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. Using administrative data from Germany spanning 1981 to 2016, we analyze firms' wage-setting behavior in response to exogenous vacancies caused by sudden worker deaths. By identifying external replacement workers, we compare positions that, ex-ante, are equally likely to hire a male or female worker. Our analysis shows that female replacement workers' starting wages are, on average, 11 log points lower than those of equally productive male counterparts. This gap is unlikely to be explained by differences in hours, within-firm adjustments, or outside options. Instead, the results suggest that firms may statistically discriminate by gender and that differences in worker bargaining play an important role. The gender hiring opportunity gap is lower in contexts where gender equality norms are stronger. These findings suggest that a significant portion of the gender wage gap originates within firms at the hiring stage, contributing to our understanding of the mechanisms behind persistent gender disparities in wages.

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1 Introduction

The gender gap in wages remains a pervasive feature of labor markets worldwide. Across all OECD countries, women working in full-time jobs earned 12% less than men in 2021 (OECD, 2023). With substantial progress in closing the gender gap in educational attainment (OECD, 2019; Goldin et al., 2006), it is increasingly difficult to take a pure human capital perspective when explaining the persistent gender wage gap. In frictional labor markets, where firms have wage-setting power, theory predicts that equally productive men and women might encounter disparities in job opportunities and bargaining prospects (Robinson, 1933; Alan, 2011). In practice, these disparities have prompted policies designed to tackle the gender pay gap that predominantly center around the role of firms.[1] This highlights the importance of analyzing gender disparities within firms. However, understanding how firm-specific hiring and compensation practices affect the gender wage gap remains challenging, particularly when men and women tend to sort into different 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 examining firm responses to exogenous vacancies created by the unexpected deaths of existing workers. We ask how similar work opportunities within firms may lead to differences in wage and career outcomes for male and female incoming hires. To answer this question, we propose to identify external replacements for these workers, making it possible to study worker-to-worker transitions within a position using German administrative data. We then examine the differential impact of the vacancy shock by the gender of the hire. We combine several additional datasets to determine the role of working hours, within-firm adjustments, amenities, outside options and bargaining. Taken together, our analysis provides important evidence on the mechanisms behind the role of firms and bargaining in the gender wage gap.

We start by identifying approximately 235,086 prime-age full-time workers who died unexpectedly in the matched employer–employee data from Germany spanning four decades. These departures create unanticipated hiring shocks, addressing concerns about the endo-

[1] 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).

geneity of worker exits (Jäger et al., 2024). Next, we focus on cases where these unforeseen vacancies are filled by external replacements. Motivated by the empirical pattern showing that excess new hires typically occur within the first six months following the death event—most concentrated in the earlier months—we define a replacement worker as the first new full-time hire in the same 3-digit occupation as the deceased worker within this time frame.[2]

Our focus on gender among replacement workers necessitates addressing a second challenge. Ideally, we would hold firm and position factors that influence the gender of the new hire fixed ex-ante, ensuring that the ex-post gender realization is effectively random. To achieve this, we employ a random forest approach to predict whether the replacement hire will be a woman, using firm and position characteristics observed prior to the exogenous departure event. This prediction is based on a comprehensive set of approximately 600 variables, including characteristics of the departing worker, firm, and labor market in the three years preceding the sudden death.[3] Our regression specifications flexibly control for the predicted ex-ante probability of hiring a female worker, as well as the most influential predictive factors, which unsurprisingly include the proportions and numbers of female employees within the firm. We support the assumption that, conditional on these controls, the gender of the new hire is as good as random by demonstrating that key firm and position characteristics measured two years prior to the departure event are comparable across replacement worker gender—not just in trends, but also in levels.

We term the wage gap arising from exogenous vacancies that are ex-ante similar in the likelihood of hiring a woman as the *gender hiring opportunity gap*. Our baseline estimate for the gender hiring opportunity gap reveals a substantial gender difference, with women earning starting wages that are 20 log points lower than men's. This gap could arise from firms either hiring workers of differing productivity levels based on gender or compensating workers of similar productivity differently. While both scenarios are of interest—particularly given our identifying assumption that the gender of the new hire is effectively random—the comparison of male and female incoming workers with equivalent productivity deserves particular attention. To investigate this further, we compare the hiring wages of male and female replacement workers with the same starting productivity, proxied by their pre-hire wage at

[2] Section 2.2 and Appendix A.1 provide a detailed discussion of our definition of sudden deaths and excess hiring.

[3] We emphasize that the use of sudden deaths is crucial for our identifying assumption here, as these factors cannot be determined by the gender of the new hire in an unexpected departing event. Appendix Table A9 provides an overview of the top 10 predictors.

their previous firm, which we term the *adjusted gender hiring opportunity gap*. Pre-hire wage captures productivity well as demonstrated by comparisons of replacement workers' education, experience, and tenure prior to being hired.[4] If firms discriminate against women, we would expect women to exhibit higher productivity at the same wage level. Controlling for replacement worker productivity reduces the gap to 11 log points for the full sample, with a declining trend over time, reaching 5.3 log points in the past decade. In comparison, a standard gender wage gap estimation that includes firm $\times$ 3-digit occupation fixed effects, using a representative sample of full-time workers reweighted to match our sample, shows that the adjusted gender hiring opportunity gap accounts for approximately 70% of the standard gender wage gap.

Several pieces of evidence corroborate that we are indeed comparing workers hired into similar positions. First, firms do not appear to reassign job tasks to coworkers or other new hires when a female replacement worker is hired. Second, we find no evidence that firms adjust their capital investment differently when hiring a female worker. Third, weekly hours worked are comparable across male and female replacement workers in the subsample with matched hours data from 2010 to 2014. Finally, there is no significant decline in output, as proxied by firm sales, and no difference in firm exit rates.

We explore potential mechanisms behind the gender hiring opportunity gap, both from the firm side and the worker side.

While the adjusted gender hiring opportunity gap accounts for workers' productivity at the time of hiring, it is possible that firms anticipate lower future productivity for female replacement workers, particularly mothers who may transition to part-time work over time. In our data, female replacement workers are indeed more likely to shift to part-time employment, and the adjusted gender hiring opportunity gap expands to 22 log points by the fifth year after the initial hiring event. However, even among highly attached replacement workers who remain in full-time positions for up to four years after being hired, the initial gap remains remarkably similar to that of the overall sample, at 8.9 log points. This suggests that firms may base their pay decisions on group identity if they are unable to predict future productivity at the individual level (Altonji and Blank, 1999; Fang and Moro, 2011). When comparing the adjusted gender hiring opportunity gap for mothers and non-mothers, we find that the gaps

[4] Sorkin (2023) also uses existing wages as a proxy for productivity to examine the differential impacts of job loss on Black and White workers.

are very similar for women below 20 and above 40, with mothers experiencing a larger gap during reproductive years. This further highlights statistical discrimination as one channel contributing to the gender gap we document. Moreover, the gender hiring opportunity gap widens over time even for highly attached workers, suggesting that employer learning does not fully mitigate the effects of path dependency. A lower starting wage may act as a negative signal of productivity to both current and future employers (Barron et al., 1993; Bernhardt, 1995; Tô, 2018), potentially leading to reduced access to on-the-job training and further exacerbating wage disparities.

On the worker side, we probe the importance of workers' differing valuations for non-wage amenities and differences in their outside options, finding that neither appears to explain the gaps we observe. Female workers do not appear to trade off wages for shorter commuting distance (Le Barbanchon et al., 2021), as changes in commuting distance are, if anything, larger for women. While women may place greater value on workplace flexibility more (Mas and Pallais, 2017; Drake et al., 2022), our data show no evidence that they systematically sort into firms with smaller gender wage gap or those with female managers. We also compare replacement workers' outside options using several measures: an index based on Caldwell and Danieli (2024), which combines information on labor market thickness with gender-specific transition patterns across 2-digit occupations, their previous firms' median full-time wages, and firm fixed effects. We find that outside options derived from occupation and labor market conditions do not account for the gaps. Furthermore, when controlling for replacement workers' productivity, women tend to come from better, higher-paying firms.

Despite having similar outside options, female workers may still be less likely to engage in individual bargaining.[5] To investigate this, we examine how the gender hiring opportunity gaps vary across characteristics related to bargaining. We find that the gender gap is lowest—but still substantial—in jobs within the bottom quartile of occupational wage variance. The gaps do not appear to vary systematically with the hiring firms' fixed effects, suggesting that worker characteristics, rather than firm-specific factors, are more predictive of bargaining outcomes (Caldwell et al., 2024). Conversely, the gaps are largest among workers classified as having lower bargaining power by Caldwell et al. (2024), including those with smaller fixed effects and labor market entrants. These findings suggest that the ability to negotiate plays a

[5] Caldwell et al. (2024) surveyed German workers and observed that female workers may "fail to ask for more because they find it uncomfortable."

role in mitigating gender differences in offered wages.

Firms' statistical discrimination and workers' individual bargaining can both vary with gender norms at the firm and regional levels, as well as over time. Our analysis shows that the gender gap decreases for younger cohorts and mostly disappears for workers born after 1990. Firm characteristics also play a significant role: the gap is smaller in firms with a higher share of women in full-time positions, in female-friendly firms, and in firms with below-average gender wage gaps. Additionally, we find that women working in East Germany, where gender equality norms are stronger, experience a 25% smaller gap.[6]

The gender hiring opportunity gaps remain consistent across a range of robustness checks. The gaps change little when we reweight firms with external replacement hires to match firms with sudden deaths but without excess hiring after the departure event, or to all other firms in the German social-security data. Similarly, the gaps are stable under two alternative definitions of the deceased-worker-replacement-worker sample, where we relax the sample restrictions for replacement workers. The gaps, if anything, slightly increase when we control for alternative proxies of replacement worker productivity, such as education, experience, and wage profiles in the three years leading up to the hiring spell.

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; Goldin, 2014; Roussille, 2024).

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

[6]Data for East Germany are available from 1992.

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.

The use of unexpected worker departures enables us to focus on exogenous hiring opportunities from the firm's perspective. Previous studies leveraging deaths as a source of variation (Jones and Olken, 2005; Jaravel et al., 2018; Isen, 2013; Fadlon and Nielsen, 2019; Bennedsen et al., 2020; Becker and Hvide, 2022; Jäger et al., 2024) typically compare treatment groups experiencing death events to matched control groups without such events. In contrast, we use these events to examine disparities among replacement workers.

Methodologically, our approach introduces two key innovations: a technique to identify replacement workers and the application of machine learning to control for ex-ante replacement probabilities. These methods are adaptable to other settings using administrative data, where job position identifiers are often unavailable, and can be applied to examine other dimensions of disparities, such as migrant-native wage gaps.

The remainder of the paper is organized as follows: Section 2 details the data and the process for identifying sudden deaths and replacement workers. Section 3 outlines our empirical strategy. In Section 4, we quantify the gender hiring opportunity gaps. Mechanisms driving the gaps are discussed in Section 5. Finally, Section 6 concludes.

2 Exogenous Vacancies and Replacement Workers

Our paper leverages rich administrative German employer-employee matched data to study the gender hiring opportunity gap. In this section, we describe the data, our use of unexpected worker deaths as exogenous hiring shocks, and the methodology for identifying replacement workers in response to these events. While building on prior research that incorporates sudden deaths in empirical strategies, we provide new evidence on the exogeneity of the shock and firms' hiring responses by analyzing entry and exit patterns. We further leverage these patterns to develop a strategy for systematically identifying external workers who replace the departing ones.

Additional analyses make use of auxiliary datasets merged to the main dataset. These include calculated worker and firm fixed effects provided by Lochner et al. (2023), the Orbis-

ADIAB data that contain business indicators for a subset of firms (Antoni et al., 2018), hours worked data from the Statutory Accident Insurance for the period 2010-2014, and the longitudinal LIAB data to compute the standard gender wage gap. These datasets are described in detail in Appendix A.3.

2.1 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] We impute information on mothers using the algorithm provided by Müller and Strauch (2017).

While the data record wages at the daily rather than hourly level, our focus on full-time workers helps mitigate this limitation. Additionally, we address potential differences in hours worked by incorporating supplementary information on weekly work hours for the period between 2010 and 2014, obtained from the Statutory Accident Insurance as detailed in Appendix A.3.

[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 enhance it adding AKM firm FE provided by the IAB (Lochner et al., 2023).Furthermore, we impute missing education information following the methodology outlined in Fitzenberger et al. (2006). To ensure consistency over time, we deflate wages using the consumer price index from the German Statistical Office, with 2010 as the base year.

2.2 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 approach is essential for our identification strategy for two key reasons.

First, firms cannot adjust internally prior to the hiring event based on the gender of the anticipated new hire. This ensures that we can control for ex-ante factors influencing the likelihood of hiring a male versus female worker without the influence of the impacts of the event itself.[10] Section 3 details our main empirical strategy for studying the role of gender in hiring outcomes.

Second, because replacement hiring occurs after the departure event, this timing facilitates the identification of replacement workers in our analysis.

We focus on deaths occurring between 1981 and 2016 in small to medium-sized firms, defined as having a minimum of three full-time employees and a maximum of 150 full-time employees or 300 total employees in the calendar year preceding the death event.[11] This selection comprises approximately one-third of all firms, representing about 55% of social-security workers, and allows us to concentrate on cases where the departure constitutes a relatively large shock.[12] In Table A6 Appendix B.4, we show that our results are not sensitive to these firm size restrictions.

Next, we analyze exit and entry patterns surrounding the death event to validate the exogeneity of the hiring shock and inform our strategy for identifying replacement workers.

Exits Figure 1a displays the monthly exits of full-time workers in our sample during the ten months surrounding the death event. A pronounced spike in exits occurs in the month of the identified death event, both for all workers and for workers in the same 3-digit or 5-digit occupation. To confirm that this spike is attributable solely to the departure of the deceased worker, we calculate excess exits relative to 24 months prior, thereby accounting for seasonality in exit patterns.

[10] This rationale is similar to the use of sudden deaths in Jäger et al. (2024) to study worker substitutability, where the empirical strategy involves matching firms with and without a departing worker based on firm characteristics prior to the sudden death events. For departures due to sudden deaths, these controls are unaffected by the death itself.

[11] A large number of firms have only one to two full-time employees.

[12] As Jäger et al. (2024) note, "in larger establishments worker exits due to death occur more frequently due to the law of large numbers, thus preventing an analysis of sharp shocks."

Figure 1b shows that the number of excess exits is exactly one, both overall and within the same occupations as the deceased worker. This provides reassurance that the unexpected death constitutes an exogenous hiring shock.

Entries Panels (c) and (d) of Figure 1 plot the number of monthly entries of full-time workers, and of excess entries compared to 24 months earlier, respectively. Hiring patterns remain stable in the ten months preceding the death event but show a sharp increase immediately afterward, staying elevated for approximately six months. Excess hiring fluctuates around zero before peaking in the first month following the death event, at approximately 0.13 workers when considering all full-time workers and 0.1 workers when focusing on new entries in the same 3-digit or 5-digit occupation, respectively. Overall, about 33% of sudden deaths (77,867 events) are followed by excess—and therefore external—hiring. Notably, 61% (57%) of this excess hiring occurs within the same 3-digit (5-digit) occupation as the departing worker, suggesting that firms aim to replace the departing worker. While our main analysis will focus on events with excess hiring, we reweight our sample to all other firms in Appendix B.2.

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, (ii) within the same 3-digit occupation as the deceased worker, (iii) occurring within the first six months following the death event. Table A6 and Appendix B.4 show that our results are largely the same when using the subset of events with exactly one full-time new hire in the same 3-digit occupation as the deceased worker.

2.3 Construction of Panel Data

Sample Selection Our main sample focuses on departure events that are followed by external hiring. To understand factors driving external hiring, we also construct a complementary sample of departure events without external hiring.

For events with excess hiring, we include all workers employed at the respective firms during the 12 calendar years surrounding the death event. For events without excess hiring, we include all workers employed at the respective firms during the four calendar years preceding the death event.

Firm Panel Our empirical strategy requires finding factors that affect hiring decisions of firms ex-ante. We construct a firm panel comprising both excess and non-excess hiring firms and gather firm characteristics for the three years preceding the sudden death events.

The cut-off date is the date of death, meaning we record the status quo in the three calendar years prior to the year of death, based on the exact day and month of the event. We calculate detailed metrics on the firm's workforce composition and its wage bill, where the wage bill is defined as the total of all employees' daily wages, multiplied by the number of days worked at the firm per year. For a comprehensive list of firm variables included in our machine learning prediction algorithm, see Appendix B.1.

For excess hiring firms, which are the primary focus of our analysis, we construct an additional firm panel that includes the wage bill for all workers, incumbents, and new hires in the years surrounding the death event, using the date of death as the cut-off. Incumbent workers are defined as employees whose work spell at the firm overlaps with the date of death, while new hires are defined as employees who worked at the firm in year t but not in $t-1$. We further categorize employees into (i) all workers and (ii) coworkers, with coworkers defined as those working in the same 3-digit occupation as the deceased and replacement worker.

Deceased-Replacement Panel Finally, we construct a yearly panel of deceased-replacement workers in excess hiring firms, which serves as our baseline sample. This dataset includes a unique pair ID linking each deceased-replacement pair, as well as a unique event ID for each firm $\times$ death event.[13]

To analyze firms' wage-setting behaviors, we focus on deceased-replacement pairs where both workers held full-time contracts at the time of death and at the time of hiring, respectively.

We exclude a small fraction of firms with unusual hiring patterns: specifically, those that hired more than 150 new workers in any given month within the three years prior to or one year after the death event, as well as firms that hired ten or more full-time workers in the same 3-digit occupation as the deceased worker in the year preceding the death.[14]

[13] Firms can appear in the dataset multiple times if sudden deaths occur in different calendar years. During our sample period, firms experience between 1 and 10 sudden worker deaths; for excess hiring firms, this range narrows to between 1 and 7 events.

[14] In less than 2% of baseline events, the deceased worker's final full-time employment spell records zero wages. This is likely due to measurement error, such as misreported wages by the firm or an earlier date of death. To minimize measurement error, we also exclude these events.

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 instance, if the final spell of a deceased worker ended on May 15, 2014, then this will serve as their cut-off date, denoted as $t = d$. All previous years are defined relative to this cut-off date; for example, May 15, 2013, corresponds to $t = d - 1$, and so forth. Similarly, if a replacement worker is hired on June 22, 2014, this date becomes their cut-off date, denoted as $t = r$. June 22, 2015, would then correspond to $t = r + 1$, and June 22, 2016, to $t = r + 2$.

