms are more likely to find an external replacement for a (sudden) vacancy. We address potential concerns with respect to external validity via a reweighting exercise detailed in Appendix Section B.3.

Predicting Female Replacement We next predict the gender of the replacement worker. This serves two purposes: First, it helps us to understand how the firms hiring women differ from the firms hiring men. Second, to control for systematic differences, we use the firm's ex-ante probability of hiring a woman as a control in our baseline analysis.

To predict the gender of the replacement worker, we restrict the sample to the 68,459 firms with excess hiring. The ROC curve shown in Panel (b) of Figure A4 indicates that the probability of being able to distinguish the two groups is 92.4% (AUC = 0.924) which means that the firm and local labor market characteristics that enter the machine learning algorithm are highly predictive of the replacement worker's gender.[16]

This confirms that firms that hire a male or a female replacement worker are different. While unexpected departures create exogenous hiring shocks, they do not create exogenous replacements. To account for this, we control for the ex-ante predicted chance of a female replacement worker being hired in all regression specifications. This requires the identifying assumption that conditional on having the same predicted chance of hiring a female replacement, the actual realization is random. We will assess this assumption by comparing firm characteristics in $d-2$ by the gender of the replacement worker.

Panel B of Table A10 lists the top 10 predictors. Not surprisingly, the most important predictor is the gender of the deceased worker. The other predictors all emphasize the importance of the workforce composition by gender: they include the share of women and variations of it, such as the share of women in full-time positions, and the share of women in the same 3-digit occupation at the hiring firm. In our baseline analysis, we therefore include a large set of pre-death firm characteristics as additional regression controls, in addition to the ex-ante probability of hiring a woman. We further

[14] The true positive rate TPR is defined as $TPR = \frac{TP}{TP+FN}$ where TP is the number of true positives, and FN is the number of false negatives. Analogously, the false positive rate FPR as $FPR = \frac{FP}{FP+TN}$ where FP is the number of false positives, and TN is the number of true negatives.

[15] The AUC of a perfect model is 1 whereas it would be 0.5 in a random model.

[16] We achieve 86.4% accuracy in predicting the gender of the replacement hire through a five-fold cross-validation.

expand these controls in a robustness check (see Table A7, discussed in Section 6).

3.2 Event Study Style Analysis

We are interested in differences in the outcomes of female versus male replacement workers. Therefore, our baseline regression specification is the following:

$$y_{it} = b_{0t} + \beta_{1t} female\_replacement_i + \gamma_t \boldsymbol{X}_i + \epsilon_{it} \tag{1}$$

where the outcome y_{it} represents log daily wages. β_{1t} is our coefficient of interest, indicating how wages of transition pairs with female replacements differ from wages of pairs with male replacements, over time. i is a hiring event associated with a sudden departure. t is time relative to the event, from four years before the death event $t = d - 4$ to the time of death in $t = d$, and then from the event of replacement $t = r$ until four years later in $t = r+4$.[17] Observations in $t = [d-4, ..., d]$ reflect outcomes of the deceased worker. $t = r$ is the first observation of the replacement worker at the hiring firm. Hence, observations in $t = [r, ..., r+4]$ refer to the replacement worker. We estimate Equation (1) separately for each t. We condition on full-time employment of deceased and replacement workers in d and r, respectively.

To ensure that we compare incoming workers with the *same hiring opportunities*, we control for a vector $\boldsymbol{X}_i$ including deciles of the ex-ante probability of female replacement at the firm, deceased worker's gender, and deceased worker's wage and 3-digit occupation at $t = d$. We moreover control for the calendar year t. In an augmented specification, we additionally control for deciles of the replacement worker's pre-hire wage at their previous firm as a proxy for their productivity.

3.3 First Differences

While the coefficients obtained from Equation (1) inform us about the broad differences between transition pairs with female vs. male replacements, we can go one step further and make use of the direct link between each deceased worker and their replacement. We can thus compute the pair-level difference in wages or other outcomes (d vs r), and show deceased-replacement gaps by replacement worker gender. We define the deceased-replacement gap as follows:

$$\Delta y_i = y_{rep,r} - y_{dec,d} \tag{2}$$

If y reports wages, then Δy_i subtracts the wage y of a given deceased worker in their last employment spell d from the starting wage of the respective replacement worker. In other words, it gives us a raw measure for the "hiring penalty" of replacement workers for a given hiring event i. In alternative forms of Equation (2), we compute the difference in outcomes (e.g., wages) of replacement workers' hiring spell r vs. their previous working spell $r-1$. We next use the Δy_i measure in cross-sectional regressions that take the following form:

[17] By definition, the replacement event takes place between 1 and 180 days after the death event.

$$\Delta y_i = \beta_0 + \beta_1 female\_replacement_i + \beta_2 \boldsymbol{X}_i + \epsilon_i \tag{3}$$

In Equation (3), the constant β_0 tells us the mean value of Δy_i for hiring events with male replacement workers, and β_1 informs us about the additional gap for pairs with female replacements. The main difference to Equation (1) is that we construct all outcomes relative to the value of each outcome for deceased workers in d. In variations of Equation (3), we interact $female\_replacement_i$ with different sets of dummy variables, e.g., age groups and birth cohorts:

$$\begin{aligned}\Delta y_i = &\beta_0 + \beta_1 female\_replacement_i + \beta_2 \boldsymbol{X}_i \\ &+ \beta_3 Z_i + \beta_4 Z_i \times female\_replacement_i + \epsilon_i\end{aligned} \tag{4}$$

where Z_i represents the group, e.g., dummies for age groups that vary across transition pairs. The coefficients β_4 then tell us how the wage gap varies for transition pairs across different group values. Group Z_i can refer to both variables measured at the worker level (e.g., age groups, birth cohorts, and tenure as in Figure 3), or variables measured at the firm level such as female leadership (Figure A6).

In one version of graphs where we visualize the results from Equation (4), we separately plot $\beta_0+\beta_3$ (deceased-replacement gap for male replacement workers) and $\beta_0+\beta_1+\beta_3+\beta_4$ (deceased-replacement gap for female replacement workers). In another version, we plot the gender gap directly, i.e., $\beta_0+\beta_4$.

In one variation of Equation (4), we in addition differentiate between female replacement workers who are mothers, and female replacement workers without children.

$$\begin{aligned}\Delta y_i = &\beta_0 + \beta_1 female\_replacement_i + \beta_2 \boldsymbol{X}_i \\ &+ \beta_3 Z_i + \beta_4 Z_i \times female\_replacement_i \\ &+ \beta_5 female\_replacement_i \times mother\_replacement_i + \\ &+ \beta_6 Z_i \times female\_replacement_i \times mother\_replacement_i + \epsilon_i\end{aligned} \tag{5}$$

In Figure 3, Panel (b), we separately plot the deceased-replacement gap for male replacement workers ($\beta_0 + \beta_3$), female replacement workers without children ($\beta_0 + \beta_1 + \beta_3 + \beta_4$), and female replacement workers with children ($\beta_0 + \beta_1 + \beta_3 + \beta_4 + \beta_5 + \beta_6$).

4 The Gender Hiring Opportunity Gap

4.1 Baseline Analysis

Baseline Sample To uncover how similar work opportunities arising within firms translate into different outcomes for male and female new hires, we estimate Equation (1) with log daily wages as the outcome variable. Figure 2 (a), Panel "Same hiring opportunity", plots the β_1 coefficients on female replacement for $t = [d-4, \ldots, d, r, \ldots, r+4]$.[18]

We gain three important insights: First, the coefficients for $t = [d-4, \ldots, d]$ are extremely close to zero and precisely estimated, implying that the same hiring opportunities arose across genders of replacement workers. Second, the starting wages of female replacement workers are 18 log points lower than the starting wages of male replacement workers. Third, this gap does not close over time; in fact, it widens to about 28 log points by $t = r+4$.

The initial wage gap might arise due to two different factors. First, it could be due to firms hiring workers of varying productivity levels based on their gender. Second, it may result from firms compensating workers with similar productivity differently. To separate these factors, we analyze the starting wages of male and female replacement workers who have similar initial productivity levels, as proxied by the pre-hire wages at their previous employers. Figure 2 (a), Panel "+ Same pre-hire wage", shows the results of this augmented specification. We find that a 10 log point difference remains, suggesting that firms respond to the same hiring shocks by hiring workers of different productivity levels based on their gender *and* by compensating workers with similar productivity differently.

Gender Wage Gap in Germany Figure A1 puts this gap into context. It plots the gender wage gap for a sample of full-time workers in Germany who are part of the *LIAB, 7519, Version 1*[19]. We plot the raw gap and then show how it changes as we add control variables. Our baseline estimates of the wage gap are comparable with the wage gap in the *LIAB* specification where we control for demographics and firm × occupation FE. While our baseline wage gap for replacement workers is somewhat higher in the 1990s, it is 1-2 log points lower in the 2000s and 2010s (see Table 4).

The gender wage gap in Figure A1 is based on the full sample of workers, without restriction on new hires. The fact that we get such similar patterns with our sample suggests that the gender wage gap arises to a large extent at the hiring stage. Once women start out with lower wages, they struggle to break out of the ensuing path dependency.

Replacements with High Labor Market Attachment Next, we explore the role of statistical discrimination. Women are more likely than men to transition into part-time work or drop out of the labor market, which employers might anticipate and offer differential starting wages based on gender. To test this hypothesis, we restrict the sample to all workers who remain in full-time positions over the four years following the hiring event.[20] Panel (b) of Figure 2 plots β_1 for the baseline specification on the left, and for the augmented specification that controls for pre-hire wage on the right, respectively. We find that the initial gender gaps observed upon hiring for these workers are remarkably similar to those in the full sample, suggesting that firms may indeed base their pay decisions on group identity (Altonji and Blank, 1999; Fang and Moro, 2011).

[18] Figure A2 plots the raw log wage gap by transition group, without control variables. We discuss the figure in Appendix Section B.2.

[19] See Appendix Section A.3 for an overview on the dataset.

[20] This includes workers who switch employers to take on full-time work at a different firm.

The initial gender hiring wage gap could be due to asymmetric information when employers are less certain about longer-term productivity when hiring women, for example, because of anticipated care work (Tô, 2018). Models of employer learning propose that firms learn about worker productivity over time, leading to a convergence of replacement workers' wages across gender (Farber and Gibbons, 1996; Altonji and Pierret, 2001). Our findings are not consistent with this prediction: While the gap does not widen over time, as opposed to what we find for the full sample, the gender pay gap remains remarkably constant over the subsequent five years, even among this highly attached sample. Initial differences in early career wages might lead to differential on-the-job training at the same employer or to negative signals to new employers, thereby exacerbating gender pay gaps over the career trajectory. This suggests that the hiring stage is crucial in the pursuit of gender equality.

Labor Supply Table 2, Panel A, provides evidence on additional worker-level outcomes. This analysis differs from the baseline analysis because it constructs wage and employment of replacements *relative to* deceased workers. While we control for deciles of deceased workers' wages in all analyses, this is a more direct way to net out wage differences across deceased workers. Reassuringly, this analysis yields exactly the same wage gap.

In addition, we examine several measures for labor supply. We condition on full-time employment in d and r, yet the number of days worked in the full-time contract may differ by gender, potentially serving as an important signal for motivation and worker productivity. The second row in Table 2 shows that this is not the case: male replacement workers in r work on average 19 fewer days relative to their predecessors' labor supply in d. Replacing women work additional 1.7 days per year less, but this difference is small and statistically insignificant.

However, even days worked full-time may reflect gender differences in labor supply: Full-time employment in Germany is defined as any contract with more than 34 hours of work per week, potentially with overtime hours on top. To investigate whether male and female replacements work different hours, we leverage a linkage of the IAB data with information on hours worked provided by the Statutory Accident Insurance for spells in 2010-2014 (see Appendix A.3 for details). We are able to merge information on hours for 2501 pairs, representing 6% of our analysis sample, so these results should be interpreted with caution. For this restricted sample, however, we can rule out differences in hours while a significant gender wage gap remains. Both male and female replacements work on average 2.2 log points more hours per week compared to their predecessors. The log gender wage gap for this sample amounts to 3.6 log points.

The last row in Panel A of Table 2 shows by how much replacement workers' wage bills change relative to deceased workers' wage bills (think of this as the labor cost for the respective position, from the firm perspective). We define wage bill as the product of total days worked for firm j at time t, multiplied by the daily wage. The wage bill decreases by around EUR 9,800 for male replacements in r compared to their predecessor in d; this is consistent with their relatively lower wages and days worked per year. For female replacements, there is an additional, significant decrease in the wage bill of around EUR 2,700.

Replacement Workers While this paper focuses on the wage gap between deceased and replacement workers, our data allows us to compare several wage and employment outcomes of replacement workers in their previous job ($r-1$) vs. the new job (r). Table 3, Panel A, shows how wages and days worked full-time change for replacement workers, separately for men and women.

Male replacements, on average, increase their daily wages by 6.6 log points. In contrast, female replacements' wages relative to the previous job decrease by 2.7 log points. The second row of Table 3 offers in part an explanation for this pattern. Women expand their labor supply relative to their previous job less than men (– 11 full-time days). Additional explanations may be compensation through non-wage amenities or differences in outside options, i.e., bargaining power. We will discuss this in more detail in Section 5.

Table 3, Panel A, moreover shows that positions filled by female replacements were vacant for around 3 additional days (baseline for male replacements: 70). This suggests that, on average, firms wait somewhat longer if they hire a woman or that these positions are harder to fill. If this is the case, then firms should be willing to pay workers hired into these positions more, which would downward-bias the gender gap that we identify. The average time out of work for male replacements is 428 days, a relatively long period. For women, the gap in days since their previous job is 37 days shorter, suggesting that they are in a better position when applying for the new job (e.g., more likely to receive higher UI benefits). In a robustness check in Section 6, we restrict the sample to replacement workers with a gap of at most 1 year between their previous job and the hiring spell and find a very similar gender gap.

4.2 Heterogeneity

Age, Birth Cohort, Skill We have established a sizable gender hiring opportunity gap, yet it is unclear whether this gap is driven by specific types of workers or firms. To gain a better understanding, we proceed by analyzing how the gap varies across replacement workers' birth cohorts and age groups (measured at r) interacted with mother status.

Figure 3 plots the deceased-replacement wage gap at the hiring stage (d vs. r) for (i) male replacements and (ii) female replacements, where we show the group on the x-axis. Panel (a) reveals a weak inverted u-shape pattern of the wage gap for male replacements by cohort, while the gap for female replacements stays more or less constant for birth cohorts from the 1940s. As a result, the gender hiring opportunity gap decreases for more recent cohorts and becomes statistically insignificant for individuals born from 1990 onwards. Strikingly, this is not driven by female upgrades, but by male downgrades. This pattern is consistent with evidence in Arellano-Bover et al. (2024) who show that the declining gender wage gap is in part driven by men of more recent birth cohorts entering the labor market with lower wages compared to older men.

In Panel (b), we show the gap by age group for three groups: male replacements, female replacements who are mothers in r, and female replacements without children in r. Replacing men below age 26, and replacing men above age 45 earn relatively lower wages compared to their predecessors.

Similarly, very young childless women (below age 21) face bigger gaps. Mothers aged 21-40 face by far the largest wage gap relative to their predecessors, and they only catch up with childless women from age 41 onwards. However, even women without kids earn consistently lower wages than male replacements, relative to their predecessors.

This shows that the *gender hiring opportunity gap* is not driven by mothers. The persistent gap that exists even for women without kids moreover makes it less likely that women are fully compensated through non-wage amenities such as more flexible employment contracts or free daycare slots. At the same time, firms may expect women with kids or in childbearing age to be less productive (Tô, 2018), and therefore offer them lower wages.

One replacement worker characteristic that is highly predictive of the gender gap is occupational skill intensity (defined following Jäger et al. (2024), see Section A.2 for details). As Columns (1) and (2) in Panel C of Table 4 show, the gender gap is particularly high for low-skilled workers (15 log points); it is still sizable, but substantially lower for medium-/high-skilled workers (8.2 log points).

Calendar Year, Tenure, Occupational Wage Variance We provide additional hints on the mechanisms behind the *gender hiring opportunity gap* in Figure 4. Panel (a) shows that the gap has decreased substantially over time, with the gap in the most recent decade corresponding to about 30% of the gap in the 1980s. This decreasing trend may reflect several dynamics on the firm- and worker-level, such as changing gender norms (Boelmann et al., 2024), policy reforms such as the expansion of public child care (Bauernschuster and Schlotter, 2015), or the fact that German firms faced increasing skilled worker shortages.

In Panel (b) of Figure 4, we move from broad trends to worker-specific characteristics and show that the gender gap is not driven by differences in occupational tenure. The gender gap remains remarkably stable across occupational tenure groups. It is only for the small sample of replacements with more than 20 years of occupational tenure that the gender gap completely disappears. Panel (b) of Figure 4 shows that gender differences in tenure can mostly not explain the *gender hiring opportunity gap*. We interpret this as supporting evidence that we are indeed comparing men and women with very similar productivity.

Finally, in Panel (c), we move to the 3-digit occupation. We classify occupations by their wage dispersion proxied by the standard deviation of wages paid within a given 3-digit occupation and county combination. The underlying idea is that occupations with lower wage dispersion offer less scope for bargaining, and therefore potentially lower gender gaps. Panel (c) of Figure 4 provides supporting evidence for this. The gender gap is lowest, though still substantial, for occupations in the bottom quartile of wage dispersion, therefore highlighting the role of bargaining for the *gender hiring opportunity gap*.

Firm Characteristics We showed that replacement worker characteristics play a (limited) role in explaining the gender hiring opportunity gap. As a next step, we investigate the role of firm characteristics, in particular the gender of bosses at the firm. Figure A6 presents our results.

As in Kunze (2017), Matsa and Miller (2011), and Cardoso and Winter-Ebmer (2010), one might expect that wage gaps are smaller for firms with more female bosses. Figure A6, Panels (a)-(c), therefore investigate whether the gender of the CEO, of the team leader, and the overall share of female team leaders in the firm correlate with the gender gap. Indeed, the wage gap is slightly smaller in firms with a female CEO and in firms with a female team leader share above 50%. However, this is primarily not because replacement women in these firms earn relatively more, but because replacement men earn relatively less. Even in firms with female CEOs, a sizeable gender gap of around 10 log points remains. Instead, Panel (c) of Figure A6 suggests that female team leaders, as proxied by the coworker in the same 3-digit occupation with the highest wage, negatively impact female replacement workers' entry wages and lead to a somewhat larger gap.

