The Gender Gap in Entry Wages: Evidence from Exogenous Vacancies

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Abstract

This paper studies the gender gap in entry wages. Using German administrative data from 1981 to 2016, we exploit sudden worker deaths to identify exogenous vacancies and compare female and male replacements hired into ex ante comparable vacancies. Female replacements earn 16 log points less at entry; the gap remains 10 log points after accounting for their wages in previous jobs. The gap is not explained by worker observables, outside options, amenities, hours, or coworker adjustments. It shrinks in tight labor markets and widens where firms have greater wage-setting power, pointing to entry wage setting as a central firm-side margin.

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1 Introduction

The gender gap in wages remains a pervasive feature of labor markets worldwide. Across OECD countries, women working in full-time jobs earned 11% less than men in 2023 (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. A large literature instead emphasizes firms, jobs, bargaining, sorting, and wage-setting institutions as central to gender wage inequality (Blau, 1977; Groshen, 1991; Petersen and Morgan, 1995; Bayard et al., 2003; Card et al., 2016; Lochner and Merkl, 2025). These mechanisms have also motivated policies targeting pay-setting practices within firms, including pay transparency and equal-pay regulations.[1] Yet despite this emphasis on firms, it remains difficult to observe how wages are set when workers enter jobs. Men and women sort into different occupations, firms, jobs, and bargaining environments before wages are observed, making it challenging to separate gender differences in entry wage setting from the broader allocation of workers across jobs.

This paper studies that margin by estimating the gender gap in entry wages. Entry wages are important because they are the terms on which workers enter firms. In frictional labor markets, they need not reflect expected productivity alone: they may also depend on outside options, beliefs about future attachment, the division of rents, and the task package assigned at hire (Robinson, 1933; Burdett and Mortensen, 1998; Manning, 2011). Entry wages may also affect later outcomes through internal pay systems, future raises, bargaining positions, outside offers, and salary histories. Understanding entry wage setting is therefore central to understanding how gender wage inequality is created, not only how it evolves after workers are already employed.

To study this margin, we examine exogenous vacancies created by sudden worker deaths. Ordinary worker departures may reflect wage dissatisfaction, outside offers, worker productivity, firm shocks, reorganization, retirement plans, or anticipated task reallocation. A wage gap measured after all separations would therefore mix entry wage setting with selection into

[1] In the United States, Title VII of the Civil Rights Act prohibits discriminatory practices against women and other protected groups in hiring, layoffs, and promotions. In Germany, since 2017, firms with more than 200 employees have been 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, 2026). 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).

why the vacancy arose. Sudden deaths instead create observable production needs attached to pre-existing jobs, firms, occupations, coworkers, and local labor markets. These features are observed before the replacement worker is hired, allowing us to characterize the vacancy independently of the replacement worker's gender.

We use German matched employer–employee data from 1981 to 2016. We begin by identifying 235,086 unexpected deaths of prime-age, full-time workers, building on the use of unexpected worker deaths to study labor-market adjustment and worker substitutability (Jäger et al., 2024). We then focus on cases in which firms hire external replacements. Because the data do not contain job-position identifiers, we use the timing and occupational composition of hiring after death events to identify replacement workers. In the months after a sudden death, firms exhibit excess hiring, and this excess hiring is concentrated in the deceased worker's occupation. Motivated by these patterns, we define the replacement worker as the first new full-time hire in the same 3-digit occupation as the deceased worker within six months of the death event.[2] This deceased–replacement panel allows us to observe the outgoing worker before the event, the firm and local labor market before replacement hiring, and the entry wage of the replacement worker.

Replacement gender is not randomly assigned across vacancies. We therefore construct a conditional comparison using double-selection lasso following Belloni et al. (2014). The procedure selects controls from approximately 600 predetermined characteristics of the deceased worker, vacancy, firm, occupation, and local labor market. The baseline specification compares female and male replacement workers across ex ante comparable vacancies. The preferred specification additionally accounts for the replacement worker's wage in the previous employment spell, measured before the wage at the hiring firm is set. This prior wage summarizes information from the worker's previous employment spell, but it is not a direct measure of productivity. The preferred estimate should therefore be interpreted as an entry-wage gap after accounting for a prior-wage signal relevant to the employer's wage-setting environment, not as a productivity-adjusted gap.

The gender gap in entry wages is large. In the baseline specification, female replacement workers earn about 16 log points less than male replacement workers at entry. In the preferred specification, the gap remains about 10 log points. The preferred estimate has declined over

[2] Section 3.2 and Appendix A.1 provide details on the definition of sudden deaths, excess hiring, and replacement workers.

time but remains 4.6 log points in the most recent decade. Relative to a standard gender wage gap estimated in the LIAB data and reweighted to match our sample, the preferred estimate accounts for approximately 70% of the adjusted gender wage gap in a specification with establishment × 3-digit occupation fixed effects. Before the replacement hire occurs, vacancies later filled by women and men look similar along the main dimensions we observe: deceased workers have similar wage paths, vacancy durations are comparable, and pre-event firm characteristics are closely aligned. Lower wages for female replacements are also not offset by fewer hours, compensating coworker wage-bill adjustments, or weaker firm-level output proxies.

We then study what drives the gap. First, the gap remains large among workers who stay full-time attached to the labor market for at least four years after hiring. This evidence is difficult to reconcile with an interpretation in which lower entry wages for women primarily reflect accurate candidate-specific forecasts of lower subsequent attachment. At the same time, firms may form beliefs about future labor supply or attachment, particularly during childbearing years (Tô, 2018). If firms lack reliable candidate-specific information and instead use group-level expectations, gender can enter wage setting through statistical discrimination (Altonji and Blank, 1999; Fang and Moro, 2011). Consistent with this channel, the gap for mothers increases during prime childbearing ages, although sizable gaps persist across most age groups and among non-mothers.

Second, the gap varies systematically with firms' wage-setting power. It disappears in bottleneck occupations, defined as occupations that are difficult to fill (Caldwell et al., 2025), and it is reduced in tighter labor markets. Using separation elasticities as a proxy for monopsony power (Bassier et al., 2022; Costas-Fernández et al., 2026), we find that the gap is largest in labor markets with low elasticities and declines monotonically across quartiles. This pattern is consistent with theoretical work showing that gender-specific wage-setting wedges are more consequential when firms face less elastic labor supply (Stelzner and Bahn, 2022), and with empirical evidence that monopsony power can account for wage penalties for other groups in Germany (Hirsch and Jahn, 2015). The gap is also smaller in firms and regions associated with stronger gender-equality norms, including East Germany (Boelmann et al., 2024), and has declined across cohorts, although it remains substantial.

Finally, observed worker-side explanations do not account for the gap. Female replacement workers are not negatively selected on education, experience, tenure, occupational tenure, or prior full-time workdays. Measures of outside options based on labor-market thickness and occupational transitions (Caldwell and Danieli, 2024) do not show a female disadvantage. Nor do commuting distance, observed firm amenities, or family-friendly firm characteristics explain the gap[3]. We also examine heterogeneity across proxies for bargaining capacity. Women may be less likely to engage in individual bargaining (Caldwell et al., 2025), but the observed patterns do not point to worker-side bargaining alone as an explanation. The gap is largest among workers with lower labor-market power, such as recent entrants and workers with lower AKM worker fixed effects, and it is not concentrated in low-wage-premium firms.

The analysis is organized around a conceptual framework of entry wage setting at vacancies. In the framework, firms set entry wages as a function of the worker's outside option, the firm's valuation of the match, and the division of rents. Gender can enter through beliefs about future attachment, through rent sharing, or through the wage–task package chosen at hire. The framework also clarifies why prior wages and AKM worker effects require caution. If prior wages enter later wage setting, wage histories may carry forward earlier wage-setting wedges. Estimated worker components may therefore partly absorb past entry-wage differences rather than only portable productivity or preferences.

The paper contributes to three strands of literature. First, it contributes to work on firms, jobs, mobility, and the gender wage gap. Job mobility plays an essential role in wage growth for male workers (Topel and Ward, 1992), while the relationship between mobility and wage growth is less clear for female workers (Loprest, 1992; Hospido, 2009; Del Bono and Vuri, 2011; Barth et al., 2021). A related literature shows that sorting across establishments, occupations, and jobs explains important shares of gender wage inequality (Groshen, 1991; Bayard et al., 2003; Card et al., 2016; Lochner and Merkl, 2025; Costas-Fernández et al., 2026).

We study a different margin: the wage set when workers enter firms. This distinction matters because entry wage differences can precede later sorting, mobility, and estimated worker components. In the language of Card et al. (2016), our evidence speaks to the rent-sharing or bargaining-related side of the gender gap, but with an important caveat: estimated worker components may themselves embed earlier wage-setting wedges through wage histories. These wedges may arise from firm-side behavior, including discrimination, or from worker-

[3]While we lack information on firms' childcare provision as in Costas-Fernández et al. (2026), we show in Table A6 that the gender gap in entry wages is not driven by mothers. We proxy family-friendliness by having at least one female manager with a child aged 0-8.

side factors such as preferences and negotiation (Babcock and Laschever, 2003; Goldin, 2014; Roussille, 2024).

Second, the paper contributes to the literature on gender and hiring. Comparing the prospects of men and women in the labor market is challenging when gender is not randomized, with rare exceptions such as blind auditioning (Goldin and Rouse, 2000). Audit and correspondence studies provide direct evidence that employer behavior can differ by gender, but they are often limited in scale, in the set of jobs studied, and in their ability to observe actual wages and subsequent careers (Azmat and Petrongolo, 2014). We join a small set of studies using quasi-experimental variation to study gender disparities in labor-market transitions, including Roussille (2024) and Mocanu (2024) in hiring settings, and Illing et al. (2024), which studies the worker side following job loss. We complement this work by observing realized hires, actual entry wages, prior wage histories, and later employment trajectories in administrative data.

Third, the paper contributes to work on wage-setting power, bargaining, monopsony, and administrative-data designs using unexpected deaths. Models of imperfect competition imply that wages depend not only on productivity, but also on outside options, match surplus, and the division of rents (Robinson, 1933; Burdett and Mortensen, 1998; Manning, 2011; Bassier et al., 2022; Stelzner and Bahn, 2022). We bring this logic to the gender gap at job entry and show that the gap is smaller in tighter labor markets and larger where firms have greater wage-setting power.

Methodologically, the paper builds on studies using unexpected 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).[4] These studies typically compare units exposed to death events to matched controls without such events. We instead use sudden deaths to identify exogenous vacancies and then compare replacement workers hired into those vacancies. This approach is useful in administrative data settings where job-position identifiers are unavailable and can be adapted to study other dimensions of wage inequality.

The remainder of the paper is organized as follows. Section 2 presents a stylized conceptual framework for entry wage setting at vacancies. Section 3 describes the data, the

[4]The paper is also related to studies analyzing worker substitutability in the context of parental leave (Brenøe et al., 2024; Huebener et al., 2025; Schmutte and Skira, 2025).

sudden-death vacancy design, and the construction of deceased–replacement worker pairs. Section 4 explains how we compare female and male replacements across ex ante comparable vacancies. Section 5 presents the main estimates of the gender gap in entry wages, and Section 6 examines the mechanisms behind the gap. Section 7 concludes.

2 Conceptual Framework

This section presents a stylized model of entry wage setting at vacancies. The central object is a wage offer made when a firm converts a production need into a worker–job match. At that moment, wages are not determined only by expected productivity. They also reflect the worker's outside option, the firm's beliefs under imperfect information, the surplus generated by the match, the share of that surplus the firm chooses or is forced to concede, and potentially the task bundle assigned after the hire. A gender gap in entry wages can therefore arise among candidates with the same productivity signal and observable characteristics. The framework makes these channels transparent and shows why entry wage setting can have consequences beyond the initial employment spell.

2.1 Setup: Vacancies as Production Needs

Consider a vacancy i at firm $j(i)$. A vacancy is a production need with predetermined characteristics X_i, including the firm's pay environment, the initial task requirements, local labor-market conditions, and other features fixed before the firm evaluates candidates. The firm observes a pool of applicants $\mathcal{K}_i$ and chooses an entry wage for the candidate it seeks to hire. Applicant $k \in \mathcal{K}_i$ is characterized by gender $g_{ik} \in \{M, F\}$, latent productivity $\theta_{ik} \in \mathbb{R}$ for this vacancy, a productivity signal s_{ik}, other observables x_{ik}, and an outside option or reservation wage B_{ik}.

The productivity signal is informative but imperfect with noise ν_{ik}:

$$s_{ik} = \theta_{ik} + \nu_{ik}. \tag{1}$$

Conditional on (s, x), firms may differ in their valuation of candidates because they form beliefs about unobserved dimensions of the match, including future attachment and separation risk.

2.2 Match Value and Beliefs about Future Attachment

Firms may care about expected future attachment, such as continued full-time work or lower separation risk, because separations generate costs. Let $a_{ik} \in \{0, 1\}$ denote an unobserved high-attachment type. Define $q_{ik} \equiv \Pr(a_{ik} = 1)$ and let $C_i \geq 0$ be the vacancy-specific disruption cost from low attachment, including training loss, vacancy costs, or reorganization.

Given (s_{ik}, x_{ik}) and predetermined vacancy characteristics X_i, the firm's expected productivity component is

$$\mu_i(s, x) \equiv \mathbb{E}[\theta_{ik} \mid s_{ik} = s, x_{ik} = x, X_i].$$

Let $A_i \equiv A(X_i)$ denote a vacancy-specific baseline surplus component, such as job capital, complementarities, and firm pay policies. The firm values applicant (g, s, x) by

$$\widetilde{V}_i(g, s, x) \equiv A_i + \mu_i(s, x) - C_i \left(1 - \bar{q}_i(g, s, x)\right), \tag{2}$$

where

$$\bar{q}_i(g, s, x) \equiv \mathbb{E}[q_{ik} \mid g_{ik} = g, s_{ik} = s, x_{ik} = x, X_i]$$

is the firm's group-conditioned expectation of attachment. Statistical discrimination arises when firms cannot observe a_{ik} and therefore use gender in forming $\bar{q}_i(g, s, x)$ (Altonji and Blank, 1999; Fang and Moro, 2011). In this formulation, gender need not enter expected productivity directly to affect match valuation. It can affect wages through beliefs about the durability or expected cost of the match. These beliefs may be accurate, inaccurate, biased, or institutionally produced; the model requires only that they enter the firm's valuation of the match.

This channel has a simple comparative static. If perceived match durability matters, gender gaps in entry wages are larger when separation, reorganization, or training losses are more costly, and smaller when individual attachment is quickly learned or disruption is easier to insure.

2.3 Entry Wages with Wage-Setting Power

Entry wages need not equal match value in frictional labor markets where firms have wage-setting power (Robinson, 1933; Burdett and Mortensen, 1998; Manning, 2011). To capture this, suppose the firm makes an offer $W \in [b, \widetilde{V}]$ to a candidate of type (g, s, x). Let the reservation wage for group (g, s, x) be

$$b_i(g, s, x) \equiv \mathbb{E}\big[B_{ik} \mid g_{ik} = g, s_{ik} = s, x_{ik} = x, X_i\big],$$

which can embed amenities and outside options, including commuting costs, flexibility, and alternative offers. The acceptance probability is assumed isoelastic in the offered surplus:

$$\Pr(\text{accept} \mid W, g, s, x) = \left(\frac{W - b_i(g, s, x)}{\widetilde{V}_i(g, s, x) - b_i(g, s, x)}\right)^{\varepsilon_i(g,s,x)}, \quad W \in \Big[b_i(g, s, x),\ \widetilde{V}_i(g, s, x)\Big], \tag{3}$$

where $\varepsilon_i(g, s, x) > 0$ indexes the sensitivity of acceptance to wages. A larger $\varepsilon_i(g, s, x)$ corresponds to tighter competition and a higher labor supply elasticity to the firm; a smaller $\varepsilon_i(g, s, x)$ corresponds to greater wage-setting power (Bassier et al., 2022; Stelzner and Bahn, 2022; Costas-Fernández et al., 2026).

Conditional on a candidate type (g, s, x), the firm chooses the offer to maximize expected profits:

$$\max_{W \in [b, \widetilde{V}]} \Pr(\text{accept} \mid W) \cdot \left(\widetilde{V} - W\right), \tag{4}$$

where $(b, \widetilde{V})$ abbreviate $(b_i(g, s, x), \widetilde{V}_i(g, s, x))$.

Proposition 1 (Optimal entry wage)**.** *Under* (3)–(4)*, the optimal entry wage is*

$$W_i(g, s, x) = b_i(g, s, x) + \beta_i(g, s, x)\left(\widetilde{V}_i(g, s, x) - b_i(g, s, x)\right), \qquad \beta_i(g, s, x) \equiv \frac{\varepsilon_i(g, s, x)}{1 + \varepsilon_i(g, s, x)} \in (0, 1). \tag{5}$$

The optimal wage has a surplus pass-through form. The worker receives the outside option plus a share $\beta_i(g, s, x)$ of the rents $\widetilde{V}_i(g, s, x) - b_i(g, s, x)$. When competition is intense, $\varepsilon_i(g, s, x)$ is large and $\beta_i(g, s, x) \longrightarrow 1$. When the firm has greater wage-setting power, $\beta_i(g, s, x)$ is smaller and the firm retains a larger share of the match surplus. Entry wages are therefore shaped jointly by the value of the match, the worker's outside option, and the division of rents.

2.4 The Vacancy-Level Gender Gap in Entry Wages

Fix a vacancy i and a common (s, x), and define the vacancy-level conditional gender entry wage gap in levels:

$$\Delta_i(s, x) \equiv W_i(M, s, x) - W_i(F, s, x).$$

When using log wages, the sign and comparative statics below carry through for small gaps since $\log W_M - \log W_F \approx (W_M - W_F)/W_F$.

Proposition 2 (Decomposition of the conditional entry wage gap)**.** *For any (s, x), the entry wage gap satisfies*

$$\Delta_i(s, x) = \underbrace{(1 - \beta_{iF}(s, x))\,(b_{iM}(s, x) - b_{iF}(s, x))}_{\textit{outside options / amenities}} + \underbrace{\beta_{iF}(s, x)\left(\widetilde{V}_{iM}(s, x) - \widetilde{V}_{iF}(s, x)\right)}_{\textit{valuation channel: beliefs about attachment}}$$
$$+ \underbrace{(\beta_{iM}(s, x) - \beta_{iF}(s, x))\left(\widetilde{V}_{iM}(s, x) - b_{iM}(s, x)\right)}_{\textit{wage-setting power / rent-sharing wedge}}, \tag{6}$$

where $\beta_{ig}(s, x) \equiv \beta_i(g, s, x)$, $b_{ig}(s, x) \equiv b_i(g, s, x)$, and $\widetilde{V}_{ig}(s, x) \equiv \widetilde{V}_i(g, s, x)$.

This decomposition uses the female wage rule as the reference point; alternative reference points yield algebraically equivalent decompositions with the same economic channels. The first term reflects differences in outside options or amenities. The second term reflects differences in the firm's valuation of male and female candidates with the same (s, x); in (2), such differences arise from beliefs about future attachment. The third term reflects differences in rent sharing. This term is scaled by the surplus $\widetilde{V}_{iM}(s, x) - b_{iM}(s, x)$, so gender differences in rent sharing are most consequential when the match generates rents above the outside option. The same observed candidate information can therefore lead to different entry wages because firms value the match differently, because workers' outside options differ, or because firms split rents differently.