We also gather information on replacement workers' characteristics at the cut-off date in their previous job, denoted as $r - 1$, before starting work at the treated firm. In our baseline analysis, we focus on replacement workers who are highly attached to the labor market. Specifically, we restrict the deceased-replacement panel to replacement workers whose employment contract in $r - 1$ was a full-time job, and who did not experience an unemployment insurance (UI) spell between $r - 1$ and r. Additionally, we exclude women whose last employment spell ended in maternity leave.

After applying these restrictions, our sample comprises 28,771 deceased-replacement worker pairs, with the baseline model identified for 28,380 pairs. We replicate the main results of the paper in Appendix E, relaxing the restrictions by (i) excluding the condition of no UI spells between $r - 1$ and r, and (ii) excluding both the no-UI-spell condition and the requirement of a full-time job in $r - 1$.[15]

Summary statistics of deceased and replacement workers in Table 1 show that deceased workers earn higher wages than replacements, likely reflecting their greater 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. For a more detailed discussion of Table 1, including patterns of sorting across 1-digit occupations and industries, see Appendix Section A.1.

[15]Table A6 and Appendix B.4 also consider the subsample of replacement workers who are within one year of their previous job, finding largely the same results.

2.4 Raw Evolution of Wages by Transition Group

We conclude this section by analyzing the evolution of wages for departing and incoming workers by gender in the raw data. As the results will show, the gender of the incoming hire plays a critical role in shaping their wage trajectory.

To examine this, we regress y_{ptg}, representing the wages of the departing or replacement worker within pair p, at time t, and in group g, on dummies for the year since death for the departing worker and year since hiring for the replacement worker.

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

Group g denotes one of four transition types: (i) male-male, (ii) male-female, (iii) female-male, and (iv) female-female.

Time is measured from four years prior to the death event $t = d - 4$ to the time of death $t = d$, and continues from the starting date of the replacement worker $t = r$ until five years after hiring $t = r + 5$. Observations for $t \in \{d-4, ..., d\}$ capture the outcomes of the departing worker, while observations in $t \in \{r, ..., r+5\}$ correspond to outcomes of the replacement worker.

The coefficients of interest are β_j, which captures the wage evolution for individuals in the male-male transition group ($g = 1$), and δ_{jg}, which measure the wage evolution for individuals in all other groups.[16]

Figure 2 plots the raw evolution of wages by transition group. In Panel (a), the outcome variable is (deflated) daily wages in EUR, in Panel (b) we plot log wages.

Consistent with Table 1, replacement workers generally earn less than departing workers, at least initially, except in the case where a male worker replaces a female outgoing worker. Male replacement workers either reach wage parity with their departing counterparts when replacing a male worker or quickly surpass their wages when replacing a female worker.

The pattern is markedly different for female replacement workers, who consistently earn less than their departing counterparts, especially when replacing male workers.

While the raw data point to the role of gender in determining the replacement worker's wages and career trajectories, we need an empirical strategy that accounts for ex-ante differ-

[16] All coefficients are estimated relative to $t = d$ for transition group (i), i.e., relative to the wages of deceased male workers followed by a male replacement in the year of death.

ences in the hiring opportunity by the gender of the new hire.

3 Empirical Strategy

To formally assess the impact of gender on new hires' wages, it is crucial to account for the non-random nature of incoming hires' gender. Leveraging exogenous vacancy shocks, we develop a novel strategy to control for factors affecting the ex-ante probabilities of hiring workers of different genders. Since this involves a prediction exercise, we employ machine learning methods to identify these factors. We then describe our main regression analysis and underlying assumptions.

3.1 Predicting Excess Hiring and Gender of the Replacement Worker

Our baseline sample consists of firms that hire replacement workers externally, identified by exhibiting excess hiring relative to 24 months prior. Within this sample, we focus on whether the firm hires a female or male replacement worker.

We conduct two prediction exercises: the first examines how firms with excess hiring differ from those without, and the second predicts the likelihood that the replacement worker is female versus male. For these prediction exercises, we employ random forests, a machine learning algorithm designed for classification and regression tasks.[17]

We evaluate the performance of the model using 5-fold cross-validation. Predictor variables include factors such as the gender composition of the establishment by full-time status and occupation, the gender, wage, and tenure of the deceased worker, detailed occupation and industry classifications, establishment size, various measures of establishment wages, and local labor market thickness. For a comprehensive list of variables, see Appendix B.1.

We evaluate the performance of our two binary classification models using a Receiver Operating Characteristic (ROC) curve. An ROC curve plots the true positive rate (sensitivity) against the false positive rate (1 - specificity) across various classification thresholds, providing a visual assessment of a model's ability to correctly classify positive instances while

[17]We use the R package `ranger` alongside the `mlr3` package, which provides a comprehensive framework for machine learning. `ranger` implements the Random Forest algorithm, combining multiple decision trees for prediction. Its multi-threading and parallel processing capabilities make it well-suited for handling large datasets and complex problems. In our case, this involves approximately 190,000 observations and 600 variables encompassing firm characteristics and labor market conditions in the three years preceding the death event.

minimizing false positives.[18] The area under the curve (AUC) quantifies the model's overall performance in distinguishing between positive and negative classes. A perfect model achieves an AUC of 1, while a random model yields an AUC of 0.5.

Predicting Excess Hiring Figure A5a presents the model's ROC curve, which lies above the 45-degree line, with an area under the curve (AUC) of 0.77. This indicates that the model has a 77% chance of ranking a randomly chosen firm with a replacement worker higher than a randomly chosen firm without one. While this suggests that firms with and without replacement workers are observably similar, there are non-negligible differences.

Panel A of Table A9 lists the top 10 predictors, which are dominated by pre-event workforce composition at the firm—particularly 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 the three years leading up to the departure event from $d-3$ to $d-1$. These findings align with Table A3, which shows that firms with excess hiring tend to be slightly larger, employ fewer high-skilled workers, and pay lower wages than firms without excess hiring. It is unsurprising that larger firms are more likely to secure an external replacement for a sudden vacancy. To address potential concerns about external validity, we conduct a reweighting exercise detailed in Appendix Section B.2, finding largely similar results.

Predicting Female Replacement We next predict the gender of the replacement worker, a key component of our identification strategy, as it allows us to control for the ex-ante probability of hiring female workers.

To predict the gender of the replacement worker, we restrict the sample to the 77,867 firms with excess hiring. The ROC curve in Figure A5b shows an area under the curve (AUC) of 0.924, indicating that the model has a 92.4% probability of ranking a randomly chosen firm with a female replacement worker higher than a randomly chosen firm with a male replacement worker. This suggests that the firm and local labor market characteristics used in the machine learning algorithm are highly predictive of the replacement worker's gender. In fact, the model achieves 86.4% accuracy in predicting the gender of the replacement worker through five-fold cross-validation.

[18] 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.

Panel B of Table A9 lists the top 10 predictors. Unsurprisingly, the gender of the deceased worker emerges as the most important predictor. The remaining predictors primarily highlight the significance of workforce composition by gender. These include metrics such as the overall share of women at the firm, the share of women in full-time positions, and the share of women in the same 3-digit occupation at the hiring firm.

3.2 Estimating Equation and Identification

Estimating Equation We are interested in the differences in the outcomes of female and male replacement workers hired into comparable opportunities. Our baseline regression specification to capture the *gender hiring opportunity gap* using our deceased-replacement worker panel is as follows:

$$y_{it} = \beta_{0t} + \beta_{1t}\text{female\_replacement}_i + \gamma_t \boldsymbol{X}_i + \epsilon_{it}, \tag{2}$$

where i is a hiring event associated with a sudden departure, $\text{female\_replacement}_i$ is an indicator if the replacement worker is female, and t is time relative to the event, from four years before the departure 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 $t = r + 4$.[19]

The vector $\boldsymbol{X}_i$ includes a set of controls designed to hold fixed the ex-ante probability of hiring a female worker. Specifically, we account for deciles of the ex-ante probability of female replacement at the firm, as predicted by the random forest machine learning algorithm described in Section 3.1.

In a linear specification, directly controlling for the probability may lack sufficient flexibility. We therefore include additional firm- and position-level factors from the top predictors influencing firms' gender-related hiring decisions. These factors include the departing worker's gender, wage deciles, and 3-digit occupation at $t = d$; the calendar year of death t; the share of full-time women in the same 3-digit occupation at the firm at $t = d$; the number of full-time workers at the firm at $t = d$; the number of women in the same 3-digit occupation at $t = d$; and deciles of the total wage bill, female-only wage bill, overall coworkers' wage bill, and female coworkers' wage bill at $t = d$.

To capture the *adjusted gender hiring opportunity gap*, we further control for deciles of

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

the replacement worker's pre-hire wage at their previous firm as a proxy for their productivity. This ensures that our results are not simply driven by differences in productivity in the pool of available workers.[20]

We estimate Equation (2) separately for each t and cluster standard errors at the event (firm $\times$ date of death) level.

Identifying Assumption Our identifying assumption is that, conditional on the ex-ante probability of hiring a female replacement worker, the realized gender of the new hire is effectively random. This assumption holds if there are no unobserved factors that simultaneously influence the firm's decision to hire a female or male worker and the outcomes of replacement workers.

In other words, given our controls, the position into which a man or woman is hired is identical in all relevant aspects that could affect their outcomes ex-ante. Any observed differences in outcomes ex-post are therefore attributable to firms' responses to the gender of the new hire. Our estimating Equation (2) allows us to test this assumption by directly comparing position- and firm-level characteristics by replacement gender in the periods leading up to the event, examining not only trends but also levels. We show the plausibility of this assumption when discussing our results in the next section.

Our identification strategy relies on the assumption that the gender of the new hire does not influence firm outcomes prior to the departure event. For instance, a potential threat to identification would arise if firms respond to performance improvements by hiring a male worker instead of a female worker, thereby offering the male worker a higher wage. The use of sudden deaths as exogenous hiring shocks circumvents these concerns. As demonstrated in Section 2.2, the events we identify are exogenous with no anticipated changes in entries or exits.

[20] If women are systematically underpaid, as our findings suggest, their previous wages will likely underestimate their productivity, leading to a downward bias in our coefficients. In a robustness check, we control for alternative proxies for replacement workers' productivity including tenure, experience, occupational skill, three-year wage profile, all measured in $r-1$. Table A7 and Appendix B.4 show that the adjusted gender hiring opportunity gap is indeed at least as large in all of these additional specifications. See also Sorkin (2023), who uses previous wages as a proxy for productivity to study racial disparities following job loss.

4 The Gender Hiring Opportunity Gap

4.1 The Gender Hiring Opportunity Gap

To investigate how similar work opportunities within firms lead to different wage trajectories for male and female new hires, we estimate Equation (2) using log daily wages as the outcome variable.

Figure 3a, Panel "Same Hiring Opportunity", displays the β_{1t} coefficients on female replacement, which we define as the *gender hiring opportunity gap*. Figure 3a, Panel "+ Same Pre-Hire Wage", presents the corresponding coefficients when deciles of the replacement worker's wage at their previous firm prior to being hired are included as controls, capturing what we term the *adjusted gender hiring opportunity gap*.[21]

The coefficients for $t \in \{d-4,\ldots,d\}$ reflect the outcomes of the departing worker during the four years leading up to the departure event at time d, while the coefficients for $t \in \{r,\ldots,r+4\}$ capture the outcomes of the incoming worker over the four years following their hiring.

Pre-trends All controls are measured at d, including deciles of the outgoing worker's wages. This setup allows coefficients β_{1t} for $t = d-4$ to $t = d-1$ to serve as tests of our empirical strategy, demonstrating that incoming workers are indeed hired into comparable positions. Since we estimate these equations separately for each t, we are effectively comparing the wage trajectories of outgoing workers in levels. The coefficients are near zero and precisely estimated, providing strong support for our identifying assumption.

We further assess this assumption by comparing relevant firm characteristics measured in $d-2$, two years before the departure event, by the gender of the replacement worker. Table A8 presents the results, showing the coefficient on *female replacement* across eight firm-level variables in 16 specifications (corresponding to "same hiring opportunity" and "+ same pre-hire wage" for each variable). The firm-level characteristics considered include the coworker wage bill (either for coworkers in the same 3-digit occupation or those with overlapping work spells at the event firm), the existing gender wage gap at the firm (excluding the outgoing worker), firm fixed effects, the share of mothers or female employees at the firm, and the share of female team leaders or the presence of at least one female manager with a child

[21] In our sample, all replacement workers were already working full-time prior to being hired.

aged 0 to 8. Although hiring firms exhibit slightly higher firm fixed effects and a greater share of female workers and female team leaders two years before the event, these differences are small in magnitude. Furthermore, as shown in Figure 5 and Table 4, the gender hiring gap is largely unaffected by these factors and, if anything, is smaller in firms with a higher share of female workers.

Wage Differences at Hire and Wage Trajectories over Time Using our data spanning between 1985 and 2016, on average, female replacement workers earn about 20 log points lower wages than their male counterparts upon being hired into a similar hiring opportunity. The initial gap is half as large, at about 11 log points, when we consider replacement workers with similar productivity prior to being hired, as proxied by their pre-hire wage. This suggests that the gender hiring opportunity gap is not simply driven by differences in the pool of available workers.

The gaps widen over time, reaching 30 log points for the gender hiring opportunity gap and 22 log points for the adjusted gender hiring opportunity gap by year five after the hiring event. These gaps translate into substantial differences in earnings, as illustrated in Figure A3. Starting from initial earnings gaps of 5,000 EUR and 2,200 EUR for the gender hiring opportunity gap and its adjusted counterpart in the year of the hiring event, the gaps grow to nearly 9,300 EUR and 6,800 EUR, respectively, within five years. The widening of the earnings gaps partly reflects the higher likelihood of female replacement workers transitioning to part-time employment over time. This difference may arise from inherent preferences, for example, as female workers become mothers, or from labor supply responses to lower wages among female workers. In Section 5, we explore mechanisms behind these gaps including firms' statistical discrimination and worker preferences.

4.2 Comparability of Replacement Worker Positions

Although our empirical strategy compares similar hiring opportunities across replacement genders ex-ante, the positions held by replacement workers may diverge ex-post if firms assign different job tasks or implement internal adjustments upon hiring based on the gender of the new hire. However, our data indicate that this is unlikely to be the case.[22]

[22] This subsection leverages several merged datasets that we describe in more details in Appendix A.3.

Work Hours First, we demonstrate that there is no evidence of differences in hour requirements between jobs held by male and female replacement workers.

In Panel A of Table 2, we present the coefficient β_{1t} at $t = r$ for replacement workers, using days worked full-time per year and log hours worked per week (for a subsample of workers with available hours data) as outcome variables.

While female replacement workers work 5.02 days fewer as full-time employees in their first year of being hired compared to male replacement workers when pre-hire productivity is not controlled for, this difference disappears when comparing equally productive workers.[23] This difference furthermore may reflect female workers' labor supply responses to lower wages rather than variations in the hour requirements of the position. To investigate further, we examine weekly hours worked using the subsample of data where this information is available.

We leverage a linkage between the IAB data and hours worked information from the Statutory Accident Insurance for the period 2010–2014. For this timeframe, we successfully merge 1,894 pairs out of 2,631 pairs, i.e., approximately 72% of our analysis sample in 2010–2014. During this period, the adjusted gender hiring opportunity gap is 6.6 log points (see Table 4, Panel A, column 6), compared to the 6.5 log points in the hours-matched subsample. Notably, across both of our main specifications, we find no significant differences in weekly hours worked by the gender of the replacement worker.

Firm-level Adjustments Next, we examine whether firms respond to the gender of the new hire by making internal adjustments. For example, firms might reassign tasks or adjust pay for coworkers in response to hiring a female worker, or they might increase capital investment. Systematic differences in the position could also differentially impact firms' output. We investigate each of these possibilities in turn.

We start with Panel B of Table 2, which examines changes in the coworkers' wage bill following the hiring event at $t = r$. Here, coworkers are defined as all workers in the same 3-digit occupation as the departing worker. We analyze the total wage bill for all coworkers, as well as the breakdown between incumbent workers and new hires. Incumbents are defined as employees whose employment spell overlaps with the date of the departing event, while new hires are those employed at the firm on the date of death in $d + 1$ but not in d. In all

[23] 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.

cases, the coefficients β_{1t} are statistically insignificant, with small or negative magnitudes. This suggests that firms are unlikely to shift responsibilities to other coworkers and increase their compensation as a result.

In Panel C of Table 2, we use the Orbis-ADIAB data for a restricted sample of large firms to examine the impact of replacement worker gender on capital and sales per worker.[24] We find that changes in capital adjustment are insignificantly negative, and sales per capital, if anything, increase slightly upon hiring an equally productive female worker. Furthermore, there is no evidence of differential effects on firm exits. These findings suggest that firms are unlikely to adjust their capital investment in response to hiring a female worker, and their output remains largely unchanged.

4.3 Discussion of Magnitudes

Figure A1 contextualizes this gap by comparing it to the gender wage gap among full-time workers in Germany, drawn from the *LIAB, 7519, Version 1* dataset, reweighted to match our baseline analysis sample.[25] The figure presents the adjusted gender gap across various specifications in the LIAB data, controlling for human capital factors in a Mincerian regression, with additional controls for industry, occupation, establishment fixed effects, and establishment × occupation fixed effects.

The adjusted gender hiring opportunity gap aligns closely with the standard adjusted gender wage gap over time. In the most recent years, the adjusted gender hiring opportunity gap is about 5 log points. On average, it accounts for approximately 70% of the gender gap in the LIAB specification that includes establishment × 3-digit occupation fixed effects.

The gap may be higher in our analysis sample compared to a sample of all female full-time workers because we focus on workers at the hiring stage, whereas female workers who remain in full-time positions over time may be positively selected and therefore earn higher wages. If female workers respond to lower initial wages by transitioning to part-time employment, the hiring stage becomes particularly critical for understanding the dynamics of the gender wage gap.

[24] The data are winsorized by setting values below the 1st percentile and above the 99th percentile to missing.
[25] See Appendix Section A.3 for an overview on the dataset.

5 Drivers of the Gender Hiring Opportunity Gap

In this section, we explore potential mechanisms underlying the gender hiring opportunity gap, both from the firm side and from the worker side.

5.1 Mechanisms on the firm side

While the adjusted gender hiring opportunity gap accounts for the productivity of replacement workers at the time of hiring, firms may still statistically discriminate if they expect one group to be less productive in the future—for instance, due to anticipated care responsibilities (Tô, 2018). As discussed in Section 4, women are more likely than men to transition into part-time work or leave the labor market, which employers might predict and use to justify offering lower starting wages based on gender.