Rather than the gender of leaders in the firm, a firm's general family-friendliness seems to be a more important predictor of the gender gap. Panel B of Table 4 shows that the wage gap is substantially smaller (7 vs. 13 log points) in *family-friendly* firms, where we classify firms as family-friendly if they have at least one female manager with a child aged 0-8. Similarly, the gap is smaller in firms with a gender wage gap below the mean (8 vs. 15 log points).

Occupation and Industry Table A2 shows that sudden deaths are over-represented in industries and occupations such as construction, motor vehicles, and traffic. To rule out that our baseline result is driven by a specific industry or occupation, Figure A5 plots deceased-replacement wage gaps by 1-digit occupation and industry. The main takeaway from this figure is that replacing women earn lower wages in almost every industry and occupation, with few exceptions.

One notable exception is public administration, where the deceased-replacement wage gap is only 4 log points. There is limited scope for wage negotiations in the German public sector, so this result supports the idea that the bargaining component of the gender gap is a key factor driving our baseline result. Similarly, the gender gap is statistically insignificant, but positive, in education, which provides limited opportunity for wage negotiations.

5 Firm Adjustments, Amenities, and Outside Options

So far, we have documented and characterized the gender hiring opportunity gap. In this subsection, we discuss several potential mechanisms.

Firm-level Adjustments We argue that we get as close as possible to comparing male and female replacements with the same productivity. Here, we provide supporting evidence for this argument. If female replacements are, on average, less productive, then firms have several potential margins of adjustment: They may shift tasks and pay systematically to coworkers. Alternatively, they may increase their capital investments. Finally, if coworker wages and capital remain the same, firms' output may decline.

Panels B and C of Table 2 provide evidence on each of these. We start in Panel B with the coworkers' wage bill, defining coworkers as all workers in the same 3-digit occupation as the deceased worker. We show the total wage bill, incumbent workers' wage bill, and new hires' wage bill. We define incumbents as all employees whose employment spell overlaps with the date of death, and new hires as everyone who worked at the firm on the date of death in $d+1$, but not in d.

If firms shifted more tasks to incumbents or other workers in the event of a female replacement, we would expect a positive β_1 coefficient in Column (2). However, this is not what we see. The coefficient on female replacement for all three wage bill measures is positive but economically small and statistically insignificant.[21] We take this as first evidence that male and female replacements are similarly capable of replacing their respective predecessors.

Next, we ask whether firms compensate for this loss of labor with an increase in capital. For this purpose, we leverage on the Orbis-ADIAB data (see Appendix Section A.3 and Antoni et al. (2018)), which is available for a restricted set of (large) firms. The second line in Panel B of Table 2 shows that if the replacement is male, firms do increase their capital by approximately EUR 728 per employee, suggesting a partial substitution of labor with capital. This is not the case in the event of a female replacement, where capital decreases; the coefficient on female replacement is, however, estimated very imprecisely, and has to be interpreted with caution.

Both incumbent worker wage bill and capital do not differ (significantly) for firms with female replacements. However, since female replacements earn lower wages, their wage bill relative to deceased workers is significantly lower. If female replacements were on average less productive than male replacements, this should lead to a decline in firms' output.

We provide suggestive evidence that this is not the case, by investigating sales data for nearly 760 firms, and thus a small fraction of our analysis sample. Sales increase by about 31,000 EUR per person for death events with male replacements; the coefficient on female replacements is positive, but estimated very imprecisely. In addition, there is no differential effect on firm exits. Considering Panels B and C of Table 2 together increases our confidence that we are effectively comparing male and female replacements with similar productivity.

Non-wage Amenities If the deceased-replacement gender wage gap does not reflect productivity differences by gender, what else explains it? As in Le Barbanchon et al. (2021) and Mas and Pallais (2017), women may trade off wages for other amenities, such as lower commutes or regular schedules. To test whether this plays a role for replacement workers, we first investigate how their commuting distance changed relative to their previous job.[22] Table 3, Panel B, shows that both male and female replacements commute on average about 4 km more to the new job, relative to the previous one.

[21]Note that in contrast to Jäger et al. (2024), who find that the incumbent workers' wage bill increases following sudden worker death, we find that it decreases for both male and female replacements. In contrast to Jäger et al. (2024), however, we focus on a sample of firms with excess hiring, and thus rule out cases where worker replacement takes place exclusively internally.

[22]We measure commuting distance based on municipality centroids, see Appendix A.2 for details. Information on a worker's place of living in the IAB data is available from 1999, such that we only observe commuting patterns for events in the 2000s and 2010s.

Gender differences in commuting thus cannot explain the replacement gender gap.

We moreover investigate whether female replacements move to firms with lower gender wage gaps. In line with Folke and Rickne (2022), such firms may moreover constitute more female-friendly work environments, including a lower risk of sexual harassment. The remaining rows in Table 3, Panel B, show that women are not more likely to move to firms with lower gender wage gaps. We cannot, however, rule out that women are offered more flexible or regular schedules, or that they are more likely to receive free access to daycare. The IAB does not collect information on workers' schedules, such that we cannot assess whether replacements' employment contracts differ systematically in attributes such as flexibility. However, we show that a persistent gender gap exists even for non-mothers across all age groups, a group that is likely to put similar value on flexible work arrangements as men.[23]

Outside Options As in Caldwell and Danieli (2024), the wage gap may reflect female replacements' relatively weaker outside options, reducing their ability to negotiate higher starting wages and promotions. To test whether this is the case, we construct three proxies for outside options measured in replacement workers' previous work spells ($r - 1$) and assess whether they differ for female replacements.

Our first proxy consists of a weighted, standardized, and gender-specific index of labor market thickness. It is based on two measures: (i) labor market thickness by 2-digit occupation and commuting zone, following a measure proposed by Jäger et al. (2024), and (ii) a matrix of occupational transitions by gender and calendar year, based on a 20% random sample of workers in Germany.[24] The index thus encompasses an approximation of workers' job opportunities across occupations, weighted by their probability to work in any of them. Row 1 in Panel C of Table 3 shows that there is no gender difference in this measure.

The other two measures, median full-time wages and firm AKM fixed effects as provided by Lochner et al. (2023), proxy the quality of the previous employer. The rationale is that if women come from lower-quality firms, they will have worse leverage in wage negotiations. Rows 2 and 3 of Panel C, Table 3 shows that in fact, the opposite is the case: Women's previous employers paid slightly higher wages, and had significantly better fixed effects. Taken together, these results suggest that differences in outside options cannot explain why replacing women face larger wage gaps.

6 Robustness

We conduct several robustness checks. We show the gender hiring opportunity gap for different sample restrictions and for regressions with different sets of control variables. We replicate our analysis for a set of transition pairs where the time between replacement workers' hiring spell and their last job did not exceed one year. We moreover replicate the baseline analysis for the "full sample" of transition pairs, where we do not condition on previous full-time employment of replacement workers.

[23] Bolotnyy and Emanuel (2022) show that women with dependents have the highest demand for flexible work hours.

[24] See Appendix A.2 for details.

Sample Restrictions We start by replicating our main result for different samples. Table A6 presents the results, where Columns (1) and (2) in Panel A show the baseline coefficients. In Table A6, we show that conditioning on a sample where replacement workers are continuously employed in full-time jobs starting in r reduces the gender wage gap only marginally; the gap is the same for a balanced panel of firms around the event.

We continue to test whether the gap is driven by mothers. For this purpose, we first exclude all pairs with replacements who are mothers by r from our analysis. These are few observations; still, the gap reduces from 10 to 9 log points. Next, we focus on pairs where replacement workers are aged 40 and above, assuming that these workers are out of childbearing age. The gender gap for these workers is 12 log points and thus larger than the baseline gap. All of this confirms that the *gender hiring opportunity gap* does not simply reflect a child penalty for female replacements.

If there is more than one full-time new hire in the same 3-digit occupation at the firm, there may be concerns that we are not identifying the correct replacement worker. In an additional analysis, we therefore restrict to events where only one full-time worker in the same 3-digit occupation was hired in the 365 days following the death. This reduces the baseline sample to about a quarter and hardly changes the gap. Similarly, one might worry that women are more likely to change their 3-digit occupation between $r-1$ and r and that their greater loss of occupation-specific human capital may drive the gap; columns (5) and (6) of Table 4, Panel C, show that this is not the case.

Table 3 shows that male replacement workers face a gap of on average 428 days between their previous work spell and the hiring spell. Women's time in days until their last working spell is shorter, though their reasons for leaving the labor market may differ from men's (e.g., unpaid care work versus training). While we explicitly exclude replacements whose last spell ended in maternity leave, this restriction may not capture everyone, e.g., if women return to the labor market for a (short) mini job arrangement. One might worry that women with long parental leave absences drive our results.

For another robustness check, we therefore restrict the sample to replacements with a gap of not more than one year between their hiring spell and their previous job. The one-year restriction is motivated institutionally since this is the duration of UI benefits (ALG type I) receipt in Germany; it helps us to focus on replacements who are relatively attached to the labor market. With this restriction, the "+ same pre-hire wage" gap reduces to 8.9 log points but it is still very close to the baseline gap of 10 log points.

Firm Type One potential concern is that the *gender hiring opportunity gap* is driven by events with a lower ex-ante probability of hiring women, or by occupations with lower female shares. One may expect lower gender gaps for firms or occupations with a higher probability of female hiring: Such firms and jobs may be more familiar with hiring female workers, they are potentially more female-friendly, and HR departments in such firms and for such occupations may be more skilled in assessing women's productivity.

To test whether this is the case, we investigate the deceased-replacement wage gap by the ex-ante probability of female replacement, derived from our machine learning exercise. Panel (a) of Figure

A7 shows that the gender gap is very flat across most deciles. Similarly, in Panel (b), we show that the gender gap does not vary systematically by deciles of a given 2-digit occupation's share of female full-time workers. We take this as evidence that the gender gap is not limited to specific types of firms or jobs that are more hostile towards women.

Finally, in Table A6 we show that the gender wage gap is marginally larger for firms with 3-50 full-time employees in $d-1$ (10 log points) vs. in firms with 51-150 full-time employees in $d-1$ (9.6 log points). Overall, this analysis leaves us confident that the gap is not driven by a particular subset of firms.

Different Sets of Control Variables To estimate the gender hiring opportunity gap, we control for a set of fixed effects that include deciles of the ex-ante probability of female replacement, the calendar year, deciles of deceased worker's wage, deceased worker's gender, and deceased worker's 3-digit occupation. To control for productivity differences, we add deciles of replacement workers' previous wages to the set of controls.

If women are systematically underpaid, as our paper suggests, then women's previous wages will underestimate their productivity, biasing our coefficients downwards. In a robustness check, we therefore control for alternative proxies for replacement workers' productivity, all measured in $r-1$. Table A7 shows that indeed, the gender hiring opportunity gap is (slightly) larger in all of these additional specifications.

Table A7, Columns (2)-(5), introduce them separately and all at once. We start with deciles of labor market experience (Column 2), skills (Column 3), deciles of firm and occupational tenure (Column 4), predicted wages based on a sample of male replacement workers (Column 5), and all productivity proxies (except predicted wages) simultaneously (Column 6).

In a next step, instead of replacement worker controls, we add a set of additional firm controls. These control for hiring firm characteristics, measured in d. They include the number of full-time workers in the same 3-digit occupation (d), the share of mothers (d), and dummies for the above median share of: full-time women in the same 3-digit occupation; full-time women; mothers with kids aged 0-8 (all in d). Once again, the coefficient for female replacement hardly changes. This holds even if we include the full set of controls, including replacement and firm characteristics, in Column (8). In fact, this regression specification estimates a slightly higher gender gap of 13 log points.

Firm Characteristics in $d-2$ Our analysis requires the key identifying assumption that conditional on a firm having the same ex-ante predicted chance of hiring a female worker, the actual realization is random. We assess this assumption by comparing relevant firm characteristics measured in $d-2$, 2 years before the death event, by the gender of the replacement worker. Table A9 provides the results.

The table presents the coefficient on *female replacement* for eight different firm-level variables, in 16 specifications (same hiring opportunity and same pre-hire wage for each variable). Panel A shows that there is no statistically significant difference in the coworker wage bill for firms who hire a female vs. male replacement worker. Panel B shows that the same holds for the gender gap of other workers (excluding the deceased worker) at the firm. There is, however, a difference in the AKM firm FE for firms with a female replacement in the "same pre-hire wage" specification: Firms that will hire a woman are, on average, more productive (coefficient of 0.014). However, if this difference biases our results, then we would expect it to work against us: more productive firms should, on average, pay their employees more.

In Panel C, we show that there remain slight differences in the workforce composition of firms with female hiring. Firms with female hiring have a higher share of mothers; albeit statistically significant, at .3ppt, the difference is economically negligible. Firms with female hiring moreover have a 2.2ppt higher share of female employees. This is of concern for our analysis if female-dominated firms pay lower wages. Reassuringly, Table 4, Panel B, shows that there is hardly any difference in the gender gap for firms with less above or below 50% female full-time share.

Finally, Panel D of Table A9 shows that firms with female hiring do not differ in terms of their family-friendliness. They have the same share of female team leaders as firms with male hiring. They are also not more or less likely to be family-friendly, where family-friendliness is proxied as a firm with at least one female manager with a child aged 0-8.

Incumbent Worker Wage Bill In Table 2, Panel B, we show that incumbents' wage bill does not adjust systematically by replacement worker gender. In Table A8 we extend this analysis and show several versions of the incumbent wage bill for 3 different samples: baseline, balanced firm panel, and full sample (incl. replacement workers without full-time employment contract in $r-1$).

We construct a measure of incumbent workers' wage bill that takes into account changes relative to $t = d$ and sets the wage bill in relation to the deceased worker's wage in d. To formalize this, we first construct a measure for the additional wage bill at a given time t, relative to the wage bill in d: $wba_t = wb_t - wb_d$. We then compute the share of the additional wage bill as a function of the deceased worker's wage in d: $\frac{wba_t}{wage_{dec,d}}$.

For this analysis, we do not take a stance on replacement worker gender and instead regress the outcome on a dummy for *male deceased worker*. The underlying idea is the following: If men are more productive than women and therefore earn higher wages, then, following a male death, firms will need to shift more tasks onto incumbent workers. We would therefore expect positive coefficients for male deceased workers. If, however, men and women are similarly productive, but men are overpaid, we would expect no differential change in incumbents' wage bills. In each regression, we control for deceased worker's 3-digit occupation, calendar year, the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), the number of female new hires in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d), the share of full-time women in the same 3-digit occupation at the firm (d).

Table A8 suggests that the latter is the case. In (almost) all specifications, the coefficient on male death is insignificant. This holds for the wage bill of all incumbents, regardless of 3-digit occupation (all, and gender-specific), and for incumbents in the same 3-digit occupation as the deceased worker (all, and gender-specific). The analysis sample makes no difference.

Full Sample For our baseline analysis, we restrict the sample to replacements who worked in a full-time contract in their previous employment spell ($r-1$). We argue that this is important because we condition on *daily* wages of the job in $r-1$, and we can only reliably compare these for full-time workers.

In an alternative regression specification, we lift this restriction on replacement workers and add a full-time dummy (measured at $r-1$) to our set of control variables. Appendix E replicates our main results for this sample, which increases to 45,165 transition pairs. Figure A8 and Table A12, Panel A, show that the wage gap increases slightly to 11 log points; this likely reflects the fact that the productivity of replacement workers is now less comparable. The main takeaways from Table A13 remain the same.

7 Conclusion

In this paper, we ask how much of the gender wage gap arises within firms during the hiring process. To answer this research question, we introduce a novel identification strategy that addresses the challenge of gender-specific sorting across firms. Specifically, we analyze the wages of external hires following exogenous vacancies caused by sudden worker deaths, using matched employer-employee data from Germany spanning four decades. We combine this analysis with a random forest approach that predicts the ex-ante probability of replacement workers being female. We thus ensure that the gender of the new hire is effectively random, eliminating bias from systematic firm-level hiring practices. This empirical strategy makes it possible for the first time to study transitions across the same position within a firm in administrative data.

We find that female replacement workers, regardless of the deceased worker's gender, start with wages that are 18 log points lower than the starting wages of their male counterparts, the *gender hiring opportunity gap*. This gap reduces to 10 log points when comparing the wages of replacement workers with similar starting productivity, proxied by their pre-hire wage at their previous firm. We conclude that firms are hiring workers of different levels of productivity based on their gender, but they are also compensating men and women with similar productivity differently. Consistent with, e.g., Blau and Kahn (2017), we show that the gender gap decreases strongly over time: it is 15 log points in the 1980s, but only 5 log points in the 2010s.

The gap does not close in replacements' subsequent spells and it exists even for a sample of highly attached workers who remain full-time employed in the four years following their hiring spell. This suggests that employers do not update their initial beliefs about female new hires' productivity. An extensive set of analyses, both on the worker- and firm-level, supports our claim that firms pay women below their productivity. We show that the gap is not driven by differences in labor supply (hours worked); within-firm adjustments do not differ by replacement worker's gender (coworker wage bill, capital, sales); and male and female replacements have the same outside options. We conclude that we are capturing the "bargaining" component of the gender gap, which may encompass firm-side factors, such as discrimination, and worker-side factors, such as preferences and negotiation strategies.

We thus contribute a novel finding to the literature on gender gaps in the labor market: women benefit less from the same hiring opportunities than men. From a policy perspective, this is particularly worrying because receiving a lower wage initially can set a trajectory for consistently lower earnings throughout one's career. Women earning relatively lower wages may be less attached to the labor market; this is concerning in particular at a time when high-income countries urgently need more workers. Policies designed to reduce wage disparities may be particularly successful if aimed at increasing women's starting wages, both for labor market entrants and for job switchers. A simple, but potentially powerful tool could be incorporating gender-specific wage negotiation training into the high school curriculum.