Corollary 1 (Competition and rents)**.** *Suppose outside options are equal conditional on (s, x),*

$b_{iM}(s,x) = b_{iF}(s,x)$, and valuation is equal conditional on (s,x), $\widetilde{V}_{iM}(s,x) = \widetilde{V}_{iF}(s,x)$. Then

$$\Delta_i(s,x) = (\beta_{iM}(s,x) - \beta_{iF}(s,x)) \cdot \left(\widetilde{V}_i(s,x) - b_i(s,x)\right). \tag{7}$$

If $\beta_{iM}(s,x) > \beta_{iF}(s,x)$, the gap is increasing in rents $\left(\widetilde{V}_i(s,x) - b_i(s,x)\right)$ and decreasing in the outside option $b_i(s,x)$.

Corollary 1 highlights the role of rents. The same gender difference in rent sharing has larger wage consequences when rents are large. Competitive pressure compresses the scope for discretionary wage setting by forcing the firm to concede more of the surplus. Conversely, when the firm has greater wage-setting power, differences in rent sharing can translate more directly into entry wage gaps. The corollary also clarifies what equality of entry wages requires: conditional on the same productivity signal and observables, gender must not affect outside options, match valuation, or the division of rents.

2.5 Task Assignment and Wage–Task Packages

The baseline model embeds the task bundle in the vacancy component A_i. It is useful to separate the initial production need from the realized task bundle because a firm need not respond to a vacancy by assigning the entire initial task bundle to a single replacement worker. It may hire a full replacement, hire a worker for a smaller job and reallocate residual tasks to coworkers, or absorb some tasks internally. Entry wage setting may therefore involve both pricing a worker and organizing work.

Let τ_0 denote the initial task requirement associated with the vacancy. The firm chooses the task intensity assigned to the replacement worker, $\tau \in [0, \tau_0]$, and the residual task allocation $\rho \equiv \tau_0 - \tau$, which may be absorbed by coworkers, reassigned, or dropped. Lower τ captures job compression, reassignment, or reduced task scope for the replacement worker. Suppose the value of hiring a candidate of type (g,s,x) and assigning task intensity τ is

$$\widetilde{V}_i(g,s,x;\tau) = A_i(\tau) + R_i(\tau_0 - \tau) + \mu_i(s,x) - C_i\,(1 - \bar{q}_i(g,s,x))\,F_i(\tau) - c_i(\tau_0 - \tau), \tag{8}$$

where $A_i'(\tau) > 0$ is the productive value of tasks assigned to the replacement worker, $R_i(\tau_0 - \tau)$ is the value of residual tasks handled elsewhere, and $c_i(\tau_0 - \tau)$ is the organizational cost of reallocating tasks away from the replacement job.[5] The function $F_i(\tau)$ captures the idea that low attachment is more costly in more intensive task bundles, with $F_i'(\tau) \geq 0$.

To isolate the assignment margin, assume that $b_i(g,s,x)$ and $\varepsilon_i(g,s,x)$ do not vary directly with τ. Under the offer problem above, optimized expected profits are increasing in the surplus generated by the chosen wage–task package, so the task choice can be characterized by maximizing $\widetilde{V}_i(g,s,x;\tau)$. If the objective is concave in τ, or more generally satisfies the usual lattice conditions for monotone comparative statics, then higher expected attachment weakly raises optimal replacement-task intensity. Thus, if $\bar{q}_i(M,s,x) > \bar{q}_i(F,s,x)$ and $F_i'(\tau) > 0$,

$$\tau_i^\star(F,s,x) \leq \tau_i^\star(M,s,x).$$

This extension distinguishes three economic margins. The fixed-task gap compares male and female wages holding the replacement worker's realized task bundle fixed. The wage–task package gap compares packages generated from the same initial production need when the firm can also choose replacement-task intensity. The external-replacement margin concerns whether the firm hires a replacement worker at all or instead absorbs the task bundle internally. The wage gap studied in the model is an entry-wage object conditional on a replacement hire, but the task-assignment margin clarifies that the observed wage may reflect both the price of labor and the scope of work assigned at entry.

2.6 Propagation through Wage Histories

Entry wage gaps may matter beyond the initial hire because wage histories can become state variables. In models of employer learning and asymmetric information, wages do not simply reveal productivity; they also shape future beliefs, bargaining positions, and outside offers. A lower entry wage can therefore persist if subsequent employers, internal pay systems, or bargaining processes condition on prior wages as signals or reference points (Waldman, 1984; Bernhardt, 1995; Farber and Gibbons, 1996; Altonji and Pierret, 2001; Tô, 2018).

This mechanism does not require women to have lower underlying productivity. Suppose two workers have the same productivity and observable characteristics, but one receives a lower entry wage. If future wages are increasing in prior wages, even partially, the initial mark-

[5] For tractability and to isolate the task-assignment response to expected attachment, we assume the worker's baseline latent productivity $\mu_i(s,x)$ is additively separable from task scope.

down can generate persistent wage differences. A previous wage is therefore an informative but contaminated statistic: it may reflect productivity-relevant information, but it may also embed earlier wage-setting wedges.

This logic also bears on static two-way fixed effect decompositions. In an AKM-style wage equation,

$$y_{it} = \alpha_i + \psi_{j(i,t)} + X_{it}'\gamma + u_{it}, \tag{9}$$

α_i is often interpreted as a portable worker component. Under the wage-history mechanism above, however, later wages depend not only on true portable productivity θ_i, but also on a history-dependent component generated by past wages. If earlier entry-wage wedges affect subsequent wages through salary histories, bargaining positions, internal pay rules, or outside offers, a static AKM regression that omits wage history will tend to absorb part of this component into α_i.

The implication is that worker effects estimated from wage histories are not mechanically equivalent to portable productivity. They may also contain persistent wage-history components generated by earlier wage-setting decisions. A gender gap in estimated worker effects therefore need not imply a gender gap in true productivity; it may partly reflect earlier wage-setting wedges that became embedded in subsequent wages.

3 Exogenous Vacancies and Replacement Workers

The conceptual framework treats a vacancy as a production need whose wage and task package are set when the firm evaluates candidates. This section describes how we construct the empirical counterpart of that object.

We focus on sudden deaths, which create observable vacancies attached to pre-existing jobs, firms, occupations, coworkers, and local labor markets. These features can be measured before the replacement worker is hired. Using rich German matched employer–employee records, we identify sudden worker deaths, document firms' hiring responses to those deaths, and construct deceased–replacement worker pairs. The section first describes the administrative data, then shows how exits and entries evolve around sudden deaths, and finally explains how we identify external replacement hires.

Additional analyses use auxiliary datasets merged to the main data. These include worker and firm fixed effects provided by Lochner et al. (2023), the Mannheim Enterprise Panel (MUP-BHP) data containing sales for a subset of firms (Gottschalk et al., 2025), hours worked data from the Statutory Accident Insurance for 2010–2014, and the longitudinal LIAB data used to compute a standard gender wage gap (Ruf et al., 2021). These datasets are described in detail in Appendix A.3.

3.1 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). These data cover 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.[6]

The primary advantage of the data is the ability to observe the precise timing of all worker entries and exits, alongside the recorded reason for separation, including death. The data moreover contain a rich set of characteristics such as wages, detailed occupation codes,[7] and education. From the linked data, we create firm-level characteristics such as workforce composition, average wage level or the firm gender wage gap.[8] 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. Because male and female workers may systematically differ in their weekly hours even within full-time employment, we incorporate supplementary data on exact weekly work hours from the Statutory Accident Insurance (2010–2014) as detailed in Appendix A.3 to validate that our estimated entry wage gaps are not driven by unobserved hours differences.

[6] 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.

[7] 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.

[8] 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.

3.2 Sudden Deaths as Exogenous Vacancies

We follow Jäger et al. (2024) and use sudden worker deaths to identify exogenous vacancies (see Appendix A.1 for details on how we define sudden worker deaths in the data). A sudden death creates an observable vacancy attached to a pre-existing job, firm, occupation, coworkers, and local labor market. This timing is valuable for two reasons. First, it anchors the vacancy before the replacement worker is chosen, allowing us to construct vacancy characteristics that are independent of the replacement worker's gender.[9] Second, because any replacement hiring occurs after the event, the timing allows us to study firms' subsequent hiring responses and to identify external workers who plausibly replace the deceased worker.

The same timing also sharpens the comparison relative to other departure events. Quits may reflect wage dissatisfaction or outside offers; layoffs may reflect firm shocks or reorganization; retirements and negotiated separations may be anticipated; and departures may coincide with planned task reallocation. Entry wage gaps after those departures can therefore combine entry wage setting with selection into why the vacancy arose.

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.[10] 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.[11] In Table A6 in 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. These patterns document the size of the worker loss, the timing of firms' hiring responses, and the empirical basis 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

[9] This rationale is related to the use of sudden deaths in Jäger et al. (2024) to study worker substitutability. In that setting, firms with and without a departing worker are matched on characteristics measured before the sudden death. Here, the same timing lets us anchor the vacancy before the replacement hire occurs.

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

[11] 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."

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.

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 vacancy.

Entries Panels (c) and (d) of Figure 1 plot the number of monthly entries of full-time workers and excess entries relative to 24 months earlier, respectively. Hiring patterns remain stable in the ten months preceding the death event, then rise sharply immediately afterward and remain elevated for approximately six months. Excess hiring fluctuates around zero before peaking in the first month after 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.

Overall, about 33% of sudden deaths, corresponding to 77,867 events, are followed by excess hiring. Notably, 61% of this excess hiring occurs within the same 3-digit occupation as the deceased worker, and 57% occurs within the same 5-digit occupation. These patterns indicate that, for a substantial subset of sudden deaths, firms respond by hiring workers who are close occupational substitutes for the deceased worker. Our main analysis focuses on this external-replacement margin. As a robustness check, Appendix B.2 reweights the main sample to the broader set of sudden-death events.

Replacement Workers These entry patterns motivate our replacement-worker definition. Because the administrative data do not report which hire replaces which departed worker, we identify the replacement as the first external full-time hire in the same 3-digit occupation as the deceased worker within six months after the death event. Table A6 and Appendix B.4 show that the results are largely unchanged when restricting to events with exactly one full-time new hire in the same 3-digit occupation as the deceased worker.

3.3 Construction of Panel Data

Sample Selection Our main sample consists of sudden-death events followed by an identified external replacement hire. To study the replacement margin and construct pre-event controls, we also build a complementary sample of sudden-death events without excess 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 We construct a firm panel to measure predetermined characteristics of vacancies and firms. The panel includes both excess-hiring and non-excess-hiring firms and records firm characteristics for the three years preceding the sudden death event.

The cut-off date is the date of death, so all pre-event firm characteristics are measured relative to the exact day and month of the event. We calculate detailed metrics on the firm's workforce composition and 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 the high-dimensional control set, 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.[12]

To study entry wage setting among replacement hires, we focus on deceased–replacement pairs where both workers held full-time contracts at the time of death and at the time of hiring,

[12] 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.

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.[13]

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 22, 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 22, 2013, corresponds to $t = d - 1$, and so forth. Similarly, if a replacement worker is hired on June 30, 2014, this date becomes their cut-off date, denoted as $t = r$. June 30, 2015, would then correspond to $t = r + 1$, and June 30, 2016, to $t = r + 2$.

We also gather information on replacement workers' characteristics at the cut-off date in their previous job, denoted by $r - 1$, before they start work at the hiring firm. In the baseline analysis, we focus on replacement workers with strong labor-market attachment by restricting the deceased–replacement panel to workers whose employment contract in $r - 1$ was full-time. We additionally exclude women whose last employment spell ended in maternity leave.

After applying these restrictions, our sample comprises 43,015 deceased-replacement worker pairs, with the baseline model identified for 42,958 pairs. We replicate the main results of the paper in Appendix F, relaxing the restrictions by dropping the requirement of a full-time job in $r - 1$.[14]

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. The next section uses this deceased–replacement panel to define the

[13] 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.

[14] 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.

estimating equation and the high-dimensional controls used to compare replacement hires across ex ante comparable vacancies.

3.4 Descriptive Wage Patterns in the Deceased–Replacement Panel

Before turning to our empirical strategy, we describe raw wage paths in the deceased–replacement panel. This descriptive exercise shows how wages evolve around replacement events by the gender of the deceased worker and the gender of the replacement worker.

Let G_p denote one of four transition groups for deceased–replacement pair p: male–male, male–female, female–male, and female–female, where the first gender refers to the deceased worker and the second to the replacement worker. Let

$$\mathcal{T} = \{d-4, \ldots, d, r, \ldots, r+5\}$$

denote event time, with observations for $t \in \{d-4, \ldots, d\}$ corresponding to the deceased worker and observations for $t \in \{r, \ldots, r+5\}$ corresponding to the replacement worker. To summarize raw wage paths, we use the following event-time normalization:

$$y_{pt} = \alpha + \sum_{\substack{j \in \mathcal{T} \\ j \neq d}} \beta_j \mathbf{1}\{t = j\} + \sum_{g \in \{MF, FM, FF\}} \sum_{j \in \mathcal{T}} \delta_{jg} \mathbf{1}\{G_p = g\} \mathbf{1}\{t = j\} + \varepsilon_{pt}, \tag{10}$$

where male–male transitions at $t = d$ are the omitted reference group. The coefficients therefore trace raw wage paths relative to deceased male workers in male–male transitions in the year of death.

Figure A2 plots the resulting wage paths. Panel (a) uses deflated daily wages in EUR, while Panel (b) uses log daily wages. Consistent with Table 1, replacement workers generally earn less than deceased workers at entry, reflecting differences in age, tenure, experience, and labor-market histories between deceased and replacement workers. Male replacement workers either return to the wage level of deceased male workers or exceed the wages of deceased female workers. Female replacement workers, by contrast, remain below the wages of deceased workers, especially when replacing men.

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 differences in the entry wage by the gender of the new hire.

4 Empirical Strategy

The conceptual framework in Section 2 studies entry wage setting at vacancies: a firm faces a production need, evaluates candidates using observed signals and beliefs, and sets an entry wage as part of a wage–task package. Empirically, sudden worker deaths identify vacancies whose pre-event characteristics are observed before the replacement worker is hired. The empirical object of interest thus is the gender gap in entry wages across ex ante comparable vacancies.

Replacement gender is not randomly assigned across vacancies. We therefore use the rich set of predetermined worker, vacancy, firm, occupation, and local-labor-market characteristics in our data to construct a conditional comparison between female and male replacement hires. We implement this comparison using the double-selection lasso estimator developed by Belloni et al. (2014).[15]

Estimating Equation Let i index a deceased–replacement pair. For each event time t, we estimate:

$$y_{it} = \beta_{0t} + \beta_{1t}\,\text{female\_replacement}_i + \boldsymbol{\gamma}_t'\tilde{\boldsymbol{X}}_{it} + \varepsilon_{it}. \tag{11}$$

The variable $\text{female\_replacement}_i$ is an indicator equal to one if the replacement worker is female. Event time runs from four years before the departure event, $t = d - 4$, to the year of death, $t = d$, and then from the replacement worker's hiring spell, $t = r$, until four years after hiring, $t = r + 4$.[16] For $t \leq d$, y_{it} refers to outcomes of the deceased worker. For $t \geq r$, y_{it} refers to outcomes of the replacement worker. At $t = r$, when y_{it} is the replacement worker's log daily wage at the hiring firm, β_{1r} is the female–male entry-wage difference.

The double-selection procedure is implemented separately for each event time and outcome, using robust standard errors. It first runs a lasso of y_{it} on the candidate controls, selecting controls predictive of the outcome. It then runs a lasso of $\text{female\_replacement}_i$

[15] In particular, we use Stata's implementation *dsregress*, applying the plugin iterative formula for the lasso penalty parameter.

[16] By construction, the replacement event occurs between 1 and 180 days after the death event.

on the candidate controls, selecting controls predictive of replacement gender. The final regression includes $\text{female\_replacement}_i$ and the union of controls selected in these two steps, denoted by $\tilde{\boldsymbol{X}}_{it}$ in Equation (11).[17]

The candidate control dictionary contains predetermined characteristics of the vacancy, deceased worker, firm, occupation, and local labor market. These include the deceased worker's occupation, wage, tenure, education, and experience; firm-level characteristics such as the hiring firm's industry, gender wage gap, workforce composition, and average wages for different groups of workers; and local-labor-market characteristics such as the share of employed women and industry composition. The goal is to compare replacement hires across vacancies that are comparable before the replacement wage is set. For a full list of candidate controls, see Appendix B.1.

The preferred specification additionally includes forced indicators for twentieth-percentile bins (vigintiles) of the replacement worker's wage in the previous employment spell, measured before entry into the event firm. From the employer's wage-setting perspective, this prior wage is an imperfect pre-hire signal: it summarizes wage information before entry, but it is not true productivity, which employers do not observe. The preferred estimate should therefore be interpreted as the gender gap in entry wages after accounting for a prior-wage signal relevant to the employer's wage-setting environment, not as a productivity-adjusted gap.[18]

Identifying Assumption The identifying assumption is conditional comparability of vacancies by replacement gender. Among sudden-death vacancies followed by an external replacement hire, and conditional on the selected controls, unobserved determinants of replacement wages are not systematically related to whether the replacement worker is female:

$$\mathbb{E}\left[\varepsilon_{it} \mid \text{female\_replacement}_i, \tilde{\boldsymbol{X}}_{it}\right] = \mathbb{E}\left[\varepsilon_{it} \mid \tilde{\boldsymbol{X}}_{it}\right],$$

[17]See Tables A10 and A11 for the selected variables used to estimate the main wage specifications.

[18]In robustness checks, we account for additional pre-hire signals, including AKM worker fixed effects, occupational skill intensity, the replacement worker's three-year wage profile, tenure, and experience, all measured before the event-firm wage is set. We do not interpret these objects as clean measures of productivity. In particular, as discussed in Section 2.6, wage histories and estimated worker effects may themselves embed earlier wage-setting wedges. Table A8 and Appendix B.4 show that the gender gap in entry wages is at least as large in these additional specifications, except when controlling for AKM worker fixed effects, where the gap falls to 7.5 log points.

where $\tilde{\boldsymbol{X}}_{it}$ denotes the union of controls selected for outcome y at event time t and for replacement gender. In the preferred specification, $\tilde{\boldsymbol{X}}_{it}$ also includes the forced vigintile indicators for the replacement worker's wage in the previous employment spell.

The event-study structure lets us examine whether vacancies later filled by women and men were indeed similar before the replacement hire occurred. For $t \leq d$, the outcomes in Equation (11) are measured for the deceased worker, before the replacement hire occurs. Differences in deceased-worker wages, careers, or firm conditions by the eventual gender of the replacement worker would indicate that vacancies later filled by women and men differ before the hiring-stage wage is set. We assess these both in trends and levels in the next section.

The estimate is conditional on an observed external replacement hire. Firms may also respond to a vacancy by absorbing tasks internally, reallocating work to coworkers, or hiring for a smaller task bundle. Consistent with the wage–task-package framework, the entry wage among observed replacements may therefore reflect both the price of labor and the scope of work assigned at hire.