To test this hypothesis, we restrict the sample to workers who remain in full-time positions for at least four years following the hiring event.[26] Figure 3b presents β_{1t} coefficients for the gender hiring opportunity gap on the left and the adjusted version, controlling for pre-hire wages, on the right. The results show that the initial gender gaps at the time of hiring for these workers are strikingly similar to those in the full sample, suggesting that firms may base pay decisions on group identity (Altonji and Blank, 1999; Fang and Moro, 2011).[27]

The persistence of the gap within this subgroup indicates that employer learning (Farber and Gibbons, 1996; Altonji and Pierret, 2001) fails to mitigate initial pay differences. This is the case even though replacement workers work comparable numbers of full-time days across genders over the five-year period, as shown in Figure A4. The hiring stage proves critical, as disparities at this point can shape career trajectories through unequal access to on-the-job training within the same employer or by acting as a negative signal to future employers (Waldman, 1984; Bernhardt, 1995; Tô, 2018), thereby compounding gender pay gaps over time.

Firms may engage in statistical discrimination against female workers based on expectations of future caregiving responsibilities. To investigate this, we analyze the gender hiring opportunity gap by age and motherhood status of replacement workers at the time of hiring, as shown in Figure 4a. Across the lifecycle, the gender hiring opportunity gap is smallest for

[26] This includes workers who switch employers but continue in full-time roles at different firms.

[27] Figure A4 confirms that, within this subgroup, replacement workers do not exhibit gender-based differences in the number of days worked full-time.

non-mothers but largest for mothers aged 26 to 35. However, this motherhood gap disappears for workers under 20 or over 40.

These patterns are consistent with firms statistically discriminating against female workers during periods when they are more likely to have younger children. However, the gender differences we observe are not solely driven by motherhood status, as a substantial gap persists for workers over 40.

We now turn to mechanisms on the worker side, distinguishing between channels driven by preferences, such as the tradeoff between wages and non-wage amenities, and those influenced by differences in bargaining.

5.2 Mechanisms on the worker side

Worker Characteristics We start by showing that the *adjusted gender hiring opportunity gap* accounts for worker productivity at the time of hiring, as measured by education, experience, tenure, occupational tenure, and full-time workdays in the previous job. Panel A of Table 3 presents the results of estimating Equation 2 with each of these characteristics as the outcome, measured at $t = r - 1$. Notably, female replacement workers, if anything, have higher occupational tenure and work approximately six more full-time days in their previous job before being hired.

Non-wage Amenities The literature has documented that female workers value a shorter commuting distance (Le Barbanchon et al., 2021) and workplace flexibility (Mas and Pallais, 2017; Drake et al., 2022). In a model of compensating differentials, workers may accept lower wages in exchange for amenities they value (Rosen, 1986).

To assess whether compensating differentials contribute to the gender hiring opportunity gap, we first examine changes in women's commuting distances relative to their previous jobs.[28] For this analysis, we estimate Equation 2, using the difference in commuting distance between the replacement worker's new job at $t = r$ and their previous job at $t = r - 1$ as the outcome variable. The first row of Panel B in Table 3 presents the results. The coefficient on female replacement is positive but insignificant across both specifications, suggesting that,

[28] Commuting distance is measured based on municipality centroids; see Appendix A.2 for details. The IAB data provides information on workers' places of residence starting in 1999, allowing us to observe commuting patterns for events in the 2000s and 2010s.

if anything, changes in commuting distance are larger for female workers. Thus, commuting distance differences cannot explain the gender hiring opportunity gaps.

Next, we examine whether women are more likely to sort into female-friendly firms. Our empirical strategy ensures that the firms and positions into which workers are hired are ex-ante comparable across replacement worker gender along dimensions relevant to worker outcomes, as demonstrated in Table A8. However, it remains possible that firms adjust ex-post, so we analyze indicators of family friendliness at the time of hire $t = r$. Rows 2 and 3 in Panel B of Table 3 indicate that women are not more likely to move to firms with lower gender wage gaps, which are often associated with more female-friendly work environments (Folke and Rickne, 2022). This finding holds for both the overall gender wage gap at the firm (relative to their previous employer) and the gender wage gap among workers in the same 3-digit occupation at the hiring firm. Furthermore, women are not more likely to join firms that can be considered female-friendly, as proxied by the presence of at least one female manager with a child aged 0-8.

Although our data do not include information on workers' schedules, we find that the gender hiring opportunity gaps persist even among non-mothers across all age groups (see Figure 4a). This suggests that differences in the value placed on amenities are unlikely to fully explain the persistence of these gaps.[29]

Outside Options Bargaining may contribute to the gender hiring opportunity gaps if female workers have weaker outside options or are less likely to engage in bargaining, regardless of their bargaining power. We employ three measures of outside options and show that differences in outside options cannot account for the adjusted gender hiring opportunity gap.

Our first proxy approximates workers' job opportunities across occupations, weighted by their likelihood of working in each.[30] It combines two measures: (i) labor market thickness by 2-digit occupation and commuting zone, as proposed by Jäger et al. (2024), and (ii) a matrix of occupational transitions by gender and calendar year, derived from a 20% random sample of workers in Germany.[31] The other two proxies assess outside options based on firm characteristics: median full-time wages and firm AKM fixed effects. Panel C of Table 3

[29] Our results do not imply that women do not value these amenities more than men. Drake et al. (2022) demonstrate that workers may face differential amenity prices, implying that worker preferences alone may not account for differences in the incidence of amenities.

[30] This proxy is based on Caldwell and Harmon (2019).

[31] See Appendix A.2 for details.

presents the results for all three measures.

We find no gender differences in the outside option index based on labor market conditions. For the firm-level proxies, under the specification for the adjusted gender hiring opportunity gap, women are found to come from firms with higher median wages and higher firm fixed effects, suggesting that differences in outside options are unlikely to drive the gap.

Bargaining Even when outside options are held constant, women may still bargain less or less effectively than men. Although our data do not directly capture negotiation behavior, we analyze heterogeneity in the gender gap across four dimensions that plausibly influence bargaining outcomes.

We begin by examining occupational wage variance, calculated at the 3-digit occupation $\times$ county level, as greater wage variance within occupations may provide more flexibility in wage setting, potentially amplifying gender gaps. Figure 5a presents the results. The gender hiring opportunity gaps are slightly smaller in the bottom quartile of occupational wage variance but remain significant, with the adjusted gap at approximately 9 log points. This suggests that while wage-setting flexibility, as proxied by occupational wage variance, plays a role in contributing to gender gaps, its overall impact appears to be limited. The smallest gaps occur in occupations with tight wage-setting behavior such as education and public administration as shown in Figure A6.

Next, we analyze heterogeneity across quartiles of the hiring firm's AKM firm fixed effect. Figure 5b demonstrates that the gender gap is remarkably consistent across all four quartiles. This finding aligns with Caldwell et al. (2024), who show that worker characteristics, rather than firm characteristics, are the primary predictors of bargaining propensity.

Finally, we investigate the role of two worker-specific characteristics identified by Caldwell et al. (2024) as strong predictors of bargaining, worker AKM fixed effects and labor market experience.[32] The latter is divided into three groups: (i) recent labor market entrants with less than three years of work experience, (ii) experienced non-managers with at least three years of work experience and without leadership tasks, and (iii) managers.[33]

Figure 5c shows that workers in the lowest quartile of AKM worker fixed effects have the

[32] It is worth noting that Caldwell et al. (2024) relies on survey data collected in 2021 and 2022, after the end of our observation period. Therefore, any comparison with their findings assumes that bargaining strategies have remained largely unchanged since the 1980s.

[33] We define managers as workers whose 5-digit occupational code ends in '3' or '4'. The result is robust to instead defining managers as workers whose fourth digit in the 5-digit occupational code is '9'.

highest gender hiring opportunity gaps, approximately 7-9 percentage points higher than the gap for workers in the other quartiles. Figure 5d shows that the adjusted gender hiring opportunity gap is approximately three times larger for recent labor market entrants compared to managers. In both cases, groups with lower labor market power exhibit the highest gender gaps.[34] Consistent with this, Figure A7c shows a (noisy) zero gender gap for "bottleneck occupations," which are hard to fill.[35]

While positions with higher scope for bargaining, such as those held by workers with higher fixed effects or managerial roles (Caldwell et al., 2024), may lead to differential negotiations by gender, it is also important to note that women with less labor market experience or lower worker fixed effects may simply ask for less.[36]

5.3 Heterogeneity by Gender Norms

Both firm discrimination and worker bargaining behavior may be shaped by gender norms inside and outside the firm.

Table 4 shows that the adjusted gender hiring opportunity gap is smaller in firms with a larger share of full-time female workers, firms with lower gender wage gaps, and firms that are more family-friendly, as proxied by having at least one female manager with a child aged 0 to 8. Additionally, the adjusted hiring opportunity gap is smaller in East Germany, where gender equality norms are stronger (Boelmann et al., 2024).

We also find that the adjusted gender hiring opportunity gap has decreased over the decades but has plateaued at around 7 log points since the 2000s. Figure 4b shows that recent cohorts experience significantly smaller gaps, and this trend is not simply attributable to age effects, as illustrated in Figure 4a.

[34] Similarly, Table 4 shows that workers in roles with higher skill intensity experience a lower adjusted gender hiring opportunity gap.

[35] We use the definition of bottleneck occupations from Caldwell et al. (2024), detailed in Appendix A.2. Note that the bottleneck occupation indicator is only available for 2011–2016, and our sample includes just 300 deaths in bottleneck occupations.

[36] For example, Caldwell et al. (2024) observe in their surveys that "[w]omen are less likely to provide salary expectations and provide lower expectations as a fraction of their current salary, even when the range is provided."

6 Conclusion

This paper investigates the gender hiring opportunity gap—wage disparities arising from similar hiring opportunities within firms—and its underlying mechanisms. Using administrative data from Germany spanning four decades, we exploit exogenous hiring events created by unexpected worker deaths to study wage-setting practices. Comparing positions with the same ex-ante probability of hiring female workers using a machine learning prediction exercise, our findings reveal substantial and persistent gender disparities: female replacement workers earn 20 log points lower starting wages overall and 11 log points when compared to their equally productive male counterparts. The gaps are persistent and widen over time, even for highly attached workers.

Our analysis demonstrates that this gap is not driven by differences in job tasks, capital investment, or working hours, nor by workers' preferences for non-wage amenities or their outside options. Instead, statistical discrimination by firms and differences in individual bargaining power emerge as key contributors. Women, particularly mothers during their reproductive years, face larger gaps, and those with lower bargaining power experience the greatest wage penalties. The persistence of the gap highlights the signaling effects of lower starting wages, which may limit women's access to on-the-job training and further career advancement.

We thus highlight a key driver of the dynamics of the gender wage gap: equally productive men and women benefit differently from a hiring opportunity. Over time, as firms condition their pay on past wages, this difference perpetuates and is captured as differences in worker fixed effects rather than firm fixed effects in a static AKM framework. In our analysis, equally productive men and women appear very similar before a hiring opportunity, yet when computing their fixed effects over the course of their careers, women are 11 log points lower. This explains why the "bargaining" component of the gender wage gap we identify is substantial relative to that of Card et al. (2016), who decompose worker and firm fixed effects into a bargaining and a sorting component using the Kitagawa-Blinder-Oaxaca decomposition.

From a policy perspective, the persistence of the gender hiring opportunity gap demonstrates that lower starting wages can fail to reflect a worker's productivity, perpetuating wage disparities as a form of systemic discrimination. Policies aimed at reducing wage disparities may be most effective when targeting starting wages, as initial pay decisions often have long-term impacts on workers' career trajectories. Pay transparency measures, in particular, should explicitly target the hiring stage to ensure equitable wage-setting practices from the outset. For example, requiring firms to disclose starting salaries and justify deviations from productivity-based benchmarks could help reduce systemic disparities and promote greater gender equity in pay structures. Addressing these systemic factors is essential for breaking the cycle of wage inequality and fostering a more equitable labor market.

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7 Tables

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

	(1) Random Sample	(2) Male-Male	(3) Opposite-Sex	(4) Female-Female
Panel A		*Deceased Worker at the departing event d*		
Daily Wage in EUR	91.7 [53.8]	97.7 [50.7]	101.0 [65.2]	78.3 [33.0]
Days Worked Full-time	332.1 [79.9]	344.2 [63.8]	344.5 [66.0]	340.8 [71.9]
Age	38.7 [11.4]	45.4 [11.2]	45.6 [11.4]	43.1 [12.3]
Tenure in Firm (years)	5.87 [5.97]	6.77 [6.37]	7.63 [6.90]	6.77 [6.07]
Occ. Tenure (years)	8.19 [7.04]	9.92 [7.71]	10.4 [8.04]	9.40 [7.24]
Experience (years)	13.0 [8.54]	14.9 [8.70]	15.1 [8.83]	13.0 [8.20]
Education (years)	12.2 [1.93]	11.9 [1.43]	12.3 [1.92]	11.8 [1.45]
Mother	0.074 [0.26]	0 [0]	0.035 [0.18]	0.11 [0.32]
Panel B		*Replacement Worker at the hiring event r*		
Daily Wage in EUR	91.7 [53.8]	89.7 [68.6]	86.0 [35.6]	71.7 [30.8]
Days Worked Full-time	332.1 [79.9]	329.5 [76.5]	331.3 [77.6]	327.6 [80.7]
Age	38.7 [11.4]	35.0 [10.0]	33.5 [10.0]	32.7 [10.4]
Tenure in Firm (years)	5.87 [5.97]	0.51 [0.68]	0.54 [0.66]	0.52 [0.58]
Occ. Tenure (years)	8.19 [7.04]	4.42 [5.67]	4.50 [5.43]	4.53 [5.22]
Experience (years)	13.0 [8.54]	10.9 [7.18]	9.83 [6.94]	9.10 [6.60]
Education (years)	12.2 [1.93]	12.1 [1.57]	12.4 [2.09]	12.0 [1.49]
Mother	0.074 [0.26]	0 [0]	0.11 [0.31]	0.16 [0.36]
Number of Individuals	14,905,321	22,595	3,582	2,594

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 of male-male transition pairs, column (3) shows characteristics of opposite-sex transition pairs, and column (4) shows characteristics of female-female transition pairs. Columns (2)-(4) in Panel A present the characteristics of deceased workers in their last working spell, and column (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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table 2: Wages, Employment, and Adjustments Within Event Firms

	(1) Coefficient Female Replacement Same Hiring Opportunity		(2) Coefficient Female Replacement + Same Pre-Hire Wage		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment					
Log Wage	**-0.20**	[0.0067]	**-0.11**	[0.0056]	28,380
Days Worked Full-Time per Year	**-5.02**	[1.59]	-0.45	[1.63]	28,380
Log Hours Worked per Week	-0.020	[0.018]	-0.022	[0.018]	1,894
Log Wage if in Hours Data (2010-2014)	**-0.14**	[0.028]	**-0.065**	[0.021]	1,894
Wage Bill Replacement Worker (EUR)	**-4523.3**	[213.0]	**-2224.2**	[196.9]	28,380
Panel B: Coworker Wage Bill					
Wage Bill All Coworkers (EUR)	-2149.2	[9936.6]	-3695.3	[9879.8]	28,380
Wage Bill Incumbents (EUR)	-4237.6	[8693.2]	-6979.2	[8543.7]	28,380
Wage Bill New Hires (EUR)	1469.1	[3374.9]	2297.4	[3529.4]	28,380
Panel C: Firm-level Adjustments					
Capital/Person (EUR)	-1619.0	[2768.3]	-1571.6	[2820.3]	1,239
Sales/Person (EUR)	52891.3	[96897.4]	35388.5	[102441.6]	607
Firm Has Disappeared by r+1	-0.00082	[0.0012]	-0.00069	[0.0012]	28,380

Notes: This table reports gender differences in replacement workers' labor market outcomes and differences in firm outcomes by the replacement worker's gender, based on Equation (2). All outcomes are measured in r, which refers to replacement workers' starting spell at the hiring firm. Column (1) reports the β_1 coefficient for female replacement for the *same hiring opportunity* regression specification, and column (2) reports the β_1 coefficient for female replacement for the + *same pre-hire wage* regression specification. Panel A focuses on replacement worker characteristics. Information on hours comes from the Statutory Accident Insurance and is available for 2010-2014. In Panel B, the outcome is 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 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 in column (1) control for deceased worker's gender and 3-digit occupation, calendar year of death, 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), full-time work in $r-1$, and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); the share of female full-time workers (d); firm wage bill, total and women (d); and coworkers' wage bill, total and women (d). In column (2), we additionally control for deciles of 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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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 5%-level.

Table 3: Replacement Worker Characteristics, Amenities, Outside Options

	(1) Coefficient Female Replacement Same Hiring Opportunity		(2) Coefficient Female Replacement + Same Pre-Hire Wage		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Replacement Worker Characteristics in $r-1$					
Education (years)	**-0.21**	[0.035]	-0.019	[0.035]	28,300
Experience (years)	**-1.50**	[0.13]	0.11	[0.12]	28,378
Tenure (years)	**-0.47**	[0.077]	0.12	[0.075]	28,367
Occupational Tenure (years)	**-0.80**	[0.11]	**0.33**	[0.11]	27,791
Days Worked Full-time	**-8.33**	[2.27]	**5.90**	[2.28]	28,380
Yearly Full-time Earnings (EUR)	**-4619.8**	[280.0]	245.8	[231.5]	28,380
Panel B: Amenities					
Δ Commuting Distance (km)	4.81	[3.91]	3.50	[3.96]	9,695
Δ Gender Wage Gap in Firm	-0.0044	[0.0076]	-0.010	[0.0078]	19,882
Gender Wage Gap Other Workers (r)	-0.0026	[0.0093]	0.0055	[0.0096]	26,256
Family Friendly Firm (r)	0.0083	[0.0073]	0.011	[0.0074]	28,375
Panel C: Outside Options $r-1$					
Outside option index $\phi_{cz,occ,t,g}$	0.0064	[0.0045]	0.0068	[0.0044]	27,788
Pre-Hire Firm Median Full-time Wage	**-3.73**	[0.52]	**4.23**	[0.46]	27,947
Pre-Hire Firm FE	**-0.017**	[0.0042]	**0.051**	[0.0038]	27,537

Notes: This table reports gender differences in replacement workers' characteristics in $r-1$, in their amenities, and in their outside options, based on Equation (2). $r-1$ refers to replacement workers' previous employment spell, and r refers to their starting spell at the hiring firm. Column (1) reports the β_1 coefficient for female replacement for the *same hiring opportunity* regression specification, and column (2) reports the β_1 coefficient for female replacement for the + *same pre-hire wage* regression specification. In Panel A, we report gender differences in replacement worker characteristics in $r-1$, their previous employment spell. The worker fixed effect comes from the dataset provided by Lochner et al. (2023), computed as the average across several sets of calendar years; it can thus be based on both pre- and post-replacement observations. In Panel B, we report four proxies for amenities: The change in commuting distance compared to the previous job (in km), the change in the firm gender wage gap, the gender wage gap of all coworkers (i.e., workers in the same 3-digit occupation) in the hiring firm, and a proxy for family-friendliness. Family-friendly firms have at least one female manager with a child aged 0-8. In Panel C, we report three proxies for replacement workers' outside options, all measured in $r-1$. $\phi_{cz,occ,t,g}$ 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 in column (1) control for deceased worker's gender and 3-digit occupation, calendar year of death, 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), full-time work in $r-1$, and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); the share of female full-time workers (d); firm wage bill, total and women (d); and coworkers' wage bill, total and women (d). In column (2), we additionally control for deciles of 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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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. Coefficients in bold are statistically significant at the 5%-level.