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8 Tables

Table 1: Demographics for Transition Pairs vs. Random Sample of Workers

	(1) Random Sample	(2) Male-Male	(3) Opposite Sex	(4) Female-Female
Panel A: Deceased Worker in d				
Daily Wage in EUR	91.7 [53.8]	94.1 [50.1]	97.8 [59.6]	76.5 [32.7]
Days Worked Full-time	332.1 [79.9]	340.7 [68.2]	342.6 [68.4]	340.0 [72.5]
Age	38.7 [11.4]	45.3 [11.3]	45.5 [11.4]	43.2 [12.2]
Tenure in Firm (Years)	5.87 [5.97]	6.54 [6.38]	7.50 [6.88]	6.72 [6.22]
Occ. Tenure (Years)	8.19 [7.04]	9.73 [7.77]	10.2 [8.08]	9.26 [7.27]
Experience (Years)	13.0 [8.54]	14.8 [8.81]	15.0 [8.85]	13.0 [8.28]
Education (Years)	12.2 [1.93]	11.9 [1.39]	12.2 [1.88]	11.8 [1.42]
Mother	0.074 [0.26]	0 [0]	0.040 [0.20]	0.12 [0.32]
Panel B: Replacement Worker in r				
Daily Wage in EUR	91.7 [53.8]	84.6 [58.0]	81.6 [34.1]	68.9 [33.1]
Days Worked Full-time	332.1 [79.9]	320.7 [83.9]	324.6 [83.8]	320.5 [87.1]
Age	38.7 [11.4]	35.3 [10.1]	34.1 [10.0]	33.5 [10.4]
Tenure in Firm (Years)	5.87 [5.97]	0.46 [0.58]	0.49 [0.60]	0.48 [0.52]
Occ. Tenure (Years)	8.19 [7.04]	4.08 [5.48]	4.07 [5.17]	4.20 [5.11]
Experience (Years)	13.0 [8.54]	10.6 [7.09]	9.64 [6.90]	8.97 [6.51]
Education (Years)	12.2 [1.93]	12.0 [1.51]	12.4 [2.02]	12.0 [1.50]
Mother	0.074 [0.26]	0 [0]	0.12 [0.33]	0.18 [0.38]
Number of Individuals	14905321	34185	5126	3757

Notes: This table presents differences in average characteristics for our baseline sample of deceased-replacement worker pairs compared to a random sample of German workers. Column (1) shows characteristics for a random 2% sample of full-time workers in the German social-security data in 1981-2016. Column (2) shows characteristics for male-male transition pairs, Column (3) shows characteristics for opposite sex transition pairs, and Column (4) shows characteristics for female-female transition pairs. Columns (2)-(4) in Panel A present the characteristics of deceased workers in their last working spell, and Columns (2)-(4) in Panel B present the characteristics of replacing workers in their hiring spell. Time period r refers to replacement workers' starting spell at the hiring firm, and time period d refers to deceased workers' last employment spell. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table 2: Adjustments Within Transition Pairs and Event Firms - Same Pre-Hire Wage

	(1) Mean Δ Male Replacement		(2) Coefficient Female Replacement		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment (r-d)					
Log Wage	-0.083	[0.0021]	**-0.10**	[0.0058]	42,837
Days Worked Full-Time per Year	-18.9	[0.74]	-1.70	[1.82]	42,837
Log Hours Worked per Week	0.022	[0.0055]	0.0012	[0.020]	2,501
Log Wage if in Hours Data	-0.10	[0.0059]	**-0.036**	[0.021]	2,501
Wage Bill Replacement-Deceased Worker (EUR)	-9846.3	[88.5]	**-2699.2**	[220.8]	42,837
Panel B: Coworker Wage Bill (t_1-t_0)					
All (EUR)	40596.4	[1308.2]	811.3	[3799.7]	42,837
Incumbents (EUR)	-26640.6	[917.9]	327.3	[2474.0]	42,837
New Hires (EUR)	22810.0	[764.8]	3514.3	[2486.0]	42,837
Panel C: Firm-level Adjustments (t_1-t_0)					
Capital/Person (EUR)	728.4	[440.1]	-1368.6	[1239.6]	1,875
Sales/Person (EUR)	31026.1	[10991.2]	8698.1	[48567.6]	757
Firm Has Disappeared by r+1	0.0034	[0.00044]	-0.00057	[0.0010]	42,837

Notes: This table reports replacement workers' vs deceased workers' labor market outcomes, and firm outcomes in t=1 vs. t=0, based on Equation (3). Column (1) reports the mean for male replacements (i.e., β_0); column (2) reports the coefficient for female replacements (i.e., β_1). Panel A reports the r-d difference in replacement vs. deceased worker labor market outcomes, measured at r and d, respectively. r refers to replacement workers' starting spell at the hiring firm, and d refers to deceased workers' last employment spell. Information on hours comes from the Statutory Accident Insurance and is available for 2010-2014. Panel B reports the r-d difference in the wage bill of all coworkers, incumbent coworkers, and new hires. Coworkers work in the same 3-digit occupation as the deceased (and replacing) worker. We define incumbents as all employees whose employment spell overlaps with the date of death. We define new hires as all employees who worked at the firm at the date of death in the post-death year t_1, but not in the calendar year of death t_0. Panel C reports the t_1-t_0 difference in firm performance indicators. Firm performance indicators come from the Orbis-ADIAB data (see Antoni et al. (2018)) and are available for linked firms in 2006-2013. All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. Coefficients in bold are statistically significant at the 10%-level.

Table 3: Replacement Worker Wage Gains, Amenities, Outside Options

	(1) Mean Δ Male Replacement		(2) Coefficient Female Replacement		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment					
Δ Log Wage	0.066	[0.0020]	**-0.093**	[0.0053]	42,837
Δ Days Worked Full-Time per Year	92.9	[1.05]	**-11.2**	[2.67]	42,837
Days Job Was Vacant	69.9	[0.36]	**2.77**	[0.90]	42,837
Days Since Last Job	428.0	[5.35]	**-37.4**	[13.7]	42,837
Panel B: Amenities					
Δ Commuting Distance (km)	4.22	[1.18]	1.12	[3.16]	15,648
Δ Gender Wage Gap in Firm	0.0073	[0.0034]	0.00077	[0.0071]	29,470
Gender Wage Gap Other Workers in Hiring Firm	0.42	[0.0035]	0.010	[0.0079]	39,528
Panel C: Outside Options					
$\phi_{cz,occ,t,g}$	-0.0098	[0.0013]	0.0033	[0.0037]	41,685
Pre-Hire Firm Median Full-time Wage	63.8	[0.13]	**4.00**	[0.38]	42,060
Pre-Hire Firm FE	0.080	[0.0013]	**0.048**	[0.0032]	41,388

Notes: This table reports regression coefficients for our sample of replacement workers, based on a version of Equation (3) that compares a given replacement worker outcome in r vs. $r-1$. r refers to replacement workers' starting spell at the hiring firm, and $r-1$ refers to their previous employment spell. Column (1) reports the mean for male replacements (i.e., β_0); column (2) reports the coefficient for female replacements (i.e., β_1). The first two rows in Panel A show how replacement workers' wages and days worked differ from those recorded in their previous job. 'Days job was vacant' counts the number of days between a replacement worker's starting date at the hiring firm and their predecessor's date of death. 'Days since last job' counts the number of days between a replacement worker's starting date at the hiring firm and their last work day in their previous job. In Panel B, we report three proxies for amenities: The change in commuting distance compared to the previous job (in km), the change in the firm gender wage gap, and the gender wage gap of all coworkers (ie, workers in the same 3-digit occupation) in the hiring firm In Panel C, we report three proxies for replacement workers' outside options. $\phi_{cz,occ,t,g}$ refers to local labor market thickness by 2-digit occupation and commuting zone, weighted by gender-specific cross-occupational transition probabilities (see Appendix A.2 for details). Pre-hire median full-time wage and firm FE characterize the quality of workers' previous employers. All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. Coefficients in bold are statistically significant at the 10%-level.

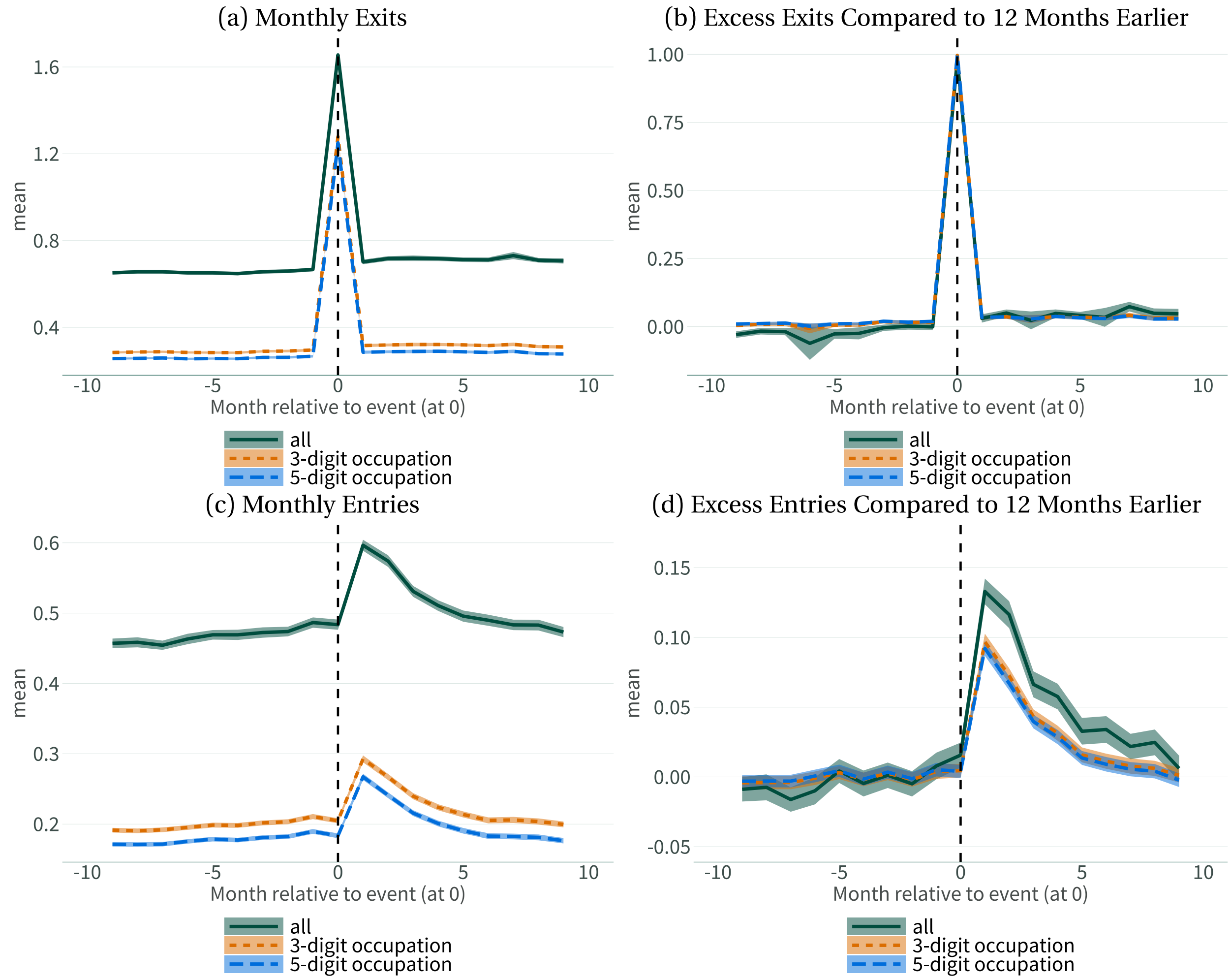
Table 4: Log Wage Gap for Different Sample Splits

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	**Baseline**	**1981-1989**	**1990-1999**	**2000-2009**	**2010-2016**	**2010-2014**
Female Replacement	-0.10	-0.15	-0.12	-0.073	-0.052	-0.055
	(0.0047)***	(0.0094)***	(0.0083)***	(0.011)***	(0.011)***	(0.014)***
Observations	42837	12331	14262	9408	6368	4324
R^2	0.614	0.617	0.604	0.640	0.720	0.734
Panel B:	**Share FT Women**		**Family-Friendly**		**Firm Gender Wage Gap**	
	< 50%	**>= 50%**	**Yes**	**No**	**< Mean**	**>= Mean**
Female Replacement	-0.10	-0.092	-0.060	-0.11	-0.073	-0.13
	(0.0062)***	(0.0080)***	(0.0099)***	(0.0055)***	(0.0061)***	(0.0076)***
Observations	34357	8327	5614	37062	20942	21725
R^2	0.593	0.701	0.706	0.604	0.604	0.634
Panel C:	**Skill-Intensity**		**West**	**East**	**3-Digit Occ. in $r-1$**	
	Low	**Medium/High**			**Same**	**Different**
Female Replacement	-0.14	-0.072	-0.11	-0.080	-0.092	-0.11
	(0.0081)***	(0.0058)***	(0.0051)***	(0.014)***	(0.0067)***	(0.0068)***
Observations	29183	13477	37384	5269	19299	23376
R^2	0.515	0.664	0.592	0.692	0.642	0.608

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for different sample splits. It is based on Equation (1), shows β_1 coefficients for $t = r$, and the outcome variable is log wages. In Panel A, we report the baseline coefficients, followed by the wage gap by decade. In Panel B, we split the sample by firm characteristics, all measured in d: The share of women in full-time jobs at the firm (columns 1 and 2), firm's family-friendliness (columns 3 and 4; family-friendly firms have at least one female manager with a child aged 0-8), and by the gender wage gap in the firm (columns 5 and 6). In Panel C, we present coefficients for replacement workers with low (column 1) vs. higher occupational skill intensity (column 2, see Appendix A.2 for details on the definition); for firms in West vs. East Germany (columns 3 and 4); and for replacement workers with below or above average outside options (columns 5 and 6, measured in $r-1$). All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. *, **, and ** correspond to 10, 5 and 1 percent significance levels, respectively.

9 Figures

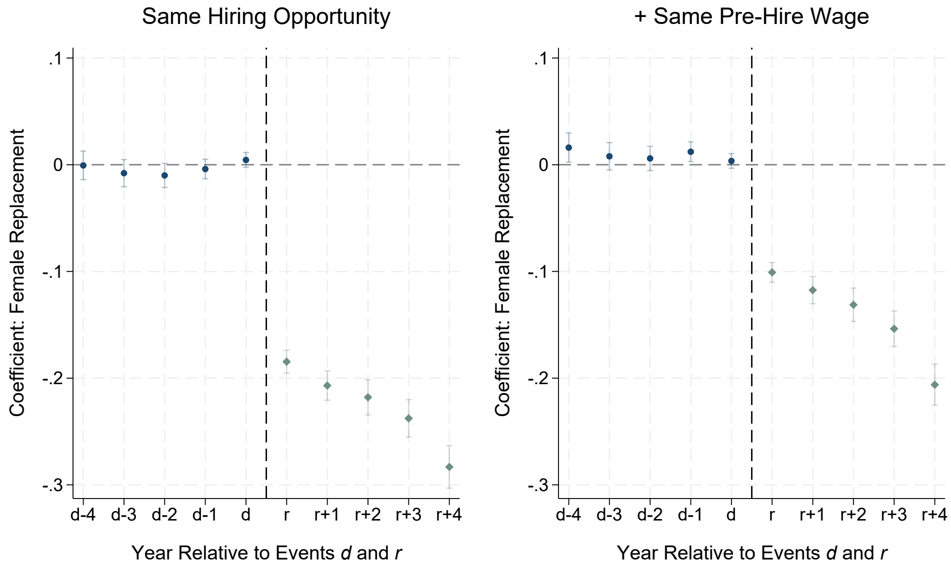
Figure 1: Exits and Entries of Full-time Workers Around Date of Death



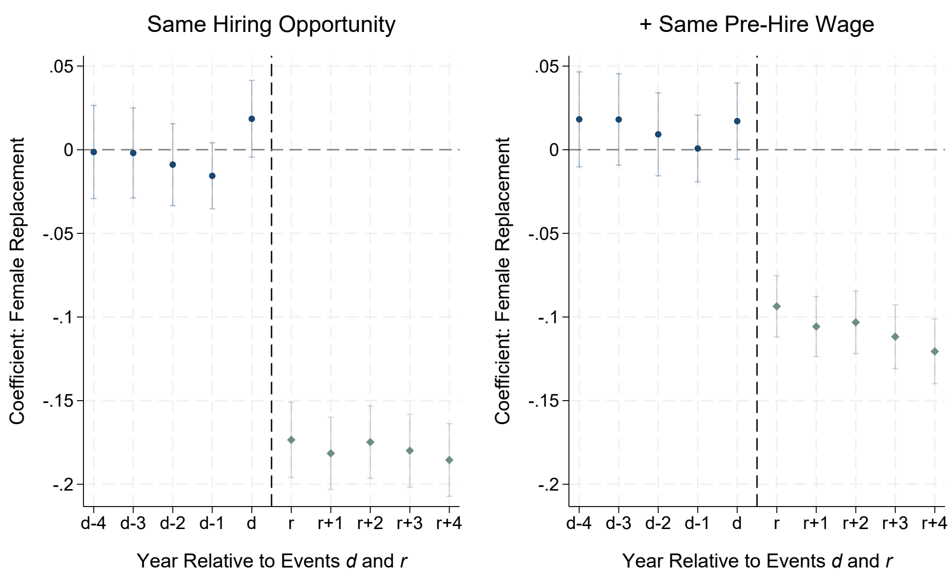
Notes: This figure plots raw means of exits and entries out of and into event firms in the year before and after the death event (at 0). Panel (a) shows the average number of monthly full-time worker exits; Panel (b) shows the average number of monthly full-time worker exits, relative to 24 months earlier. Panel (c) shows the average number of monthly full-time worker entries; Panel (d) shows the average number of monthly full-time worker entries, relative to 24 months earlier. The sample includes all firms with exactly one sudden death in a given year. The solid green line refers to all workers, the orange dashed line refers to 3-digit occupations, and the blue dashed line refers to 5-digit occupations. Deaths occur in 1981-2016, and our sample spans 1975-2021. In this figure, we condition on a balanced panel of firms in the 10 years around the death event.