5 The Gender Gap in Entry Wages

5.1 Main Estimates

The descriptive wage paths in Section 3.4 show a raw gender difference at replacement hiring. We now estimate Equation (11) to compare female and male replacement workers across ex ante comparable vacancies.

Figure 2a displays the β_{1t} coefficients on female replacement using log daily wages as the outcome. The baseline specification conditions on predetermined vacancy, firm, occupation, and local-labor-market controls. The preferred specification additionally includes vigintile indicators for the replacement worker's wage in the previous employment spell, measured before entry into the event firm.[19]

Because the regression codes female replacement as the indicator, negative coefficients indicate lower wages for female replacement workers relative to male replacement workers. We report magnitudes below as male–female gaps.

[19] In our baseline sample, all replacement workers were employed full-time before being hired by the event firm.

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 that relate to the deceased worker's position are measured at the time of death d. 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, supporting the 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 A9 reports the coefficient on *female replacement* across eight firm-level outcomes, with baseline and preferred specifications for each outcome. 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 aged 0 to 8. Although hiring firms exhibit slightly higher firm fixed effects, a lower gender wage gap, and a greater share of female team leaders two years before the event, these differences are small in magnitude. Furthermore, as shown in Table 4, the entry-wage gap is largely unaffected by these factors and, if anything, is smaller in firms with a higher share of female workers and with lower gender wage gaps.

Entry wages and subsequent wage paths In the baseline specification, female replacement workers earn about 16 log points less than male replacement workers at entry. The preferred estimate is about 10 log points. Thus, adding controls for the replacement worker's wage in the previous employment spell reduces the entry-wage gap by about six log points, but leaves a large 10-log-point gender gap at entry.

The wage gaps remain large in subsequent years. By $t = r+4$, the baseline gap reaches 22 log points, while the preferred estimate reaches 17 log points. As discussed in Section 2.6, these later wage-path differences may partly inherit the entry-wage wedge through wage histories, internal pay rules, bargaining positions, or future outside offers.

The gaps also translate into substantial differences in full-time earnings, as illustrated in Figure A4. Starting from initial earnings gaps of 3,300 EUR and 1,770 EUR for the baseline and preferred specifications in the year of hiring, the gaps grow to nearly 6,100 EUR and 5,000 EUR, respectively, by $t = r + 4$. 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 reflect worker-side preferences and constraints, including motherhood, or labor-supply responses to lower entry wages. Section 6 examines these channels.

5.2 Wage–Task Packages and Firm Adjustment

The framework distinguishes a fixed-task wage gap from a wage–task-package gap. Even when vacancies are comparable before hiring, firms may assign different task scopes, reallocate residual work to coworkers, or adjust the organization of production after choosing a replacement worker. We therefore examine whether lower entry wages for female replacements are accompanied by observable differences in hours, coworker wage bills, or firm-level outcomes.[20]

Work hours Panel A of Table 2 examines two observable measures of task intensity: days worked full-time during the year and log weekly hours for the subsample with hours data. If lower entry wages for female replacements reflected systematically smaller observed work packages, we would expect female replacements to work fewer days or fewer hours.

The estimates do not point in that direction. Female replacement workers work around 7 days *more* as full-time employees in their first year at the hiring firm than male replacement workers.[21] We then examine weekly hours using a linkage between the IAB data and hours worked information from the Statutory Accident Insurance for 2010–2014. For this period, we successfully merge 3,169 pairs out of 4,491 pairs, approximately 71% of the analysis sample in 2010–2014. During this period, the preferred estimate is 4.8 log points in the full sample (Table 4, Panel A, column 6), compared with 3.7 log points in the hours-matched subsample.

[20] This subsection uses several merged datasets described in Appendix A.3.

[21] Full-time employment in Germany is defined as any contract exceeding 34 hours per week, excluding overtime.

Across both main specifications, we find no significant differences in weekly hours worked by replacement gender.

Firm-level adjustments We next examine whether lower entry wages for female replacements are accompanied by internal reallocation at the firm. Firms could assign residual tasks to coworkers, adjust coworker pay, change the mix of new hires, or alter production in ways that show up in output.

Panel B of Table 2 examines coworker wage bills after the hiring event at $t = r$. Coworkers are defined as workers in the same 3-digit occupation as the deceased worker. We analyze the total wage bill for all coworkers, as well as the breakdown between incumbent workers and new hires. Incumbents are employees whose employment spell overlaps with the date of the death event, while new hires are those employed at the firm in d+1 but not in d. In all cases, the coefficients β_{1t} are statistically insignificant and small in magnitude. The estimates therefore do not indicate compensating wage-bill increases among coworkers when the replacement worker is female.

Panel C of Table 2 uses the Mannheim Enterprise Panel (MUP) data for a restricted sample of large firms to examine sales per worker. The estimated differences are insignificantly positive. We also find no evidence of differential firm exit four years after the replacement worker starts at the hiring firm. Taken together, the hours, coworker-wage-bill, and output proxies do not support the interpretation that the entry-wage gap is driven by female replacements receiving systematically smaller observed task packages.

5.3 Discussion of Magnitudes

Figure A1 contextualizes the entry-wage gap by comparing it to the gender wage gap among full-time workers in Germany, drawn from the *LIAB, 7519, Version 1* dataset and reweighted to match our baseline analysis sample.[22] The figure presents adjusted gender wage gaps in the LIAB data from Mincerian regressions with human-capital controls and, in progressively richer specifications, controls for industry, occupation, establishment fixed effects, and establishment × occupation fixed effects.

The preferred estimate is close in magnitude to standard adjusted gender wage gaps. In the most recent years, the preferred estimate is about 5 log points. On average, it accounts for

[22]See Appendix A.3 for an overview of the dataset.

approximately 70% of the gender gap in the LIAB specification that includes establishment $\times$ 3-digit occupation fixed effects.

This comparison suggests that entry wage setting is quantitatively important relative to conventional adjusted gender wage gaps. The gap may be higher in our analysis sample than in a sample of all female full-time workers because we focus on workers at the point of entry into a new firm, whereas women who remain in full-time positions over time may be positively selected. If lower entry wages also affect subsequent labor supply decisions, the entry margin becomes particularly important for understanding later gender wage inequality.

6 Drivers of the Gender Gap in Entry Wages

This section uses the conceptual framework to interpret the gender gap in entry wages. Proposition 2 separates three channels: outside options and amenities, firm valuation of the match, and rent sharing under wage-setting power. The task-assignment extension also clarifies that an entry wage may reflect a wage–task package rather than a fixed-task wage alone, while Section 2.6 shows how entry wages can persist through wage histories. We use this structure to organize the evidence in three steps. We first ask whether observed worker-side differences, outside-option proxies, amenities, or wage–task packages can explain the preferred estimate. We then study whether the gap is consistent with gender-specific valuation of match durability, focusing on attachment, motherhood, learning, and gender norms. Finally, we examine whether the gap is larger when firms have more wage-setting power, as implied by Proposition 1 and Corollary 1.

6.1 Worker Characteristics, Outside Options, and Wage–Task Packages

We begin with explanations that operate through the worker-side terms of the framework. If female replacements enter with weaker observed characteristics, lower outside options, stronger preferences for amenities, or smaller assigned task packages, then the preferred estimate could reflect those differences rather than gender-specific wage setting by firms. The evidence does not point in this direction.

Observed pre-hire characteristics. Panel A of Table 3 examines whether female replacement workers differ from male replacement workers in observed pre-hire characteristics. We estimate Equation 11 using education, experience, tenure, occupational tenure, and the number of full-time workdays in the previous job, all measured at $t = r - 1$, as outcomes. Female replacement workers are not negatively selected on these dimensions. If anything, they exhibit slightly higher occupational tenure and work approximately eight more full-time days in their previous job before being hired. These patterns indicate that the preferred estimate is not explained by observable pre-hire characteristics moving in favor of male replacements.

Outside options. We next examine the outside-option term in Proposition 2. We use three proxies for outside options. The first captures workers' job opportunities across occupations, weighted by their likelihood of working in each, following Caldwell and Danieli (2024). This index combines measures of labor-market thickness at the 2-digit occupation by commuting-zone level (Jäger et al., 2024) with a gender- and year-specific matrix of occupational transitions constructed from a 20 percent random sample of workers in Germany.[23] The remaining two proxies are based on characteristics of the previous employer: median full-time wages and firm AKM fixed effects. Panel C of Table 3 shows no gender differences in the labor-market-based outside-option index. In the preferred specification, women are more likely to come from firms with higher median wages and higher firm fixed effects. These observed outside-option proxies therefore do not explain the entry-wage gap.

Bargaining capacity and labor-market power. We also examine whether the gap is concentrated among workers or firms for which bargaining-related explanations are more plausible. Figure A8c plots the entry-wage gap by quartiles of the hiring firm's AKM firm fixed effect. The gap is remarkably stable across the distribution, suggesting that it is not concentrated in low-wage-premium firms. This pattern is also consistent with evidence that worker characteristics, rather than firm characteristics, are the primary predictors of bargaining propensity (Caldwell et al., 2025). An important exception is the firm's existing gender wage gap: the entry-wage gap is substantially larger at firms in the top quartile of the gender-wage-gap distribution.[24]

We then examine heterogeneity by two worker characteristics that Caldwell et al. (2025) identify as strong predictors of bargaining behavior: worker AKM fixed effects and labor-

[23] See Appendix A.2 for details.

[24] The entry-wage gap remains fairly constant across 2-digit occupations with varying shares of female full-time workers (Figure A8a) and across differences in work-from-home feasibility (Figure A8b).

market experience.[25] Figure A9a shows that workers in the lowest quartile of AKM worker fixed effects experience substantially larger entry-wage gaps than workers in the upper quartiles. Figure A9b shows that the preferred estimate is approximately three times larger for recent labor-market entrants than for managers.[26] These patterns suggest that the gap is largest among workers with lower labor-market power, rather than among workers with stronger outside options or greater scope for bargaining.[27] This is consistent with Frimmel et al. (2024), who find that higher-paid workers are better informed about their labor-market opportunities and are therefore in a better bargaining position. Finally, the type of origin region, from large cities to rural municipalities, has little effect on the gap (Figure A9c).

Amenities and compensating differentials. The literature has documented that female workers value shorter commutes (Le Barbanchon et al., 2021) and workplace flexibility (Mas and Pallais, 2017; Drake et al., 2022). In a compensating-differentials framework, women may therefore accept lower wages in exchange for amenities they value (Rosen, 1986). To assess this channel, we first examine changes in commuting distance between the new job at $t = r$ and the previous job at $t = r - 1$.[28] The first row of Panel B in Table 3 shows that the coefficient on female replacement is positive but statistically insignificant across specifications, indicating that commuting distances actually increase slightly more for women.

We also examine indicators of family friendliness at the hiring firm. 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 the previous employer and the gender wage gap among workers in the same 3-digit occupation at the hiring firm. Women are also not more likely to join firms that can be considered family-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 work schedules, the entry-wage gaps persist

[25] Caldwell et al. (2025) rely on survey data collected in 2021 and 2022, after the end of our observation period. Therefore, this comparison assumes that bargaining strategies have not changed enough over time to overturn the qualitative relationship.

[26] 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'.

[27] Similarly, Table 4 shows that workers in roles with higher skill intensity experience a lower preferred estimate.

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

even among non-mothers across all age groups (Figure 3a). Taken together, the observed amenity proxies do not explain the gender gap in entry wages.[29]

Wage–task packages. The task-assignment extension in the framework distinguishes a fixed-task wage gap from a wage–task-package gap. Even when vacancies are comparable before hiring, firms may assign different task scopes, reallocate residual work to coworkers, or adjust production after choosing a replacement worker. The evidence in Section 5 does not support an interpretation in which lower entry wages for female replacements are offset by systematically smaller observed task packages. Female replacements do not work fewer full-time days or fewer weekly hours. Coworker wage bills do not rise when the replacement worker is female, and firm-level output proxies do not decline. These results do not rule out all unobserved differences in assigned tasks, but they substantially narrow the set of wage–task explanations for the preferred estimate.

Overall, observed worker-side characteristics, outside-option proxies, amenity proxies, and observable wage–task package measures do not account for the gender gap in entry wages. We therefore turn to the firm valuation channel in the framework.

6.2 Beliefs about Attachment and Match Valuation

The valuation term in Proposition 2 allows gender to affect entry wages through firms' beliefs about the expected value of the match. The preferred estimate controls for the replacement worker's wage in the previous employment spell, but this prior wage captures only part of what firms may consider at hire. Firms may also form beliefs about unobserved match dimensions, including expected attachment and separation risk.

One salient dimension is future attachment. If employers can forecast individual candidates' future labor supply or separation risk, for instance because of anticipated care responsibilities (Tô, 2018), lower entry wages for workers expected to have shorter or more interrupted careers could reflect candidate-specific valuation of expected match durability. As shown in Section 5, women are more likely than men to transition into part-time work or leave full-time employment over time.

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

A distinct mechanism is group-based statistical discrimination. If firms lack reliable candidate-specific information about future attachment and instead use group-level expectations, they may offer lower entry wages to women even among workers who subsequently display similar attachment (Altonji and Blank, 1999; Fang and Moro, 2011). In the framework, this channel operates through the valuation term: gender affects the firm's expected value of the match through beliefs about future attachment.

Highly attached workers. We begin by restricting the sample to workers who remain in full-time positions for at least four years following the hiring event.[30] Figure 2b presents the β_{1t} coefficients for the baseline and preferred specifications in this highly attached sample. The entry-wage gaps are strikingly similar to those in the full sample. Figure A5 confirms that, within this subgroup, female and male replacement workers do not differ in the number of days worked full-time. In addition, Figure A6 shows that highly attached women are as likely as men to remain at the same firm.

This evidence is difficult to reconcile with an interpretation in which lower entry wages for women primarily reflect accurate candidate-specific forecasts of lower subsequent attachment. It is more consistent with firms using coarser beliefs about group-level attachment, or with other gender-specific wage-setting factors that operate before individual attachment is learned. The stability of the gap in the highly attached sample also suggests that initial pay differences are not quickly undone once subsequent attachment is observed. This pattern is consistent with the wage-history mechanism in Section 2.6: initial pay differences may persist through internal pay rules, bargaining positions, or signals to future employers (Waldman, 1984; Bernhardt, 1995; Farber and Gibbons, 1996; Altonji and Pierret, 2001; Tô, 2018).

Motherhood and age. We next examine whether the gap varies over the life cycle in ways consistent with beliefs about anticipated caregiving responsibilities. Figure 3a reports the gender gap in entry wages by age and motherhood status at the time of hiring. Across most age groups, the gaps for mothers and non-mothers are similar in magnitude and remain substantial. A notable exception occurs in the prime childbearing ages, where the gap for mothers increases starting in the mid twenties and peaks for women aged 31 to 35. This pattern is consistent with firms differentially pricing expected future attachment during periods

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

when young children are most likely to affect labor supply. At the same time, the persistence of sizable gaps for both mothers and non-mothers at older ages indicates that motherhood risk alone cannot account for the overall entry-wage gap.

Firm, regional, and cohort environments. We finally examine whether the gap varies with firm, regional, and cohort environments that proxy for gender norms. Table 4 shows that the preferred estimate is smaller in firms with a higher share of full-time female workers, in firms with lower overall gender wage gaps, and in firms that are more family-friendly, proxied by the presence of at least one female manager with a child aged 0 to 8. The gap is also smaller in East Germany, where gender-equality norms are stronger (Boelmann et al., 2024). These patterns are consistent with gender norms shaping how beliefs about attachment or rent sharing enter wage-setting decisions. Figure 3b shows that more recent cohorts experience smaller gaps, and this decline cannot be explained by age effects alone.

Taken together, the evidence is consistent with the valuation channel in the framework. The gap is not limited to workers whose subsequent attachment is low, it varies over the life cycle in ways related to motherhood, and it is smaller in firm and regional environments associated with stronger gender-equality norms. The evidence is suggestive rather than a direct observation of beliefs, but it is difficult to reconcile with explanations based only on observed worker characteristics or realized lower attachment.

6.3 Wage-Setting Power and Rent Sharing

The final step asks when valuation or rent-sharing wedges translate into entry wages. Beliefs about attachment can lower entry wages by reducing the firm's expected value of the match. Wage-setting power matters because it governs how much of that value, and any gender-specific rent sharing, is passed through to wages. Proposition 1 shows that entry wages depend on how rents are split between the worker and the firm, and Corollary 1 implies that gender differences in rent sharing have larger wage consequences when rents are large and competition is weaker. We therefore examine whether the gender gap in entry wages varies systematically with measures of labor-market competition and wage-setting power.

Bottleneck occupations and labor-market tightness. Figure 4a focuses on bottleneck occupations, defined as occupations that are particularly hard to fill. In these occupations, both the baseline and preferred point estimates collapse to near zero, albeit with wide confidence intervals. This pattern is consistent with stronger hiring constraints limiting firms' ability to translate valuation or rent-sharing wedges into lower entry wages.[31]

Figure 4b splits the sample by quartiles of labor-market tightness measured at the 3-digit occupation × commuting zone level. The entry-wage gap is substantially smaller in tighter labor markets, and the preferred estimate is statistically indistinguishable from zero in the third and fourth quartiles. This pattern is consistent with stronger competition for workers constraining firms' wage-setting discretion at hire.

Separation elasticities. Figure 4c examines heterogeneity by labor-market-specific separation elasticities, measured at the 2-digit occupation × commuting zone level. Separation elasticities are commonly used as measures of firms' wage-setting power, with lower elasticities indicating greater monopsony power (Bassier et al., 2022; Costas-Fernández et al., 2026). Theoretical work shows that under monopsonistic wage setting, workers with lower labor-supply elasticities are more exposed to discriminatory wage setting (Stelzner and Bahn, 2022). Empirically, Hirsch and Jahn (2015) show that immigrants in Germany supply labor less elastically to firms and that the resulting monopsony power can account for much of the native–immigrant wage gap. Consistent with this mechanism, the entry-wage gap is largest in labor markets with the lowest separation elasticities and declines monotonically across quartiles. This gradient suggests that gender-specific wage setting is more consequential when firms face weaker competitive constraints.

Occupational wage variance. Figure 4d examines heterogeneity by occupational wage variance, measured at the 3-digit occupation × commuting zone level. Wage variance is often interpreted as a proxy for wage-setting flexibility, but it can also reflect sorting and market competitiveness. The baseline entry-wage gap is smallest in occupations with the lowest wage variance and increases monotonically across quartiles, consistent with compressed wage structures limiting both sorting and discretionary pay setting. The preferred estimate is less monotonic, increasing over the lower and middle quartiles and becoming smallest in the highest-variance occupations. This pattern suggests that occupational wage variance

[31] We use the definition of bottleneck occupations from Caldwell et al. (2025), 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.

is a noisier proxy for wage-setting power than bottleneck status, labor-market tightness, or separation elasticities. Consistent with this interpretation, the smallest gaps are observed in sectors with relatively tight wage-setting regimes, such as education and public administration, as shown in Figure A7.[32]

Across these measures, the pattern is consistent: the preferred estimate is smaller when firms face stronger competitive pressure and larger when firms have more wage-setting power. This does not require wage-setting power to create gender differences in beliefs or outside options. Rather, wage-setting power determines how strongly valuation and rent-sharing wedges are reflected in entry wages.