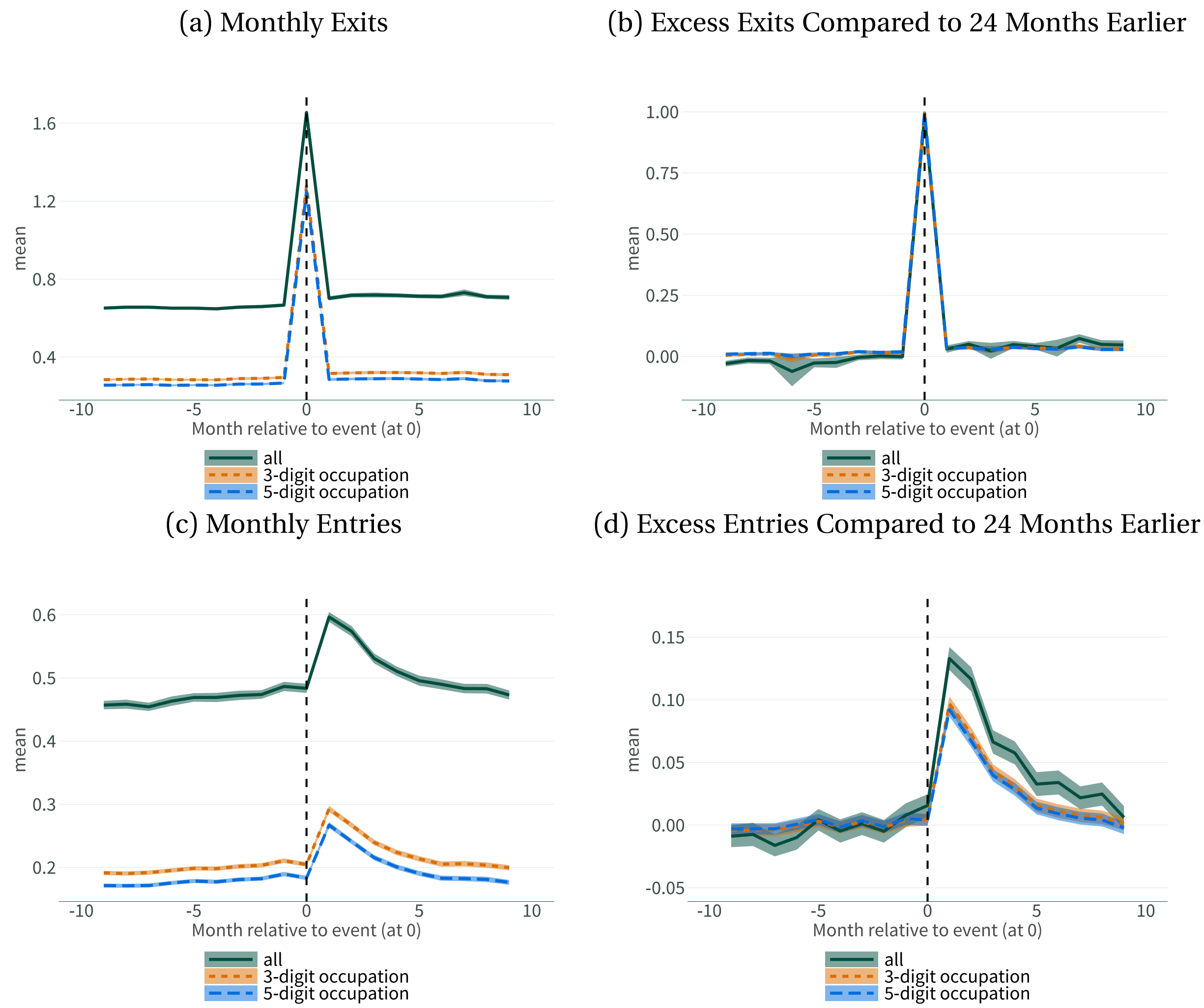
Table 4: Adjusted Gender Hiring Opportunity Gap for Different Sample Splits

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	**Baseline**	**1981-1989**	**1990-1999**	**2000-2009**	**2010-2016**	**2010-2014**
Female Replacement	-0.11	-0.14	-0.12	-0.073	-0.053	-0.066
	(0.0056)***	(0.011)***	(0.0096)***	(0.015)***	(0.013)***	(0.019)***
Observations	28380	8582	9953	5457	3964	2631
R^2	0.635	0.653	0.632	0.644	0.769	0.785
Panel B:	**Share FT Women**		**Family-Friendly**		**Firm Gender Wage Gap**	
	< 50%	**>= 50%**	**Yes**	**No**	**< Mean**	**>= Mean**
Female Replacement	-0.11	-0.096	-0.069	-0.11	-0.083	-0.13
	(0.0076)***	(0.0097)***	(0.012)***	(0.0066)***	(0.0071)***	(0.0094)***
Observations	22492	5723	3800	24437	13647	14605
R^2	0.608	0.735	0.760	0.620	0.624	0.661
Panel C:	**Skill-Intensity**		**Gender Deceased Worker**		**3-Digit Occ. in $r-1$**	
	Low	**Medium/High**	**Male**	**Female**	**Same**	**Different**
Female Replacement	-0.15	-0.072	-0.097	-0.11	-0.092	-0.12
	(0.0099)***	(0.0070)***	(0.0069)***	(0.012)***	(0.0074)***	(0.0090)***
Observations	18592	9649	24794	3405	13866	14398
R^2	0.540	0.661	0.619	0.738	0.665	0.629
Panel D:	**Worker FE**		**West**	**East**	**Days to Fill Vacancy**	
	< Mean	**>= Mean**			**< Mean**	**>= Mean**
Female Replacement	-0.11	-0.070	-0.11	-0.082	-0.11	-0.10
	(0.0083)***	(0.0073)***	(0.0060)***	(0.020)***	(0.0074)***	(0.0092)***
Observations	15458	12787	25226	2982	16500	11763
R^2	0.494	0.606	0.619	0.736	0.633	0.644

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for different sample splits. It is based on Equation (2), 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. medium to high occupational skill intensity (column 2, see Appendix A.2 for details on the definition); by gender of the deceased worker (columns 3 and 4); and for replacement workers with below or above average outside options (columns 5 and 6, measured in $r-1$). In Panel D, we present coefficients for replacement workers with below and above mean worker FE (columns 1 and 2), for firms located in West vs. East Germany (columns 3 and 4), and for positions with a time to fill below or above the mean (columns 5 and 6). All regressions control for deceased worker's gender and 3-digit occupation, calendar year of detah, 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); the share of female full-time workers at the firm (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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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.

8 Figures

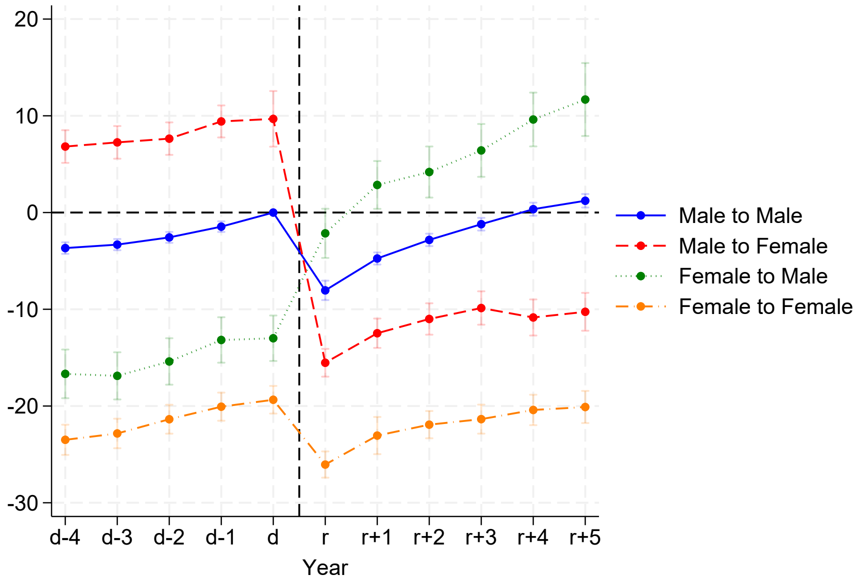
Figure 1: Exits and Entries of Full-time Workers Around Date of Death



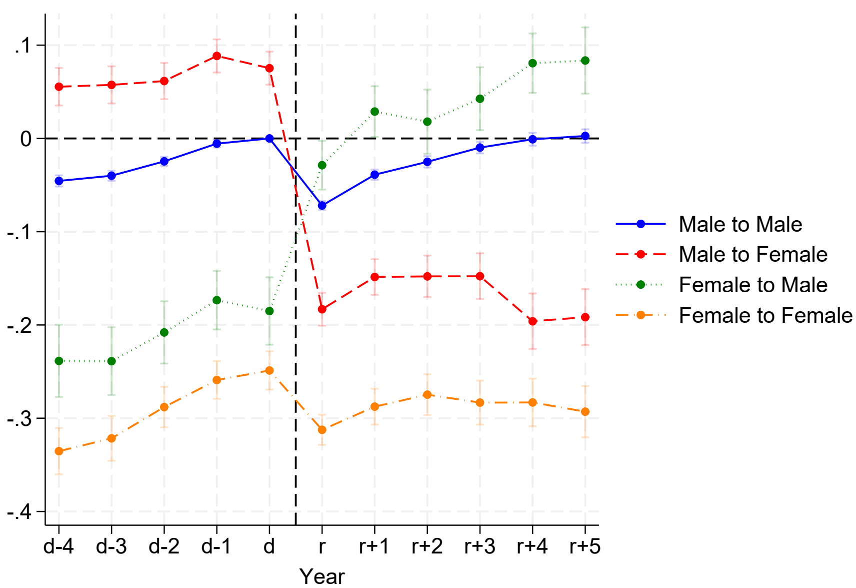
Notes: This figure plots raw means of exits and entries out of and into event firms in the year before and after the death event (at 0). Panel (a) shows the average number of monthly full-time worker exits; Panel (b) shows the average number of monthly full-time worker exits, relative to 24 months earlier. 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: Raw Evolution of Wages by Transition Group

(a) Daily Wage (EUR)



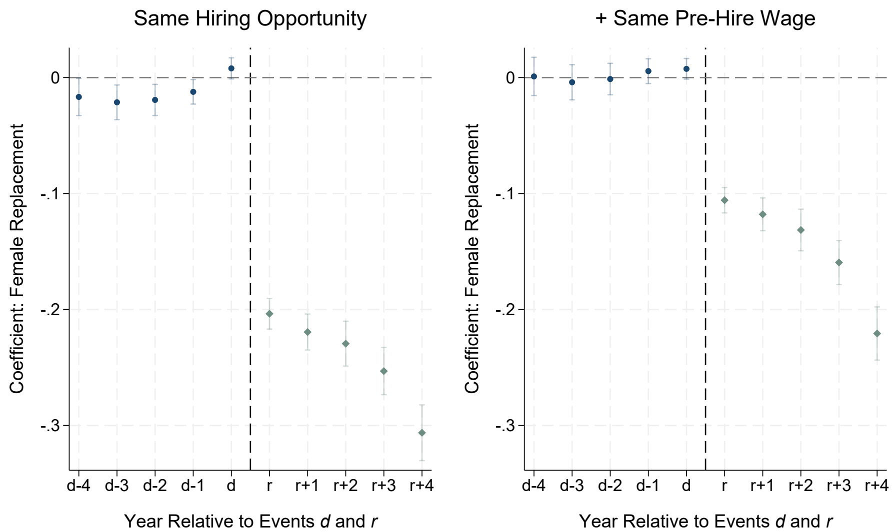
(b) Log Daily Wage



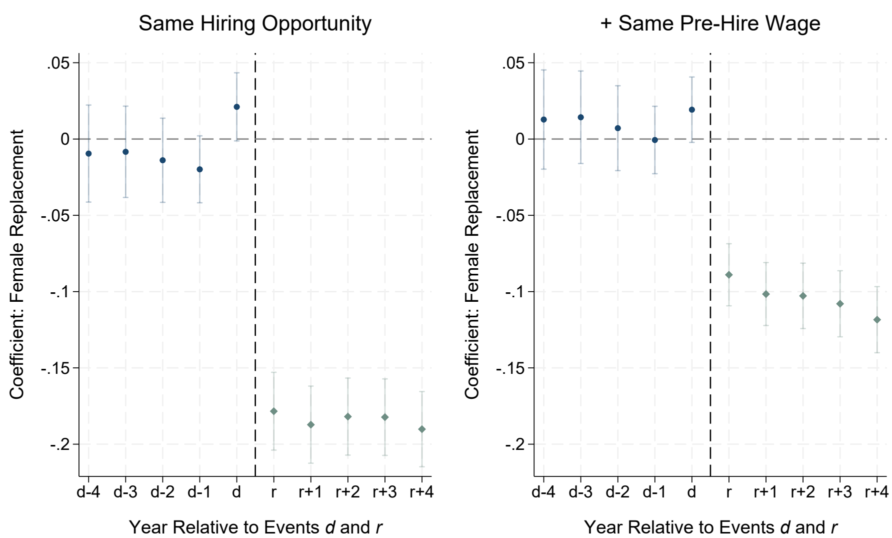
Notes: This figure presents raw means of wage trajectories for our baseline sample of deceased and replacement workers, relative to wages of the male-male group in d. The four lines plot the normalized wages for the four transition groups: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dot-dashed line). See Appendix 2.4 for details. Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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: The Gender Hiring Opportunity Gap

(a) Baseline Sample



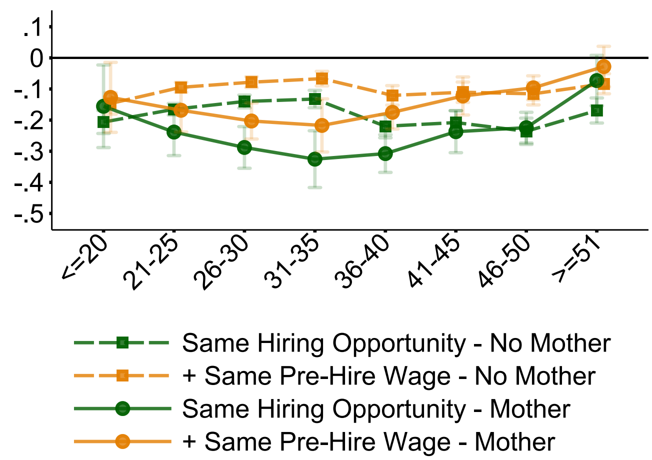
(b) Replacement Works Full-time from r to $r + 4$



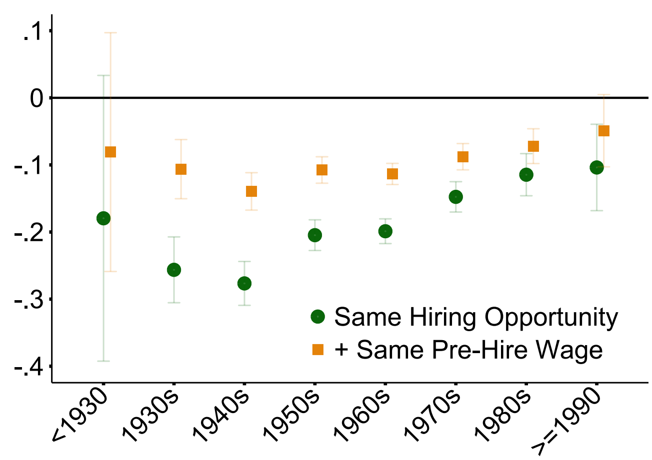
Notes: This figure presents β_1 coefficients of Equation (2). The outcome variable is log wages. The figure on the left ("Same hiring opportunity") refers to the baseline specification that controls for deceased worker's gender and 3-digit occupation, calendar year of death, the share of full-time women 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); the share of female full-time workers (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 restrict to replacement workers with a full-time contract in $r - 1$, and without UI spell between $r - 1$ and r. 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: Gender Hiring Opportunity Gap Over the Lifecycle, by Motherhood Status, and by Cohort