Figure 2: The Wage Gap for Female Replacement Workers

(a) Baseline Sample



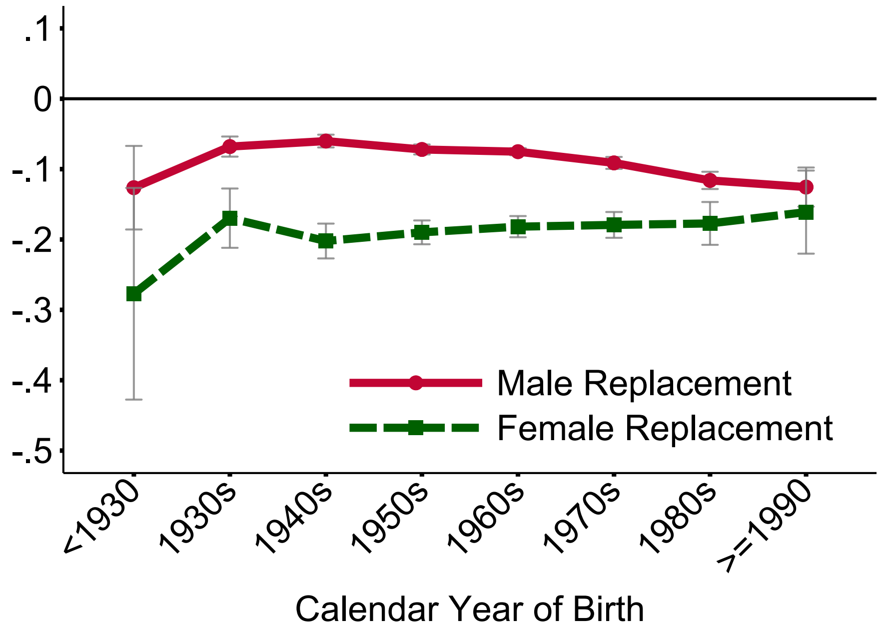
(b) Replacement Works Full-time from r to r+4



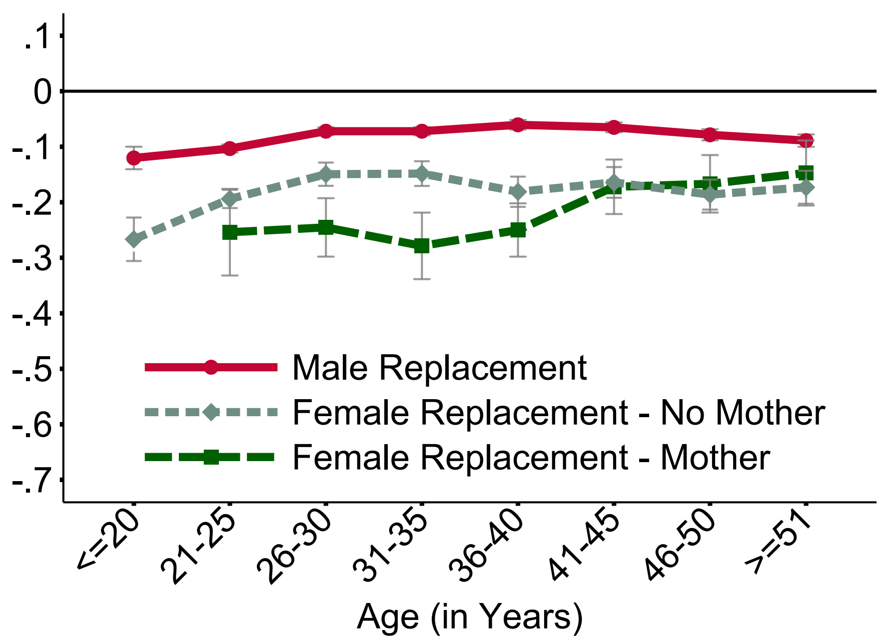
Notes: This figure presents β_1 coefficients of Equation (1). The outcome variable is log wages. The figure on the left ("Same hiring opportunity") refers to the baseline specification that controls for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d). In addition, we control for deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). The figure on the right ("+ Same pre-hire wage") plots coefficients of the specification that additionally controls for deciles of the pre-hire wage of the replacement worker ($r-1$). Coefficients in navy ($t = d-4, ..., d$) refer to log wages of the deceased worker, while coefficients in teal ($t = r, ..., r+4$) refer to log wages of the replacement worker. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm × date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.

Figure 3: Deceased-Replacement Wage Gap Over the Lifecycle and by Cohort

(a) Replacement Worker Age (r)



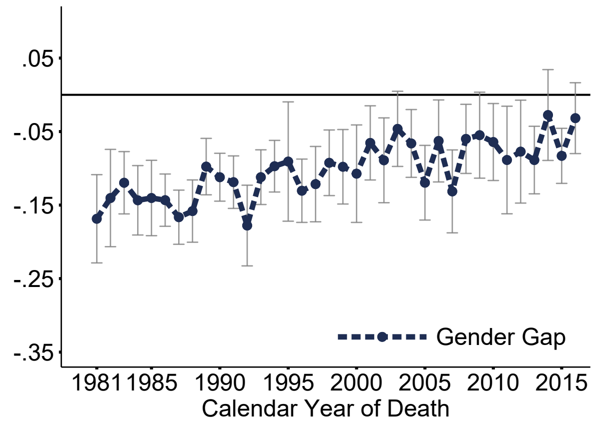
(b) Replacement Worker Birth Cohort



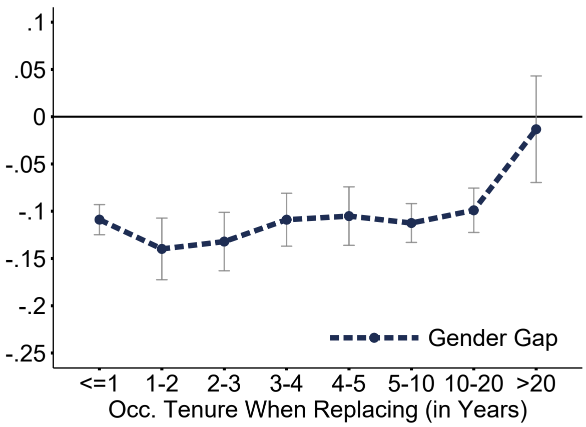
Notes: This figure plots the log wage difference for male vs. female replacements in r, relative to their predecessor in d, based on Equation (4). Panel (a) plots the gap by replacement workers' birth cohort, where the solid red line plots coefficients for male replacements ($\beta_0 + \beta_3$), and the dashed green line plots coefficients for female replacements ($\beta_0 + \beta_1 + \beta_3 + \beta_4$). Panel (b) plots the gap by replacement workers' age (in years, measured at r) and mother status (at r). All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm $\times$ date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.

Figure 4: Deceased-Replacement Wage Gap by Calendar Year, Tenure, and Type of Occupation

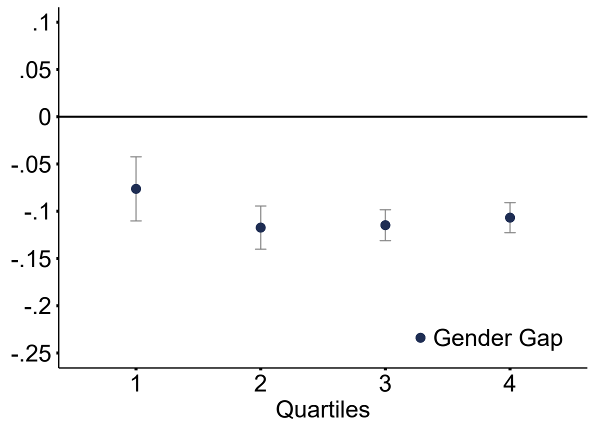
(a) Calendar Year of Death



(b) Replacement Worker Occupational Tenure (r)



(c) Quartiles of an Occupation's Wage Variance



Notes: This figure plots the log wage difference for male vs. female replacements in r, relative to their predecessor in d, based on Equation (4). Panel (a) plots the gender gap by calendar year of death. Panel (b) plots the gender gap by replacing workers' occupational tenure (in years in the same 5-digit occupation, measured at r). Panel (c) plots the gap by quartiles of a given 3-digit occupation's wage variance, proxied by the standard deviation of real wages within cells of 3-digit occupation and county for a random 2%-sample of workers in Germany. Blue dots subtract the deceased-replacement worker gap for male replacements from the deceased replacement worker gap for female replacements, i.e., they correspond to $\beta_1 + \beta_4$. All regressions control for deceased worker's gender and 3-digit occupation, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Panels (b) and (c) also control for calendar year. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm × date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.

A Data Appendix

A.1 Sudden Deaths and Replacement Workers

Sudden Deaths In the spirit of Jäger et al. (2024), 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 Jäger et al. (2024) 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. Last, we drop establishments with multiple sudden deaths in the same year. By focusing on small- to medium-sized establishments with at least 3 and at most 150 full-time workers and 300 total workers, we start from a point of about 209,500 unexpected death events.

As Table A4 shows, we classify about 14.5% of all spells ending with a death as "sudden". Statistics from the German Federal Statistical Office list 17.8% of all deaths as sudden (own calculation based on the cause of death, statistics from 1981-2016). Note that our share of 14.5% is a lower bound, since it compares death events at all firms (regardless of firmsize) to sudden death events at firms with 3-150 full-time and max. 300 total employees.

Excess Hiring Our baseline sample focuses on firms with excess hiring. These are firms which hire at least one additional full-time worker in the same 3-digit occupation as the deceased worker, in the 6 months following the death event, compared to 24 months earlier. They make up approximately 30% of our sudden death sample, and 4% of all spells that end with death (incl. non-sudden deaths, see Table A4). Table A3 shows how excess hiring firms (Column 3) compare to non-excess hiring firms (Column 2) in the year of death, and the full population of all other firms averaged over 1981-2016 (Column 1).

Excess hiring firms are somewhat larger than non-excess hiring firms (+2.4 workers), their workforce is a bit younger (half a year), and they pay lower median full-time wages (-1.4 EUR per day). The workforce composition is comparable, with the same share of full-time workers and female workers, but slightly fewer high-skilled workers. To account for these differences, we include a set of the top predictors of excess hiring from our machine learning exercise as controls in a robustness check (see Section 6).[25]

Compared to all other firms, firms in our sample of death events are more than twice as large. They moreover have a higher overall full-time share (6ppt), but a lower share of full-time women (-16ppt). They are also characterized by a slightly higher share of workers with vocational training, and fewer with a university degree.

[25] Table A5 shows the industry distribution by firm type. Excess and non-excess hiring firms are distributed across very similar sectors. Compared to all other firms, firms with a death event are strongly over-represented in manufacturing and construction.

Replacement Workers 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 (i.e., new establishment entrants). Motivated by the patterns of excess hiring documented in Figure 1, we define a new hire to be the (first) replacement of a deceased worker if they fulfill the following conditions: They are (i) the first hire after the death event with the same 3-digit occupation code as the deceased worker, (ii) working full-time, and (iii) hired in the first 6 months after the worker's death.[26] As an additional restriction, we only consider new hires if excess hiring within the same 3-digit occupation of the outgoing worker within the first 6 months is strictly positive. This is the case in about 30% of death events. Finally, we focus on worker pairs where the replacement worker transitioned from a full-time employment, which brings us to a final sample of 24,790 deceased-worker-replacement-worker pairs.

Summary Statistics Table 1 presents summary statistics for the deceased worker in Panel A (measured in the death spell d) and the replacement worker in Panel B (measured in the replacement spell r). We show sample mean values (with standard deviations in parentheses) for wages, days worked, and several demographics separately by three groups of deceased-replacement worker pairs: (i) male-male, (ii) opposite sex, and (iii) female-male transitions. We compare these to the characteristics of a random 2% sample of full-time workers in the German data in Column (1).

The table offers a few key takeaways. First, the sample of random workers is relatively similar in average characteristics to deceased workers in the male-male and opposite sex transition groups, but positively selected compared to workers in the female-female transition group (e.g. in terms of wages and education). One exception is age: Deceased workers are on average 4-6 years older than the average full-time worker in the German admin data.

Compared to replacement workers, the sample of random workers earns higher wages, which is likely due to their higher age (about +3-5 years), firm tenure (about +5 years), occupational tenure (about +4 years), and labor market experience (about +4 years). This is in line with the observation that wages of (relatively more experienced) deceased workers are substantially higher than those of replacement workers, with a gap ranging from 9 EUR in the male-male group to 16 EUR in the opposite-sex group.

Finally, demographics, including tenure, are remarkably comparable across transition pairs. Two differences stand out: Daily wages for replacement workers are highest in the male-male transition group (EUR 84.2), followed by the opposite sex group (EUR 81.1), and the female-female transition group (EUR 68.9); female-female replacements have about 1.5 years less labor market experience compared to male-male replacements.

Transition pairs moreover differ in terms of their distribution across 1-digit occupations and industries. Table A1 shows that events involving male-male transitions cluster in occupations concerned with the operation and maintenance of machines (12% vs. 8.9% for opposite-sex and 3.9% for female-

[26] In cases where more than one worker fulfilling these restrictions was hired on the same day, we randomly choose one as the replacement (regardless of gender).

female pairs) and traffic/security (26% vs. 9.1% for opposite sex and 3.3% for female-female pairs). In contrast, female-female and opposite sex transitions happen much more often in trade/sales (13% for female-female, 9.8% for opposite sex, and 5.7% for male-male pairs), and in service occupations (39% for female-female, 34% for opposite sex, and 5.1% for male-male pairs). The sorting patterns are less striking for 1-digit industries, though male-male pairs are very clearly over-represented in the construction sector (see Table A2).

A.2 Variable Definitions

Commuting Distance We compute a worker's commuting distance using the distance (in km) between the municipality centroid of the workplace and the municipality centroid of the residence, using the Haversine formula. There is a dense net of approximately 11,000 municipalities in Germany, such that this measure comes very close to reliably capturing the workplace-to-residence distance. Note that information on workers' residence is available in the IAB data from 1999 onwards, such that we can investigate commuting distances only for part of our sample.

Managers We follow Jäger et al. (2024) and classify managers according to the 5-digit occupational classification based on the *Klassifikation der Berufe 2010*. More precisely, we classify all workers as managers if their occupation requires "complex specialist activities" or "highly complex activities". The level of complexity is signified by the last digit of the 5-digit occupational code; if the last digit is greater than 2, we classify the corresponding spell as a spell with managing tasks.

Outside Options Our measure of outside options consists of two parts. First, we follow Jäger et al. (2024) and construct a measure of *labor market thickness* that takes on the following form:

$$\mu_{cz,occ,t} = \frac{Workers_{cz,occ,t}}{Workers_{cz,t}} \div \frac{Workers_{DE,occ,t}}{Workers_{DE,t}} \tag{6}$$

where $\frac{Workers_{cz,occ,t}}{Workers_{cz,t}}$ represents the share of employed workers in a specific commuting zone and 2-digit occupation for a given year, and $\frac{Workers_{DE,occ,t}}{Workers_{DE,t}}$ represents the share of employed workers in the same 2-digit occupation for that year across Germany.

In the next step, we use a 20% random sample of the IAB worker-level data (*IEB, version 16.1*) and construct a matrix of transitions across 2-digit occupations in Germany, by year and gender. For each 2-digit occupation $occ = n$, we then compute the gender-specific share of workers transitioning from $occ = n$ to $occ = n + x$ between t and $t + 1$, separately for each transition.

$$\gamma_{occ_{t=n},occ_{t+1=n+x},g} = \frac{Workers_{occ_{t+1=n+x},g}}{Workers_{occ_{t=n},g}} \tag{7}$$

$\gamma_{occ_{t=n}, occ_{t+1=n+x}, g}$ tells us the share of workers of gender g, employed in 2-digit occupation $occ = n$ at time t, who moved to 2-digit occupation $occ = n + x$ in $t + 1$.

Finally, for a given 2-digit occupation $occ = n$ at time t, we interact each transition share characterizing transitions between $occ = n$ and $occ = n+x$ with the respective labor market thickness indicator at time t: $\mu_{cz,occ=n+x,t}$. Our final outside options measure consists of the sum of these interactions:

$$\phi_{cz,occ_{t=n},t,g} = \sum_{occ_{t+1=n}}^{occ_{t+1=n+x}} \mu_{cz,occ_{t+1},t} \times \gamma_{occ_{t=n},occ_{t+1},g} \tag{8}$$

This measure combines two sets of information: (i) the relative importance of a given 2-digit occupation in a given commuting zone in t, and (ii) the gender-specific potential for occupational mobility of a given 2-digit occupation on the national level.

Occupational Skill Intensity We construct our skill measure based on education in three steps. First, we use a 20% sample of the IAB's worker-level data (*IEB, version 16.1*) spanning all available years, and impute missing education values based on Fitzenberger et al. (2006). Next, we construct a measure for years of education that takes into account years spent at school, years spent in vocational training, and years spent at university. Following Jäger et al. (2024) we then compute the average years of education required by each 5-digit occupation. Finally, we define three education groups on the level of 5-digit occupations. We classify jobs that require education levels below the 20th percentile as "low-skilled"; jobs in the 20th-80th percentile are classified as "medium-skilled"; jobs above the 80th percentile are "high-skilled".

A.3 Additional Datasets

AKM Firm Fixed Effects We use the dataset on AKM firm fixed effects provided by Lochner et al. (2023) for our proxy of firm productivity. AKM firm effects are provided as the average across several calendar years: [1985-1992; 1993-1999; 2000-2006; 2007-2013; 2014-2021]. We link them to our data using a unique firm identifier provided by the IAB.

Orbis-ADIAB For parts of our analysis, we use the Orbis-ADIAB data provided by the IAB (see Antoni et al. (2018) for details). This dataset is based on a record linkage of the Bureau van Dijk (BvD) business data and the IAB's Establishment History Panel (BHP).

The linkage comprises a merge of 535,000 firms from the BvD data to the Establishment History Panel (BHP). All firms that were part of the BvD data on January 30th, 2014, were considered for the linkage; business data from the BvD database is available for 2006-2013. When interpreting the coefficients from our firm-level analysis in Table 2, Panel B, it is therefore important to keep in mind that the information on capital and sales is only available for a a restricted time period.

In addition, due to the nature of the BvD data, larger firms are over-represented in the data. Note also that even if a BvD firm can be linked to the BHP, the business indicators may be missing. For example, while we have information on capital for 1,052 treated firms in our baseline sample, information on sales is available for 498 firms, only.

Hours Worked from the Statutory Accident Insurance We complement our analysis of daily wages with information on weekly hours worked used in, e.g., Jäger et al. (2024), Dustmann et al. (2022), and Gudgeon and Trenkle (2024). Employers report hours directly to the German Statutory Accident Insurance, and the administrative nature of this dataset makes it highly reliable. The data is available at the IAB for 2010-2014 (linkable to the *IEB* on the spell level).

We follow part of the steps suggested by Dustmann et al. (2022) to clean the hours data. From the spell information, we first construct a measure for hours worked per week. Next, we set implausible values to missing. For full-time jobs, these are hours outside the range of 20-70 hours per week; for part-time jobs we ignore values outside the range of 2-45 hours per week; for minijobs we ignore values outside the range of 2-25.

One challenge with the hours data is that employers were allowed to report different measures: i.e., actual hours, contractual hours, hours stated in collective bargaining agreements (Dustmann et al. (2022), Online Appendix). As Dustmann et al. (2022), we assume that reporting behavior does not differ across firms, such that we can compare hours reported for the deceased worker to hours reported for the replacement worker. Reassuringly, Gudgeon and Trenkle (2024) show that employers correctly report changes in hours worked within workers across years.

The IAB's Linked Employer-Employee Data (LIAB) For parts of our analysis, in particular Figure A1, we use the *LIAB longitudinal model 1975-2017 LIAB LM 7517*. This is a dataset provided by the IAB that links firms that are surveyed in the *Establishment Survey* to their administrative records. The longitudinal LIAB covers a subsample of firms that are repeatedly surveyed in the *Establishment Survey*. The dataset moreover contains information on the respective firms' employees and their full employment biographies. See Schmidtlein et al. (2019) for an overview.