Overall, the mechanism evidence points to entry wage setting as a firm-side margin of gender inequality. Observed worker characteristics, outside-option proxies, amenities, and observable wage–task package measures do not explain the preferred estimate. The gap is consistent with firms valuing male and female matches differently through beliefs about attachment, and it is largest precisely where firms have the greatest scope to translate valuation and rent-sharing wedges into wages.

7 Conclusion

This paper studies the gender gap in entry wages. Using sudden worker deaths to identify exogenous vacancies, we compare female and male replacement workers hired into ex ante comparable vacancies. Female replacement workers enter at substantially lower wages than male replacement workers. The baseline gap is about 16 log points. After additionally controlling for the replacement worker's wage in the previous employment spell, the gap remains about 10 log points.

The evidence is difficult to reconcile with observed worker-side explanations alone. Female replacements are not negatively selected on observed pre-hire characteristics, measured outside-option proxies, commuting distance, or observed firm amenities. Nor do lower entry wages appear to be offset by fewer hours, lower coworker wage bills, or weaker output proxies. The gap also persists among workers who remain full-time attached to the labor market.

The patterns instead point to entry wage setting as a firm-side margin of gender inequality.

[32] While public sector firms are typically subject to collective bargaining agreements, these agreements still allow for some degree of wage setting within firms (Coskun et al., 2025).

Consistent with our conceptual framework, the gap is smaller or near zero in bottleneck occupations and tighter labor markets, and larger where separation elasticities indicate greater firm wage-setting power. These results suggest that gender differences in valuation and rent sharing matter most where firms have more discretion over pay.

This interpretation also has direct implications for AKM-style decompositions of the gender wage gap. In such models, worker fixed effects are often interpreted as portable worker components, while differences in firm wage premia or rent sharing are interpreted as firm-side or bargaining-related components. However, as the wage-history discussion in Section 2.6 highlights, prior wages can become state variables in later wage setting. If initial entry-wage wedges are carried forward through salary histories or internal pay rules, AKM worker effects may absorb persistent wage-history components as well as portable productivity. In our robustness checks, controlling for AKM worker effects reduces the entry gap, but it remains sizable. This suggests that part of what appears as a worker component in cross-sectional decompositions may originate in earlier wage-setting decisions.

From a policy perspective, the results suggest that the hiring stage deserves more direct attention in efforts to reduce gender wage inequality. These findings imply that policies focused only on pay progression among incumbent workers may intervene too late: part of the gap is already present when workers enter firms.

Pay transparency rules, salary-range disclosure, and restrictions on the use of prior wages in salary negotiations are therefore particularly relevant. By making starting salaries more visible and reducing the weight placed on wage histories, such policies can limit the scope for gender-specific wage-setting wedges to enter initial offers. More generally, the evidence suggests that equitable pay policy should treat starting wages as a central object, not merely as the first step in later wage growth.

References

Alipour, J.-V., Falck, O., and Schüller, S. (2023). Germany's capacity to work from home. *European Economic Review*, 151:104354.

Altonji, J. G. and Blank, R. M. (1999). Race and gender in the labor market. In *Handbook of Labor Economics*, volume 3, pages 3143–3259. Elsevier.

Altonji, J. G. and Pierret, C. R. (2001). Employer Learning and Statistical Discrimination. *Quarterly Journal of Economics*, 116(1):313–350.

Azmat, G. and Petrongolo, B. (2014). Gender and the labor market: What have we learned from field and lab experiments? *Labour Economics*, 30:32–40.

Babcock, L. and Laschever, S. (2003). *Women Don't Ask: Negotiation and the Gender Divide*. Princeton University Press.

Barth, E., Kerr, S. P., and Olivetti, C. (2021). The dynamics of gender earnings differentials: Evidence from establishment data. *European Economic Review*, 134:103713.

Bassier, I., Dube, A., and Naidu, S. (2022). Monopsony in movers: The elasticity of labor supply to firm wage policies. *Journal of Human Resources*, 57(S):S50–s86.

Bayard, K., Hellerstein, J., Neumark, D., and Troske, K. (2003). New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data. *Journal of Labor Economics*, 21(4):887–922.

Becker, S. O. and Hvide, H. K. (2022). Entrepreneur death and startup performance. *Review of Finance*, 26(1):163–185.

Belloni, A., Chernozhukov, V., and Hansen, C. (2014). Inference on treatment effects after selection among high-dimensional controls. *Review of Economic Studies*, 81(2):608–650.

Bennedsen, M., Pérez-González, F., and Wolfenzon, D. (2020). Do CEOs Matter? Evidence from Hospitalization Events. *Journal of Finance*, 75(4):1877–1911.

Bernhardt, D. (1995). Strategic Promotion and Compensation. *Review of Economic Studies*, 62(2):315–339.

Blau, F. D. (1977). *Equal Pay in the Office*. Lexington MA: Lexington Books.

Boelmann, B., Raute, A., and Schönberg, U. (2024). Wind of Change? Cultural Determinants of Maternal Labor Supply. *American Economic Journal: Applied Economics*.

Börschlein, E.-B., Bossler, M., and Popp, M. (2024). Scarce workers, high wages? IZA Discussion Papers 17447, IZA Network @ LISER.

Bossler, M., Geis, G., and Stegmaier, J. (2018). Comparing survey data with an official administrative population: Assessing sample-selectivity in the IAB establishment panel. *Quality & Quantity*, 52:899–920.

Bossler, M. and Popp, M. (2026). Labor demand on a tight leash. *ILR Review*. Forthcoming.

Brenøe, A. A., Canaan, S., Harmon, N. A., and Royer, H. N. (2024). Is parental leave costly for firms and coworkers? *Journal of Labor Economics*, 42(4):1135–1174.

Bruns, B. (2019). Changes in Workplace Heterogeneity and How They Widen the Gender Wage Gap. *American Economic Journal: Applied Economics*, 11(2):74–113.

Brütt, K. and Yuan, H. (2026). Transparency upon request: the right to pay information and the gender pay gap. *Economica*. Forthcoming.

Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR) (2021). Stadt- und Gemeindetypen in Deutschland. Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR), Bonn, Germany. Accessed: 2025-12-15.

Burdett, K. and Mortensen, D. T. (1998). Wage differentials, employer size, and unemployment. *International Economic Review*, 39(2):257–273.

Caldwell, S. and Danieli, O. (2024). Outside Options in the Labour Market. *Review of Economic Studies*, 91(6):3286–3315.

Caldwell, S., Haegele, I., and Heining, J. (2025). Bargaining and Inequality in the Labor Market. *Quarterly Journal of Economics*, 141(1):315–371.

Card, D., Cardoso, A. R., and Kline, P. (2016). Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women. *Quarterly Journal of Economics*, 131(2):633–686.

Coskun, S., Gartner, H., and Taskin, A. A. (2025). Rent sharing and the gender bargaining gap: Evidence from the banking sector. IAB-Discussion Paper, Institute for Employment Research (IAB).

Costas-Fernández, J., Findeisen, S., Raute, A., and Schönberg, U. (2026). Family-friendly workplace policies. RFBerlin Discussion Paper 141/26, Rockwool Foundation Berlin.

Cullen, Z. (2024). Is Pay Transparency Good? *Journal of Economic Perspectives*, 38(1):153–180.

Del Bono, E. and Vuri, D. (2011). Job mobility and the gender wage gap in Italy. *Labour Economics*, 18(1):130–142.

Diegmann, A., Doherr, T., Hälbig, M., and Wolter, S. (2025). Linking the Mannheim Enterprise Panel (MUP) with Administrative Establishment Data of IAB–an update. FDZ-Methodenreport, Institute for Employment Research (IAB).

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64(5):1001–1044.

Drake, M., Thakral, N., and Tô, L. T. (2022). Wage Differentials and the Price of Workplace Flexibility. *Mimeo*.

Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M., and Vom Berge, P. (2022). Reallocation Effects of the Minimum Wage. *Quarterly Journal of Economics*, 137(1):267–328.

Fadlon, I. and Nielsen, T. H. (2019). Household labor supply and the gains from social insurance. *Journal of Public Economics*, 171:18–28.

Fang, H. and Moro, A. (2011). Theories of Statistical Discrimination and Affirmative Action: A Survey. In *Handbook of Social Economics*, volume 1, pages 133–200. Elsevier.

Farber, H. S. and Gibbons, R. (1996). Learning and Wage Dynamics. *Quarterly Journal of Economics*, 111(4):1007–1047.

Fitzenberger, B., Osikominu, A., Völter, R., et al. (2006). Imputation Rules to Improve the Education Variable in the IAB Employment Subsample. *Schmollers Jahrbuch*, 126(3):405–436.

Folke, O. and Rickne, J. (2022). Sexual Harassment and Gender Inequality in the Labor Market. *Quarterly Journal of Economics*, 137(4):2163–2212.

Frimmel, W., Schmidpeter, B., Wiesinger, R., and Winter-Ebmer, R. (2024). External pay transparency and the gender wage gap. RF Berlin-CReAM Discussion Paper Series.

Goldin, C. (2014). A Grand Gender Convergence: Its Last Chapter. *American Economic Review*, 104(4):1091–1119.

Goldin, C., Katz, L. F., and Kuziemko, I. (2006). The Homecoming of American College Women: The Reversal of the College Gender Gap. *Journal of Economic Perspectives*, 20(4):133–156.

Goldin, C. and Rouse, C. (2000). Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians. *American Economic Review*, 90(4):715–741.

Gottschalk, S., Schmucker, A., Wolter, S., and Zimmermann, F. (2025). The Mannheim Enterprise Panel linked to the Establishment History Panel of the IAB 2010–2023 (MUP-BHP 1023). FDZ-Datenreport, Institute for Employment Research (IAB).

Groshen, E. L. (1991). The Structure of the Female/Male Wage Differential: Is It Who You Are, What You Do, or Where You Work? *Journal of Human Resources*, 26(3):457–472.

Gudgeon, M. and Trenkle, S. (2024). The Speed of Earnings Responses to Taxation and the Role of Firm Labor Demand. *Journal of Labor Economics*, 42(3):793–835.

Gulyas, A., Seitz, S., and Sinha, S. (2023). Does Pay Transparency Affect the Gender Wage Gap? Evidence from Austria. *American Economic Journal: Economic Policy*, 15(2):236–255.

Hirsch, B. and Jahn, E. J. (2015). Is there monopsonistic discrimination against immigrants? *ILR Review*, 68(3):501–528.

Hospido, L. (2009). Gender Differences in Wage Growth and Job Mobility of Young Workers in Spain. *Investigaciones Económicas*, 33(1):5–37.

Huebener, M., Jessen, J., Kühnle, D., and Oberfichtner, M. (2025). Parental leave, worker substitutability and firms' employment. *The Economic Journal*, 135(669):1467–1495.

Illing, H., Schmieder, J., and Trenkle, S. (2024). The Gender Gap in Earnings Losses After Job Displacement. *Journal of the European Economic Association*, 22(5):2108–2147.

Isen, A. (2013). Dying to Know: Are Workers Paid Their Marginal Product? Working Paper.

Jäger, S., Heining, J., and Lazarus, N. (2024). How Substitutable Are Workers? Evidence from Worker Deaths. Working Paper.

Jaravel, X., Petkova, N., and Bell, A. (2018). Team-specific capital and innovation. *American Economic Review*, 108(4-5):1034–1073.

Jones, B. F. and Olken, B. A. (2005). Do Leaders Matter? National Leadership and Growth Since World War II. *Quarterly Journal of Economics*, 120(3):835–864.

Kropp, P. and Schwengler, B. (2016). Three-step method for delineating functional labour market regions. *Regional Studies*, 50(3):429–445.

Le Barbanchon, T., Rathelot, R., and Roulet, A. (2021). Gender Differences in Job Search: Trading off Commute against Wage. *Quarterly Journal of Economics*, 136(1):381–426.

Lochner, B. and Merkl, C. (2025). Gender-Specific Application Behaviour, Matching, and the Residual Gender Earnings Gap. *Economic Journal*, 136(673):97–124.

Lochner, B., Wolter, S., and Seth, S. (2023). AKM Effects for German Labour Market Data from 1985 to 2021. *Jahrbücher für Nationalökonomie und Statistik*, 244(4):425–431.

Loprest, P. J. (1992). Gender Differences in Wage Growth and Job Mobility. *American Economic Review*, 82(2):526–532.

Manning, A. (2011). Imperfect Competition in the Labor Market. In *Handbook of Labor Economics*, volume 4, pages 973–1041. Elsevier.

Mas, A. and Pallais, A. (2017). Valuing Alternative Work Arrangements. *American Economic Review*, 107(12):3722–3759.

Mocanu, T. (2024). Designing Gender Equity: Evidence from Hiring Practices. Working Paper.

Müller, D. and Strauch, K. (2017). Identifying mothers in administrative data. *FDZ-Methodenreport*, 13:2017.

OECD (2019). Education at a Glance 2019. Organisation for Economic Co-operation and Development, OECD Publishing, Paris.

OECD (2023). Reporting Gender Pay Gaps in OECD Countries: Guidance for Pay Transparency Implementation, Monitoring and Reform. OECD Publishing, Paris.

Paulus, W., Matthes, B., et al. (2013). The German Classification of Occupations 2010–Structure, Coding and Conversion Table. *FDZ-Methodenreport*, 8:2013.

Petersen, T. and Morgan, L. A. (1995). Separate and Unequal: Occupation-Establishment Sex Segregation and the Gender Wage Gap. *American Journal of Sociology*, 101(2):329–365.

Robinson, J. (1933). The Theory of Money and the Analysis of Output. *Review of Economic Studies*, 1(1):22–26.

Rosen, S. (1986). The Theory of Equalizing Differences. In *Handbook of Labor Economics*, volume 1, pages 641–692. Elsevier.

Roussille, N. (2024). The Role of the Ask Gap in Gender Pay Inequality. *Quarterly Journal of Economics*, 139(3):1557–1610.

Ruf, K., Schmidtlein, L., Seth, S., Stüber, H., and Umkehrer, M. (2021). Linked Employer-Employee Data from the IAB: LIAB Longitudinal Model (LIAB LM) 1975-2019. FDZ-Datenreport, Institute for Employment Research (IAB).

Schmidtlein, L., Seth, S., and Umkehrer, M. (2019). Linked Employer-Employee Data from the IAB: LIAB Longitudinal Model (LIAB LM) 1975-2017. FDZ-Datenreport, Institute for Employment Research (IAB).

Schmutte, I. M. and Skira, M. M. (2025). The response of firms to maternity leave and sickness absence. *Journal of Human Resources*, 60(6):2125–2167.

Stelzner, M. and Bahn, K. (2022). Discrimination and monopsony power. *Review of Black Political Economy*, 49(2):152–174.

Tô, L. T. (2018). The Signaling Role of Parental Leave. Working Paper.

Topel, R. H. and Ward, M. P. (1992). Job Mobility and the Careers of Young Men. *Quarterly Journal of Economics*, 107(2):439–479.

Waldman, M. (1984). Job assignments, signalling, and efficiency. *Rand Journal of Economics*, 15(2):255–267.

8 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]	92.9 [51.4]	95.9 [61.1]	72.9 [35.9]
Days Worked Full-time	332.1 [79.9]	338.9 [71.4]	339.5 [73.4]	331.9 [84.5]
Age (years)	38.7 [11.4]	45.4 [11.3]	45.5 [11.5]	43.0 [12.2]
Tenure in Firm (years)	5.87 [5.97]	6.54 [6.39]	7.45 [6.86]	6.56 [6.21]
Occ. Tenure (years)	8.19 [7.04]	9.73 [7.76]	10.1 [8.04]	9.24 [7.25]
Experience (years)	13.0 [8.54]	14.8 [8.79]	15.0 [8.80]	12.9 [8.27]
Education (years)	12.2 [1.93]	11.8 [1.40]	12.2 [1.89]	11.8 [1.43]
Mother	0.074 [0.26]	0 [0]	0.049 [0.21]	0.14 [0.35]
Panel B		*Replacement worker at the hiring event r*		
Daily Wage in EUR	91.7 [53.8]	84.5 [29.4]	82.0 [34.2]	69.1 [33.0]
Days Worked Full-time	332.1 [79.9]	320.9 [83.6]	324.9 [83.5]	321.5 [86.4]
Age (years)	38.7 [11.4]	35.3 [10.1]	34.1 [10.0]	33.4 [10.3]
Tenure in Firm (years)	5.87 [5.97]	0.44 [0.31]	0.47 [0.32]	0.45 [0.31]
Occ. Tenure (years)	8.19 [7.04]	4.07 [5.48]	4.06 [5.18]	4.23 [5.12]
Experience (years)	13.0 [8.54]	10.6 [7.08]	9.63 [6.88]	8.97 [6.49]
Education (years)	12.2 [1.93]	12.0 [1.51]	12.4 [2.04]	12.0 [1.51]
Mother	0.074 [0.26]	0 [0]	0.12 [0.32]	0.17 [0.38]
Number of Individuals	14,905,321	33,972	5,152	3,891

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 from 1981–2016. Columns (2)–(4) show characteristics for male–male, opposite-sex, and female–female transition pairs, respectively. In Panel A, columns (2)–(4) present characteristics of deceased workers in their last employment spell, and in Panel B, columns (2)–(4) present characteristics of replacement workers in their starting spell at the hiring firm (r). Here, d refers to the deceased worker's last employment spell. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Deaths occur between 1981 and 2016, and the sample spans 1975–2021. Standard deviations are reported in brackets.