(a) Replacement Worker Age and Motherhood Status at r

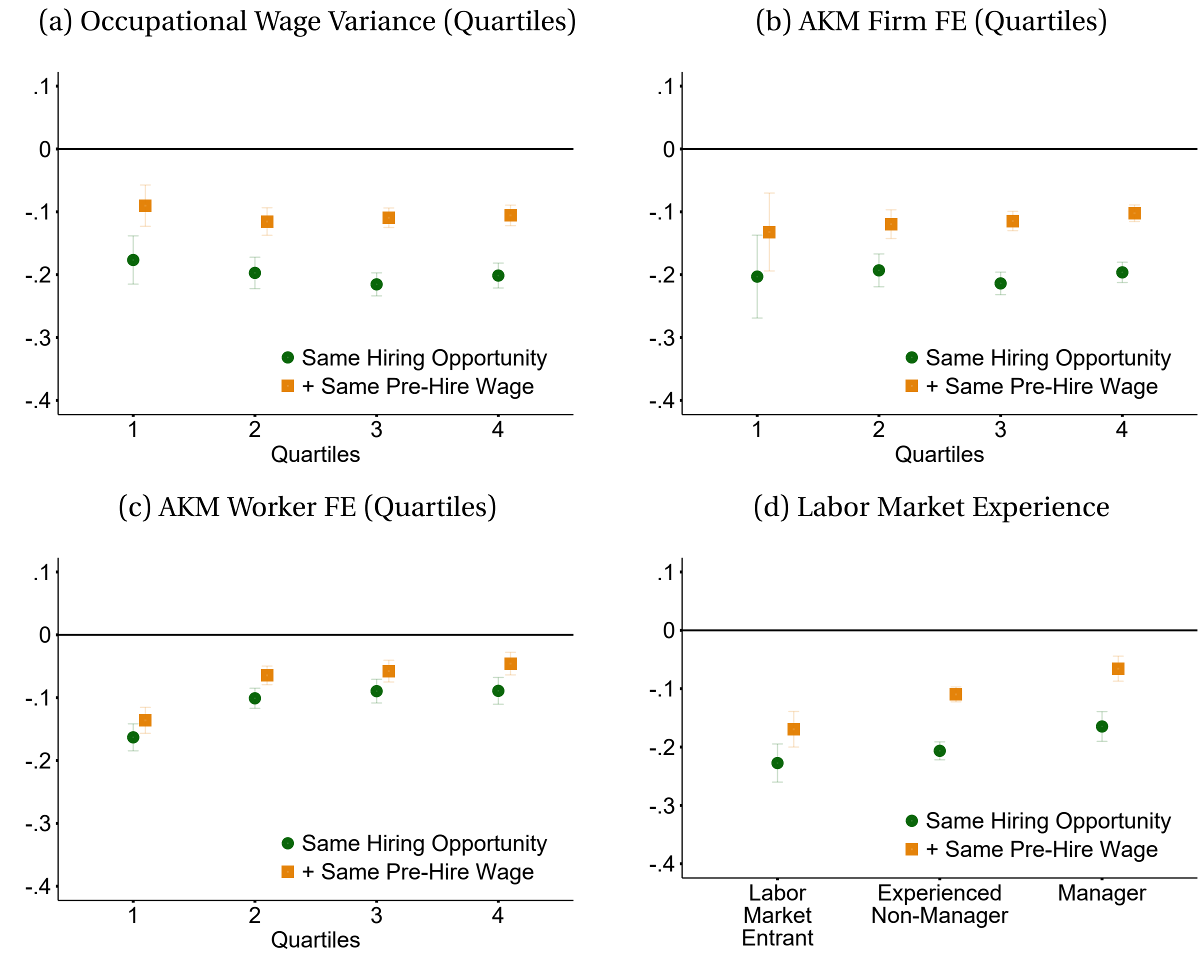


(b) Replacement Worker Birth Cohort



Notes: This figure present β_1 coefficients of Equation (2). The outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots the gender hiring opportunity gaps by replacement worker age and mother status, and Panel (b) plots the gender hiring opportunity gaps by replacement worker birth cohort. In Panel (a), we plot *same hiring opportunity* coefficients for non-mothers (green squares, dashed line) and mothers (green dots, solid line), and we plot *same pre-hire wage* coefficients for non-mothers (orange squares, dashed line) and mothers (orange dots, solid line). In Panel (b), green dots refer to the regression specification for *same hiring opportunity*, and orange squares refer to the *same pre-hire wage* specification. To measure same hiring opportunity, we control for deceased worker's gender and 3-digit occupation, calendar year of death, 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); the share of female full-time workers (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). Same pre-hire wage specifications additionally control for deciles of the pre-hire wage of the replacement worker ($r-1$). Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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 5: Heterogeneity by Occupation, Firm, and Worker Type



Notes: The green dots and orange squares in this figure present β_1 coefficients of Equation (2). The outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots the gender gap by quartiles of occupational wage variance, measured at the 3-digit occupation × county level. Panel (b) plots the gender gap by quartiles of the hiring firm's AKM firm FE. Panel (c) plots the gap by quartiles of replacement workers' AKM worker FE. Panel (d) plots the gap by labor market experience as defined by Caldwell et al. (2024). Green dots refer to the regression specification for *same hiring opportunity*, where we control for deceased worker's gender and 3-digit occupation (Panel b, only), calendar year of death, 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); the share of female full-time workers (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). Orange squares refer to the regression specification for *same pre-hire wage* that additionally controls for deciles of the pre-hire wage of the replacement worker ($r-1$). Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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. We obtain AKM firm and worker FE from Lochner et al. (2023). We measure AKM firm FE in r, and AKM worker FE in $r-1$; since the dataset pools FE across several years, both measures may include pre- and post hiring observations (see Appendix A.3 for details). Following Caldwell et al. (2024), labor market entrants have less than three years of labor market experience, managers are workers whose 5-digit occupational code ends in '3' or '4', and experienced non-managers are all other workers.

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 28,771 unexpected death events.

As Table A5 shows, we classify about 16.2% 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 16.2% is a lower bound since it compares death events at all firms (regardless of firm size) 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 that 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 33% of our sudden death sample, and 5.4% of all spells that end with death (incl. non-sudden deaths, see Table A5). 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 (+4.4 workers), their workforce is a bit younger, and they pay lower median full-time wages (-1.3 EUR per day). The workforce composition is comparable, with almost 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 Appendix B.4).[37]

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 (7ppt), 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.

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.[38] 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 33% of death events. Finally, we focus on worker pairs where the replacement worker transitioned from a full-time employment and did not have a UI spell between their previous job and the hiring spell, which brings us to a final sample of 28,771 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-female 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

[37]Table A4 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.

[38]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).

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 (+4-7 years), firm tenure (about +5 years), occupational tenure (about +4 years), and labor market experience (+2-4 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 6.6 EUR in the female-female group to 15 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 89.7), followed by the opposite-sex group (EUR 86), and the female-female transition group (EUR 71.7); female-female replacements have 1.8 years lower 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. 7.9% for opposite-sex and 3.5% for female-female pairs) and traffic/security (25% vs. 7.4% for opposite-sex and 2.6% for female-female pairs). In contrast, female-female and opposite-sex transitions happen much more often in trade/sales (13% for female-female, 10% for opposite-sex, and 6.5% for male-male pairs), and in service occupations (41% for female-female, 37% for opposite-sex, and 5.7% for male-male pairs). The sorting patterns are less striking for 1-digit industries, though male-male pairs are 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:

$$\mu_{cz,occ,t} = \frac{Workers_{cz,occ,t}}{Workers_{cz,t}} \div \frac{Workers_{DE,occ,t}}{Workers_{DE,t}} \tag{3}$$

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. This indicator is based on a 20% random sample of the IAB worker-level data (*IEB, version 16.1*).

In the next step, we use the same 20% random sample of the IAB worker-level data 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.

$$\gamma_{occ_{t=n},occ_{t+1=n+x},g} = \frac{Workers_{occ_{t+1=n+x},g}}{Workers_{occ_{t=n},g}} \tag{4}$$

$\gamma_{occ_{t=n},occ_{t+1=n+x},g}$ 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:

$$\phi_{cz,occ_{t=n},t,g} = \sum_{occ_{t+1=n}}^{occ_{t+1=n+x}} \mu_{cz,occ_{t+1},t} \times \gamma_{occ_{t=n},occ_{t+1},g} \tag{5}$$

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. 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 and worker effects are provided as the average across several calendar years: $t \in \{1985-1992; 1993-1999; 2000-2006; 2007-2013; 2014-2021\}$. We link them to our data using unique firm and worker identifiers 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 C, it is therefore important to keep in mind that the information on capital and sales is only available for 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 1,239 treated firms in our baseline sample, information on sales is available for 607 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., Dustmann et al. (2022), Jäger et al. (2024), 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 are 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 mini-jobs, 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, and hours stated in collective bargaining agreements (Dustmann et al. (2022), Online Appendix). According to Dustmann et al. (2022), reporting behavior differs across firms. This would be of concern for our analysis if firms that hire women exhibit systematically different reporting behavior than firms that hire men. However, as Table A8 shows, our empirical strategy ensures that we compare workers hired into very similar firms based on their gender, so this is likely not an issue.

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.

Bottleneck Occupations We obtain information on bottleneck occupations, i.e. occupations that are hard to fill, from the Statistics Department of the German Federal Employment Agency for 2011-2016 (*Fachkräfteengpassanalyse*). We extract the information from several reports covering December 2011 and June and December each of 2012-2016. We collect information on bottleneck occupations on the yearly level, both nationally and for federal states. If an occupation is classified as bottleneck for either December or June, we classify it as bottleneck for the full year.

The Statistics Department of the German Federal Employment Agency classifies an occupation as "bottleneck" based on the following variables: (i) average vacancy duration, (ii) job entries and stock of social security-contributory jobs reported to the Federal Employment Agency, (iii) stock of unemployed individuals, and (iv) the occupation-specific unemployment rate.

For Germany and 2013-2016, we merge the bottleneck indicator on the year × 5-digit occupation level. For Germany and 2011-2012 and for federal states, we merge the bottleneck indicator on the year × 4-digit occupation level (first three digits and last digit of the 5-digit occupational code). About 300 out of 3,400 death events between 2011 and 2016 are classified as events involving bottleneck occupations.

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 $age \in \{15-19; 20-24; 25-29; 30-34; 35-39; 40-44; 45-49; 50-54; 55-59; 60-64; 65+\}$, 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 $age \in \{15-19; 20-24; 25-29; 30-34; 35-39; 40-44; 45-49; 50-54; 55-59; 60-64; 65+\}$, 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[39], number of workers by 1-digit occupation, number of (full-time) workers by skill group, num-

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

ber 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. All variables are based on a 20% random sample of the IAB worker-level data.

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.

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). Except for West Germany and commuting zone, all variables are based on a 20% random sample of the IAB worker-level data.

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 $t \in \{-2.5, ..., 1\}$ year(s) before and after death (d).

B.2 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, 57 employees; the corresponding number is 52 employees for non-excess hiring firms, and 15 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 Table A4). 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 firm size, log number of full-time workers in firm, median wages, and median wages women. Tables A3 and A4, columns (4) and (5), show 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 A2, 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.3 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, this means we will estimate a lower bound of the true adjusted gender hiring opportunity 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:

$$y_i = \beta_0 + \beta_1 \boldsymbol{X_i} + \gamma_t + \varepsilon_{it} \tag{6}$$

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. γ_t 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 × demographics × 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 (22 log points, while the baseline gap is 11 log points).

B.4 Robustness

In this section, we show that the gender hiring opportunity gap that we document is robust to different sample restrictions and versions, different sets of control variables, and are not driven by any particular firm type, industry, or occupation.

Sample Restrictions Table A6 shows the gender hiring opportunity gap and the adjusted gap across different subsamples.

Columns (1) and (2) of Panel A show the baseline coefficients. As discussed in Section 5.1, conditioning on a sample where replacement workers are continuously employed in full-time jobs starting in r reduces the gender wage gap only marginally, as shown in columns (3) and (4). Columns (5) and (6) confirm that the gaps are almost the same for a balanced panel of firms around the event.

In Panel B, columns (1) through (4), we show that the gaps are not driven by mothers or workers of reproductive age. We first exclude all pairs with replacements who are mothers by r from our analysis. These are few observations; still, the gaps reduce to 19 log points and 9.7 log points respectively, as shown in columns (1) and (2). Next, we focus on pairs where replacement workers are aged 41 and above, assuming that these workers are out of reproductive age. The adjusted gender hiring opportunity gap for these workers is 9.9 log points and thus marginally smaller than the baseline gap. The results show 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 8,600 observations and hardly changes the gap as shown in columns (5) and (6) in Panel B.

Similarly, one might be concerned that women are more likely than men to change their 3-digit occupation between $r-1$ and r, and that their greater loss of occupation-specific human capital could drive the gap. However, columns (5) and (6) in Panel C of Table 4 indicate that this is not the case.

For another robustness check, we restrict the sample to replacements with a gap of not more than one year between their hiring spell and their previous job, to focus on replacements who are relatively attached to the labor market. With this restriction, the adjusted gender hiring opportunity gap reduces to 9.4 log points but it is still very close to the baseline gap of 11 log points.

Finally, in Panel C of Table A6, columns (1) through (4) show that the gender hiring opportunity gap is largely the same for firms with 3-50 full-time employees in $d-1$ and firms with 51-150 full-time employees in $d-1$.

The gap is thus not driven by a particular subset of firms.

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 gender hiring opportunity gap by the ex-ante probability of female replacement, derived from our machine learning exercise discussed in Section 3. Figure A7a shows that the gender hiring opportunity 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 hiring opportunity gap is not limited to specific types of firms or jobs that are more hostile towards women.

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 A6 plots the gender hiring opportunity gap by 1-digit occupation and industry. Replacement women earn lower wages in almost every industry and occupation and across both service and manufacturing sector, with few exceptions. Notably, the gap is lower in education and public administration where there are tighter wage-setting regulations.

Different Sets of Control Variables To estimate the adjusted gender hiring opportunity gap, we control for deciles of replacement workers' previous wages in addition to the baseline 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 adjusted gender hiring opportunity gap is larger or equal in all of these additional specifications.

Table A7, columns (2)-(6), introduce them separately and all at once. We start with deciles of labor market experience (column 2), skills (column 3), and deciles of firm and occupational tenure (column 4). We next control for predicted wages based on a sample of male replacement workers (column 5).[40] In Column (6), we control for a replacement worker's previous three wages, measured in $r-1$, $r-2$, and $r-3$ to account for potentially different wage growth trajectories of replacing men and women.

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.

Alternative Sample Versions For our baseline analysis, we restrict the sample to replacements who worked in a full-time contract in their previous employment spell ($r-1$). First, we are interested in wage-setting behaviors for full-time workers. Second, daily wages are more comparable among full-time workers. In addition, we restrict to replacement workers who

[40]See Appendix B.3 for details on how we obtain the predicted values.

were not registered in the UI system between their previous job in $r-1$ and the hiring spell in r. This ensures that we focus on workers who are highly attached to the labor market; in particular, we do not need to worry about gender differences in the propensity to take up UI prior to the hiring spell.

We show that our results are robust to lifting these restrictions. Appendix E, Tables A10 and A11 present summary statistics for the alternative samples of hiring events (i) without additional restriction and (ii) allowing for UI spells of replacement workers between $r-1$ and r. These alternative samples are very comparable to our baseline sample. Figure A8 and Tables A12 and A14 replicate our main results for the sample without additional restrictions, where we add a dummy for full-time work measured at $r-1$ to our set of controls; Figure A9 and Tables A13 and A15 replicate our main results for the sample without the UI spell restriction. The key takeaways remain the same.

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]	0.021 [0.14]	0.015 [0.12]	0.0031 [0.056]
Education	0.011 [0.10]	0.0053 [0.072]	0.024 [0.15]	0.015 [0.12]
Machine Operations/Maintenance	0.12 [0.32]	0.12 [0.32]	0.079 [0.27]	0.035 [0.18]
Trade/Sales	0.082 [0.27]	0.065 [0.25]	0.10 [0.31]	0.13 [0.34]
Traffic/Security	0.11 [0.32]	0.25 [0.43]	0.074 [0.26]	0.026 [0.16]
Food/Cleaning	0.053 [0.22]	0.028 [0.17]	0.057 [0.23]	0.094 [0.29]
Services	0.18 [0.38]	0.057 [0.23]	0.37 [0.48]	0.41 [0.49]
Technicians	0.11 [0.31]	0.074 [0.26]	0.061 [0.24]	0.015 [0.12]
Law/Management/Economics	0.042 [0.20]	0.037 [0.19]	0.051 [0.22]	0.035 [0.18]
Arts	0.014 [0.12]	0.0067 [0.081]	0.020 [0.14]	0.012 [0.11]
Health/Care	0.082 [0.27]	0.012 [0.11]	0.084 [0.28]	0.18 [0.38]
Education	0.011 [0.10]	0.0053 [0.072]	0.024 [0.15]	0.015 [0.12]
Number of Individuals	14,905,321	22,595	3,582	2,594

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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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]	0.0087 [0.093]	0.0042 [0.065]
Mining	0.0078 [0.088]	0.0080 [0.089]	0.0017 [0.041]	0 [0]
Manufacturing	0.31 [0.46]	0.25 [0.43]	0.19 [0.39]	0.17 [0.38]
Energy	0.010 [0.10]	0.010 [0.10]	0.0042 [0.065]	0.0015 [0.039]
Water Supply	0.0079 [0.089]	0.017 [0.13]	0.0047 [0.069]	0.0027 [0.052]
Construction	0.085 [0.28]	0.19 [0.39]	0.018 [0.13]	0.029 [0.17]
Motor Vehicles	0.14 [0.34]	0.17 [0.37]	0.18 [0.38]	0.19 [0.39]
Traffic, Warehousing	0.051 [0.22]	0.11 [0.31]	0.049 [0.22]	0.019 [0.14]
Hospitality	0.027 [0.16]	0.013 [0.11]	0.037 [0.19]	0.047 [0.21]
ICT	0.026 [0.16]	0.014 [0.12]	0.032 [0.18]	0.025 [0.16]
Finance, Insurance	0.037 [0.19]	0.022 [0.15]	0.094 [0.29]	0.043 [0.20]
Housing	0.0071 [0.084]	0.0086 [0.092]	0.013 [0.11]	0.014 [0.12]
PST Services	0.051 [0.22]	0.026 [0.16]	0.051 [0.22]	0.065 [0.25]
Economic Services	0.043 [0.20]	0.036 [0.19]	0.033 [0.18]	0.025 [0.16]
Public Sector	0.058 [0.23]	0.058 [0.23]	0.13 [0.33]	0.087 [0.28]
Education	0.022 [0.15]	0.013 [0.11]	0.029 [0.17]	0.042 [0.20]
Health, Social Services	0.078 [0.27]	0.021 [0.14]	0.082 [0.27]	0.15 [0.36]
Arts, Entertainment	0.0074 [0.086]	0.0047 [0.069]	0.013 [0.11]	0.010 [0.100]
Other Services	0.023 [0.15]	0.017 [0.13]	0.037 [0.19]	0.070 [0.26]
Domestic Services	0.0013 [0.037]	0.00031 [0.018]	0.00056 [0.024]	0.0012 [0.034]
NGOs	0.0022 [0.047]	0.00040 [0.020]	0 [0]	0.00039 [0.020]
Number of Individuals	14,905,321	22,595	3,582	2,594

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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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	(4)	(5)
			No weights	Weights	
				To (1)	To (2)
Panel A: Workforce					
Firm Size	15.1 [29.8]	52.2 [49.8]	56.6 [52.5]	21.4 [29.6]	48.6 [46.6]
Full-time Share	0.76 [0.23]	0.82 [0.18]	0.83 [0.18]	0.76 [0.23]	0.83 [0.18]
Share Full-time Women	0.43 [0.35]	0.27 [0.26]	0.27 [0.26]	0.47 [0.31]	0.31 [0.26]
Share Medium-Skilled	0.88 [0.32]	0.91 [0.29]	0.91 [0.29]	0.90 [0.31]	0.91 [0.29]
Share High-Skilled	0.047 [0.21]	0.031 [0.17]	0.027 [0.16]	0.047 [0.21]	0.034 [0.18]
Mean Age	37.7 [7.07]	39.8 [5.62]	39.4 [5.54]	38.9 [6.69]	39.1 [5.58]
Panel B: Wages					
Median Full-time Wage	64.0 [31.2]	70.2 [29.1]	68.9 [27.2]	66.1 [31.2]	68.8 [28.6]
Median Full-time Wage Women	55.3 [28.5]	61.6 [27.7]	60.6 [26.8]	58.5 [30.1]	60.4 [27.7]
Gender Wage Gap	0.30 [0.43]	0.23 [0.32]	0.23 [0.31]	0.28 [0.40]	0.23 [0.33]
Number of Observations	24,922,011	157,219	77,867	77,867	77,867