B Analysis Details

B.1 Machine Learning: Variables

This section lists the variables that serve as predictors in the machine learning analysis. We use the same set of variables for both predictions, i.e., for predicting excess hiring and female replacement. If not specified otherwise, each variable enters for three time periods: $d-1$, $d-2$, and $d-3$, where d is the year of death. For details on the machine learning algorithm, see Section 3.1. Note that *same 3-digit occupation* refers to the 3-digit occupation of the deceased (and thus replacement) worker.

Wage Bill/Wages: Wage bill all workers, wage bill men, wage bill women, mean/median wages of full-time workers, mean/median wage at firm, mean/median wage of women/men at firm, gender wage gap, top and bottom quartile of mean wage at firm, sum of all employees' daily wages, median wage of high-skilled/medium-skilled/low-skilled workers, mean/median wages of workers with/without German nationality, mean wages of workers in a different/in the same 3-digit occupation.

Workforce Shares: Share of women, share of full-time workers in the same 3-digit occupation, share of workers in the same 3-digit occupation, share of full-time workers in the same 5-digit occupation, share of workers in the same 5-digit occupation, share of (female) full-time workers, share of (female) full-time workers in a different 3-digit occupation, share of new hires, share of new hires in the same 3-digit occupation, share of new hires of the same gender, share of new hires of the same gender and 3-digit occupation, share of new hires in full-time employment, share of (full-time) workers aged [15-19; 20-24; 25-29; 30-34; 35-39; 40-44; 45-49; 50-54; 55-59; 60-64; 65+], share of women in a different 3-digit occupation, share of women with at least one child aged 0-8, share of mothers, share of women aged 18-40, share of women in the top wage decile, share of workers by 1-digit occupation, share of (full-time) workers by skill group, share of trainees.

Workforce Counts: Number of (full-time) (part-time) workers, number of (full-time) (part-time) women, number of workers with German citizenship, number of workers in the same 3-digit occupation, number of full-time workers in the same 3-digit occupation, number of workers in the same 5-digit occupation, number of full-time workers in the same 5-digit occupation, number of full-time new hires, number of new hires in the same 3-digit occupation, number of new hires of the same gender, number of high-skilled/medium-skilled/low-skilled (full-time) workers, workers in regular employment, workers in regular and full-time employment, number of (full-time) workers aged [15-19; 20-24; 25-29; 30-34; 35-39; 40-44; 45-49; 50-54; 55-59; 60-64; 65+], number of women in the top wage decile, number of women with at least one child aged 0-8, number of mothers, number of female experts[27], number of workers by 1-digit occupation, number of (full-time) workers by skill group, number of trainees, number of workers with censored wages, number of workers with/without German citizenship, number of workers with EU citizenship.

1-Digit Industry/Occupation: Share of women aged 18-40, share of full-time workers, share of female full-time workers, gender wage gap, overall turnover, gender-specific turnover, share of women with a child aged 0-8, gender wage gap.

Deceased Worker Characteristics (measured in d): Gender, 2-digit occupation, labor market experience in years, tenure in years, occupational tenure in years, age in years, German citizenship, wage in EUR, log wage, wage deciles.

[27] We define experts as workers where the last digit in the 5-digit occupational code has the value 4.

Local Labor Market: 1-digit industry composition by county, share of employed women by all women in commuting zone, dummy for West Germany (d), labor market thickness by 3-digit occupation, labor market thickness by 3-digit industry, commuting zone (d).

Other Variables: Calendar year (d), average labor market experience of (female) workers at the firm, average tenure of (female) workers at the firm, average age of (female) workers at the firm, average education of (female) workers at the firm, firm age (d), average age of employees at the firm, 1-digit industry dummies (d), AKM worker FE, share hiring firm industry in commuting zone, indicator whether firm ever hired more than 150 new workers/50 full-time workers per month in the [-2.5 years, ... , +1] year(s) before and after death (d).

B.2 Raw Evolution of Wages by Transition Group

Figure A2 plots the raw evolution of wages by transition group, where the transition group is defined by the gender of deceased and replacement workers. We define four transition groups: (i) male-male, (ii) male-female, (iii) female-male, and (iv) female-female. To plot the raw patterns, we estimate an event study type of regression of (log) daily wages by relative event time. This does not only allow us to estimate the transition gender wage gap, but we can also study how wages evolve over time. We estimate one model that includes all transition groups simultaneously, where we regress the outcome y_{ptg} of deceased-replacement worker pair p, at time t, and in group g, on dummies for year since death and year since replacement, respectively:

$$y_{ptg} = \beta_j \times \sum_{j=d-4, j\neq d}^{j=r+5} I(t=j) \times I(g_p=1) + \delta_{jg} \times \sum_{j=d-4}^{j=r+5} \sum_{g=2}^{g=4} I(t=j) \times I(g_p=g) + \varepsilon_{ptg} \tag{9}$$

The coefficients of interest are β_j and δ_{jg} which show the evolution of wages for individuals in the male-male transition group, and individuals in all other groups, respectively. We estimate all coefficients relative to $t = d$ for transition group 1, i.e., relative to wages of deceased male workers followed by a male replacement, in the year of death.

Time runs from four years before the death event $t = d-4$ to the time of death in $t = d$, and then from the starting date of the replacement worker $t = r$ until five years later in $t = r+5$. Observations in $t = [d-4, ..., d]$ reflect wages of the departing worker. $t = r$ is the first observation of the replacement worker at the hiring firm. Hence, observations in $t = [r, ..., r+5]$ refer to the replacement worker. The first part of Equation (9) corresponds to the interaction between a dummy for group $g = 1$ (male-male transitions) and dummies for year $t = d - n$ before death, and $t = r + n$ after death, excluding the observation a year before death. The second part of Equation (9) corresponds to the time-group interactions for the other three transitions groups $g = 2, 3, 4$ (male-female, female-male, and female-female).

B.3 Reweighting Excess Hiring Firms

As Table A3 shows, firms with excess hiring differ from firms with non excess hiring, and from all other firms with 3-150 full-time workers in the German administrative data. For example, firms with excess hiring are larger as they have, on average, 44 employees; the corresponding number is 41 employees for non excess hiring firms, and 14 employees for all other firms. Excess and non excess hiring firms have a higher full-time share, but, compared to all other firms, a lower share of women in a full-time job (27 vs. 43 %). Firms with sudden deaths moreover differ in terms of their industry composition, in particular compared to all other firms (see A5). One potential concern is therefore external validity: Excess hiring firms may be special with respect to gender dynamics, and the *gender hiring opportunity gap* may look different for all other German firms, or for non excess hiring firms.

To address this concern, we follow DiNardo et al. (1996) and apply a reweighting exercise to make excess hiring firms comparable to (i) all other firms and (ii) non excess hiring firms. In particular, we regress a dummy for *all other firms / non excess hiring firms* on a set of firm-level controls to predict firm type. We then use the predicted propensity scores $\hat{p}$ to construct the weights as $\hat{\phi} = \hat{p}/(1-\hat{p})$. We control for the following variables: 1-digit industries, share of women in firm, log firmsize, log number of full-time workers in firm, median wages, median wages women. Tables A3 and A5, Columns (4) and (5), shows that applying the weights helps to make excess hiring firms much more comparable to all other firms and non excess hiring firms, respectively. In Figure A3, we present our baseline results with weights and show that the gender gap remains essentially the same, thus alleviating concerns with respect to external validity.

B.4 Wage Prediction

In our baseline analysis, we control for replacement workers' wages in their last work spell, $r-1$, to proxy for their productivity. If women are discriminated against in $r-1$ and therefore earn lower wages, then we will estimate a lower bound of the true gender wage gap. To estimate an upper bound of the effect, we implement a prediction exercise that is based exclusively on male replacements' wages in their last job. The idea is that by basing predicted values solely on the wages of male replacements, we can eliminate bias that may arise from the discrimination of female workers.

We first restrict the sample to male replacement workers in $r-1$. Next, we estimate regressions of the following form:

$$y_i = \beta_0 + \beta_1 \boldsymbol{X_i} + \gamma_t + \varepsilon_{it} \tag{10}$$

where we regress log wages y_i on a set of fixed effects $\boldsymbol{X_i}$ that include replacement workers' 3-digit occupation, their skill group, their full-time status, and deciles of tenure. ε_{it} are calendar year fixed effects. Next, we assign both men *and* women predicted wages based on these characteristics; there are some men for which the regression model is not identified, and we lose some women whose group is not represented in the analysis (ie., because no group of men has their combination of occupation $\times$ demographics $\times$ calendar year).

We use the predicted values instead of replacement workers' last wage as controls for their productivity in a robustness check. Column (5) of Table A7 shows that the estimated coefficient is indeed an upper bound (20 log points, while the baseline gap is 10 log points).

C Appendix Tables

Table A1: 1-Digit Occupations for Transition Pairs vs. Random Sample

	(1) Random Sample	(2) Male-Male	(3) Opposite Sex	(4) Female-Female
1-Digit Occupations				
Raw Materials	0.019 [0.14]	0.024 [0.15]	0.019 [0.13]	0.0048 [0.069]
Education	0.011 [0.10]	0.0051 [0.071]	0.023 [0.15]	0.013 [0.11]
Machine Operations/Maintenance	0.12 [0.32]	0.12 [0.33]	0.088 [0.28]	0.038 [0.19]
Trade/Sales	0.082 [0.27]	0.058 [0.23]	0.100 [0.30]	0.13 [0.34]
Traffic/Security	0.11 [0.32]	0.26 [0.44]	0.086 [0.28]	0.032 [0.18]
Food/Cleaning	0.053 [0.22]	0.028 [0.17]	0.062 [0.24]	0.099 [0.30]
Services	0.18 [0.38]	0.050 [0.22]	0.34 [0.48]	0.39 [0.49]
Technicians	0.11 [0.31]	0.070 [0.26]	0.059 [0.24]	0.017 [0.13]
Law/Management/Economics	0.042 [0.20]	0.029 [0.17]	0.049 [0.22]	0.035 [0.18]
Arts	0.014 [0.12]	0.0058 [0.076]	0.019 [0.14]	0.012 [0.11]
Health/Care	0.082 [0.27]	0.011 [0.10]	0.084 [0.28]	0.17 [0.38]
Education	0.011 [0.10]	0.0051 [0.071]	0.023 [0.15]	0.013 [0.11]
Number of Individuals	14905321	34185	5126	3757

Notes: This table presents differences in the distribution across 1-digit occupations for our baseline sample of deceased-replacement worker pairs compared to a random sample of German workers. Column (1) presents the distribution across 1-digit occupations for a random 2% sample of full-time workers in the German social-security data in 1981-2016. We moreover present the distribution across 1-digit occupations for male-male transition pairs (Column 2), opposite sex transition pairs (Column 3), and for female-female transition pairs (Column 4). We show the 1-digit occupations of deceased workers in their last working spell; per definition, this corresponds to the 1-digit occupation of replacement workers in their hiring spell. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table A2: 1-Digit Industry for Transition Pairs vs. Random Sample

	(1) Random Sample	(2) Male-Male	(3) Opposite Sex	(4) Female-Female
1-Digit Industries				
Agriculture, Forestry, Fishing	0.0091 [0.095]	0.011 [0.10]	0.0098 [0.098]	0.0051 [0.071]
Mining	0.0078 [0.088]	0.0081 [0.090]	0.0020 [0.044]	0 [0]
Manufacturing	0.31 [0.46]	0.25 [0.43]	0.21 [0.40]	0.18 [0.39]
Energy	0.010 [0.10]	0.0081 [0.090]	0.0045 [0.067]	0.0013 [0.036]
Water Supply	0.0079 [0.089]	0.017 [0.13]	0.0047 [0.068]	0.0029 [0.054]
Construction	0.085 [0.28]	0.20 [0.40]	0.020 [0.14]	0.027 [0.16]
Motor Vehicles	0.14 [0.34]	0.16 [0.37]	0.17 [0.38]	0.19 [0.39]
Traffic, Warehousing	0.051 [0.22]	0.11 [0.32]	0.053 [0.22]	0.021 [0.14]
Hospitality	0.027 [0.16]	0.013 [0.11]	0.041 [0.20]	0.049 [0.22]
ICT	0.026 [0.16]	0.012 [0.11]	0.028 [0.17]	0.021 [0.14]
Finance, Insurance	0.037 [0.19]	0.017 [0.13]	0.076 [0.26]	0.036 [0.19]
Housing	0.0071 [0.084]	0.0086 [0.092]	0.012 [0.11]	0.013 [0.11]
PST Services	0.051 [0.22]	0.025 [0.16]	0.049 [0.22]	0.062 [0.24]
Economic Services	0.043 [0.20]	0.046 [0.21]	0.044 [0.20]	0.030 [0.17]
Public Sector	0.058 [0.23]	0.054 [0.23]	0.12 [0.32]	0.084 [0.28]
Education	0.022 [0.15]	0.012 [0.11]	0.029 [0.17]	0.042 [0.20]
Health, Social Services	0.078 [0.27]	0.020 [0.14]	0.085 [0.28]	0.15 [0.36]
Arts, Entertainment	0.0074 [0.086]	0.0049 [0.070]	0.013 [0.11]	0.014 [0.12]
Other Services	0.023 [0.15]	0.016 [0.13]	0.037 [0.19]	0.069 [0.25]
Domestic Services	0.0013 [0.037]	0.00023 [0.015]	0.00059 [0.024]	0.00080 [0.028]
NGOs	0.0022 [0.047]	0.00032 [0.018]	0.00039 [0.020]	0.00027 [0.016]
Number of Individuals	14905321	34185	5126	3757

Notes: This table presents differences in the distribution across 1-digit industries for our baseline sample of deceased-replacement worker pairs compared to a random sample of German workers. Column (1) presents the distribution across 1-digit industries for a random 2% sample of full-time workers in the German social-security data in 1981-2016. We moreover present the distribution across 1-digit industries for male-male transition pairs (Column 2), opposite sex transition pairs (Column 3), and for female-female transition pairs (Column 4). We show the 1-digit industries of deceased workers in their last working spell; per definition, this corresponds to the 1-digit industry of replacement workers in their hiring spell. PST is an abbreviation for *Professional, Scientific, Technical.* Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table A3: Firm Characteristics

	(1) All Other Firms	(2) Non Excess Hiring Firms	(3) Excess Hiring Firms No weights	(4) Excess Hiring Firms Weights To (1)	(5) Excess Hiring Firms Weights To (2)
Panel A: Workforce					
Firmsize	14.3 [26.5]	41.4 [37.6]	43.8 [38.9]	19.4 [24.6]	39.5 [35.6]
Full-time Share	0.76 [0.23]	0.82 [0.19]	0.82 [0.18]	0.75 [0.23]	0.82 [0.18]
Share Full-time Women	0.43 [0.35]	0.27 [0.26]	0.27 [0.26]	0.48 [0.31]	0.31 [0.26]
Share Medium-Skilled	0.88 [0.32]	0.91 [0.29]	0.91 [0.28]	0.90 [0.31]	0.91 [0.29]
Share High-Skilled	0.047 [0.21]	0.031 [0.17]	0.026 [0.16]	0.047 [0.21]	0.033 [0.18]
Mean Age	37.7 [7.08]	39.8 [5.76]	39.3 [5.70]	38.9 [6.72]	39.1 [5.69]
Panel B: Wages					
Median Full-time Wage	63.9 [31.2]	69.5 [28.8]	68.1 [26.7]	66.0 [31.2]	68.2 [28.2]
Median Full-time Wage Women	55.2 [28.4]	60.8 [27.8]	59.8 [26.7]	58.3 [30.1]	59.9 [27.7]
Gender Wage Gap	0.30 [0.43]	0.24 [0.33]	0.24 [0.33]	0.28 [0.40]	0.24 [0.34]
Number of Observations	24791072	141077	68459	68459	68459

This table compares firms with a sudden death event to all other firms of similar size in Germany. Column (1) presents characteristics for all other firms with 3-150 full-time workers, averaged for 1981-2016. Column (2) presents characteristics for event firms without excess hiring, and Column (3) presents characteristics for event firms with excess hiring, both restricted to observations in the year(s) of death. Column (4) shows weighted characteristics when reweighting excess hiring firms to all other German firms. Column (5) shows weighted characteristics when reweighting excess hiring firms to non excess hiring firms. See Appendix B.3 for details on the reweighting exercise. Medium-Skilled workers have vocational training, and high-skilled workers have a university degree. Gender wage gap refers to the log difference in median female wages, subtracted from median male wages. Data source is the Establishment History Panel (*BHP, 7519, Version 2*), where firm characteristics are reported on June 30 in a given year. For our definition of excess hiring, see Appendix A.1. The number of observations for (non-)excess hiring firms corresponds to the number of events, i.e., firms can appear more than once if they are subject to more than one death event in separate years. Standard deviations in brackets.

Table A4: Number of Deaths in Admin Data

	Counts	**Share of All Deaths**	**Share of Sudden Deaths**
All Deaths no firmsize restriction	1,448,184	100	–
Sudden Deaths 3-150 full-time employees, max. 300 employees	209,536	14.5	100
Excess Hiring Firms	68,459	4.7	32.7
Excess Hiring & Full Sample	57,146	3.9	27.3
Excess Hiring & Baseline Full-time Sample	43,068	2.973	20.6
Baseline Regression Sample	42,837	2.958	20.4

Row 1 of this table shows the number of workers who have spells that end with a death in the worker-level admin data (*Abmeldegrund 149* in the IEB). This counts all spells, regardless of firm size. Row 2 shows the number of sudden deaths that we identify using the following restrictions: Aged below 65, not more than 30 days between date of death and last spell in the admin data, no sick leave that exceeded 6 weeks in the 5 years pre death, full-time employment at death, working at firms with 3-150 full-time employees and max. 300 total employees, only one death event per firm and year. Row 3 shows the number of deaths that remain if we restrict these to firms with excess hiring. Row 4 shows the number of deaths in our regression analysis sample, where we condition on full-time employment of deceased/replacement worker in d and r, and drop firms with excessive hiring around the death event. Row 5 shows the number of deaths in our baseline sample, where we condition on full-time employment of the replacement worker in their last work spell before replacing in $r-1$. Row 6 shows the number of observations for our regression sample.