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

	(1) Coefficient Female Replacement Baseline		(2) Coefficient Female Replacement Preferred		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment					
Log Wage	**-0.16**	[0.0048]	**-0.10**	[0.0044]	42,958
Days Worked Full-Time per Year	**6.58**	[1.29]	**7.20**	[1.32]	42,958
Log Hours Worked per Week	-0.011	[0.012]	-0.011	[0.012]	3,169
Log Wage if in Hours Data	**-0.087**	[0.016]	**-0.037**	[0.014]	3,169
Wage Bill Replacement-Deceased Worker (EUR)	**-3229.1**	[159.4]	**-1922.2**	[152.9]	42,958
Panel B: Coworker Wage Bill					
Wage Bill All Coworkers (EUR)	6538.7	[7003.5]	5670.5	[7024.2]	42,958
Wage Bill Incumbents (EUR)	5683.2	[6123.7]	3553.9	[6207.5]	42,958
Wage Bill New Hires (EUR)	-30.0	[2434.8]	489.8	[2390.5]	42,958
Panel C: Firm-level Adjustments					
Sales/Worker	389.2	[563.5]	389.2	[563.5]	2,009
Firm Has Disappeared by r+4	0.0024	[0.0021]	0.0029	[0.0021]	35,643

Notes: This table reports gender differences in replacement workers' labor market outcomes and in firm outcomes by the replacement worker's gender, based on Equation (11). If not indicated otherwise, outcomes are measured in r, which refers to the replacement worker's starting spell at the hiring firm. Column (1) reports the β_1 coefficient for female replacement in the *baseline* specification, and column (2) reports the β_1 coefficient for female replacement in the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. 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 replacement worker. Incumbents are defined as all employees whose employment spell overlaps with the date of death, and new hires are defined as employees who worked at the firm in the post-death year t_1 but not in the calendar year of death t_0. Panel C reports firm-level adjustments. Sales come from the MUP-BHP dataset (see Gottschalk et al. (2025)) and are available for linked firms from 2010. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the 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 Baseline		(2) Coefficient Female Replacement Preferred		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Replacement Worker Characteristics in $r-1$					
Education (years)	**-0.12**	[0.028]	0.024	[0.028]	42,850
Experience (years)	**-0.98**	[0.099]	0.077	[0.096]	42,955
Tenure (years)	**-0.17**	[0.057]	**0.16**	[0.057]	42,941
Occupational Tenure (years)	**-0.36**	[0.085]	**0.39**	[0.084]	41,853
Days Worked Full-time	**15.0**	[1.43]	**8.06**	[1.43]	42,958
Yearly Full-time Earnings (EUR)	**-812.6**	[66.8]	-106.1	[58.4]	42,958
Log Wage	**-0.20**	[0.0063]	0.0011	[0.0022]	42,958
Days Job Was Vacant	0.97	[0.87]	1.72	[0.88]	42,958
Panel B: Amenities					
Δ Commuting Distance (km)	2.30	[3.11]	1.67	[3.08]	15,753
Δ Gender Wage Gap in Firm	-0.0048	[0.0064]	-0.012	[0.0065]	29,634
Gender Wage Gap Other Workers (r)	0.0011	[0.0047]	0.00048	[0.0049]	42,958
Family Friendly Firm (r)	0.000074	[0.0055]	-0.00055	[0.0056]	42,958
Panel C: Outside Options in $r-1$					
Outside Option Index $\phi_{cz,occ,t,g}$	0.0025	[0.0031]	0.0034	[0.0033]	41,849
Pre-Hire Firm Median Full-time Wage	**-3.14**	[0.39]	**3.08**	[0.35]	42,186
Pre-Hire Firm FE	**-0.019**	[0.0034]	**0.042**	[0.0030]	41,511

Notes: This table reports gender differences in replacement workers' characteristics in $r-1$, their amenities, and their outside options, based on Equation (11). $r-1$ refers to the replacement worker's previous employment spell, and r refers to their starting spell at the hiring firm. Column (1) reports the β_1 coefficient for female replacement in the *baseline* specification, and column (2) reports the β_1 coefficient for female replacement in the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. In Panel A, we report gender differences in replacement worker characteristics in $r-1$, as well as in the time it takes firms to fill a position, measured as the duration between the date of death and the start of the replacement's employment spell. In Panel B, we report four proxies for amenities: the change in commuting distance relative to the previous job (in km), the change in the firm gender wage gap, the gender wage gap among coworkers in the same 3-digit occupation at 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 fixed effects, as provided by Lochner et al. (2023), characterize the quality of workers' previous employers. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975–2021. Coefficients in bold are statistically significant at the 5% level.

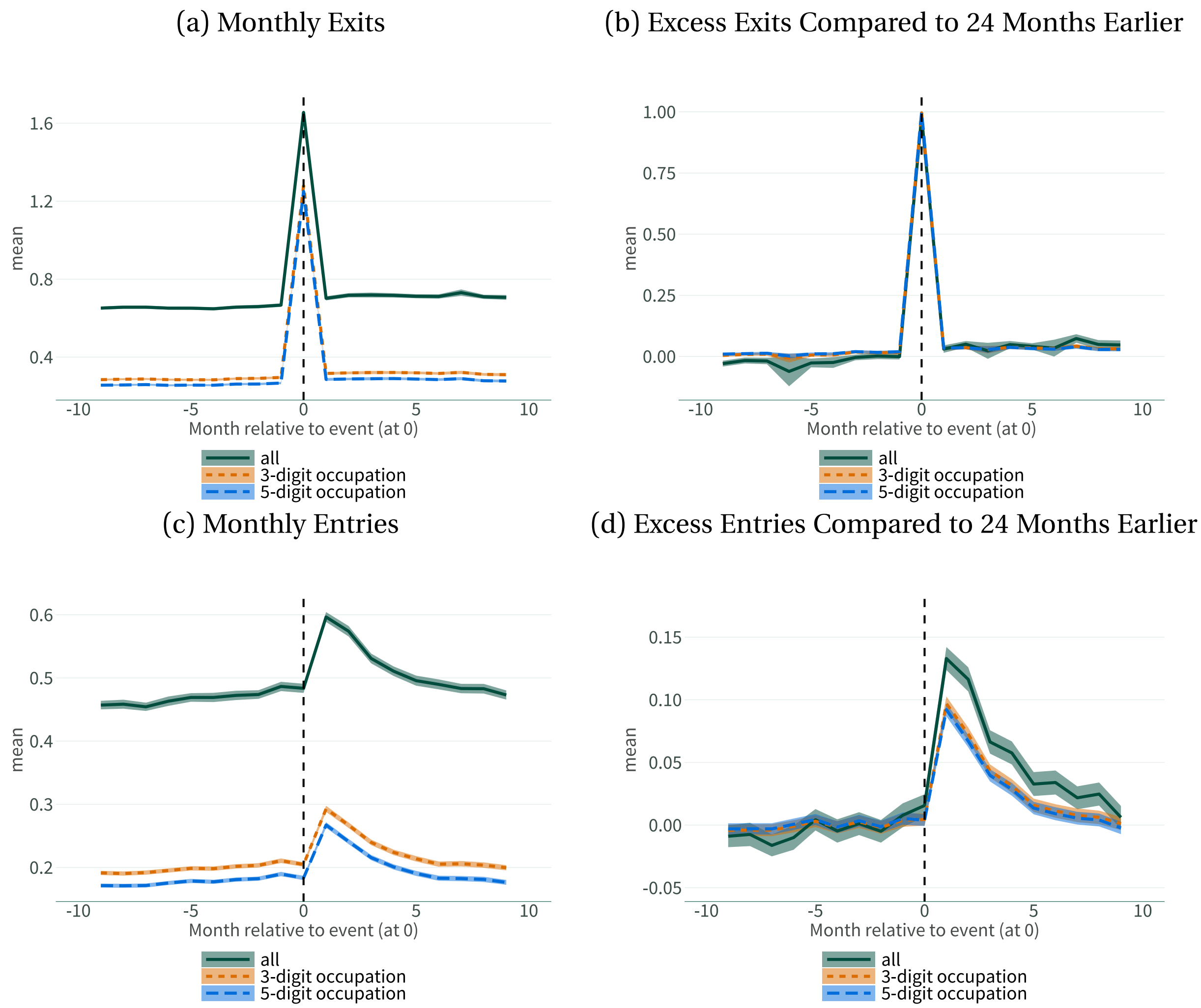
Table 4: The Gender Gap in Entry Wages for Different Sample Splits – Preferred Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	**All Years**	**1981-1989**	**1990-1999**	**2000-2009**	**2010-2016**	**2010-2014**
Female Replacement	-0.10	-0.16	-0.12	-0.072	-0.046	-0.048
	(0.0044)***	(0.0087)***	(0.0075)***	(0.0093)***	(0.0094)***	(0.012)***
Observations	42958	12463	14457	9509	6529	4491
Panel B:	**Share FT Women**		**Family-Friendly**		**Firm Gender Wage Gap**	
	< 50%	**>= 50%**	**Yes**	**No**	**< Mean**	**>= Mean**
Female Replacement	-0.11	-0.095	-0.062	-0.12	-0.092	-0.13
	(0.0056)***	(0.0073)***	(0.0086)***	(0.0051)***	(0.0054)***	(0.0074)***
Observations	34399	8559	5812	37146	25651	17307
Panel C:	**Skill-Intensity**		**Gender Deceased Worker**		**3-Digit Occ. in $r-1$**	
	Low	**Medium/High**	**Male**	**Female**	**Same**	**Different**
Female Replacement	-0.13	-0.083	-0.094	-0.10	-0.098	-0.11
	(0.0072)***	(0.0054)***	(0.0052)***	(0.0088)***	(0.0061)***	(0.0063)***
Observations	29525	13433	37557	5401	19635	23323
Panel D:	**Worker FE**		**West**	**East**	**Days to Fill Vacancy**	
	< Mean	**>= Mean**			**< Mean**	**>= Mean**
Female Replacement	-0.098	-0.080	-0.11	-0.091	-0.11	-0.099
	(0.0059)***	(0.0063)***	(0.0047)***	(0.011)***	(0.0056)***	(0.0070)***
Observations	23206	19752	37555	5403	25330	17628

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for different sample splits. Coefficients are from Equation (11), show β_1 for $t = r$, and the outcome variable is log wages. All regressions use the preferred specification, which controls for vigintiles of the replacement worker's wage in the previous employment spell. In Panel A, we report coefficients for the full sample, followed by the wage gap by decade. In Panel B, the sample is split by firm characteristics measured in d: the share of women in full-time jobs at the firm (columns 1–2), firm family-friendliness (columns 3–4; family-friendly firms have at least one female manager with a child aged 0–8), and the firm-level gender wage gap (columns 5–6). In Panel C, we present coefficients for replacement workers with low (column 1) versus medium-to-high occupational skill intensity (column 2; see Appendix A.2 for details), by gender of the deceased worker (columns 3–4), and for replacement workers who worked in the same 3-digit occupation in $r-1$ (columns 5–6). In Panel D, we present coefficients for replacement workers with below- versus above-mean worker fixed effects (columns 1–2), for firms located in West versus East Germany (columns 3–4), and for positions with below- or above-average time to fill (columns 5–6). Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975-2021. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

9 Figures

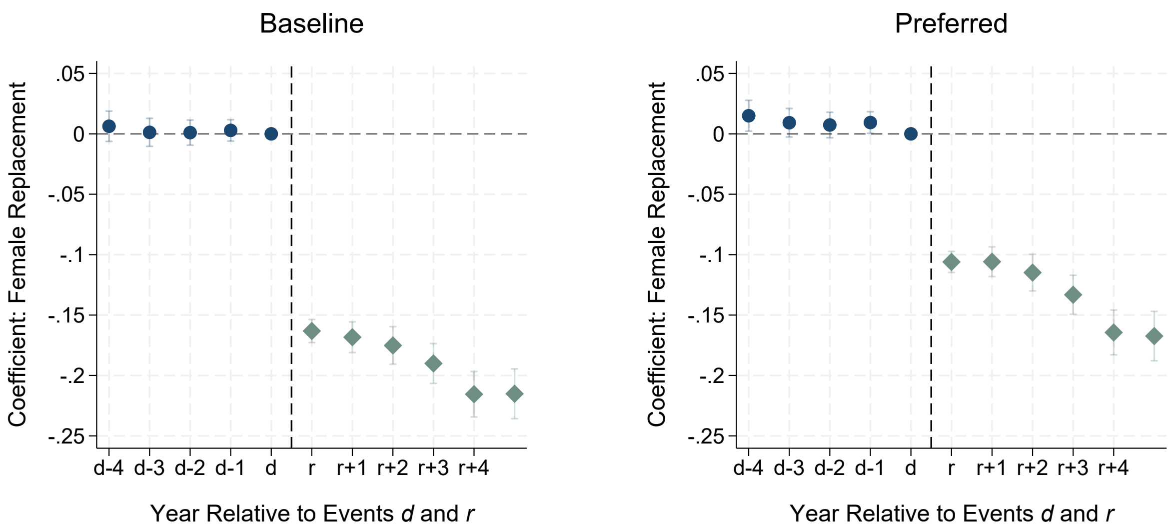
Figure 1: Exits and Entries of Full-time Workers Around Date of Death



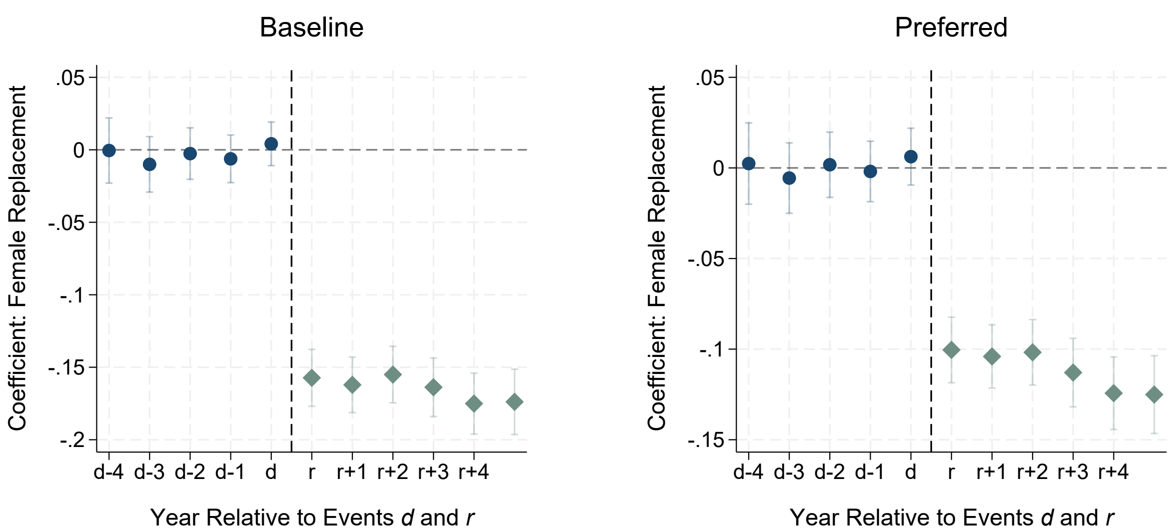
Notes: This figure plots raw means of exits and entries out of and into event firms in the year before and after the death event (at 0). Panel (a) shows the average number of monthly full-time worker exits; Panel (b) shows the average number of monthly full-time worker exits, relative to 24 months earlier.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

Figure 2: The Gender Gap in Entry Wages

(a) Baseline Sample



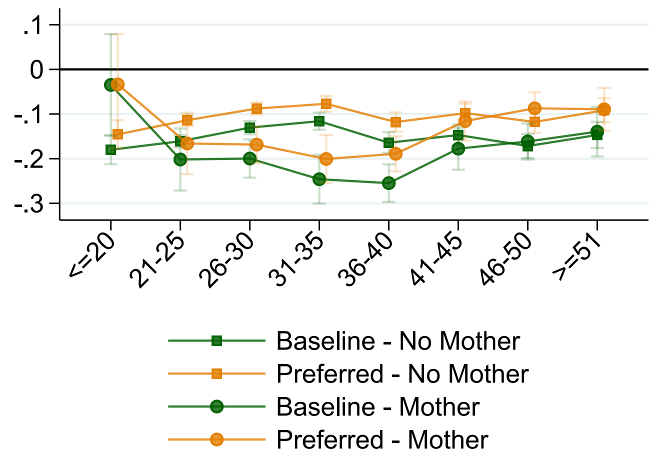
(b) Replacement Works Full-time from r to $r+4$



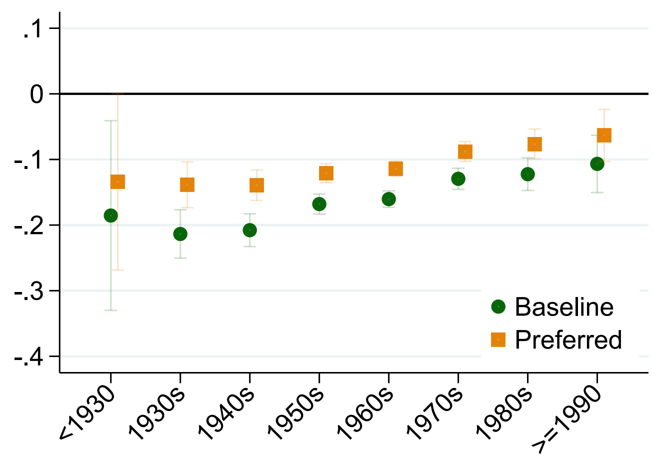
Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is log wages. The left panel ("Baseline") corresponds to the baseline specification. The right panel ("Preferred") shows coefficients from a specification that controls for vigintiles of the replacement worker's wage in the previous employment spell. Coefficients in navy ($t = d-4, ..., d$) refer to log wages of the deceased worker, and coefficients in teal ($t = r, ..., r+4$) refer to log wages of the replacement worker. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure 3: The Gender Gap in Entry Wages Over the Lifecycle, by Motherhood Status, and by Cohort

(a) Replacement Worker Age and Motherhood Status at r

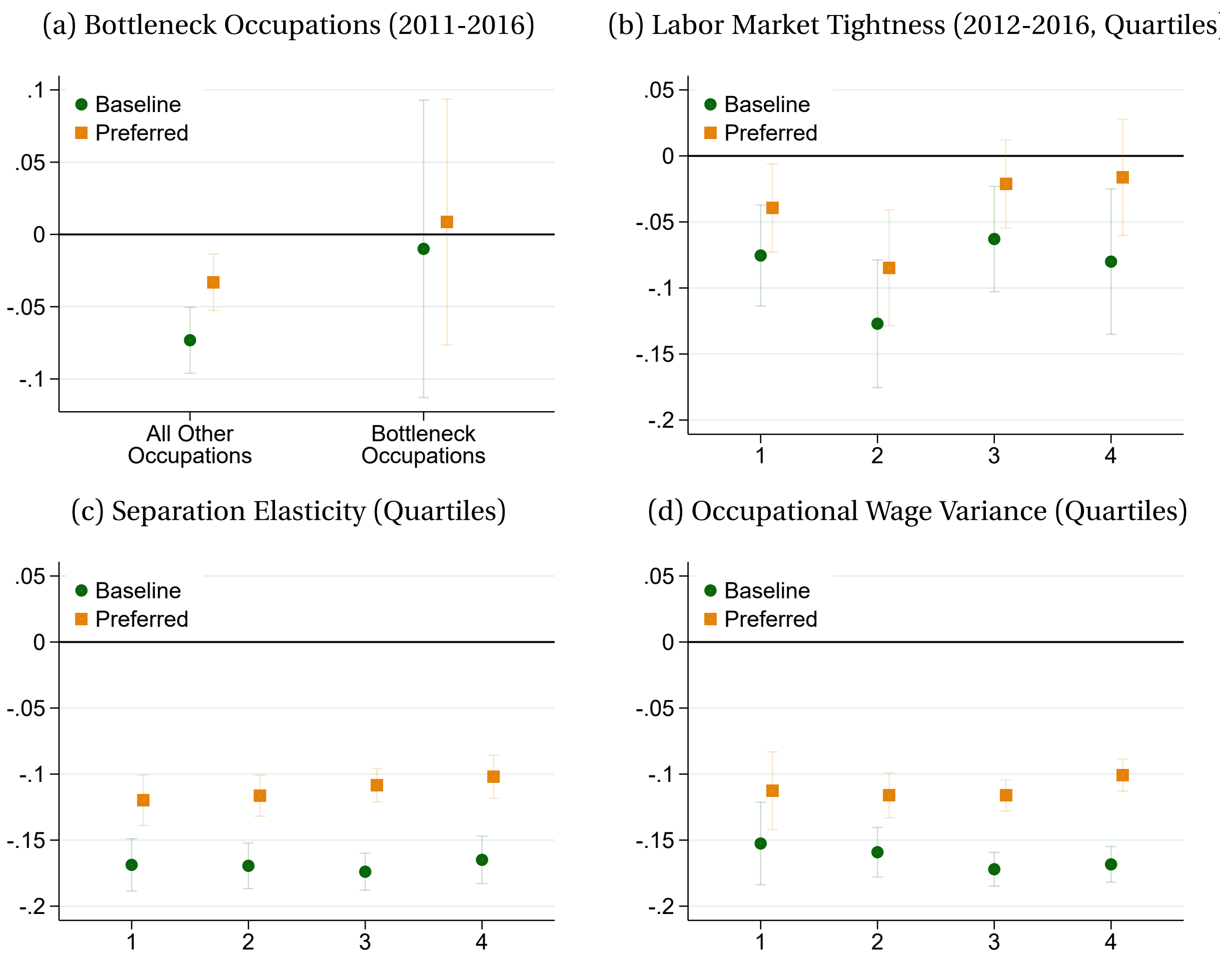


(b) Replacement Worker Birth Cohort



Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots gender gaps in entry wages by replacement worker age and mother status, and Panel (b) plots the gaps by replacement worker birth cohort. In Panel (a), green squares (dashed line) and green dots (solid line) show *baseline* coefficients for non-mothers and mothers, respectively, while orange squares (dashed line) and orange dots (solid line) show *preferred* coefficients for non-mothers and mothers. In Panel (b), green dots correspond to the *baseline* specification, and orange squares correspond to the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure 4: The Role of Hiring Firms' Market Power



Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots the gender gap by bottleneck status (d), with the sample restricted to 2011–2016 when the classification is available. Panel (b) plots the gap by quartiles of labor market tightness provided by Bossler and Popp (2026), measured at the 3-digit occupation × commuting zone level (d). Panel (c) plots the gap by quartiles of labor-market-specific separation elasticity, measured at the 2-digit occupation × commuting zone level. Panel (d) plots the gender gap by quartiles of occupational wage variance at the 3-digit occupation × commuting zone level (d). See Section A.3 for definitions of bottleneck occupations and the tightness data, and Section A.2 for details on the construction of the separation elasticity. Green dots correspond to the *baseline* specification, while orange squares correspond to the *preferred* specification, which controls for vigintiles of the replacement worker's wage in the previous employment spell. Deceased and replacement workers are employed in full-time contracts in d and r, respectively; we further restrict the sample to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Online Appendix

for

The Gender Gap in Entry Wages: Evidence from Exogenous Vacancies

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June 2026

A Data

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 42,958 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).