This table compares firms with a sudden death event to all other firms with 3-150 full-time workers 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 1). Column (5) shows weighted characteristics when reweighting excess hiring firms to non-excess hiring firms (column 2). See Appendix B.2 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: 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]	0.012 [0.11]	0.010 [0.10]	0.011 [0.10]	0.011 [0.11]
Mining	0.0029 [0.053]	0.0077 [0.087]	0.0063 [0.079]	0.0022 [0.047]	0.0058 [0.076]
Manufacturing	0.15 [0.35]	0.25 [0.43]	0.24 [0.43]	0.17 [0.37]	0.25 [0.43]
Energy	0.0031 [0.056]	0.0091 [0.095]	0.0073 [0.085]	0.0031 [0.056]	0.0065 [0.081]
Water Supply	0.0062 [0.078]	0.011 [0.11]	0.011 [0.11]	0.0062 [0.079]	0.011 [0.10]
Construction	0.11 [0.31]	0.13 [0.33]	0.13 [0.34]	0.072 [0.26]	0.11 [0.31]
Motor Vehicles	0.20 [0.40]	0.16 [0.37]	0.15 [0.36]	0.20 [0.40]	0.17 [0.38]
Traffic, Warehousing	0.093 [0.29]	0.095 [0.29]	0.10 [0.30]	0.098 [0.30]	0.094 [0.29]
Hospitality	0.061 [0.24]	0.031 [0.17]	0.033 [0.18]	0.067 [0.25]	0.037 [0.19]
ICT	0.022 [0.15]	0.025 [0.16]	0.029 [0.17]	0.020 [0.14]	0.025 [0.15]
Finance, Insurance	0.023 [0.15]	0.022 [0.15]	0.026 [0.16]	0.028 [0.17]	0.025 [0.16]
Housing	0.0034 [0.058]	0.0017 [0.041]	0.0014 [0.037]	0.0034 [0.058]	0.0018 [0.042]
PST Services	0.11 [0.31]	0.062 [0.24]	0.060 [0.24]	0.11 [0.32]	0.072 [0.26]
Economic Services	0.026 [0.16]	0.029 [0.17]	0.037 [0.19]	0.027 [0.16]	0.031 [0.17]
Public Sector	0.019 [0.14]	0.066 [0.25]	0.062 [0.24]	0.024 [0.15]	0.056 [0.23]
Education	0.049 [0.22]	0.028 [0.17]	0.030 [0.17]	0.052 [0.22]	0.031 [0.17]
Health, Social Services	0.059 [0.24]	0.019 [0.14]	0.021 [0.14]	0.049 [0.22]	0.020 [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]	0.00016 [0.013]	0.00019 [0.014]	0.00025 [0.016]	0.00014 [0.012]
NGOs	0.00016 [0.013]	0.00017 [0.013]	0.000091 [0.0095]	0.000018 [0.0042]	0.00010 [0.010]
Number of Observations	24,922,011	157,219	77,867	77,867	77,867

This table compares the distribution across 1-digit industries of firms with a sudden death event to all other firms with 3-150 full-time workers 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 1). Column (5) shows weighted characteristics when reweighting excess hiring firms to non-excess hiring firms (column 2). See Appendix B.2 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 Services 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 A5: Number of Observations and Sample Restrictions

	Counts	**Share of All Deaths**	**Share of Sudden Deaths**
(1) All Deaths no firm size restriction	1,448,184	100	–
(2) Sudden Deaths 3-150 full-time employees, max. 300 employees	235,086	16.2	100
(3) Excess Hiring Firms	77,867	5.4	33.1
(4) Excess Hiring Worker Sample	57,146	3.95	24.3
(5) Excess Hiring & Full-time Job in $r-1$	43,070	2.97	18.3
(6) Excess Hiring & Baseline Sample	28,771	1.99	12.2
(7) Baseline Regression Sample	28,380	1.96	12.1

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 when 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 baseline sample, where we in addition restrict to replacement workers without UI spells between $r-1$ and r. Row 7 shows the number of observations for our regression sample.

Table A6: The Gender Hiring Opportunity 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**		**Highly-Attached Sample**		**Balanced Panel**	
Female Replacement	-0.20	-0.11	-0.18	-0.089	-0.21	-0.11
	(0.0067)***	(0.0056)***	(0.013)***	(0.010)***	(0.0076)***	(0.0064)***
Observations	28380	28380	7765	7765	22131	22131
R^2	0.496	0.635	0.499	0.652	0.494	0.639
Panel B:	**No Mothers**		**Workers Aged >40**		**Only 1 Full-time Hire**	
Female Replacement	-0.19	-0.097	-0.22	-0.099	-0.20	-0.11
	(0.0067)***	(0.0056)***	(0.014)***	(0.011)***	(0.013)***	(0.010)***
Observations	27591	27591	8050	8050	8628	8628
R^2	0.498	0.639	0.564	0.672	0.587	0.715
Panel C:	**Firm Size 3-50**		**Firm Size 51-150**		**Max. 1 Year Since Last Job**	
Female Replacement	-0.20	-0.11	-0.21	-0.11	-0.20	-0.094
	(0.0091)***	(0.0076)***	(0.010)***	(0.0083)***	(0.0066)***	(0.0052)***
Observations	18142	18142	10134	10134	26256	26256
R^2	0.492	0.621	0.539	0.684	0.505	0.657

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 (2), and shows β_1 coefficients for $t = r$. Columns (1) and (3) report coefficients for the *same hiring opportunity specification*, where we control for deceased worker's gender and 3-digit occupation, calendar year of death, 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); the share of female full-time workers (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). Columns (2) and (4) 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 41 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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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 A7: The Adjusted Gender Hiring Opportunity 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 3 Wages	(7) Baseline +Firm	(8) All
Panel A: Full Sample								
Female Replacement	-0.11	-0.18	-0.21	-0.20	-0.22	-0.11	-0.12	-0.13
	(0.0056)***	(0.0065)***	(0.0067)***	(0.0067)***	(0.010)***	(0.0057)***	(0.0082)***	(0.0086)***
Observations	28380	28378	28373	27778	17324	27157	20996	19531
R^2	0.635	0.537	0.506	0.525	0.545	0.638	0.670	0.679
Panel B: Re-run for Regression Sample in Column (8)								
Female Replacement	-0.12	-0.20	-0.22	-0.21	-0.23	-0.12	-0.13	-0.13
	(0.0076)***	(0.0088)***	(0.0090)***	(0.0089)***	(0.013)***	(0.0076)***	(0.0086)***	(0.0086)***
Observations	19531	19531	19531	19531	12111	19531	19531	19531
R^2	0.637	0.547	0.517	0.535	0.575	0.638	0.672	0.679

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for specifications with different control variables. It is based on Equation (2), 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 of death, 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); the share of female full-time workers (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 a 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 wages in $r-1$, $r-2$, and $r-3$. 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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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 A8: 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: Coworker Wage Bill	**All**		**Incumbents**	
Female Replacement	-853.9	2509.4	-3218.1	-993.8
	(9165.5)	(9109.9)	(8717.5)	(8643.2)
Observations	27751	27751	27751	27751
R^2	0.866	0.866	0.866	0.866
Panel B: Wage Gap & Firm FE	**GWG Other Workers**		**AKM Firm FE**	
Female Replacement	-0.018	-0.010	0.0043	0.016
	(0.0093)*	(0.0096)	(0.0031)	(0.0032)***
Observations	25539	25539	26630	26630
R^2	0.199	0.200	0.427	0.436
Panel C: Workforce Composition	**Share of Mothers**		**Share of Women**	
Female Replacement	0.0023	0.0028	0.023	0.025
	(0.0016)	(0.0016)*	(0.0032)***	(0.0032)***
Observations	22692	22692	26835	26835
R^2	0.315	0.315	0.779	0.780
Panel D: Female-Friendliness	**Share Female Team Leaders**		**Family-Friendly Firm**	
Female Replacement	0.025	0.025	-0.0067	-0.0034
	(0.0044)***	(0.0044)***	(0.0073)	(0.0074)
Observations	27746	27746	27739	27739
R^2	0.476	0.476	0.299	0.299

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for different outcome variables. It is based on Equation (2), 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 of death, 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); the share of female full-time workers (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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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.

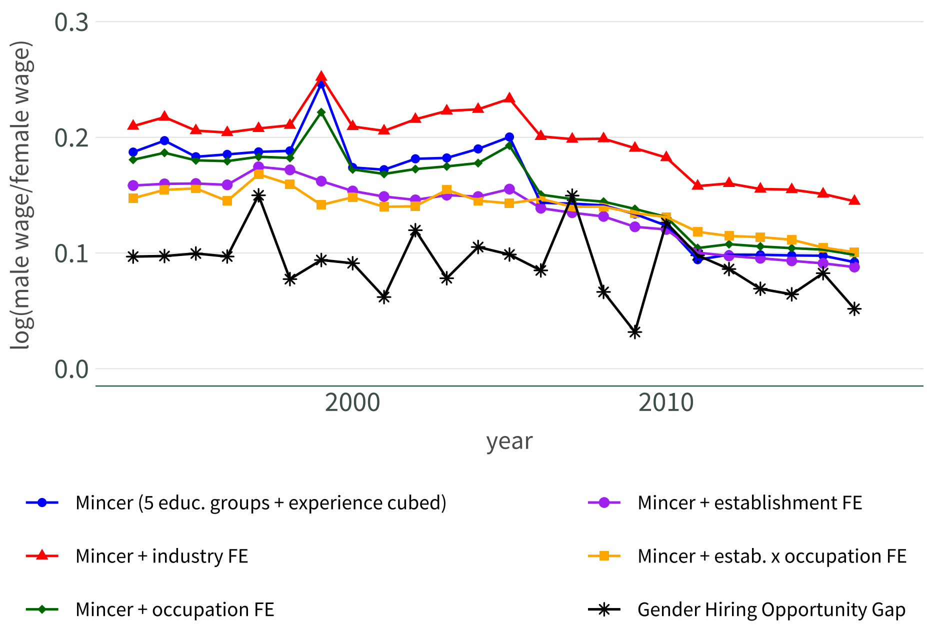
Table A9: Top 10 Predictors Identified by Random Forest Algorithm

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 $d-2$
9	Share of Women in Same 5-Digit Occ. at Hiring Firm $d-3$
10	Share of Women Aged 18-40 in Same 2-Digit Occ. in Germany $d-1$

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, 77,867 are subject to excess hiring, and 157,219 are not. Each of these is the top 10 out of approximately 600 variables in total that enter the machine learning algorithm.

D Appendix Figures

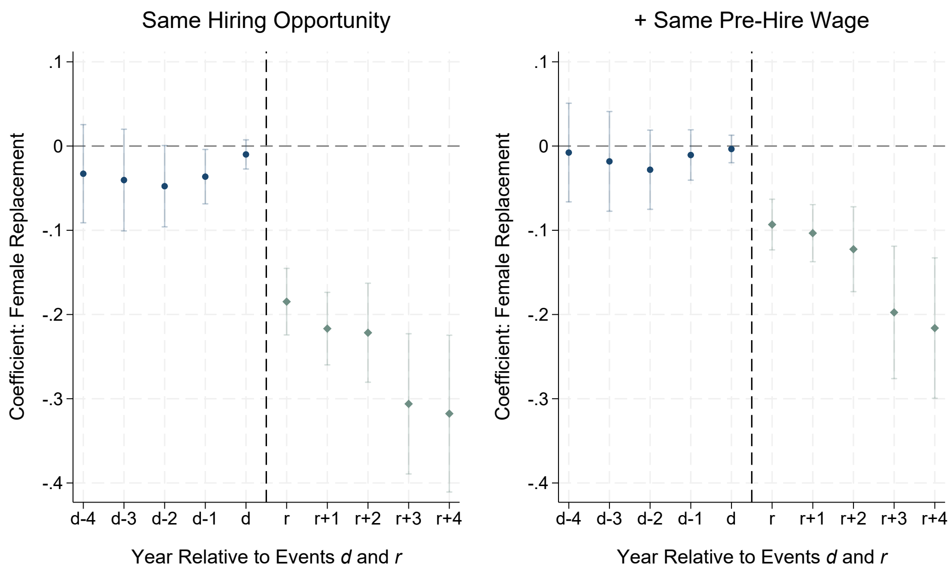
Figure A1: The Gender Wage Gap in Germany 1993-2017



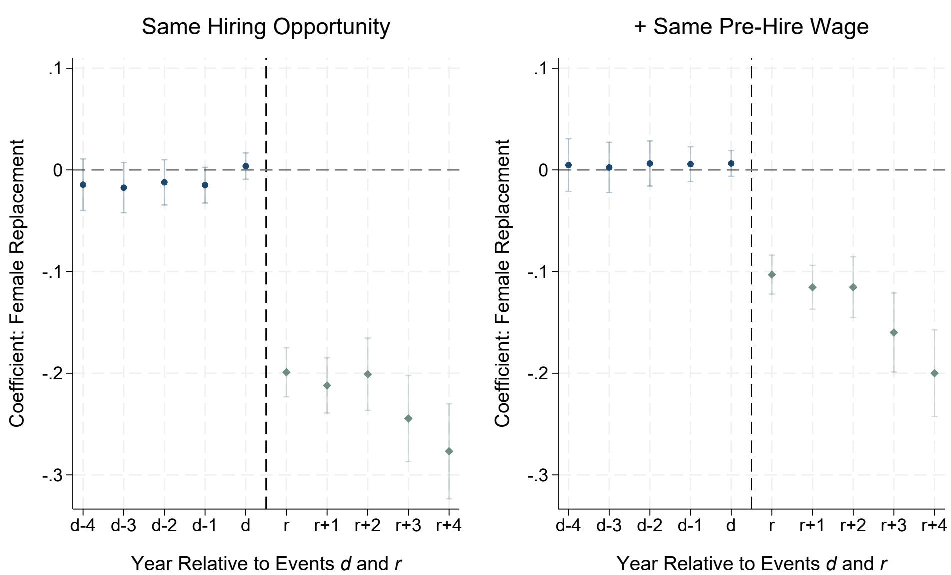
Notes: This figure shows several versions of the adjusted gender wage gap for a sample of full-time workers in Germany that are part of the longitudinal LIAB (*7519, Version 1*); in addition, it plots coefficients for the *adjusted gender hiring opportunity gap* over time (black stars) for our baseline sample. Blue dots plot the gender wage gap when controlling for 5 groups of education and a cubic polynomial in years of labor market experience ("Mincer covariates"); red triangles plot the gap for Mincer plus 3-digit industries; green diamonds plot the gap for Mincer plus 3-digit occupations; purple dots plot the gap for Mincer plus establishment FE; yellow squares plot the gap for Mincer plus establishment × occupation FE. These specifications are in part a replication of Figure 1 in Bruns (2019); we run an individual-level linear regression of log wages on a dummy for male workers. To address the issue of sample selectivity in the LIAB, we follow Bossler et al. (2018) and control for 10 categories of firm size, federal state, 1-digit industry, and state × firm size × industry dummies. To make the LIAB sample comparable to our baseline sample, we reweight observations in the LIAB to our baseline sample at r, using propensity score reweighting based on the following characteristics: Log wage, age, experience, education, a dummy for West Germany, 10 firm size categories, 2-digit occupations. In the reweighting exercise, we pool the following years: 1993-1999, 2000-2005, 2006-2010, 2011-2017. We report patterns from 1993 since this is when East German establishments were first added to the LIAB.

Figure A2: The Gender Hiring Opportunity Gap – Firm Reweighting

(a) Reweighting to All Other Firms



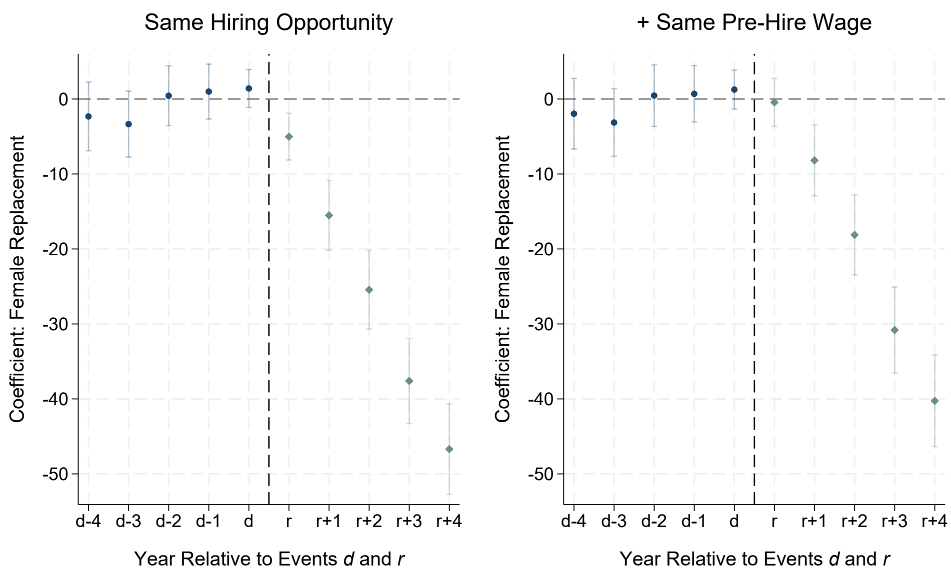
(b) Reweighting to Non-Excess Hiring Firms



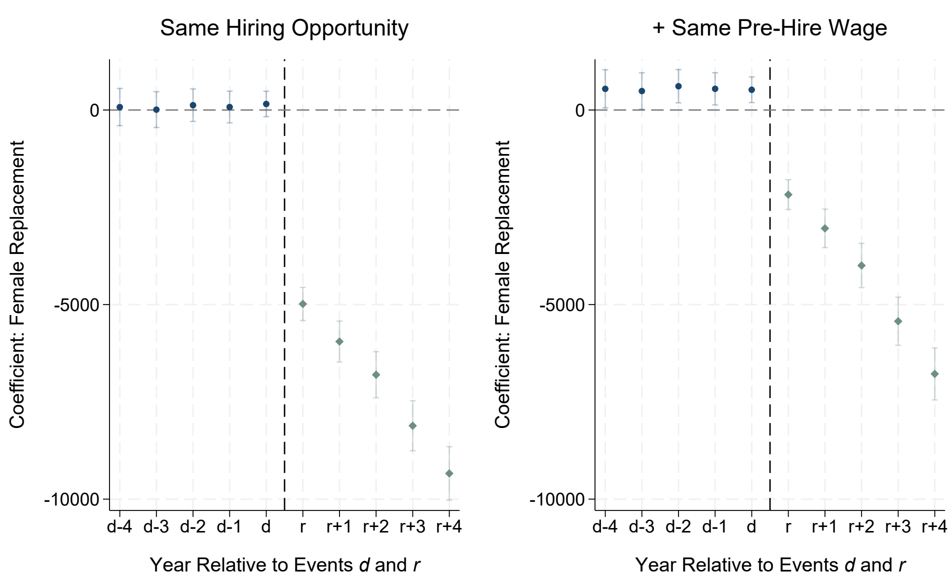
Notes: This figure presents β_1 coefficients of Equation (2). The outcome variable is log wages. In Panel (a) we use weights to make excess hiring firms comparable to all other German firms; in Panel (b), we reweight excess hiring firms to non-excess hiring firms. See Appendix B.2 for details on the 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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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 A3: The Gender Gap in Full-time Employment and Earnings