Table A5: Distribution Across 1-Digit Industries by Firm Type

	(1) All Other Firms	(2) Non Excess Hiring Firms	(3) Excess Hiring Firms No weights	(4) Excess Hiring Firms Weights To (1)	(5) Excess Hiring Firms Weights To (2)
1-Digit Industries					
AFF	0.013 [0.11]	0.013 [0.11]	0.011 [0.11]	0.011 [0.11]	0.012 [0.11]
Mining	0.0029 [0.054]	0.0080 [0.089]	0.0065 [0.080]	0.0022 [0.047]	0.0058 [0.076]
Manufacturing	0.15 [0.35]	0.24 [0.42]	0.22 [0.42]	0.17 [0.37]	0.24 [0.43]
Energy	0.0031 [0.055]	0.0083 [0.091]	0.0068 [0.082]	0.0031 [0.055]	0.0060 [0.078]
Water Supply	0.0062 [0.078]	0.011 [0.10]	0.011 [0.11]	0.0062 [0.079]	0.011 [0.10]
Construction	0.11 [0.31]	0.13 [0.34]	0.14 [0.35]	0.072 [0.26]	0.11 [0.32]
Motor Vehicles	0.20 [0.40]	0.17 [0.38]	0.16 [0.36]	0.20 [0.40]	0.18 [0.38]
Traffic, Warehousing	0.093 [0.29]	0.097 [0.30]	0.11 [0.31]	0.099 [0.30]	0.096 [0.29]
Hospitality	0.061 [0.24]	0.033 [0.18]	0.035 [0.18]	0.068 [0.25]	0.039 [0.19]
ICT	0.022 [0.15]	0.025 [0.16]	0.030 [0.17]	0.020 [0.14]	0.025 [0.16]
Finance, Insurance	0.023 [0.15]	0.021 [0.15]	0.025 [0.16]	0.028 [0.16]	0.024 [0.15]
Housing	0.0034 [0.058]	0.0018 [0.042]	0.0014 [0.038]	0.0035 [0.059]	0.0019 [0.043]
PST	0.11 [0.31]	0.064 [0.24]	0.060 [0.24]	0.11 [0.32]	0.073 [0.26]
Economic Services	0.026 [0.16]	0.028 [0.17]	0.035 [0.18]	0.026 [0.16]	0.030 [0.17]
Public Sector	0.019 [0.14]	0.063 [0.24]	0.058 [0.23]	0.023 [0.15]	0.054 [0.23]
Education	0.049 [0.22]	0.028 [0.17]	0.029 [0.17]	0.052 [0.22]	0.031 [0.17]
Health, Social Services	0.059 [0.24]	0.018 [0.13]	0.019 [0.14]	0.049 [0.22]	0.019 [0.14]
Arts, Entertainment	0.022 [0.15]	0.017 [0.13]	0.016 [0.13]	0.024 [0.15]	0.017 [0.13]
Other Services	0.031 [0.17]	0.022 [0.15]	0.027 [0.16]	0.031 [0.17]	0.025 [0.16]
Domestic Services	0.00078 [0.028]	0.00018 [0.013]	0.00022 [0.015]	0.00026 [0.016]	0.00016 [0.013]
NGOs	0.00016 [0.013]	0.00019 [0.014]	0.00010 [0.010]	0.000018 [0.0043]	0.00011 [0.011]
Number of Observations	24791072	141077	68459	68459	68459

This table compares the distribution across 1-digit industries of firms with a sudden death event to all other firms in Germany. Column (1) presents industries for all other firms with 3-150 full-time workers, averaged for 1981-2016. Column (2) presents industries for event firms without excess hiring, and Column (3) presents industries for event firms with excess hiring, both restricted to observations in the year(s) of death. Column (4) shows weighted characteristics when reweighting excess hiring firms to all other German firms. Column (5) shows weighted characteristics when reweighting excess hiring firms to non excess hiring firms. See Appendix B.3 for details on the reweighting exercise. Data source is the Establishment History Panel (*BHP, 7519, Version 2*), where firm characteristics are reported on June 30 in a given year. AFF is an abbreviation for "Agriculture, Forestry, Fishing", and PST is an abbreviation for "Professional, Scientific, Technical Services". The number of observations for (non-)excess hiring firms corresponds to the number of events, i.e., firms can appear more than once if they are subject to more than one death event in separate years. Standard deviations in brackets.

Table A6: Log Wage Gap With Different Sample Restrictions

	(1) Same Hiring Opportunity	(2) + Same Pre-Hire Wage	(3) Same Hiring Opportunity	(4) + Same Pre-Hire Wage	(5) Same Hiring Opportunity	(6) + Same Pre-Hire Wage
Panel A:	**Baseline**		**Full-time Rep. Only**		**Balanced Panel**	
Female Replacement	-0.18	-0.10	-0.17	-0.094	-0.19	-0.10
	(0.0055)***	(0.0047)***	(0.011)***	(0.0094)***	(0.0062)***	(0.0054)***
Observations	42837	42837	10661	10661	33132	33132
R^2	0.495	0.614	0.498	0.633	0.489	0.612
Panel B:	**No Mothers**		**Workers Aged 40+**		**Only 1 Full-time Hire**	
Female Replacement	-0.17	-0.090	-0.21	-0.12	-0.19	-0.10
	(0.0056)***	(0.0047)***	(0.011)***	(0.0098)***	(0.011)***	(0.0090)***
Observations	41558	41558	14459	14459	12201	12201
R^2	0.498	0.619	0.538	0.630	0.572	0.688
Panel C:	**Firmsize 3-50**		**Firmsize 51-150**		**Max. 1 Year Since Last Job**	
Female Replacement	-0.18	-0.10	-0.18	-0.096	-0.18	-0.089
	(0.0073)***	(0.0063)***	(0.0083)***	(0.0070)***	(0.0058)***	(0.0047)***
Observations	27821	27821	14906	14906	33452	33452
R^2	0.489	0.598	0.539	0.668	0.507	0.652

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for different regressions samples, where the outcome variable is log wages in r. It is based on Equation (1), and shows β_1 coefficients for $t = r$. Columns (1), (3), and (5) report coefficients for the *same hiring opportunity specification*, where we control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). Columns (2), (4), and (6) additionally control for replacement workers' wages at the previous job (deciles). In Panel A, we (i) report the baseline coefficients, followed by (ii) a specification where we condition on full-time employment from r through $r+4$, and (iii) a specification where we restrict to a balanced panel of firms (10 years around death). In Panel B, we (i) exclude female replacements who were mothers at r, (ii) restrict to replacements who were aged at least 40 at r, and (iii) restrict to firms with only 1 full-time hire in the same 3-digit occupation in the 365 days after the event. In Panel C, we restrict to (i) firms with 3-50 full-time employees, (ii) firms with 51-150 full-time employees, and (iii) transition pairs where replacement workers were out of work for not more than 1 year. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. *, **, and ** correspond to 10, 5 and 1 percent significance levels, respectively.

Table A7: Log Wage Gap with Different Sets of Control Variables

	(1) Baseline + Previous Wage	(2) Baseline + Experience	(3) Baseline + Occ. Skill	(4) Baseline +Tenure	(5) Baseline +Predicted Wage	(6) Baseline + Previous Wage + Mincer	(7) Baseline +Firm	(8) All
Panel A: Full Sample								
Female Replacement	-0.100	-0.17	-0.18	-0.18	-0.20	-0.10	-0.12	-0.13
	(0.0047)***	(0.0053)***	(0.0054)***	(0.0054)***	(0.0084)***	(0.0047)***	(0.0064)***	(0.0065)***
Observations	42837	42834	42428	41674	26959	41333	32431	31213
R^2	0.614	0.533	0.502	0.521	0.521	0.621	0.649	0.655
Panel B: Re-run for Regression Sample in Column (8)								
Female Replacement	-0.12	-0.19	-0.21	-0.20	-0.22	-0.12	-0.12	-0.13
	(0.0060)***	(0.0068)***	(0.0068)***	(0.0068)***	(0.011)***	(0.0059)***	(0.0065)***	(0.0065)***
Observations	31213	31213	31213	31213	20269	31213	31213	31213
R^2	0.616	0.541	0.515	0.532	0.542	0.625	0.647	0.655

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for specifications with different control variables. It is based on Equation (1), presents β_1 coefficients for $t = r$, and the outcome variable is log wages. In each regression, we control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). In Column (1), we moreover control for replacement workers' wages at the previous job (deciles). In Column (2), we instead control for labor market experience (measured in years in $r-1$). In Column (3), we instead add replacement workers' occupational skill intensity as control variable. In Column (4), we add deciles of occupational and firm tenure (measured in years in $r-1$). In Column (5), we in addition control for predicted values of the wage in $r-1$, based on male replacements and their demographics, occupation, and calendar year (details in Appendix B). In Column (6), we control for the baseline controls and add previous wages, experience, skill, and tenure on top. The regression model in Column (7) combines our baseline controls with detailed firm-level controls. These are the number of full-time workers in the same 3-digit occupation (d), the share of mothers (d), and dummies for the above median share of: full-time women in the same 3-digit occupation; full-time women; mothers with kids aged 0-8 (all in d). Column (8) controls for everything at once (except the predicted wage). Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. We cluster standard errors at the event (firm $\times$ date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. *, **, and ** correspond to 10, 5 and 1 percent significance levels, respectively.

Table A8: Incumbent Workers' Wage Bill by Deceased Worker Gender

	(1)	(2)	(3)	(4)	(5)	(6)
		All Incumbents			Incumbents in Same 3-Digit Occupation	
	All	Women	Men	All	Women	Men
Panel A: Baseline						
Male Deceased Worker	2.81	0.16	2.66	1.13	0.39	0.74
	(1.78)	(0.60)	(1.46)*	(0.81)	(0.37)	(0.71)
Observations	32938	32938	32938	32938	32938	32938
R^2	0.016	0.106	0.013	0.017	0.333	0.014
Panel B: Balanced Panel of Firms						
Male Deceased Worker	2.11	-0.27	2.39	1.44	0.35	1.09
	(1.59)	(0.64)	(1.30)*	(0.85)*	(0.40)	(0.74)
Observations	25364	25364	25364	25364	25364	25364
R^2	0.018	0.108	0.017	0.015	0.219	0.014
Panel C: Full Sample						
Male Deceased Worker	0.089	0.075	0.014	-0.39	0.33	-0.72
	(1.70)	(0.60)	(1.33)	(1.16)	(0.42)	(1.02)
Observations	43507	43507	43507	43507	43507	43507
R^2	0.014	0.086	0.011	0.016	0.161	0.013

Notes: This table reports the coefficient on male deceased worker in cross-sectional regressions with different variations of incumbents' wage bill in r. Each outcome variable is a measure of the incumbent wage bill *share*, which takes into account wage bill changes relative to $t = d$, and relates the wage bill to the deceased worker's wage in d (see Section 6 for details). In each regression, we control for deceased worker's 3-digit occupation, calendar year, the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), the number of female new hires in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d), the share of full-time women in the same 3-digit occupation at the firm (d). The first three columns list the wage bill of all incumbents, regardless of their occupation, for all (Column 1), women (Column 2), and men (Column 3). The last three columns list the wage bill of incumbents in the same 3-digit occupation as the deceased worker, for all (Column 1), women (Column 2), and men (Column 3). We define incumbents as everyone whose working spell at the event firm overlaps with the date of death. Panel A reports coefficients for our baseline sample, Panel B reports coefficients for a balanced panel of firms in the 10 years around the death event, and Panel C reports coefficients for the full excess hiring sample, without conditioning on replacement workers working full-time in $r - 1$. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. *, **, and ** correspond to 10, 5 and 1 percent significance levels, respectively.

Table A9: Firm Characteristics in $d-2$

	(1) Same Hiring Opportunity	(2) + Same Pre-Hire Wage	(3) Same Hiring Opportunity	(4) + Same Pre-Hire Wage
Panel A: Wage Bill Coworkers	**All**		**Incumbents**	
Female Replacement	-3538.2	825.4	-4781.0	-1334.6
	(7019.3)	(7027.3)	(6672.8)	(6672.7)
Observations	41898	41898	41898	41898
R^2	0.865	0.865	0.865	0.865
Panel B: Wage Gap and Firm FE	**GWG Other Workers**		**AKM Firm FE**	
Female Replacement	-0.012	-0.0045	0.0031	0.014
	(0.0078)	(0.0080)	(0.0026)	(0.0027)***
Observations	38466	38466	39810	39810
R^2	0.202	0.203	0.445	0.453
Panel C: Workforce Composition	**Share of Mothers**		**Share of Women**	
Female Replacement	0.0023	0.0030	0.021	0.022
	(0.0012)*	(0.0013)**	(0.0026)***	(0.0027)***
Observations	34408	34408	40082	40082
R^2	0.314	0.314	0.768	0.768
Panel D: Family-Friendliness	**Share Female Team Leaders**		**Family-Friendly Firm**	
Female Replacement	-0.0022	-0.0032	-0.0042	-0.0020
	(0.0088)	(0.0090)	(0.0060)	(0.0061)
Observations	14568	14568	41829	41829
R^2	0.246	0.246	0.285	0.286

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for different outcome variables. It is based on Equation (1), and shows β_1 coefficients for $t = d-2$. Columns (1), (3), and (5) report coefficients for the *same hiring opportunity specification*, where we control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). Columns (2), (4), and (6) additionally control for replacement workers' wages at the previous job (deciles). In Panel A, we (i) report coefficients for the wage bill of (i) all coworkers and (ii) incumbents. We define coworkers as all workers with the same 3-digit occupation as the deceased workers, and incumbents as everyone whose working spell at the event firm overlaps with the date of death. In Panel B, we report coefficients for (i) the log gender wage gap of other workers (excl. the deceased worker) at the firm and (ii) for the firm's AKM firm FE as provided by Lochner et al. (2023). In Panel C, we report coefficients for (i) the share of mothers at the firm, and for (ii) the share of female employees. In Panel D, we report coefficients for (i) the share of female team leaders (proxied as the employee with the highest wage in a given 3-digit occupation), and for (ii) the probability of being a family-friendly firm. We classify firms as family-friendly if they have at least one female manager with a child aged 0-8. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. *, **, and ** correspond to 10, 5 and 1 percent significance levels, respectively.

Table A10: Top 10 Predictors Identified by Random Forest Algorithm

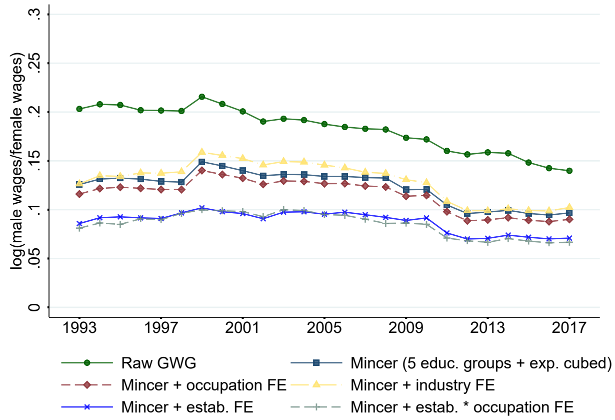
Panel A: Excess Hiring	
1	Number of Full-time Workers in Same 3-Digit Occ. at Hiring Firm $d-1$
2	Number Workers in Same 3-Digit Occ. at Hiring Firm $d-1$
3	Wage Bill All Workers at Hiring Firm $d-1$
4	Share of Full-time Workers in Same 3-Digit Occ. at Hiring Firm $d-1$
5	Share of New Hires at Hiring Firm $d-2$
6	Number of Workers in Same 5-Digit Occ. at Hiring Firm $d-1$
7	Number of Full-time Workers in Same 5-Digit Occ. at Hiring Firm $d-1$
8	Wage Bill All Workers at Hiring Firm $d-3$
9	Wage Bill All Workers at Hiring Firm $d-2$
10	Number of Full-time Workers in Same 3-Digit Occ. at Hiring Firm $d-3$
Panel B: Female Replacement	
1	Gender of Deceased Worker
2	Share of Women in Same 5-Digit Occ. at Hiring Firm $d-1$
3	Share of Women in Full-time Job in Same 5-Digit Occ. at Hiring Firm $d-1$
4	Share of Women in Same 3-Digit Occ. at Hiring Firm $d-1$
5	Share of Women in Same 3-Digit Occ. at Hiring Firm $d-2$
6	Share of Women in Same 5-Digit Occ. at Hiring Firm $d-2$
7	Share of Women in Same 3-Digit Occ. at Hiring Firm $d-3$
8	Share of Women Aged 18-40 in Same 2-Digit Occ. in Germany $2-1$
9	Share of Women at Hiring Firm $d-1$
10	Share of Women in Full-time Job in Same 5-Digit Occ. at Hiring Firm $d-3$

This table lists the top 10 variables (in descending order) identified as important predictors in the machine learning exercise. Panel A lists the most important predictors for "excess hiring", and Panel B lists the most important predictors for "female replacement" among excess hiring firms. $d-1$, $d-2$, and $d-3$ refer to 1, 2, and 3 years before the death event, respectively. There are 182,840 death events; of these, 68,459 are subject to excess hiring, and 141,077 are not. Each of these are the top 10 out of approximately 600 variables in total that enter the machine learning algorithm.