To define excess hiring firms, we impose the following restrictions on new hires: (i) they remain at the firm for at least 30 days, and their previous spell at the firm ended at least six months earlier; additionally, their previous employment spell did not end due to maternity leave.

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.[33]

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.[34] 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. We exclude firms with multiple deaths per year, and drop cases with excessive hiring around the death event.[35] We further require replacement workers to have been absent from the hiring firm for at least six months, to remain at the firm for at least 30 days, and to have not separated from their previous employer due to maternity leave. For the baseline analysis, we moreover restrict to cases where both deceased and replacement were working full-time in d and r, respectively. Focusing on worker pairs where the replacement worker transitioned from a full-time employment brings us to a final sample of 42,958 deceased-worker-replacement-worker pairs.

[33] 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. Through a reweighting exercise (Appendix Section B.2), we show that our baseline results are robust to making excess hiring firms comparable to all other firms and non-excess hiring firms, respectively.

[34] 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).

[35] Specifically, this includes firms 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.

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 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 4-7 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 (+3-5 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 3.8 EUR in the female-female group to 13.9 EUR in the opposite-sex group.

Finally, demographics, including tenure, are remarkably comparable across transition pairs. Two differences stand out: Daily wages for replacement workers are highest in the male-male transition group (EUR 84.5), followed by the opposite-sex group (EUR 82), and the female-female transition group (EUR 69.1); female-female replacements have 1.6 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. 8.9% for opposite-sex and 3.8% for female-female pairs) and traffic/security (26% vs. 8.6% for opposite-sex and 3.1% 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 5.8% for male-male pairs), and in service occupations (39% for female-female, 34% for opposite-sex, and 5.1% for male-male pairs). The sorting patterns are less striking for 1-digit industries, though male-male pairs are 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:

$$\mu_{cz,occ,t} = \frac{Workers_{cz,occ,t}}{Workers_{cz,t}} \div \frac{Workers_{DE,occ,t}}{Workers_{DE,t}} \tag{12}$$

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*). Throughout the paper, we use the classification of 51 commuting zones proposed by Kropp and Schwengler (2016).

In the next step, we construct a matrix of transitions across 2-digit occupations in Germany, by year and gender. We restrict the sample to workers with a full-time job at baseline. 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.

$$\gamma_{occ_{t=n}, occ_{t+1=n+x}, g} = \frac{Workers_{occ_{t+1=n+x}, g}}{Workers_{occ_{t=n}, g}} \tag{13}$$

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

$$\phi_{cz, occ_{t=n}, t, g} = \sum_{occ_{t+1=n}}^{occ_{t+1=n+x}} \mu_{cz, occ_{t+1}, t} \times \gamma_{occ_{t=n}, occ_{t+1}, g} \tag{14}$$

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 employee 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".

Labor-market-specific separation elasticity We compute labor-market-specific separation elasticities using the full sample of full-time workers in the IAB Employment History (BeH), as of November 2025. We restrict the data to 1985-2016.[36] Following the literature

[36]Note that 1985 is the first data for which AKM firm FE are available, and 2016 is the last event year in our baseline sample.

that interprets worker separation responses to firm wage premia as a measure of monopsony power (Bassier et al., 2022; Costas-Fernández et al., 2026), we define each labor market as a distinct combination of 2-digit occupation × commuting zone (51 CZs as defined by Kropp and Schwengler, 2016). For each labor market separately and pooling all calendar years, we then estimate fixed-effects regressions of the form:

$$Y_{it} = \alpha_0 + \gamma\, AKM_{jt} + \delta\,(IND_{jt} \times tenure_{it}) + \beta\, Year_t + \epsilon_{ijt} \tag{15}$$

where Y_{it} refers to a dummy indicating whether a worker leaves firm j from year t to $t+1$. AKM_{jt} refers to the AKM firm fixed effect as provided by Lochner et al. (2023), IND_{jt} refers to a firm's 2-digit industry, $tenure_{it}$ refers to worker i's tenure at the firm (in years) at time t, and $Year_t$ indicates year fixed effects. The estimated γ coefficients capture the labor-market-specific separation elasticity.

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.

Mannheim Enterprise Panel (MUP-BHP) For parts of our analysis, we use the Mannheim Enterprise Panel (MUP) provided by the Leibniz Centre for European Economic Research (ZEW) and linked to the Establishment History Panel (BHP) of the IAB (see Gottschalk et al. (2025) for details). The main advantage of the MUP is that it includes the variable "sales in Euro", which is not available in the IAB data.

MUP data is provided by the credit reference agency *Creditreform* and consists of all economically active German firms, encompassing around 10.3 million firms in total. The statistical unit is the "legally independent company" (Gottschalk et al., 2025). This is opposed to the statistical unit in the BHP – establishments – where several establishments can be part of one firm.

The MUP-BHP comprises 811,383 firms that were merged via record linkage based on company name, street, postcode, and city (see Diegmann et al. (2025) for details). The linked data is available for 2010-2023; 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 sales is only available for a restricted time period.

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 exhibited systematically different reporting behavior than firms that hire men. However, as Table A9 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 (Ruf et al., 2021). 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.

Tightness Data For parts of our mechanism analysis, we use labor market tightness data provided by Bossler and Popp (2026) and Börschlein et al. (2024). The data is available for 2012-2022. We use a version that is aggregated to the level of 3-digit occupations and commuting zones.

To compute the actual stock of vacancies, Bossler and Popp (2026) and Börschlein et al. (2024) combine data on vacancies registered with the Federal Employment Agency with data from the IAB Job Vacancy Survey, a representative firm survey. Since firms are not required to register their vacancies with the Federal Employment Agency, enriching the official statistics with survey data provides a more complete picture. Finally, to derive labor market tightness, the vacancy stock is divided by the number of registered job seekers.

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 $\times$ 5-digit occupation level. For Germany and 2011-2012 and for federal states, we merge the bottleneck indicator on the year $\times$ 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 Double-Selection Lasso: Variables

This section lists the variables considered as potential controls in the double-selection lasso algorithm. 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 double-selection lasso procedure, see Section 4. 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[37], number of workers by 1-digit occupation, number of (full-time) workers by skill group, number of trainees, number of workers with censored wages, number of workers with/without German citizenship, number of workers with EU citizenship.

1-Digit Industry/Occupation: Share of women aged 18-40, share of full-time workers, share of female full-time workers, gender wage gap, overall turnover, gender-specific turnover, share of women with a child aged 0-8, gender wage gap. 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, education in years, age in years, occupational skill intensity, deceased worker tenure greater than median, wage in EUR, log wage, wage deciles/quintiles, deceased worker wage greater than median, full-time earnings deciles, frequency of full-time employment, mother, number of children.

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, county and 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

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

employees at the firm, 1-digit and 5-digit industry dummies (d), 5-digit occupation dummies, AKM worker FE, share hiring firm industry in commuting zone, new hire wages (d, $d-1$), at least one female manager with children aged 0-8 at firm (d), share of mothers with children aged 0-8 (d), share of mothers (d), number of full-time workers in same 3-digit occupation greater than median (d), (female worker) wage bill at firm (d), deciles of (female worker) wage bill at firm (d), (female worker) wage bill decile in same 3-digit occupation as deceased worker (d), female worker wage bill in same 3-digit occupation (d), number of women in same 3-digit occupation (d), number of (full-time) workers in same 3-digit occupation (d), number of full-time workers (d), number of (female) new-hires in same 3-digit occupation (d), median gender wage gap in same 3-digit occupation (d), share of female full-time workers (in same 3-digit occupation, d), gender wage gap (d), gender wage gap in same 3-digit occupation (d), gender wage gap (in 3-digit occupation) greater than median gender wage gap (d), number of full-time workers in 3-digit occupation greater than median (d), share of female full-time workers (in same 3-digit occupation) greater than median (d), share of mothers with children aged 0-8 greater than median (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 gap in entry wages 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 A3, we present our baseline results with weights and show that the gender gap remains essentially the same, thus alleviating concerns with respect to external validity.

B.3 Wage Prediction

In the preferred specification, we control for the replacement worker's wage in the previous employment spell, $r-1$, as a prior-wage signal relevant to the wage-setting environment before entry into the event firm. This prior wage is not a direct measure of productivity and may itself embed earlier wage-setting wedges. We therefore examine whether the results are sensitive to replacing the worker's realized prior wage with a predicted wage constructed from observed characteristics. To construct this measure, we estimate the prediction equation using male replacement workers and then assign predicted wages to both male and female replacement workers based on the same set of characteristics.

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

$$y_i = \beta_0 + \beta_1 \boldsymbol{X_i} + \gamma_t + \varepsilon_{it} \tag{16}$$

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 $\times$ demographics $\times$ calendar year).

We use these predicted values instead of the replacement worker's realized wage in the previous employment spell as an alternative pre-hire control. Column (5) of Table A8 shows that the resulting estimate is larger, at 18 log points, compared with 10 log points in the preferred specification.

B.4 Robustness

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

Sample Restrictions Table A6 shows the gender gap in entry wages (baseline and preferred specifications) across different subsamples.

Columns (1) and (2) of Panel A show the baseline coefficients. As discussed in Section 6.2, 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, and the gaps remain at 16 log points and 10 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 preferred gender entry wage gap for these workers is 8.9 log points and thus marginally smaller than the baseline gap. The results show that the gender gap in entry wages does not simply reflect a child penalty for female replacements.

If there is more than one full-time new hire in the same 3-digit occupation at the firm, there may be concerns that we are not identifying the correct replacement worker. In an additional analysis, we therefore restrict to events where only one full-time worker in the same 3-digit occupation was hired in the 365 days following the death. This reduces the baseline sample to about 12,400 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 gender gap in entry wages (preferred specification) is reduced to 9.1 log points but it is still very close to the original gap of 10 log points (Panel C, Columns 5-6, Table A6).

Finally, in Panel C of Table A6, columns (1) through (4) show that the gender gap in entry wages 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.

Worker Type Table A7 presents additional heterogeneity by worker type. The gender gap in entry wages remains essentially unchanged for workers who do and do not move geographically (at the county level) between $r-1$ and r (Panel A). Similarly, the gap differs little between replacement workers whose wages increase and those whose wages decrease between $r-1$ and r (Panel B). The vast majority of deceased-worker–replacement-worker pairs share the same 5-digit occupation; if anything, the gender gap in entry wages (preferred specification) is slightly larger for this group (11 log points, Panel C). Finally, the gap is largest in rural regions (13 log points), somewhat smaller in towns (12 log points), and lowest, but close to the baseline gap, in cities (9.8 log points).

Occupation and Industry Table A2 shows that sudden deaths are over-represented in industries and occupations such as construction, motor vehicles, and traffic. To rule out that our baseline result is driven by a specific industry or occupation, Figure A7 plots the gender gap in entry wages 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.

Additional Pre-Hire Controls The preferred specification controls for the replacement worker's wage in the previous employment spell in addition to the baseline set of controls. We also examine robustness to other pre-hire controls: AKM worker fixed effects, occupational skill intensity, tenure and experience, predicted wages from observed characteristics, and the replacement worker's recent wage profile. These variables are informative about the worker's prior labor-market history and wage-setting environment, but we do not interpret them as clean measures of productivity.

Table A8, columns (2)–(8), introduces these controls separately and jointly. We start with AKM worker fixed effects (column 2), skills (column 3), and tenure and experience (column 4). We next control for predicted wages based on male replacement workers (column 5).[38] In column (6), we control for the replacement worker's previous three wages, measured in $r-1$, $r-2$, and $r-3$, to account for differences in recent wage profiles.

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 deciles of total wage bill, same 3-digit occupation wage bill, female worker wage bill, and the wage bill of female workers in the same 3-digit occupation; deciles of the share of full-time women; the number of all full-time workers, women in the same 3-digit occupation, and full-time workers in the same 3-digit occupation; the share of mothers; and dummies for the above median share of: full-time women in the same 3-digit occupation, full-time women, and mothers with children aged 0-8. Column (8) controls for everything at once. Once again, the coefficient for female replacement hardly changes. Once we include the full set of replacement-worker and firm controls in column (8), the gap decreases to 7.5 log points. This reduction appears to be largely driven by the inclusion of AKM worker fixed effects. As discussed in Section 2.6, AKM worker effects may themselves embed earlier wage-setting wedges through wage histories, so this specification should not be interpreted as controlling cleanly for productivity.

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.

We show that our results are robust to lifting this restriction. Appendix F, Table A12 presents summary statistics for the alternative sample of hiring events without restriction on full-time employment in $r-1$. The sample is very comparable to our baseline sample. Figure A10 and Tables A13 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. The key takeaways remain the same.

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

C Conceptual Framework Proofs

This section provides the proofs for the conceptual framework in Section 2.

C.1 Proof of Proposition 1

Fix (i, g, s, x) and suppress arguments. Let $b \equiv b_i(g, s, x)$, $\widetilde{V} \equiv \widetilde{V}_i(g, s, x)$, and $\varepsilon \equiv \varepsilon_i(g, s, x)$. For $W \in [b, \widetilde{V}]$, acceptance is

$$A(W) = \left(\frac{W - b}{\widetilde{V} - b}\right)^{\varepsilon}.$$

Expected profits are

$$\Pi(W) = A(W) \cdot (\widetilde{V} - W) = \left(\frac{W - b}{\widetilde{V} - b}\right)^{\varepsilon} (\widetilde{V} - W).$$

Let $x \equiv W - b$ and $c \equiv \widetilde{V} - b$, so $x \in [0, c]$ and $W = b + x$. Then

$$\Pi(W) = \left(\frac{x}{c}\right)^{\varepsilon} (c - x) = c^{-\varepsilon}(c - x)x^{\varepsilon}.$$

Differentiate with respect to x:

$$\frac{d\Pi}{dx} = c^{-\varepsilon}\left[-x^{\varepsilon} + (c - x)\varepsilon x^{\varepsilon - 1}\right] = c^{-\varepsilon}x^{\varepsilon - 1}\left[\varepsilon c - (\varepsilon + 1)x\right].$$

For an interior optimum with $x \in (0, c)$, the first-order condition is

$$\varepsilon c - (\varepsilon + 1)x = 0 \quad \Rightarrow \quad x^{\star} = \frac{\varepsilon}{1 + \varepsilon}c.$$

Thus

$$W^{\star} = b + x^{\star} = b + \frac{\varepsilon}{1 + \varepsilon}\left(\widetilde{V} - b\right).$$

Define $\beta \equiv \varepsilon/(1 + \varepsilon) \in (0, 1)$ to obtain (5).

To verify that $W^{\star}$ is a maximizer, note that for $\varepsilon > 0$ and $x \in (0, c)$, the factor $c^{-\varepsilon}x^{\varepsilon - 1}$ is strictly positive and the sign of $d\Pi/dx$ is the sign of $\varepsilon c - (\varepsilon + 1)x$. Hence $d\Pi/dx > 0$ for $x < x^{\star}$ and $d\Pi/dx < 0$ for $x > x^{\star}$, so Π is single-peaked on $(0, c)$ and $x^{\star}$ is the unique global maximizer on $(0, c)$. Because the boundaries $x = 0$ and $x = c$ yield $\Pi = 0$, the interior maximizer is also the maximizer on $[0, c]$, proving optimality.

C.2 Proof of Proposition 2

From Proposition 1, for each $g \in \{M, F\}$,

$$W_g = b_g + \beta_g(\widetilde{V}_g - b_g) \quad \text{with} \quad \beta_g \in (0,1).$$

Hence

$$\Delta \equiv W_M - W_F = (b_M - b_F) + \beta_M(\widetilde{V}_M - b_M) - \beta_F(\widetilde{V}_F - b_F).$$

Add and subtract $\beta_F(\widetilde{V}_M - b_M)$:

$$\begin{aligned}\Delta &= (b_M - b_F) + \Big[\beta_F(\widetilde{V}_M - b_M) - \beta_F(\widetilde{V}_F - b_F)\Big] + \Big[\beta_M(\widetilde{V}_M - b_M) - \beta_F(\widetilde{V}_M - b_M)\Big] \\ &= (b_M - b_F) + \beta_F\Big[(\widetilde{V}_M - \widetilde{V}_F) - (b_M - b_F)\Big] + (\beta_M - \beta_F)(\widetilde{V}_M - b_M).\end{aligned}$$

Rearranging yields (6).

C.3 Proof of Corollary 1

Under $b_M = b_F = b$ and $\widetilde{V}_M = \widetilde{V}_F = \widetilde{V}$, Proposition 2 gives

$$\Delta = (\beta_M - \beta_F)(\widetilde{V} - b),$$

which is (7). Moreover,

$$\frac{\partial \Delta}{\partial b} = -(\beta_M - \beta_F), \qquad \frac{\partial \Delta}{\partial \widetilde{V}} = \beta_M - \beta_F,$$

so if $\beta_M > \beta_F$ the gap decreases in b and increases in rents.