(a) Days Worked in Full-time Job per Year



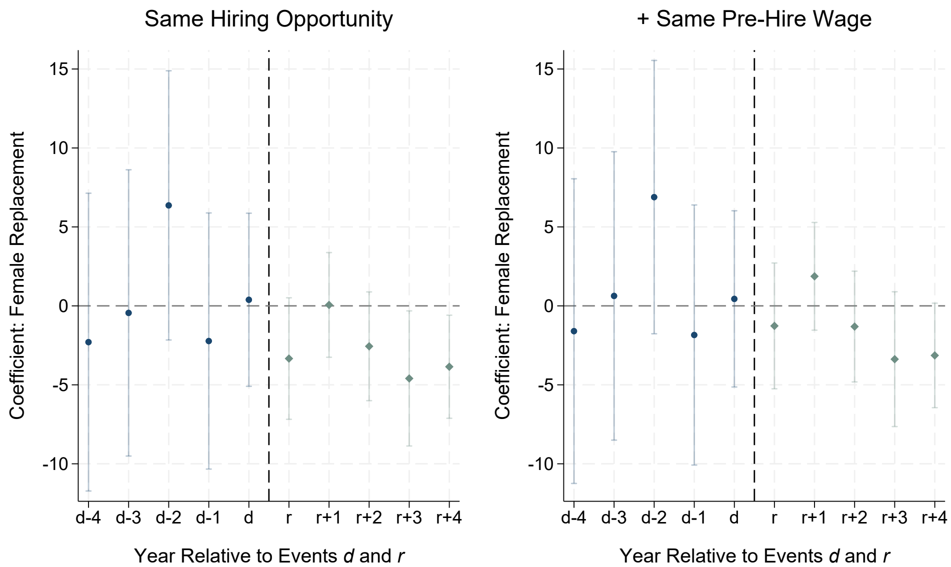
(b) Earnings from Full-time Job (EUR) per Year



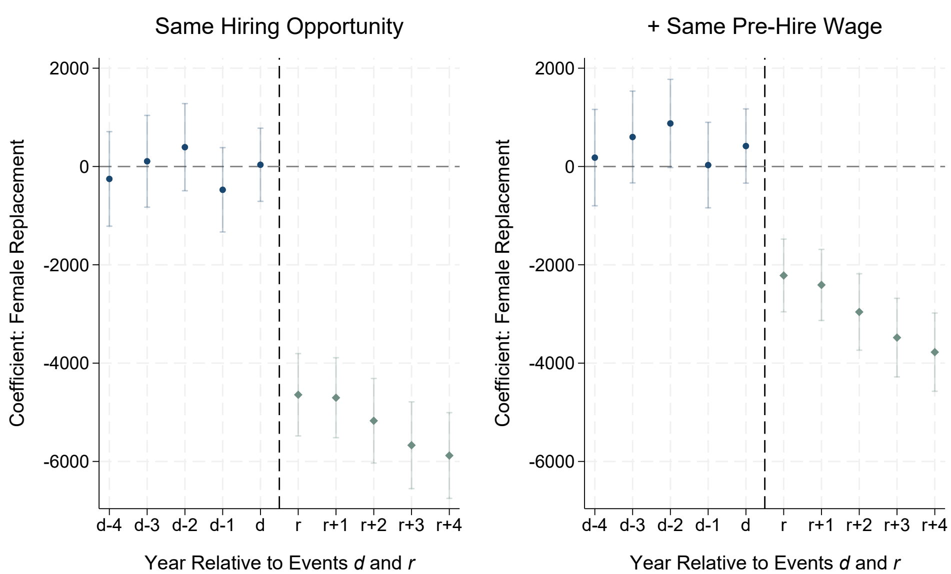
Notes: This figure presents β_1 coefficients of Equation (2). The outcome variables are days worked in a full-time job per year (Panel a), and full-time earnings per year (Panel b). The figure on the left ("Same hiring opportunity") refers to the baseline specification that controls for deceased worker's 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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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: The Gender Gap in Full-time Employment and Earnings – Replacement Works Full-time from r to $r+4$

(a) Days Worked in Full-time Job per Year



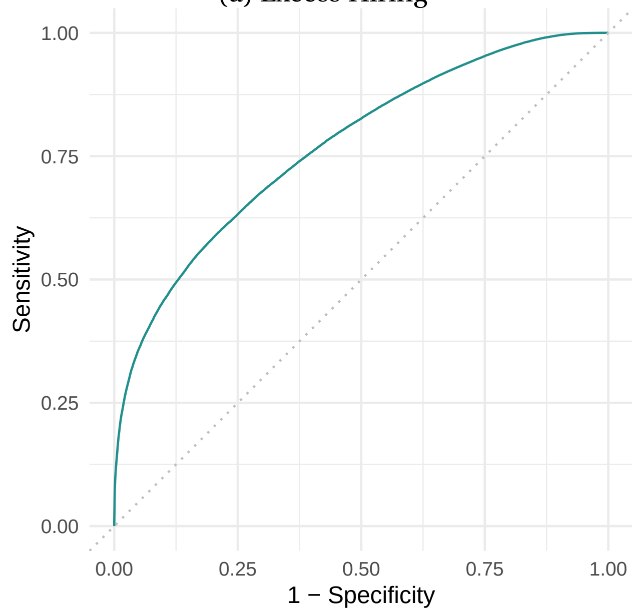
(b) Earnings from Full-time Job (EUR) per Year



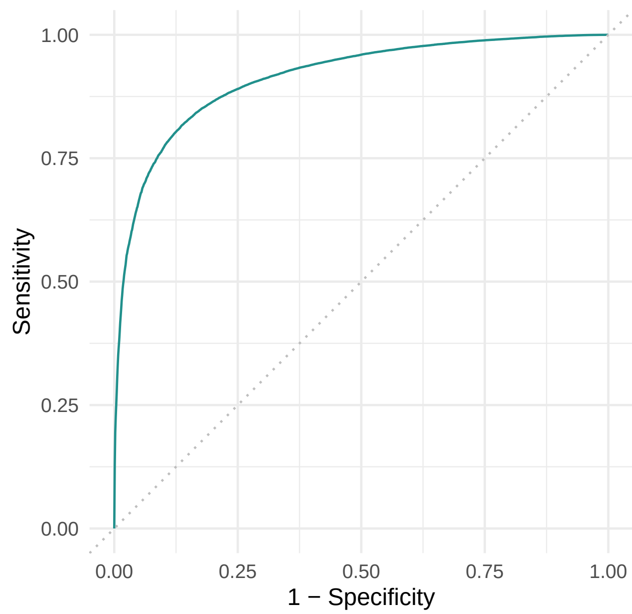
Notes: This figure presents β_1 coefficients of Equation (2). The outcome variables are days worked in a full-time job per year (Panel a), and full-time earnings per year (Panel b). The figure on the left ("Same hiring opportunity") refers to the baseline specification that controls for deceased worker's 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 restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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 A5: Machine Learning Prediction Accuracy

(a) Excess Hiring



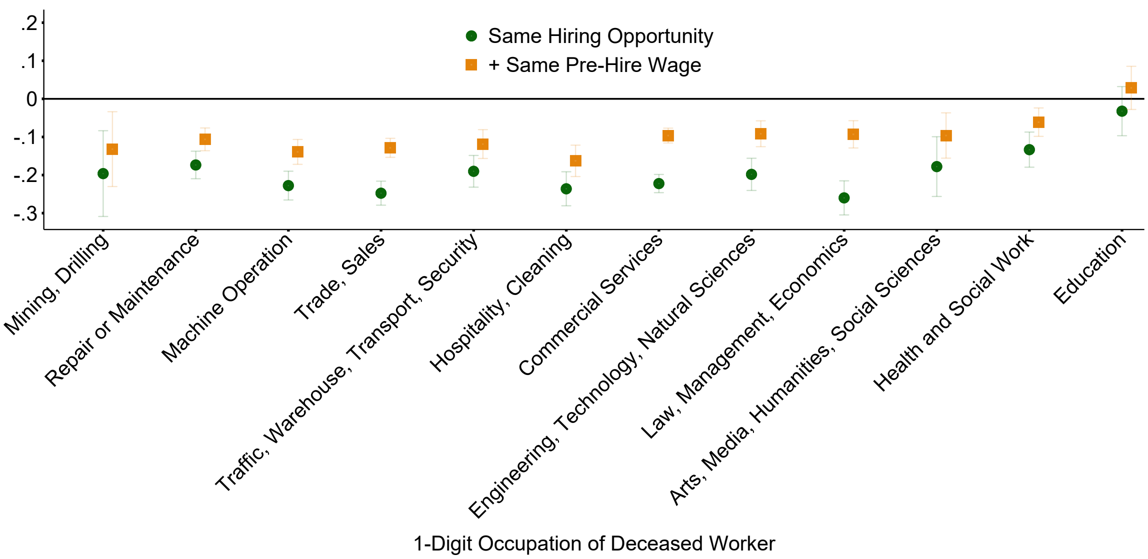
(b) Female Replacement



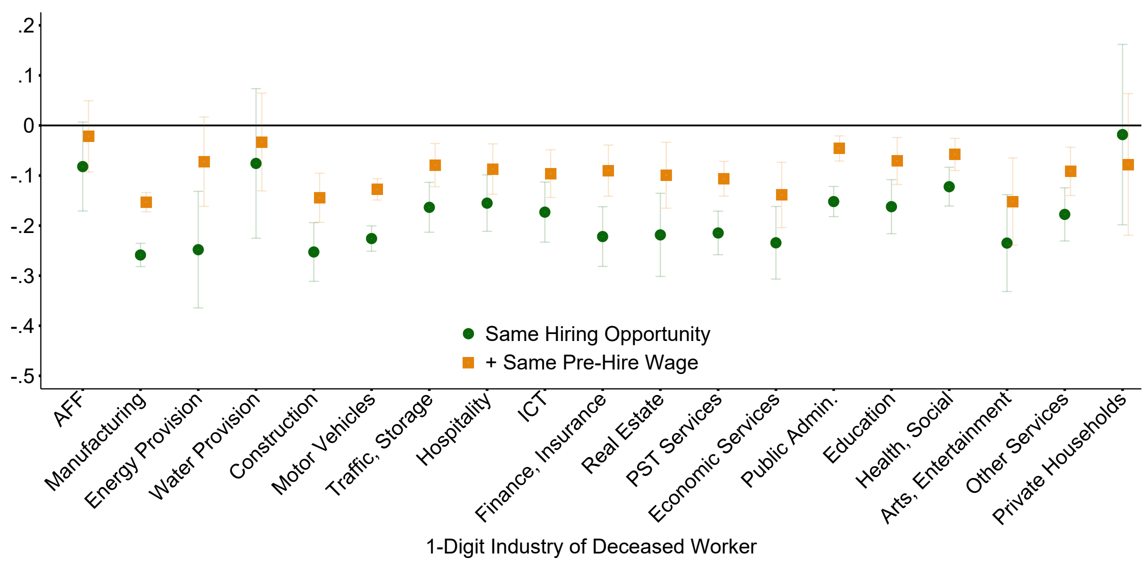
Notes: This ROC (Receiver Operating Characteristic) curve plots the prediction accuracy of our ranger algorithm model predicting the incidence of excess hiring (Panel a) and female replacement (Panel b) after a sudden death. The sample includes firms with exactly one sudden death in a given year. The 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, 77,867 are subject to excess hiring, and 157,219 are not. See Section 3.1 and Appendix Section B.1 for details on the machine learning algorithm.

Figure A6: Gender Hiring Opportunity Gap by Occupation/Industry

(a) 1-Digit Occupations



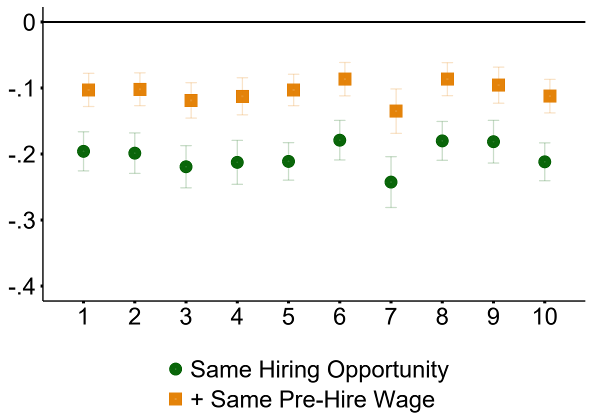
(b) 1-Digit Industries



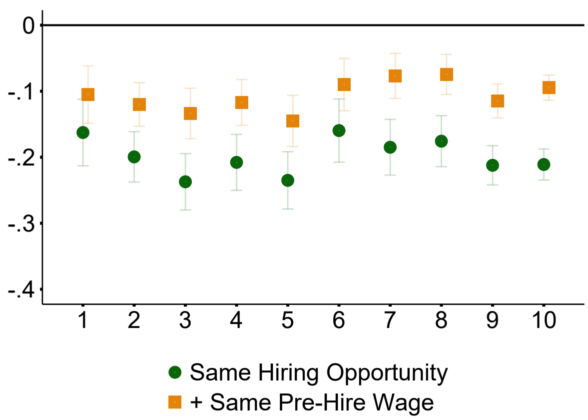
Notes: The green dots and orange squares in this figure present β_1 coefficients of Equation (2). The outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots the gender wage gap by 1-digit occupation and Panel (b) plots the gender wage gap by 1-digit industry. Green dots refer to the regression specification for *same hiring opportunity*, where we control for deceased worker's gender and 3-digit occupation (Panel b, only), calendar year of death, 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); the share of female full-time workers (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). Orange squares refer to the regression specification for *same pre-hire wage* that additionally controls for deciles of the pre-hire wage of the replacement worker ($r-1$). Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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. To improve the graph's readability, we exclude 2 industries with a low number of women and thus large standard errors from Panel (b): Mining and NGOs. AFF is an abbreviation for "Agriculture, Forestry, and Fishing", ICT stands for "Information and Communication Technology", and PST means "Professional, Scientific, and Technical Services".

Figure A7: Gender Hiring Opportunity Gap by Firm and Occupation Type

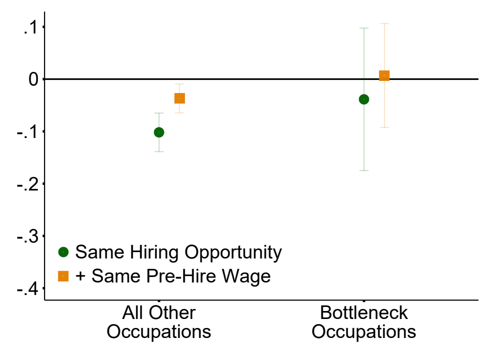
(a) Ex-Ante Female Replacement Probability



(b) 2-Digit Occ. Share of Female Full-time Workers



(c) Bottleneck Occupations (2011-2016)



Notes: The green dots and orange squares in this figure present β_1 coefficients of Equation (2). The outcome variable is replacement workers' log wages in the hiring spell (r). 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. Panel (c) plots the gap for bottleneck occupations and all other occupations for death events occurring in 2011-2016. Green dots refer to the regression specification for *same hiring opportunity*, where we control for deceased worker's gender and 3-digit occupation, calendar year of death, 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 (Panel b, only); deceased worker's wage (d); the share of female full-time workers (d); firm wage bill, total and women (d); coworkers' wage bill, total and women (d). Orange squares refer to the regression specification for *same pre-hire wage* that additionally controls for deciles of the pre-hire wage of the replacement worker ($r-1$). Deceased and replacement workers work in a full-time contract in d and r, respectively. In addition, we restrict to replacement workers with a full-time contract in $r-1$, and without UI spell between $r-1$ and r. 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. Bottleneck occupations are positions that are hard to fill, see Appendix A.3 for details.

E Replication of Main Results for Alternative Samples

Table A10: Demographics for Transition Pairs vs. Random Sample of Workers – No Additional Restrictions

	(1) Random Sample	(2) Male-Male	(3) Opposite-Sex	(4) Female-Female
Panel A		*Deceased Worker at the departing event 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 at the hiring event r*		
Daily Wage in EUR	91.7 [53.8]	81.5 [53.5]	74.7 [33.0]	64.0 [30.4]
Days Worked Full-time	332.1 [79.9]	315.4 [89.3]	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 [0.55]	0.46 [0.51]	0.45 [0.44]
Occ. Tenure (years)	8.19 [7.04]	3.56 [5.15]	3.24 [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	14,905,321	42,676	8,193	6,277

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, and we allow for UI spells of replacement workers between $r-1$ and r. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table A11: Demographics for Transition Pairs vs. Random Sample of Workers – Sample With UI Spells Between $r - 1$ and r

	(1) Random Sample	(2) Male-Male	(3) Opposite-Sex	(4) Female-Female
Panel A		*Deceased Worker at the departing event 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]	7.49 [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 at the hiring event 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]	320.6 [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 [0.59]	0.49 [0.60]	0.48 [0.51]
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	14,905,321	34,186	5,127	3,757

Notes: This table presents differences in average characteristics for an alternative sample of deceased-replacement worker pairs, where we restrict to replacement workers who worked full-time in their previous job. 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 allow for UI spells of replacement workers between $r - 1$ and r. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table A12: Wages, Employment, and Adjustments Event Firms – No Additional Restrictions

	(1) Coefficient Female Replacement Same Hiring Opportunity		(2) Coefficient Female Replacement + Same Pre-Hire Wage		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment					
Log Wage	**-0.17**	[0.0048]	**-0.11**	[0.0044]	51,271
Days Worked Full-Time per Year	**-3.04**	[1.29]	0.32	[1.35]	51,362
Log Hours Worked per Week	-0.017	[0.011]	-0.015	[0.012]	3,823
Log Wage if in Hours Data (2010-2014)	**-0.096**	[0.018]	**-0.049**	[0.016]	3,821
Wage Bill Replacement Worker (EUR)	**-3466.9**	[138.0]	**-2023.1**	[137.8]	51,362
Panel B: Coworker Wage Bill					
Wage Bill All Coworkers (EUR)	-10378.6	[6321.8]	-9690.5	[6858.0]	51,362
Wage Bill Incumbents (EUR)	-6873.9	[5708.3]	-8465.2	[6150.1]	51,362
Wage Bill New Hires (EUR)	**-3734.7**	[1890.1]	-1689.1	[2092.6]	51,362
Panel C: Firm-level Adjustments					
Capital/Person (EUR)	-730.7	[2046.3]	-394.3	[2177.8]	3,131
Sales/Person (EUR)	2096.2	[28941.4]	-2797.0	[31906.0]	1,666
Firm Has Disappeared by r+1	-0.00015	[0.00083]	-0.00064	[0.00083]	51,362

Notes: This table reports gender differences in replacement workers' labor market outcomes and differences in firm outcomes by the replacement worker's gender, based on Equation (2). All outcomes are measured in r, which refers to replacement workers' starting spell at the hiring firm. We do not restrict to transition pairs where the replacement worker's last employment contract was a full-time job, and we allow for UI spells of replacement workers between $r-1$ and r. Column (1) reports the β_1 coefficient for female replacement for the *same hiring opportunity* regression specification, and column (2) reports the β_1 coefficient for female replacement for the + *same pre-hire wage* regression specification. Panel A focuses on replacement worker characteristics. Information on hours comes from the Statutory Accident Insurance and is available for 2010-2014. In Panel B, the outcome is 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 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 in column (1) control for deceased worker's gender and 3-digit occupation, calendar year of death, 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), full-time work in $r-1$, and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); the share of female full-time workers (d); firm wage bill, total and women (d); and coworkers' wage bill, total and women (d). In column (2), we additionally control for deciles of replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. Number of observations refer to the specification with same pre-hire wages, where we lose replacement workers whose hiring spell is their first entry in the social-security records. 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 5%-level.