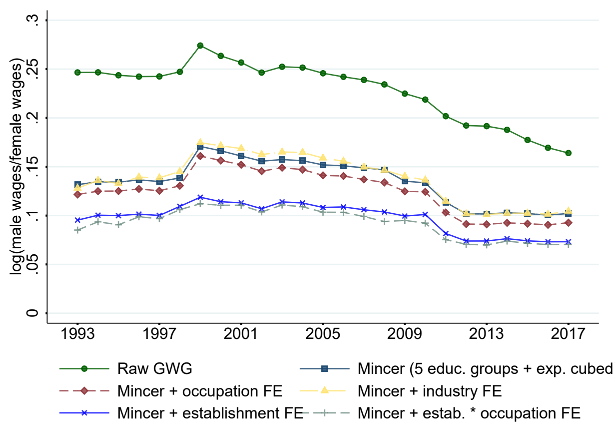
D Appendix Figures

Figure A1: The Gender Wage Gap in Germany 1993-2017

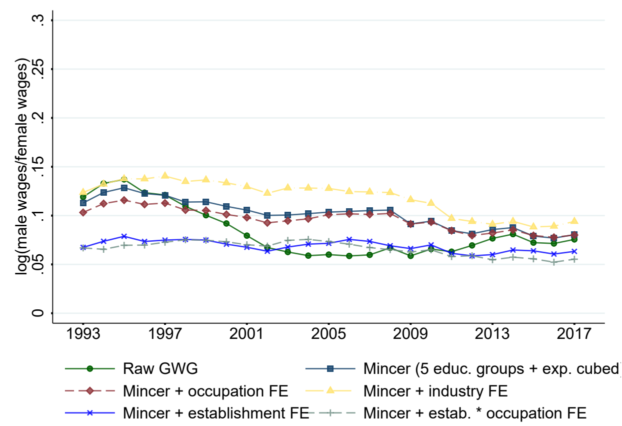
(a) All



(b) West Germany



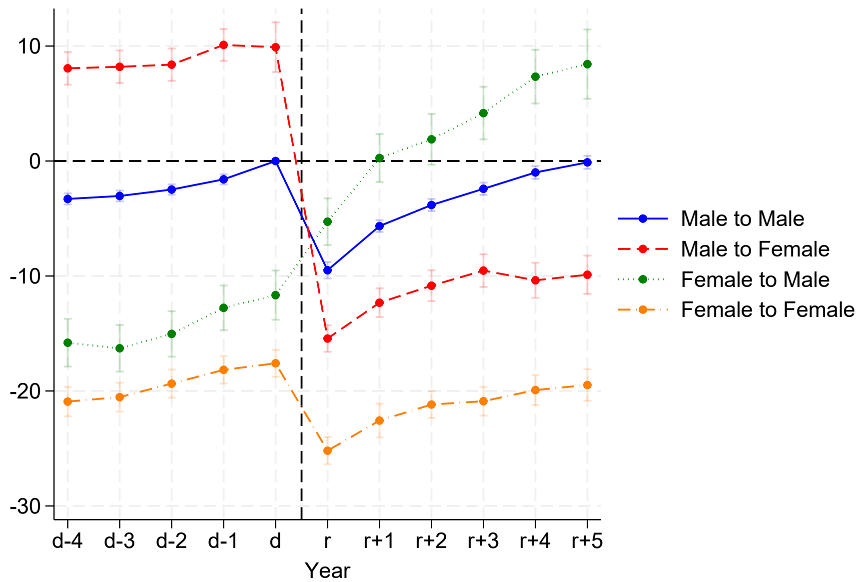
(c) East Germany



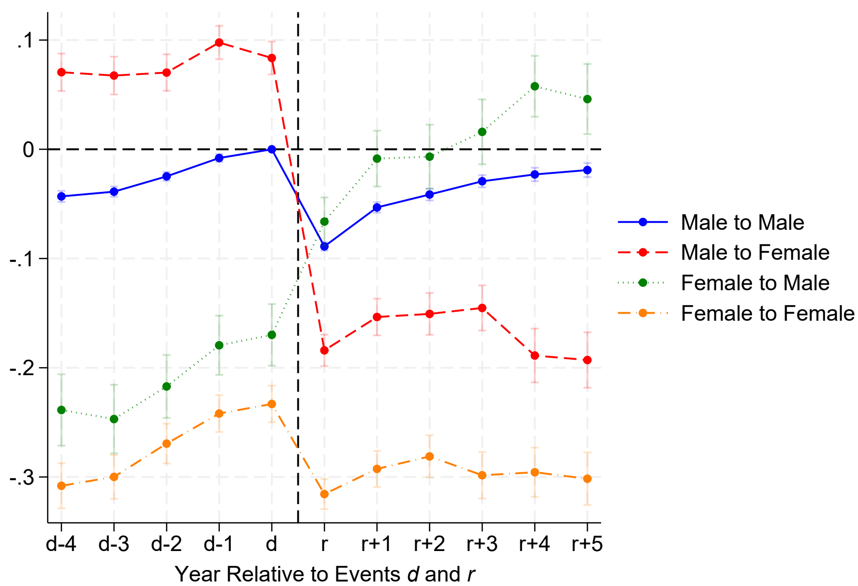
Notes: This figure is in part a replication of Figure 1 in Bruns (2019). It shows the raw gender wage gap and several versions of the adjusted gender wage gap for a sample of full-time workers, all derived from an individual-level linear regression of log wages on a dummy for male workers. Green dots plot the raw gender wage gap; blue squares plot the gap that remains when we control for 5 groups of education and a cubic polynomial in years of labor market experience ("Mincer covariates"); red diamonds plot the gap for Mincer plus 3-digit occupations; yellow triangles plot the gap for Mincer plus 3-digit industries; blue stars plot the gap for Mincer plus establishment fixed effects; and teal crosses plot the gap for Mincer plus establishment × 3-digit occupation fixed effects. Panel (a) presents the pattern for all of Germany, while Panels (b) and (c) restrict to firms in West and East Germany, respectively. We use the longitudinal LIAB (*7519, Version 1*). To address the issue of sample selectivity in the LIAB, we follow Bossler et al. (2018) and control for 10 categories of firmsize, federal state, 1-digit industry, and state × firmsize × industry dummies. We report patterns from 1993, since this is when East German establishments were first added to the LIAB.

Figure A2: Raw Evolution of Wages by Transition Group

(a) Daily Wage (EUR)



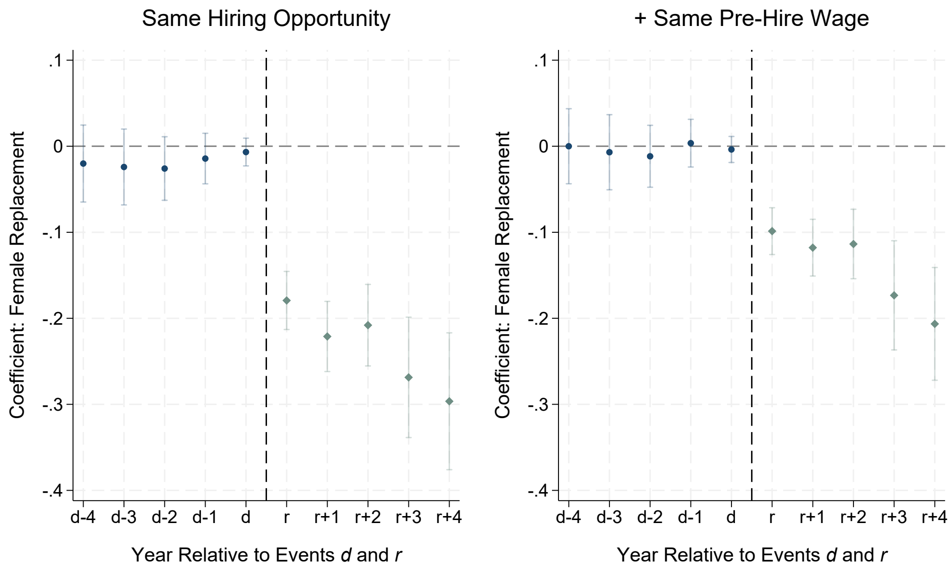
(b) Log Daily Wage



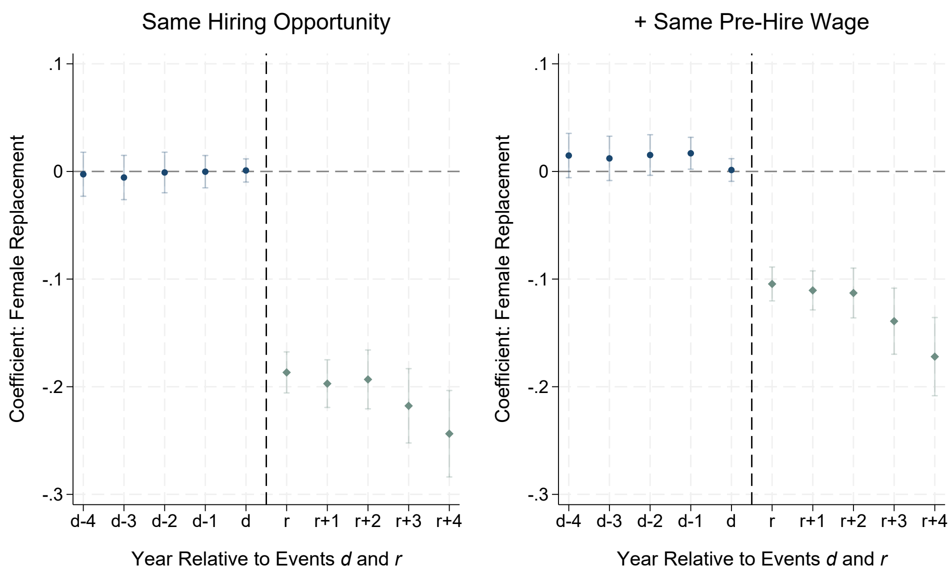
Notes: This figure presents raw means of wage trajectories for our baseline sample of deceased and replacement workers, relative to wages of the male-male group in d. The four lines plot the normalized wages for the four transition groups: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dot-dashed line). See Appendix B.2 for details. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. ertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm × date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.

Figure A3: The Wage Gap for Female Replacement Workers - Firm Reweighting

(a) Reweighting to All Other Firms



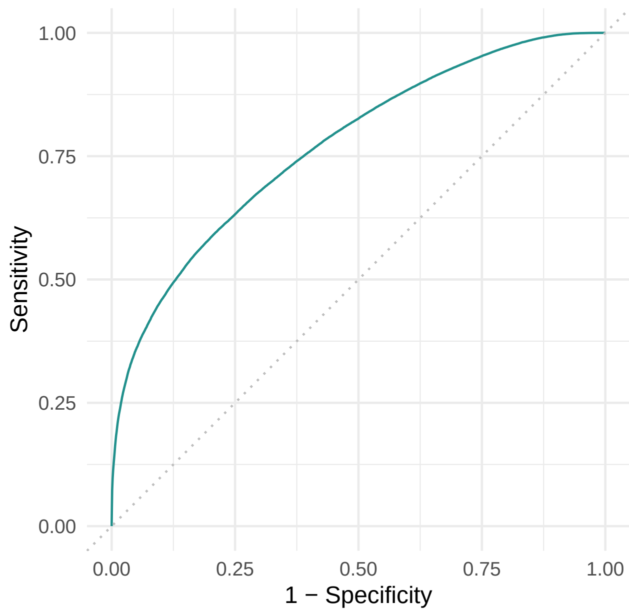
(b) Reweighting to Non Excess Hiring Firms



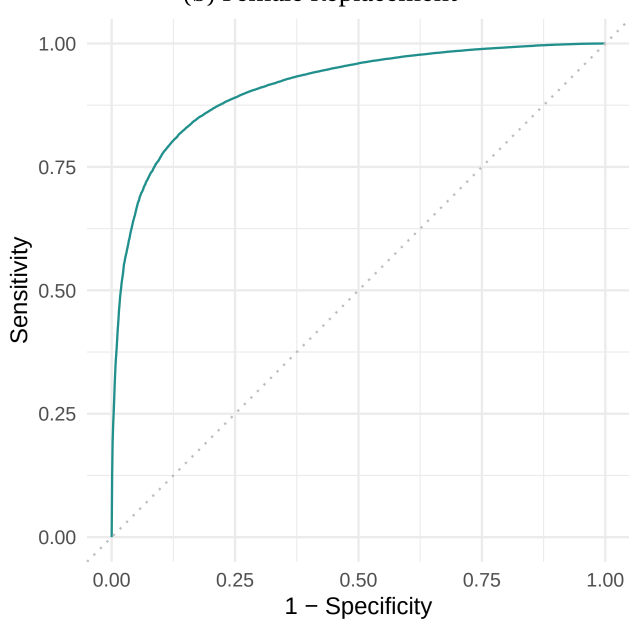
Notes: This figure presents β_1 coefficients of Equation (1). The outcome variable is log wages. In Panel (a) we use weights to make excess hiring firms comparable to all other German firms; in Panel (b), we reweight excess hiring firms to non excess hiring firms. See Appendix B.3 for details on the reweighting exercise. The figure on the left ("Same hiring opportunity") refers to the baseline specification that controls for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d). In addition, we control for deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). The figure on the right ("+ Same pre-hire wage") plots coefficients of the specification that additionally controls for deciles of the pre-hire wage of the replacement worker ($r-1$). Coefficients in navy ($t = d-4, ..., d$) refer to log wages of the deceased worker, while coefficients in teal ($t = r, ..., r+4$) refer to log wages of the replacement worker. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm $\times$ date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.

Figure A4: Machine Learning Prediction Accuracy

(a) Excess Hiring



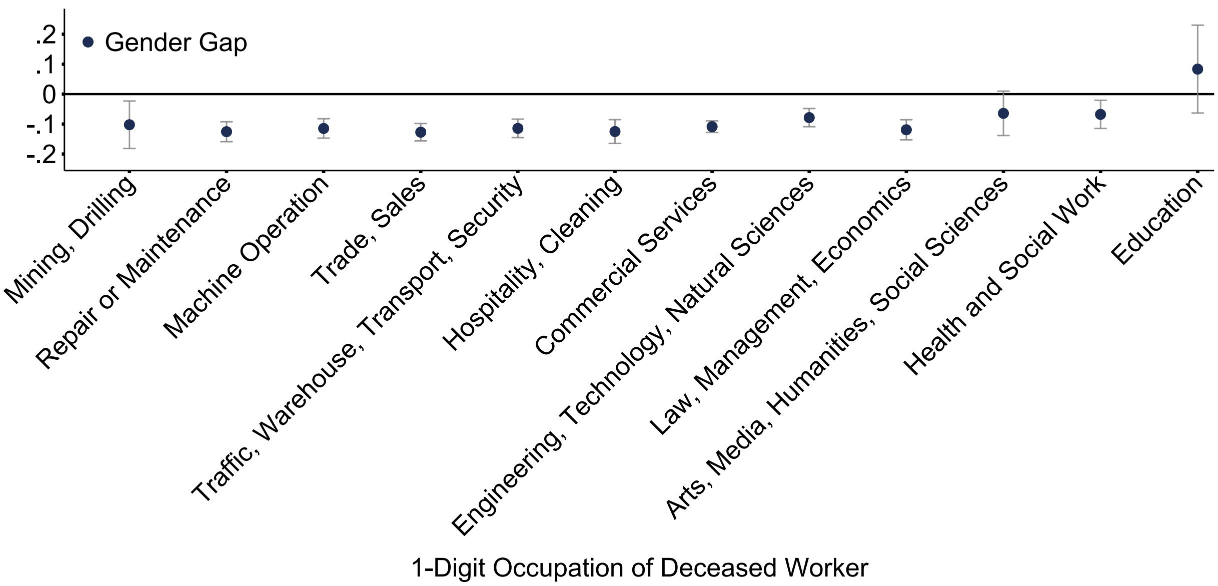
(b) Female Replacement



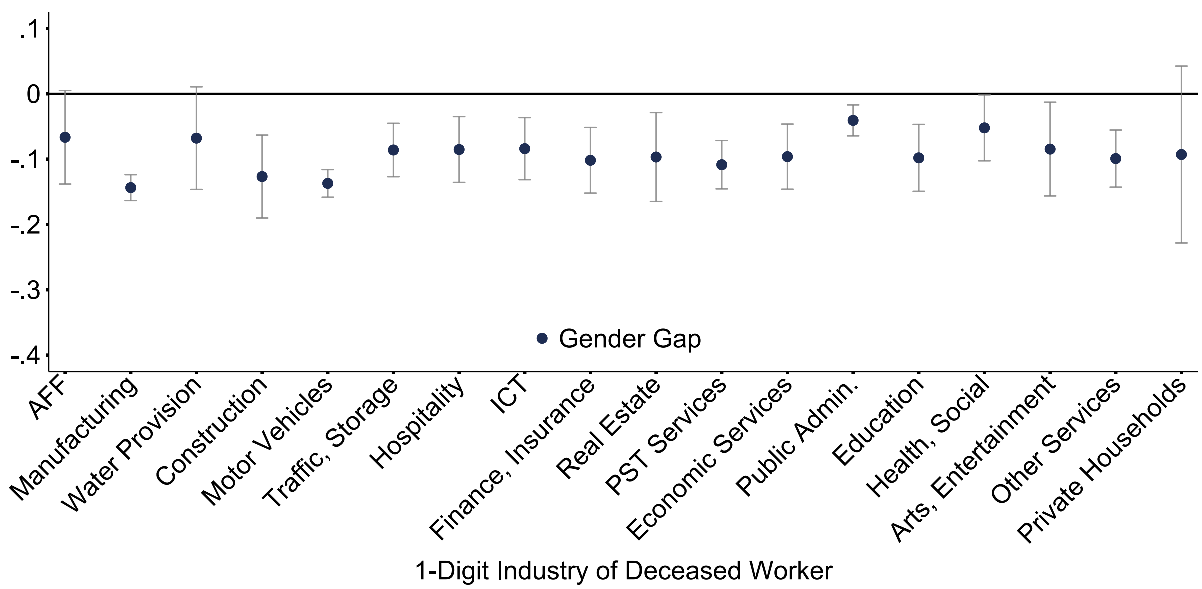
Notes: This ROC (Receiver Operating Characteristic) curve plots the prediction accuracy of our ranger algorithm model predicting the incidence of excess hiring (Panel a) and female replacement (Panel b) after a sudden death. The sample includes firms with exactly one sudden death in a given year. The AUC (area under the curve) is 77% for the prediction of excess hiring, and 92.4% for the prediction of the replacement worker's gender. In Panel (b), we restrict the sample to excess hiring firms. There are 182,840 death events; of these, 68,459 are subject to excess hiring, and 141,077 are not. See Section 3.1 and Appendix Section B.1 for details on the machine learning algorithm.

Figure A5: Deceased-Replacement Wage Gap by Occupation/Industry

(a) 1-Digit Occupations



(b) 1-Digit Industries

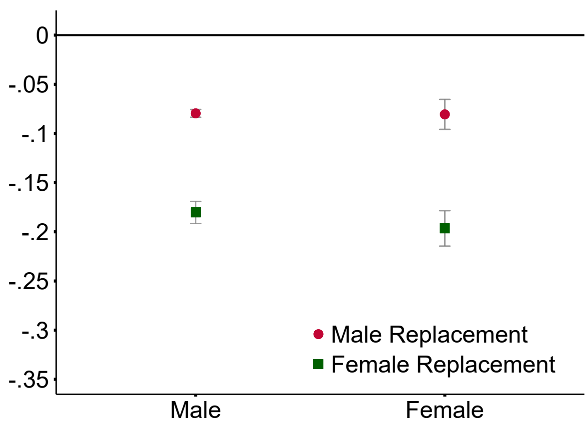


Notes: This figure plots the log wage difference for male vs. female replacements in r, relative to their predecessor in d, based on Equation (4). Panel (a) plots the gap by 1-digit occupation, and Panel (b) plots the gap by 1-digit industry. Blue dots subtract the deceased-replacement worker gap for male replacements from the deceased replacement worker gap for female replacements, i.e., they correspond to $\beta_1 + \beta_4$. All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm × date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021. To improve the graph's readability, we exclude 3 industries with a low number of women and thus large standard errors from Panel (b): Mining, energy provision, and NGOs. AFF is an abbreviation for "Agriculture, Forestry, and Fishing", PST means "Professional, Scientific, and Technical Services".