D 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]	0.023 [0.15]	0.018 [0.13]	0.0046 [0.068]
Education	0.011 [0.10]	0.0049 [0.070]	0.023 [0.15]	0.013 [0.11]
Machine Operations/Maintenance	0.12 [0.32]	0.12 [0.33]	0.089 [0.28]	0.038 [0.19]
Trade/Sales	0.082 [0.27]	0.058 [0.23]	0.10 [0.30]	0.13 [0.34]
Traffic/Security	0.11 [0.32]	0.26 [0.44]	0.086 [0.28]	0.031 [0.17]
Food/Cleaning	0.053 [0.22]	0.028 [0.17]	0.061 [0.24]	0.099 [0.30]
Services	0.18 [0.38]	0.051 [0.22]	0.34 [0.48]	0.39 [0.49]
Technicians	0.11 [0.31]	0.070 [0.26]	0.059 [0.24]	0.016 [0.13]
Law/Management/Economics	0.042 [0.20]	0.030 [0.17]	0.050 [0.22]	0.035 [0.18]
Arts	0.014 [0.12]	0.0059 [0.077]	0.020 [0.14]	0.012 [0.11]
Health/Care	0.082 [0.27]	0.011 [0.10]	0.083 [0.28]	0.17 [0.38]
Number of Individuals	14,905,321	33,972	5,152	3,891

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 $r-1$. 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]	0.0097 [0.098]	0.0049 [0.070]
Mining	0.0078 [0.088]	0.0081 [0.090]	0.0019 [0.044]	0 [0]
Manufacturing	0.31 [0.46]	0.25 [0.43]	0.20 [0.40]	0.18 [0.38]
Energy	0.010 [0.10]	0.0081 [0.090]	0.0047 [0.068]	0.0013 [0.036]
Water Supply	0.0079 [0.089]	0.016 [0.13]	0.0045 [0.067]	0.0031 [0.055]
Construction	0.085 [0.28]	0.21 [0.40]	0.021 [0.14]	0.027 [0.16]
Motor Vehicles	0.14 [0.34]	0.16 [0.37]	0.17 [0.38]	0.19 [0.39]
Traffic, Warehousing	0.051 [0.22]	0.11 [0.32]	0.054 [0.23]	0.021 [0.14]
Hospitality	0.027 [0.16]	0.013 [0.11]	0.041 [0.20]	0.049 [0.22]
ICT	0.026 [0.16]	0.013 [0.11]	0.029 [0.17]	0.021 [0.14]
Finance, Insurance	0.037 [0.19]	0.017 [0.13]	0.077 [0.27]	0.036 [0.19]
Housing	0.0071 [0.084]	0.0086 [0.092]	0.012 [0.11]	0.013 [0.11]
PST Services	0.051 [0.22]	0.025 [0.16]	0.050 [0.22]	0.064 [0.24]
Economic Services	0.043 [0.20]	0.044 [0.21]	0.040 [0.20]	0.030 [0.17]
Public Sector	0.058 [0.23]	0.054 [0.23]	0.11 [0.32]	0.083 [0.28]
Education	0.022 [0.15]	0.012 [0.11]	0.029 [0.17]	0.043 [0.20]
Health, Social Services	0.078 [0.27]	0.020 [0.14]	0.085 [0.28]	0.15 [0.36]
Arts, Entertainment	0.0074 [0.086]	0.0049 [0.070]	0.013 [0.11]	0.014 [0.12]
Other Services	0.023 [0.15]	0.016 [0.13]	0.036 [0.19]	0.068 [0.25]
Domestic Services	0.0013 [0.037]	0.00024 [0.015]	0.00058 [0.024]	0.00077 [0.028]
NGOs	0.0022 [0.047]	0.00032 [0.018]	0.00039 [0.020]	0.00026 [0.016]
Number of Individuals	14,905,321	33,972	5,152	3,891

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. ICT is an abbreviation for "Information and Communication Technology", and PST Services refers to "Professional, Scientific, Technical Services". 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 $r-1$. Deaths occur in 1981-2016, and our baseline sample spans 1975-2021. Standard deviations in brackets.

Table A3: Firm Characteristics

	(1) All Other Firms	(2) Non-Excess Hiring Firms	(3) Excess Hiring Firms: No weights	(4) Excess Hiring Firms: Weights To (1)	(5) Excess Hiring Firms: Weights To (2)
Panel A: Workforce					
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	(2) Non-Excess Hiring	(3) Excess Hiring Firms	(4)	(5)
	Firms	Firms	No weights	Weights	
				To (1)	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", ICT is an abbreviation for "Information and Communication Technology", and PST Services refers to "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	57,186	3.95	24.3
(5) Excess Hiring & Full-time Job in $r-1$	43,015	2.97	18.3
(6) Baseline Regression Sample	42,958	2.97	18.3

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 *Integrated Employment Biographies (IEB)* data). 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 regression sample.

Table A6: The Gender Gap in Entry Wages With Different Sample Restrictions

	(1) Baseline	(2) Preferred	(3) Baseline	(4) Preferred	(5) Baseline	(6) Preferred
Panel A:	**Full Sample**		**Highly-Attached Sample**		**Balanced Panel**	
Female Replacement	-0.16	-0.10	-0.16	-0.099	-0.17	-0.13
	(0.0048)***	(0.0044)***	(0.0098)***	(0.0090)***	(0.0054)***	(0.0051)***
Observations	42958	42958	10754	10754	33303	33303
Panel B:	**No Mothers**		**Workers Aged >40**		**Only 1 Full-time Hire**	
Female Replacement	-0.16	-0.100	-0.16	-0.089	-0.16	-0.10
	(0.0049)***	(0.0044)***	(0.0092)***	(0.0081)***	(0.0090)***	(0.0081)***
Observations	41666	41666	13007	13007	12360	12360
Panel C:	**Firm Size 3-50**		**Firm Size 51-150**		**Max. 1 Year Since Last Job**	
Female Replacement	-0.16	-0.10	-0.16	-0.10	-0.14	-0.091
	(0.0063)***	(0.0058)***	(0.0073)***	(0.0066)***	(0.0048)***	(0.0043)***
Observations	28249	28249	14709	14709	33524	33524

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 (11), and shows β_1 coefficients for $t = r$. Columns (1), (3), and (5) report coefficients for the *baseline* specification. Columns (2), (4), and (6) report the *preferred* specification, which controls for vigintiles of the replacement worker's wage in the previous employment spell. 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 are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975-2021. *, **, and *** correspond to 10, 5 and 1 percent significance levels, respectively.

Table A7: The Gender Gap in Entry Wages: Additional Heterogeneity

	(1) Baseline	(2) Preferred	(3) Baseline	(4) Preferred	(5) Baseline	(6) Preferred
Panel A:	**Full Sample**		**Replacement Does Not Move**		**Replacement Moves**	
Female Replacement	-0.16	-0.10	-0.16	-0.11	-0.16	-0.098
	(0.0048)***	(0.0044)***	(0.0069)***	(0.0066)***	(0.0066)***	(0.0058)***
Observations	42958	42958	20567	20567	22391	22391
Panel B:	**Replacement Gains Wages**		**Replacement Loses Wages**		**City**	
Female Replacement	-0.16	-0.071	-0.19	-0.073	-0.16	-0.098
	(0.0053)***	(0.0041)***	(0.0085)***	(0.0067)***	(0.0058)***	(0.0052)***
Observations	24720	24720	18238	18238	28547	28547
Panel C:	**Town**		**Rural Region**		**5-Digit Occ. Same**	
Female Replacement	-0.18	-0.12	-0.18	-0.13	-0.16	-0.11
	(0.0092)***	(0.0084)***	(0.022)***	(0.021)***	(0.0051)***	(0.0047)***
Observations	11118	11118	3172	3172	38448	38448

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 (11), and shows β_1 coefficients for $t = r$. Columns (1), (3), and (5) report coefficients for the *baseline* specification. Columns (2), (4), and (6) report the *preferred* specification, which controls for vigintiles of the replacement worker's wage in the previous employment spell. In Panel A, we (i) report the baseline coefficients, followed by (ii) a specification where we restrict to replacement workers who do not move county between $r-1$ and r, and (iii) a specification where we restrict to replacement workers who move county. In Panel B, we (i) show the gap for replacement workers who gain wages between $r-1$ and r, (ii) and for replacement workers who lose wages or have a zero increase. In (iii), we restrict to firms located in large or medium cities. In Panel C, we restrict to (i) firms located in large or small towns, (ii) firms located in rural municipalities (classification provided by Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR), 2021), and (iii) transition pairs where deceased and replacement worker have the same 5-digit occupation. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975-2021. *, **, and *** correspond to 10, 5 and 1 percent significance levels, respectively.

Table A8: The Gender Gap in Entry Wages with Different Sets of Control Variables

	(1) Preferred	(2) Baseline + AKM Worker FE	(3) Baseline + Occ. Skill	(4) Baseline + Tenure + Experience	(5) Baseline + Predicted Wage	(6) Baseline + Previous 3 Wages	(7) Baseline +Firm	(8) All
Panel A: Full Sample								
Female Replacement	-0.10	-0.075	-0.16	-0.16	-0.18	-0.16	-0.16	-0.075
	(0.0044)***	(0.0041)***	(0.0047)***	(0.0048)***	(0.0068)***	(0.0050)***	(0.0048)***	(0.0060)***
Observations	42958	42059	42958	41836	28150	38239	42958	23820
Panel B: Re-run for Regression Sample in Column (8)								
Female Replacement	-0.12	-0.082	-0.18	-0.17	-0.18	-0.18	-0.18	-0.075
	(0.0066)***	(0.0062)***	(0.0072)***	(0.0071)***	(0.0072)***	(0.0072)***	(0.0072)***	(0.0060)***
Observations	23820	23820	23820	23820	23820	23820	23820	23820

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for specifications with different control variables. It is based on Equation (11), presents β_1 coefficients for $t = r$, and the outcome variable is log wages. In each regression, we force different control variables to be included in the estimation. Column (1) shows the preferred specification, which controls for vigintiles of the replacement worker's wage in the previous employment spell. In column (2), we instead include worker fixed effects ($r-1$). In column (3), we control for replacement workers' occupational skill intensity. In column (4), we add deciles of occupational and firm tenure (measured in years in $r-1$). In column (5), we 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 deceased worker wages in d, $d-1$, and $d-2$. The regression model in column (7) includes detailed firm-level controls, all measured at d. These are the deciles of total wage bill, same 3-digit occupation wage bill, female worker wage bill, and the wage bill of female workers in the same 3-digit occupation; deciles of the share of full-time women; the number of all full-time workers, women in the same 3-digit occupation, and full-time workers in the same 3-digit occupation; the share of mothers; and dummies for the above median share of: full-time women in the same 3-digit occupation, full-time women, and mothers with children aged 0-8. Column (8) controls for everything at once. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975-2021. *, **, and *** correspond to 10, 5, and 1 percent significance levels, respectively.

Table A9: Firm Characteristics in $d-2$

	(1) Baseline	(2) Preferred	(3) Baseline	(4) Preferred
Panel A: Coworker Wage Bill	**All**		**Incumbents**	
Female Replacement	4290.4	6964.7	837.1	2452.7
	(5932.0)	(5947.2)	(5827.2)	(5846.8)
Observations	42002	42002	42002	42002
Panel B: Wage Gap & Firm FE	**GWG Other Workers**		**AKM Firm FE**	
Female Replacement	-0.013	-0.013	0.0015	0.0022
	(0.0046)***	(0.0047)***	(0.0011)	(0.0012)*
Observations	42002	42002	39943	39943
Panel C: Workforce Composition	**Share of Mothers**		**Share of Women**	
Female Replacement	0.00057	0.00068	0.0013	0.0012
	(0.00059)	(0.00060)	(0.0017)	(0.0017)
Observations	34461	34461	40223	40223
Panel D: Female-Friendliness	**Share Female Team Leaders**		**Family-Friendly Firm**	
Female Replacement	0.0093	0.0099	-0.0037	-0.0046
	(0.0030)***	(0.0031)***	(0.0041)	(0.0042)
Observations	42002	42002	42002	42002

Notes: This table reports the coefficient on female replacement in cross-sectional regressions for different outcome variables. It is based on Equation (11), and shows β_1 coefficients for $t = d-2$. Columns (1), and (3) report coefficients for the *baseline* specification. Columns (2) and (4) report the *preferred* specification, which controls for vigintiles of the replacement worker's wage in the previous employment spell. 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 women. 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 are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975-2021. *, **, and *** correspond to 10, 5, and 1 percent significance levels, respectively.

Table A10: Control Variables Selected by the Double-Selection Lasso, Baseline Specification

Panel A: Deceased Worker Characteristics (at d)	
Demographics:	Gender; tenure/wage greater than median tenure of deceased workers; wages; wage deciles/quintiles; full-time earnings deciles; years of education; occupational skill intensity; frequency of full-time employment
Panel B: Hiring Firm Characteristics	
5-Digit Industry:	Hunting, trapping, and related activities; manufacture of commercial vehicles and commercial vehicle engines; freshwater aquaculture; retail sale of textiles, clothing, and footwear at market stalls and markets; pawnshops; patent law firms
Characteristics at d:	Gender wage gap in 3-digit occupation greater than median gender wage gap; share of female full-time workers greater than median; number of full-time workers in same 3-digit occupation greater than median; location in West Germany, deciles of female wage bill in same 3-digit occupation, number of female workers in same 3-digit occupation; share of full-time female workers in same 3-digit occupation
Characteristics at $d-1$:	Number of full-time workers in same 3-digit occupation, AKM establishment FE; share of full-time female workers in same 5-digit occupation; share of female workers; share of female workers in a different occupation; share of full-time workers in the same 5-digit occupation; share of female expert workers; male worker median wage at hiring firm ($d-1$); medium-skilled worker median wage at hiring firm; mean wage bottom quartile at hiring firm; mean wage; mean wage same occupation; share of full-time female workers in same 3-digit occupation
Characteristics at $d-2$:	Number of high-skilled workers; AKM establishment FE; share of women; share of women in the same 5-digit occupation; share of full-time workers in the same 5-digit occupation; mean full-time wage; share of female full-time workers in same 5-digit occupation
Characteristics at $d-3$:	Share of female (full-time) workers in same 5-digit occupation; share of women; mean full-time wages; mean wage in same 3-digit occupation
Panel C: Deceased Worker 5-Digit Occupation	
Assistant/semi-skilled activities:	Cleaning (without specialization)
Assistant/trainee activities:	Mining and quarrying; building construction (without specialization)
Technically-oriented activities:	Viticulture; plastics and rubber manufacturing (without specialization); meat processing; building services engineering (without specialization); pipeline construction; waste management; technical computer science; warehouse management; air transport service specialists; courier, express and postal service clerks; professional drivers (freight transport/trucks); medical assistants (without specialization)
Specialized activities:	Road transport drivers (other specific activities); property, asset and personal protection; detectives; disinfection and pest control; music retail; tour guides and tour leaders; office and secretarial staff (without specialization); stenographers and phonotypists (typists); home economics; community work
Skilled occupations:	Metalworking and bell foundries; building electrical engineering
Complex specialist activities:	Laser metalworking; construction planning and supervision (without specialization); technical railway operations; sales occupations (except information and communication technologies); accounting professions
Highly complex activities:	Horticulture (without specialization); civil engineering and hydraulic engineering; sanitary, heating, and air conditioning engineering, managing directors and board members; insurance clerks; doctors (without specialization); nutrition and health counseling, wellness; editors and journalists
Supervisory occupations:	Production planning and control (technical); beverage production; passenger transport (service sector), corporate organization and strategy; administration
Managers:	Transport and logistics (commercial sector)
Panel D: Other	
	Share of women with children aged 0-8 in 1-digit occupation ($d-1$); share of female full-time workers in 1-digit occupation ($d-1$); female turnover 1-digit occupation ($d-1, d-2, d-3$); share of employed women by all women in commuting zone ($d-2$); county share of public admin workers ($d-3$)

Notes: This table lists the control variables selected by the double-selection lasso algorithm in the baseline specification for $k = r$.

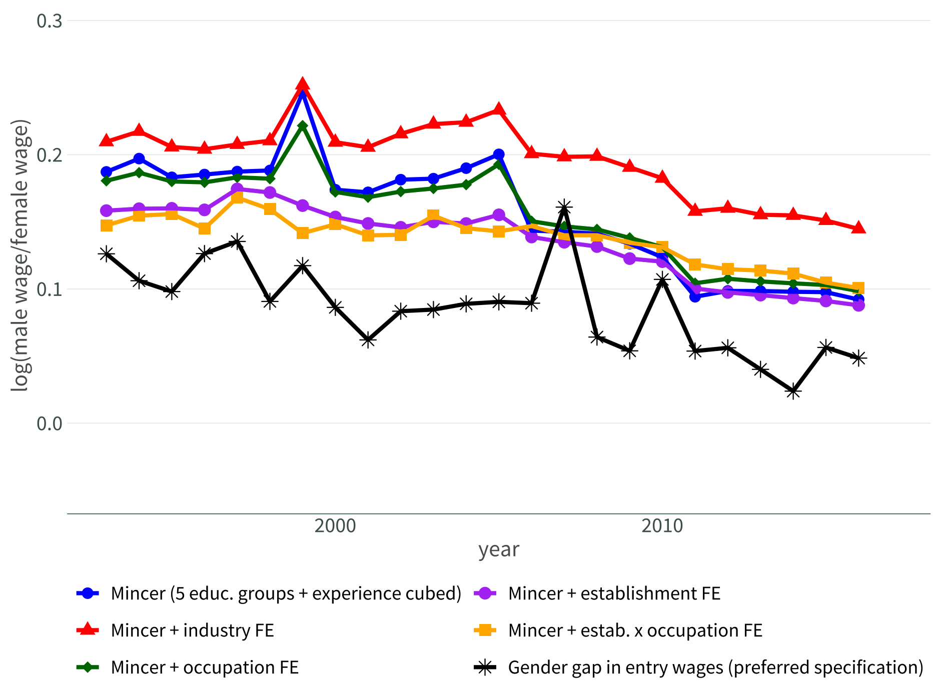
Table A11: Control Variables Selected by the Double-Selection Lasso, *Preferred* Specification

Panel A: Deceased Worker Characteristics (at d)	
Demographics:	Gender; wage greater than median wage of deceased workers in baseline sample; wage decile; wage quintile; full-time earnings; died in 1990; occupational skill intensity; years of education; frequency of full-time employment; wage
Panel B: Hiring Firm Characteristics	
5-Digit Industry:	Production and primary processing of copper; manufacture of solar cells and solar modules; manufacture of testing machines; gas trading via pipelines; bars; translation services; provision of educational support services; dental practices; independent restorers and conservators
Characteristics at d:	Gender wage gap in 3-digit occupation greater than median gender wage gap; share of female full-time workers in 3-digit occupation greater than median; number of full-time workers in same 3-digit occupation greater than median; location in West Germany; female worker wage bill in same 3-digit occupation; number of women in same 3-digit occupation; median gender wage gap in same 3-digit occupation; share of female full-time workers in same 3-digit occupation
Characteristics at $d-1$:	Number of full-time workers in same 3-digit occupation; AKM establishment FE; share of full-time women in the same 5-digit occupation; share full-time workers in the same 5-digit occupation; share of full-time women; share of (full-time) women in a different occupation; female share; share women in expert occupation; average wage; share of female full-time workers in same 3-digit occupation; male worker median wage at hiring firm ($d-1$); medium-skilled worker median wage at hiring firm ($d-1$); mean wage bottom quartile at hiring firm ($d-1$)
Characteristics at $d-3$:	Average full-time wage; average wage in same 3-digit occupation
Panel C: Deceased Worker 5-Digit Occupation	
Unskilled/semi-skilled occupations:	Event service and management
Assistant/trainee activities:	Building construction; cleaning professions
Technically-oriented activities:	Viticulture; plastics and rubber manufacturing; metalworking and bell foundries; meat processing; grill, roast, and fish cooks; parquet laying; building services engineering; pipeline construction; waste management; environmental protection; administration and consulting; technical computer science; warehouse management; courier; express and postal service clerks; property; asset and personal protection; detectives
Specialized activities:	Music retail; tour guides and tour leaders; office and secretarial staff (without specialization); stenographers and phonotypists/typists; archiving professions; library professions; medical assistants (without specialization); curative education and special education; home economics; community work
Complex specialist activities:	Agricultural engineering; laser metalworking; metal surface treatment; chemistry; technical railway operations; occupational safety and safety engineering; sales professions (except information and communication technologies); accounting professions
Highly complex activities:	Metal construction, civil engineering and hydraulic engineering, chemical and pharmaceutical engineering; managing directors and board members; insurance clerks; secondary school teachers
Supervisory occupations:	Beverage production; chemistry; corporate organization and strategy; administration
Panel D: Other	
	Share of women with a child aged 0-8 in same 1-digit occupation ($d-1$); share of full-time female workers in same 1-digit occupation ($d-1$); share of workers in same 1-digit industry ($d-1$); (gender-specific) turnover 1-digit occupation ($d-1$)

Notes: This table lists the control variables selected by the double-selection lasso algorithm in the *preferred* specification for $k = r$. In addition to the listed variables, we force the algorithm to include replacement worker pre-hire wages (in vigintiles).