Table A13: Wages, Employment, and Adjustments Within Event Firms – Sample With UI Spells Between $r-1$ and r

	(1) Coefficient Female Replacement Same Hiring Opportunity		(2) Coefficient Female Replacement + Same Pre-Hire Wage		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment					
Log Wage	**-0.19**	[0.0055]	**-0.10**	[0.0047]	42,454
Days Worked Full-Time per Year	**-4.00**	[1.42]	0.43	[1.45]	42,454
Log Hours Worked per Week	-0.0031	[0.014]	-0.0070	[0.014]	2,957
Log Wage if in Hours Data (2010-2014)	**-0.12**	[0.021]	**-0.055**	[0.017]	2,957
Wage Bill Replacement Worker (EUR)	**-3938.9**	[172.1]	**-2005.6**	[160.5]	42,454
Panel B: Coworker Wage Bill					
Wage Bill All Coworkers (EUR)	-5522.4	[7677.6]	-4994.7	[7662.2]	42,454
Wage Bill Incumbents (EUR)	-5569.1	[6815.5]	-6044.1	[6755.8]	42,454
Wage Bill New Hires (EUR)	-544.6	[2495.5]	182.9	[2587.7]	42,454
Panel C: Firm-level Adjustments					
Capital/Person (EUR)	-576.0	[3153.1]	-750.0	[3221.6]	2,415
Sales/Person (EUR)	11095.2	[47609.4]	9986.2	[47278.5]	1,285
Firm Has Disappeared by r+1	-0.00054	[0.0010]	-0.00048	[0.0010]	42,454

Notes: This table reports gender differences in replacement workers' labor market outcomes and differences in firm outcomes by the replacement worker's gender, based on Equation (2). All outcomes are measured in r, which refers to replacement workers' starting spell at the hiring firm. We restrict to transition pairs where the replacement worker's last employment contract was a full-time job. In contrast to the baseline sample, we allow for UI spells of replacement workers between $r-1$ and r. Column (1) reports the β_1 coefficient for female replacement for the *same hiring opportunity* regression specification, and column (2) reports the β_1 coefficient for female replacement for the + *same pre-hire wage* regression specification. Panel A focuses on replacement worker characteristics. Information on hours comes from the Statutory Accident Insurance and is available for 2010-2014. In Panel B, the outcome is 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 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 in column (1) control for deceased worker's gender and 3-digit occupation, calendar year of death, 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), full-time work in $r-1$, and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); the share of female full-time workers (d); firm wage bill, total and women (d); and coworkers' wage bill, total and women (d). In column (2), we additionally control for deciles of 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 5%-level.

Table A14: Replacement Worker Characteristics, Amenities, Outside Options – No Additional Restrictions

	(1) Coefficient Female Replacement Same Hiring Opportunity		(2) Coefficient Female Replacement + Same Pre-Hire Wage		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Replacement Worker Characteristics in $r-1$					
Education (years)	**-0.14**	[0.025]	-0.00097	[0.025]	51,726
Experience (years)	**-0.73**	[0.087]	**0.44**	[0.084]	51,874
Tenure (years)	**-0.24**	[0.047]	**0.19**	[0.046]	51,858
Occupational Tenure (years)	**-0.34**	[0.071]	**0.46**	[0.068]	50,186
Days Worked Full-time	**-6.12**	[1.51]	**5.26**	[1.62]	51,882
Yearly Full-time Earnings (EUR)	**-2711.8**	[173.0]	6.51	[168.6]	51,882
Panel B: Amenities					
Δ Commuting Distance (km)	0.77	[2.45]	-0.36	[2.48]	20,258
Δ Gender Wage Gap in Firm	**0.013**	[0.0060]	0.0077	[0.0061]	35,141
Gender Wage Gap Other Workers (r)	**0.018**	[0.0062]	**0.020**	[0.0068]	47,967
Family Friendly Firm (r)	-0.0023	[0.0049]	-0.0024	[0.0053]	51,809
Panel C: Outside Options in $r-1$					
Outside option index $\phi_{cz,occ,t,g}$	0.000040	[0.0029]	-0.00032	[0.0029]	50,180
Pre-Hire Firm Median Full-time Wage	**-3.29**	[0.38]	**2.55**	[0.34]	50,199
Pre-Hire Firm FE	**-0.018**	[0.0034]	**0.032**	[0.0031]	49,557

Notes: This table reports gender differences in replacement workers' characteristics in $r-1$, in their amenities, and in their outside options, based on Equation (2). $r-1$ refers to replacement workers' previous employment spell, and r refers to their starting spell at the hiring firm. We do not restrict to transition pairs where the replacement worker's last employment contract was a full-time job, and we allow for UI spells of replacement workers between $r-1$ and r. Column (1) reports the β_1 coefficient for female replacement for the *same hiring opportunity* regression specification, and column (2) reports the β_1 coefficient for female replacement for the + *same pre-hire wage* regression specification. In Panel A, we report gender differences in replacement worker characteristics in $r-1$, their previous employment spell. The worker fixed effect comes from the dataset provided by Lochner et al. (2023), computed as the average across several sets of calendar years; it can thus be based on both pre- and post-replacement observations. In Panel B, we report four proxies for amenities: The change in commuting distance compared to the previous job (in km), the change in the firm gender wage gap, the gender wage gap of all coworkers (i.e., workers in the same 3-digit occupation) in the hiring firm, and a proxy for family-friendliness. Family-friendly firms have at least one female manager with a child aged 0-8. In Panel C, we report three proxies for replacement workers' outside options, all measured in $r-1$. $\phi_{cz,occ,t,g}$ 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 in column (1) control for deceased worker's gender and 3-digit occupation, calendar year of death, 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), full-time work in $r-1$, and deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); the share of female full-time workers (d); firm wage bill, total and women (d); and coworkers' wage bill, total and women (d). In column (2), we additionally control for deciles of replacement workers' wages at the previous job. Deceased and replacement workers work in a full-time contract in d and r, respectively. Number of observations refer to the specification with same pre-hire wages, where we lose replacement workers whose hiring spell is their first entry in the social-security records. 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. Coefficients in bold are statistically significant at the 5%-level.

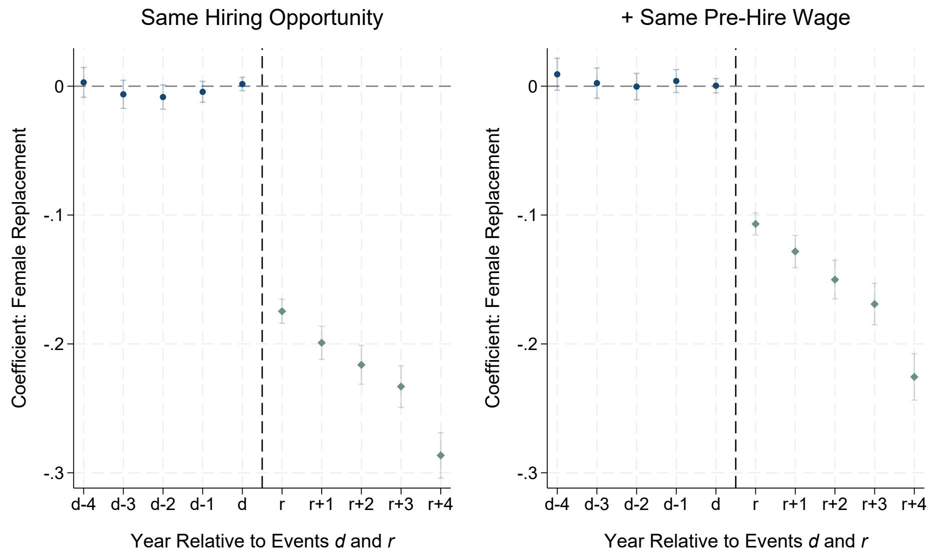
Table A15: Replacement Worker Characteristics, Amenities, Outside Options – Sample With UI Spells Between $r-1$ and r

	(1) Coefficient Female Replacement Same Hiring Opportunity		(2) Coefficient Female Replacement + Same Pre-Hire Wage		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Replacement Worker Characteristics in $r-1$					
Education (years)	**-0.14**	[0.025]	-0.0030	[0.025]	51,208
Experience (years)	**-0.74**	[0.088]	**0.42**	[0.084]	51,354
Tenure (years)	**-0.24**	[0.047]	**0.20**	[0.047]	51,338
Occupational Tenure (years)	**-0.30**	[0.072]	**0.50**	[0.069]	49,741
Days Worked Full-time	**-6.15**	[1.52]	**5.38**	[1.64]	51,362
Yearly Full-time Earnings (EUR)	**-2721.8**	[174.5]	41.5	[170.1]	51,362
Panel B: Amenities					
Δ Commuting Distance (km)	0.43	[2.48]	-0.88	[2.50]	19,988
Δ Gender Wage Gap in Firm	**0.015**	[0.0060]	0.010	[0.0061]	34,760
Gender Wage Gap Other Workers (r)	**0.016**	[0.0063]	**0.019**	[0.0069]	47,519
Family Friendly Firm (r)	-0.0011	[0.0049]	-0.0011	[0.0053]	51,345
Panel C: Outside Options $r-1$					
Outside Option Index $\phi_{cz,occ,t,g}$	0.0013	[0.0030]	0.00092	[0.0030]	49,735
Pre-Hire Firm Median Full-time Wage	**-3.24**	[0.38]	**2.59**	[0.34]	49,697
Pre-Hire Firm FE	**-0.018**	[0.0034]	**0.032**	[0.0031]	49,071

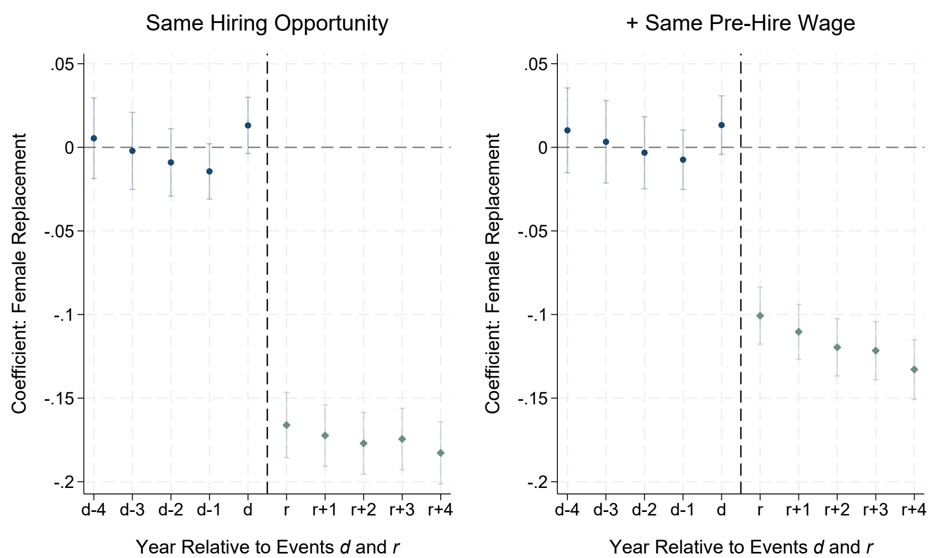
Notes: This table reports gender differences in replacement workers' characteristics in $r-1$, in their amenities, and in their outside options, based on Equation (2). $r-1$ refers to replacement workers' previous employment spell, and r refers to their starting spell at the hiring firm. We restrict to transition pairs where the replacement worker's last employment contract was a full-time job. In contrast to the baseline sample, we allow for UI spells of replacement workers between $r-1$ and r. Column (1) reports the β_1 coefficient for female replacement for the *same hiring opportunity* regression specification, and column (2) reports the β_1 coefficient for female replacement for the + *same pre-hire wage* regression specification. In Panel A, we report gender differences in replacement worker characteristics in $r-1$, their previous employment spell. The worker fixed effect comes from the dataset provided by Lochner et al. (2023), computed as the average across several sets of calendar years; it can thus be based on both pre- and post-replacement observations. In Panel B, we report four proxies for amenities: The change in commuting distance compared to the previous job (in km), the change in the firm gender wage gap, the gender wage gap of all coworkers (i.e., workers in the same 3-digit occupation) in the hiring firm, and a proxy for family-friendliness. Family-friendly firms have at least one female manager with a child aged 0-8. In Panel C, we report three proxies for replacement workers' outside options, all measured in $r-1$. $\phi_{cz,occ,t,g}$ 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 in column (1) control for deceased worker's gender and 3-digit occupation, calendar year of death, 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); the share of female full-time workers (d); firm wage bill, total and women (d); and coworkers' wage bill, total and women (d). In column (2), we additionally control for deciles of 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 5%-level.

Figure A8: The Gender Hiring Opportunity Gap – No Additional Restrictions

(a) Baseline Sample



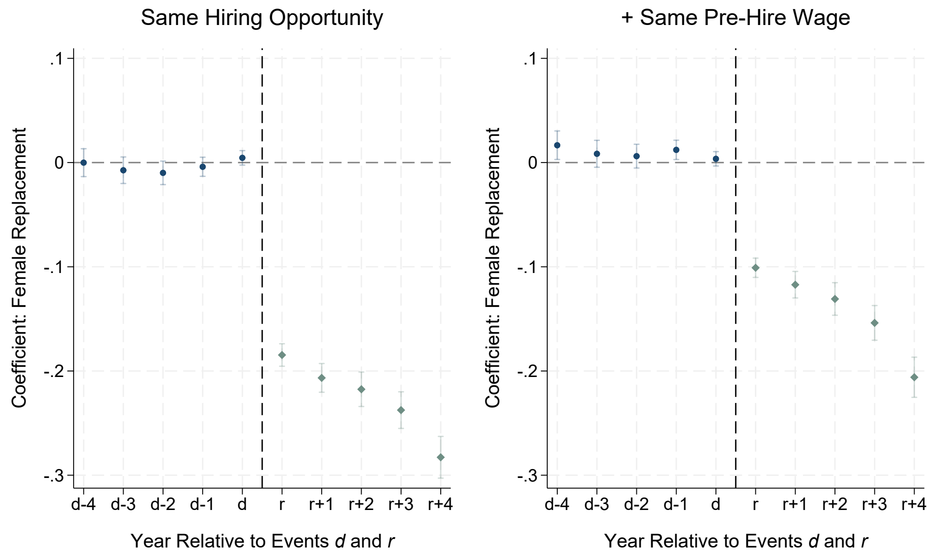
(b) Replacement Works Full-time from r to $r+4$



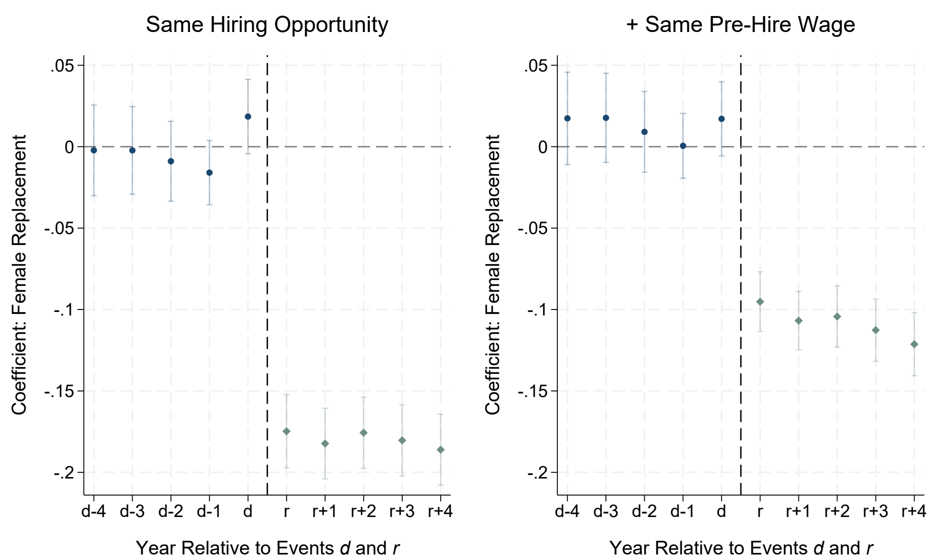
Notes: This figure presents β_1 coefficients of Equation (2). The outcome variable is log wages. We do not restrict to transition pairs where the replacement worker's last employment contract was a full-time job, and we allow for UI spells of replacement workers between $r-1$ and r. The figure on the left ("Same hiring opportunity") refers to the baseline specification that controls for deceased worker's gender and 3-digit occupation, calendar year of death, 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 full-time work in $r-1$. In addition, we control for deciles of: the ex-ante probability of female replacement; deceased worker's wage (d); the share of female full-time workers (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.

Figure A9: The Gender Hiring Opportunity Gap – Sample With UI Spells Between $r-1$ and r

(a) Baseline Sample



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



Notes: This figure presents β_1 coefficients of Equation (2). The outcome variable is log wages. We restrict to transition pairs where the replacement worker's last employment contract was a full-time job. In contrast to the baseline sample, we allow for UI spells of replacement workers between $r-1$ and r. 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 of death, 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); the share of female full-time workers (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.