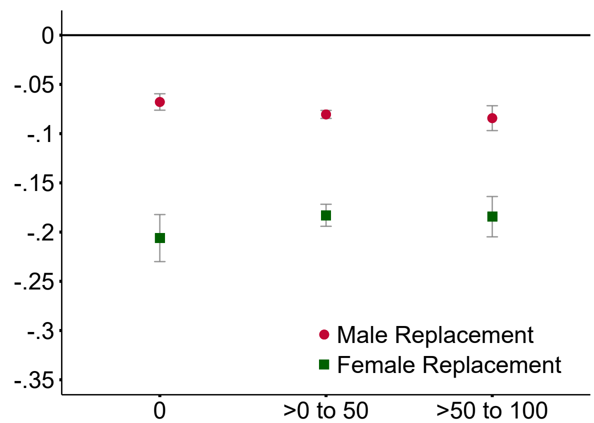
Figure A6: Deceased-Replacement Wage Gap by the Gender of Bosses

(a) Gender of CEO

(b) Gender of Team Leader (Same 3-Digit Occ.)



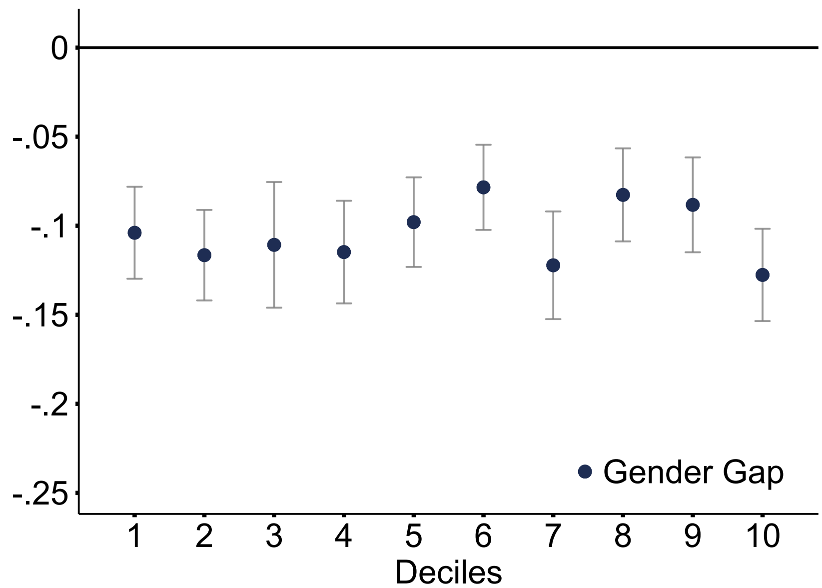
(c) Overall Share of Female Team Leaders in Firm



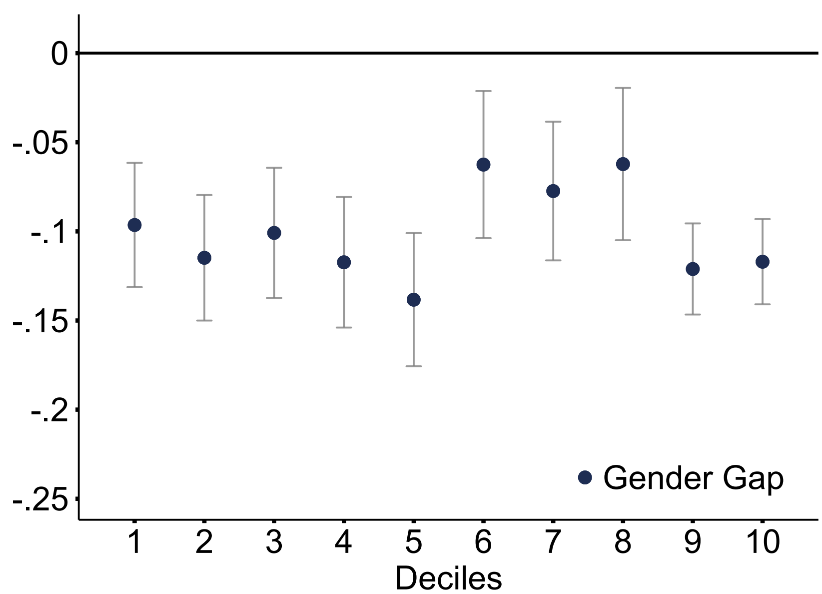
Notes: This figure plots the log wage difference for male vs. female replacements in r, relative to their predecessor in d, based on Equation (4). Panel (a) plots the gap by the gender of a firm's CEO (proxied by the employee with the highest wage), Panel (b) plots the gap by the gender of the transition pair's team leader (proxied by the employee with the highest wage in the same 3-digit occupation), and Panel (c) plots the gap by the overall share of female team leaders in the firm (proxied by the employee with the highest wage in each 3-digit occupation). All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. In Panel (b), we also control for deciles of the ex-ante probability of female replacement. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm × date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.

Figure A7: Deceased-Replacement Wage Gap Female Hiring Probability

(a) Deciles of Female Replacement Probability



(b) Deciles of the 2-Digit Occupation's Share of Female Full-time Workers



Notes: This figure plots the log wage difference for male vs. female replacements in r, relative to their predecessor in d, based on Equation (4). Panel (a) plots the gap by firm's ex-ante probability of hiring a female worker (derived in the machine learning exercise, in deciles). Panel (b) plots the gap by the share of female full-time workers in the deceased/replacement worker's 2-digit occupation (in deciles), based on a random 20% sample of German worker biographies. Blue dots subtract the deceased-replacement worker gap for male replacements from the deceased replacement worker gap for female replacements, i.e., they correspond to $\beta_1 + \beta_4$. All regressions control for deceased worker's gender, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. In Panel (b), we also control for the deceased worker's 3-digit occupation. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we condition on transition pairs where the replacement worker's last employment contract was a full-time job. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm × date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.

E Replication of Main Results for Full Sample

Table A11: Demographics for Transition Pairs vs. Random Sample of Workers - Full Sample

	(1) Random Sample	(2) Male-Male	(3) Opposite Sex	(4) Female-Female
Panel A: Deceased Worker in d				
Daily Wage in EUR	91.7 [53.8]	92.9 [49.7]	95.9 [53.4]	74.3 [32.5]
Days Worked Full-time	332.1 [79.9]	339.1 [70.6]	341.6 [70.1]	338.9 [74.3]
Age	38.7 [11.4]	45.0 [11.5]	45.5 [11.6]	43.0 [12.2]
Tenure in Firm (Years)	5.87 [5.97]	6.47 [6.36]	7.50 [6.90]	6.70 [6.28]
Occ. Tenure (Years)	8.19 [7.04]	9.57 [7.75]	10.1 [8.11]	9.13 [7.28]
Experience (Years)	13.0 [8.54]	14.6 [8.84]	15.0 [8.98]	13.0 [8.43]
Education (Years)	12.2 [1.93]	11.9 [1.42]	12.2 [1.91]	11.8 [1.46]
Mother	0.074 [0.26]	0 [0]	0.036 [0.19]	0.13 [0.33]
Panel B: Replacement Worker in r				
Daily Wage in EUR	91.7 [53.8]	81.5 [53.5]	74.7 [33.1]	64.0 [30.4]
Days Worked Full-time	332.1 [79.9]	315.4 [89.2]	314.1 [95.4]	315.2 [93.3]
Age	38.7 [11.4]	33.9 [10.5]	32.4 [10.4]	32.3 [10.7]
Tenure in Firm (Years)	5.87 [5.97]	0.45 [0.54]	0.47 [0.51]	0.45 [0.44]
Occ. Tenure (Years)	8.19 [7.04]	3.56 [5.15]	3.25 [4.63]	3.51 [4.72]
Experience (Years)	13.0 [8.54]	9.26 [7.22]	7.96 [6.89]	7.63 [6.56]
Education (Years)	12.2 [1.93]	12.0 [1.57]	12.3 [2.10]	12.0 [1.58]
Mother	0.074 [0.26]	0 [0]	0.13 [0.34]	0.19 [0.39]
Number of Individuals	14905321	42676	8193	6277

Notes: This table presents differences in average characteristics for the full sample of deceased-replacement worker pairs compared to a random sample of German workers. Column (1) shows characteristics for a random 2% sample of full-time workers in the German social-security data in 1981-2016. Column (2) shows characteristics for male-male transition pairs, Column (3) shows characteristics for opposite sex transition pairs, and Column (4) shows characteristics for female-female transition pairs. Columns (2)-(4) in Panel A present the characteristics of deceased workers in their last working spell, and Columns (2)-(4) in Panel B present the characteristics of replacing workers in their hiring spell. Time period r refers to replacement workers' starting spell at the hiring firm, and time period d refers to deceased workers' last employment spell. Deceased and replacement workers work in a full-time contract in d and r, respectively. We *do not* restrict to transition pairs where the replacement worker's last employment contract was a full-time job. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table A12: Adjustments Within Transition Pairs and Event Firms - Full Sample

	(1) Mean Δ Male Replacement		(2) Coefficient Female Replacement		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment (r-d)					
Log Wage	-0.10	[0.0021]	**-0.11**	[0.0052]	51,788
Days Worked Full-Time per Year	-21.5	[0.73]	-2.66	[1.66]	51,882
Log Hours Worked per Week	0.023	[0.0053]	0.0021	[0.015]	3,269
Log Wage if in Hours Data	-0.14	[0.0070]	**-0.063**	[0.019]	3,267
Wage Bill Replacement-Deceased Worker (EUR)	-10163.9	[84.1]	**-2577.0**	[187.5]	51,882
Panel B: Coworker Wage Bill (t_1-t_0)					
All (EUR)	41939.4	[1243.2]	-1457.7	[3166.5]	51,882
Incumbents (EUR)	-26755.9	[880.5]	638.0	[2162.8]	51,882
New Hires (EUR)	22866.6	[713.5]	2106.3	[1984.4]	51,882
Panel C: Firm-level Adjustments (t_1-t_0)					
Capital/Person (EUR)	1120.1	[624.3]	8.99	[1495.3]	2,476
Sales/Person (EUR)	40037.1	[11812.6]	-63318.9	[38587.3]	1,005
Firm Has Disappeared by r+1	0.0032	[0.00041]	-0.00081	[0.00081]	51,882

Notes: This table reports replacement workers' vs deceased workers' labor market outcomes, and firm outcomes in t=1 vs. t=0, based on Equation (3). We *do not* restrict to transition pairs where the replacement worker's last employment contract was a full-time job. Column (1) reports the mean for male replacements (i.e., β_0); column (2) reports the coefficient for female replacements (i.e., β_1). Panel A reports the r-d difference in replacement vs. deceased worker labor market outcomes, measured at r and d, respectively. r refers to replacement workers' starting spell at the hiring firm, and d refers to deceased workers' last employment spell. Information on hours comes from the Statutory Accident Insurance and is available for 2010-2014. Panel B reports the t_1-t_0 difference in the wage bill of all coworkers, incumbent coworkers, and new hires. Coworkers work in the same 3-digit occupation as the deceased (and replacing) worker. We define incumbents as all employees whose employment spell overlaps with the date of death. We define new hires as all employees who worked at the firm at the date of death in the post-death year t_1, but not in the calendar year of death t_0. Panel C reports the t_1-t_0 difference in firm performance indicators. Firm performance indicators come from the Orbis-ADIAB data (see Antoni et al. (2018)) and are available for linked firms in 2006-2013. All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. Coefficients in bold are statistically significant at the 10%-level.

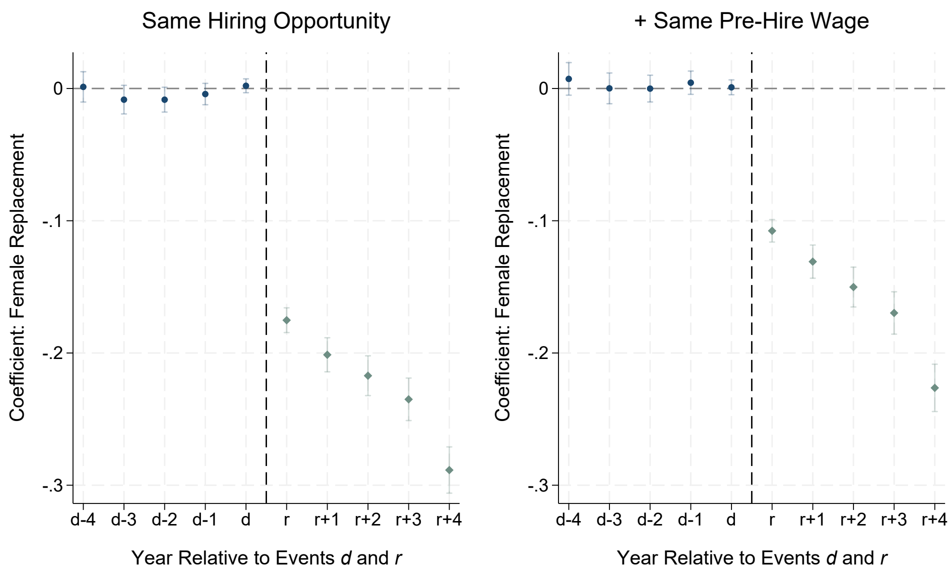
Table A13: Replacement Worker Wage Gains, Amenities, Outside Options - Full Sample

	(1) Mean Δ Male Replacement		(2) Coefficient Female Replacement		(5) Number of Observations
	Change	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment					
Δ Log Wage	0.25	[0.0023]	**-0.096**	[0.0056]	51,788
Δ Days Worked Full-Time per Year	121.9	[0.98]	**-7.36**	[2.20]	51,882
Days Job Was Vacant	69.2	[0.34]	**3.05**	[0.77]	51,882
Days Since Last Job	457.3	[5.27]	**-59.1**	[12.2]	51,882
Panel B: Amenities					
Δ Commuting Distance (km)	6.38	[1.08]	-0.15	[2.48]	20,257
Δ Gender Wage Gap in Firm	0.0051	[0.0032]	0.0077	[0.0061]	35,139
Gender Wage Gap Other Workers in Hiring Firm	0.41	[0.0033]	**0.020**	[0.0068]	47,967
Panel C: Outside Options					
$\phi_{cz,occ,t,g}$	-0.010	[0.0011]	-0.00040	[0.0029]	50,180
Pre-Hire Firm Median Full-time Wage	64.2	[0.14]	**2.52**	[0.34]	50,199
Pre-Hire Firm FE	0.071	[0.0013]	**0.032**	[0.0031]	49,558

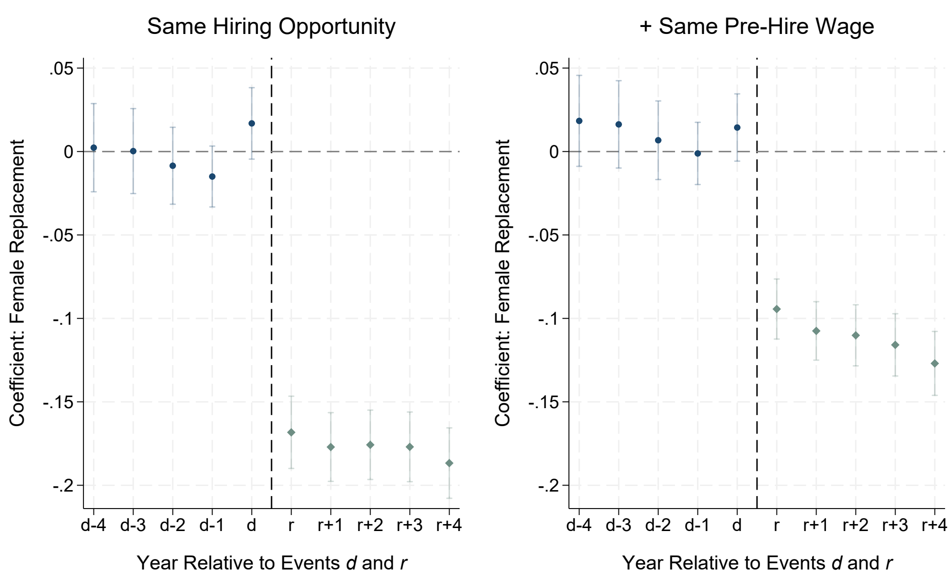
Notes: This table reports regression coefficients for our sample of replacement workers, based on a version of Equation (3) that compares a given replacement worker outcome in r vs. $r-1$. r refers to replacement workers' starting spell at the hiring firm, and $r-1$ refers to their previous employment spell. We *do not* restrict to transition pairs where the replacement worker's last employment contract was a full-time job. Column (1) reports the mean for male replacements (i.e., β_0); column (2) reports the coefficient for female replacements (i.e., β_1). The first two rows in Panel A show how replacement workers' wages and days worked differ from those recorded in their previous job. 'Days job was vacant' counts the number of days between a replacement worker's starting date at the hiring firm and their predecessor's date of death. 'Days since last job' counts the number of days between a replacement worker's starting date at the hiring firm and their last work day in their previous job. In Panel B, we report three proxies for amenities: The change in commuting distance compared to the previous job (in km), the change in the firm gender wage gap, and the gender wage gap of all coworkers (ie, workers in the same 3-digit occupation) in the hiring firm In Panel C, we report three proxies for replacement workers' outside options. $\phi_{cz,occ,t,g}$ refers to local labor market thickness by 2-digit occupation and commuting zone, weighted by gender-specific cross-occupational transition probabilities (see Appendix A.2 for details). Pre-hire median full-time wage and firm FE characterize the quality of workers' previous employers. All regressions control for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d), and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d); and replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. We cluster standard errors at the event (firm × date of death) level and report standard deviations in brackets. Deaths occur in 1981-2016, and our sample spans 1975-2021. Coefficients in bold are statistically significant at the 10%-level.

Figure A8: The Wage Gap for Female Replacement Workers - Full Sample

(a) Baseline Sample



(b) Replacement Works Full-time from r to r+4



Notes: This figure presents β_1 coefficients of Equation (1). The outcome variable is log wages. We *do not* restrict to transition pairs where the replacement worker's last employment contract was a full-time job. The figure on the left ("Same hiring opportunity") refers to the baseline specification that controls for deceased worker's gender and 3-digit occupation, calendar year, the share of full-time women in the same 3-digit occupation at the firm (d), the number of full-time workers at the firm (d), the number of women in the same 3-digit occupation (d). In addition, we control for deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). The figure on the right ("+ Same pre-hire wage") plots coefficients of the specification that additionally controls for deciles of the pre-hire wage of the replacement worker ($r - 1$). Coefficients in navy ($t = d - 4, ..., d$) refer to log wages of the deceased worker, while coefficients in teal ($t = r, ..., r + 4$) refer to log wages of the replacement worker. Deceased and replacement workers work in a full-time contract in d and r, respectively. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the event (firm × date of death) level. Deaths occur in 1981-2016, and our sample spans 1975-2021.