E Appendix Figures

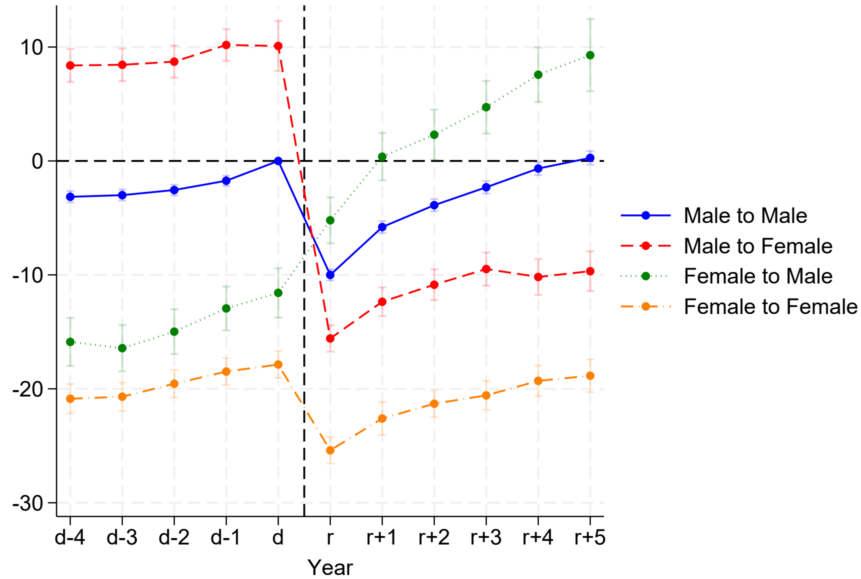
Figure A1: The Gender Wage Gap in Germany 1993-2017



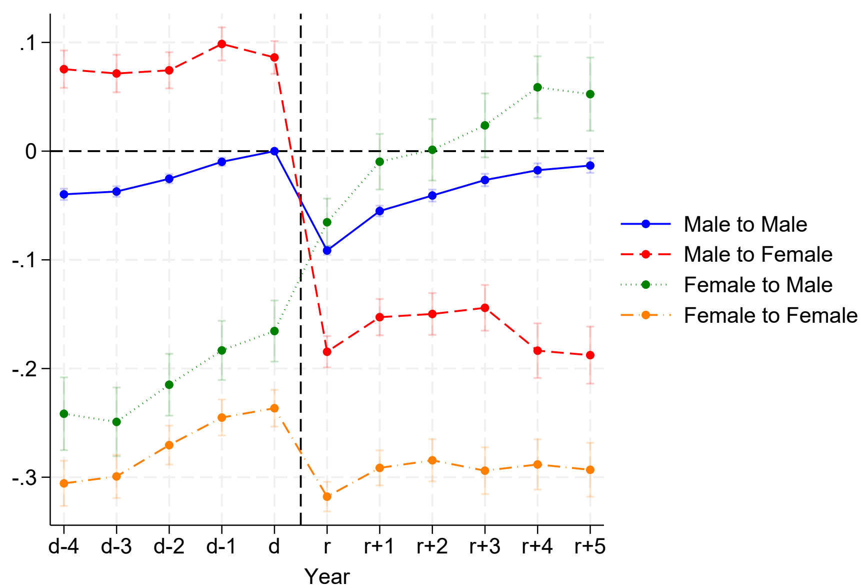
Notes: This figure shows several versions of the adjusted gender wage gap for a sample of full-time workers in Germany that are part of the longitudinal LIAB (*7519, Version 1*); in addition, it plots coefficients for the gender gap in entry wages (preferred specification) over time (black stars) for 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: Raw Evolution of Wages by Transition Group

(a) Daily Wage (EUR)



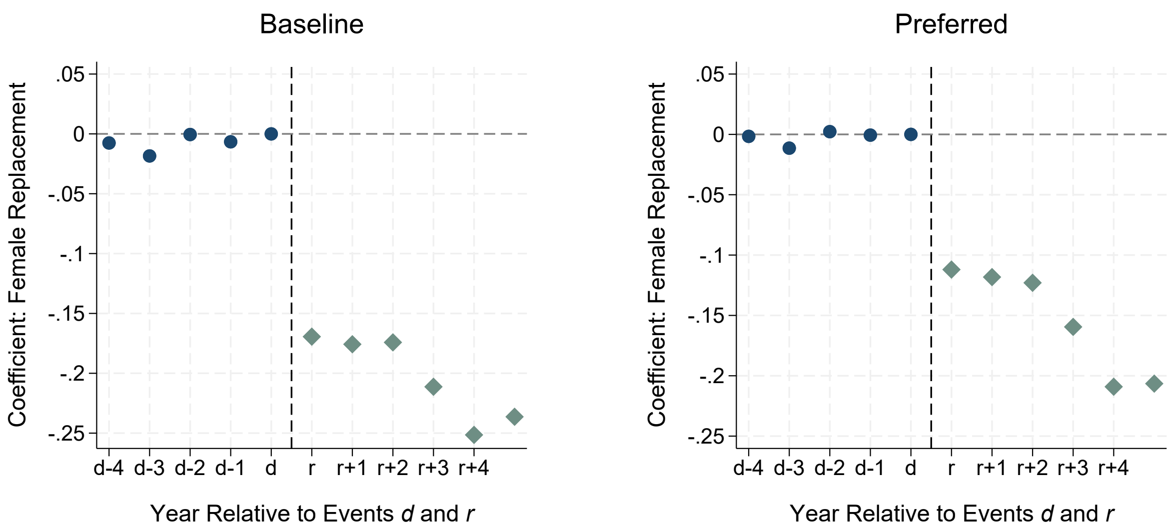
(b) Log Daily Wage



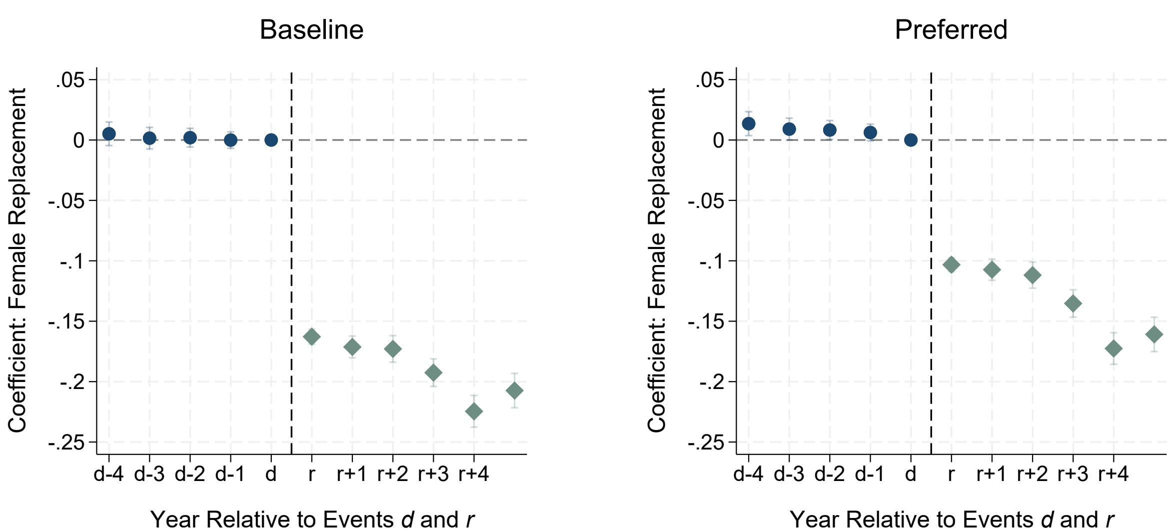
Notes: This figure presents raw means of wage trajectories for our baseline sample of deceased and replacement workers, relative to wages of the male-male group in d. The four lines plot the normalized wages for the four transition groups: Male-male transitions (blue solid line), male-female transitions (red dashed line), female-male transitions (green dotted line), and female-female transitions (orange dot-dashed line). See Section 3.4 for details. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure A3: The Gender Gap in Entry Wages – Firm Reweighting

(a) Reweighting to All Other Firms



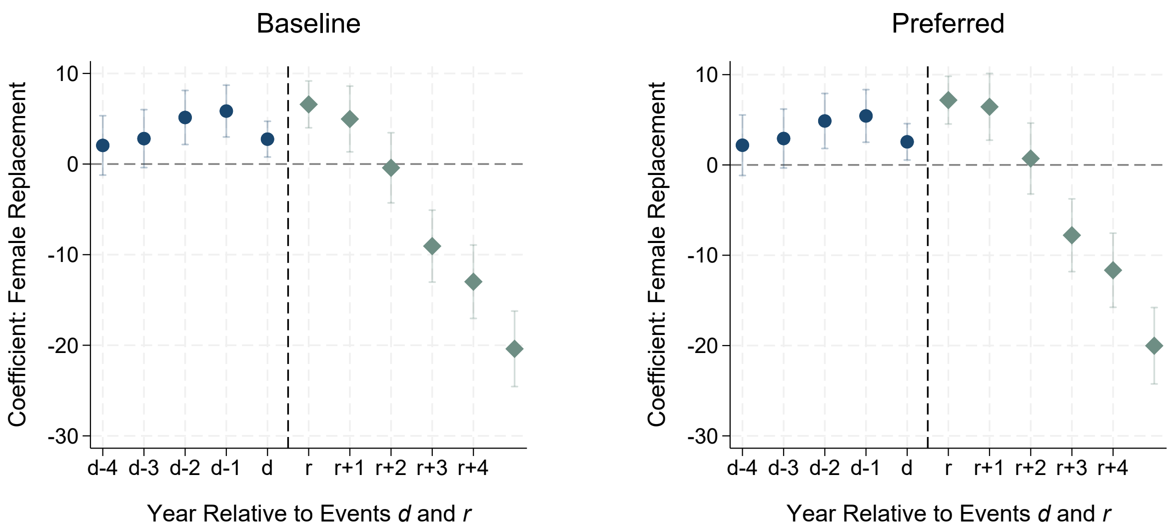
(b) Reweighting to Non-Excess Hiring Firms



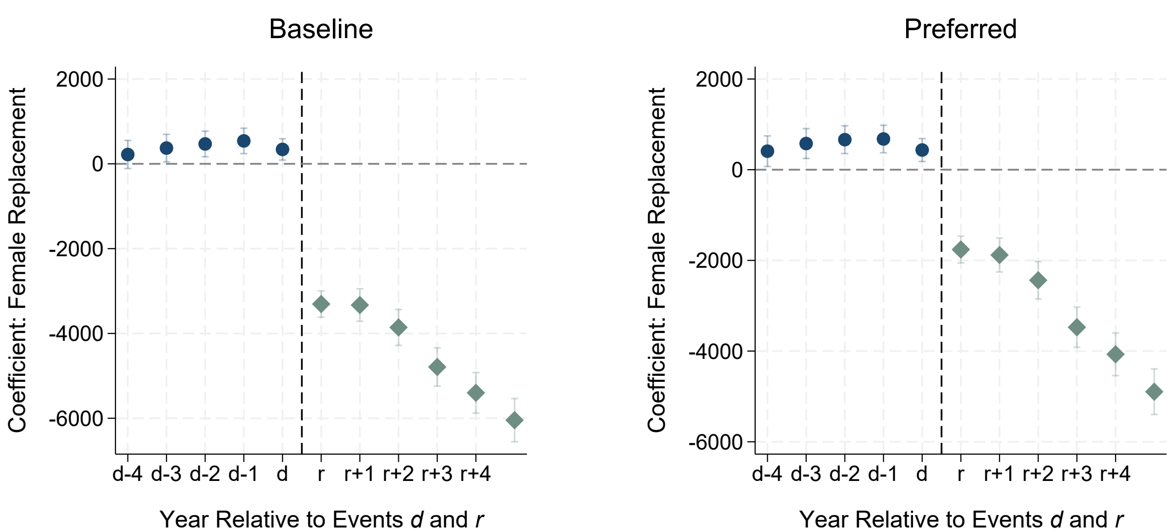
Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is log wages. In Panel (a) we use weights to make excess hiring firms comparable to all other German firms; in Panel (b), we reweight excess hiring firms to non-excess hiring firms. See Appendix B.2 for details on the reweighting exercise. The left panel ("Baseline") corresponds to the baseline specification, while the right panel ("Preferred") shows coefficients from a specification which controls for vigintiles of the replacement worker's wage in the previous employment spell. Coefficients in navy ($t = d - 4, ..., d$) refer to log wages of the deceased worker, and coefficients in teal ($t = r, ..., r + 4$) refer to log wages of the replacement worker. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r - 1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure A4: The Gender Gap in Full-time Employment and Earnings

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



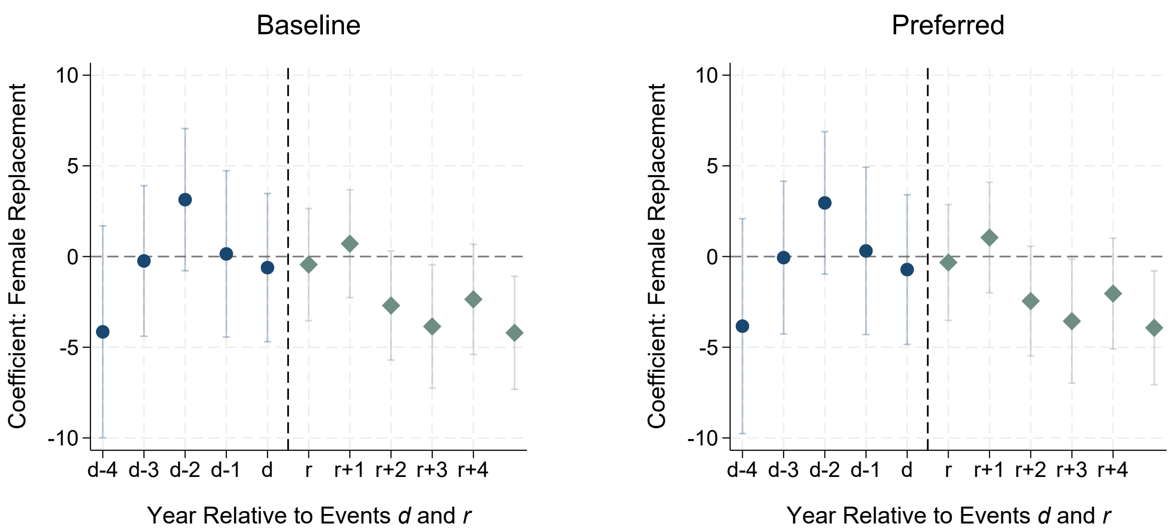
(b) Earnings from Full-time Job (EUR) per Year



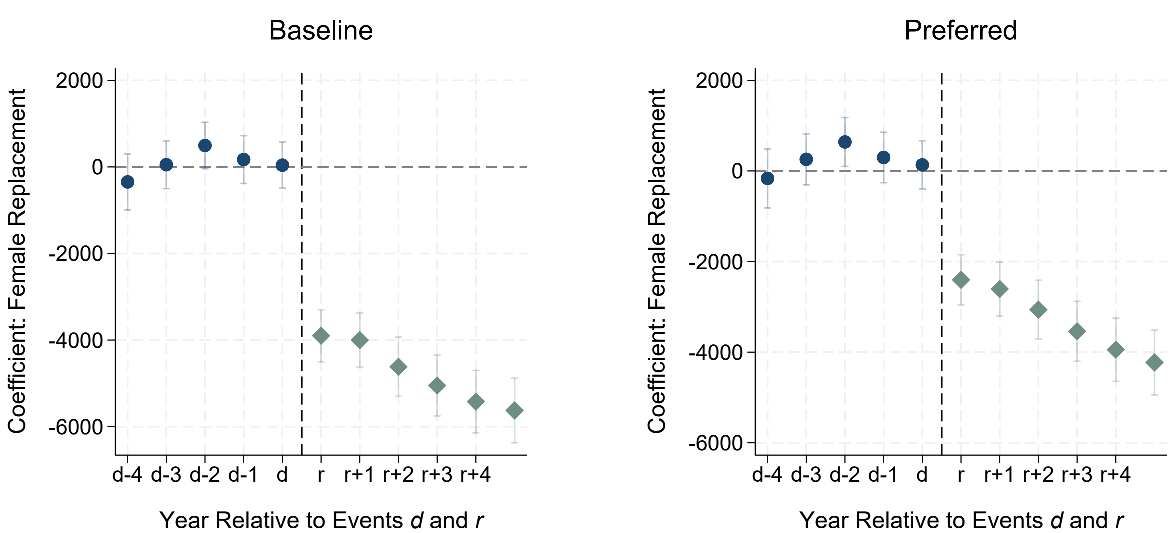
Notes: This figure shows the β_1 coefficients from Equation (11). The outcome variables are days worked in a full-time job per year (Panel a), and full-time earnings per year (Panel b). The left panel ("Baseline") corresponds to the baseline specification, while the right panel ("Preferred") shows coefficients from a specification which controls for vigintiles of the replacement worker's wage in the previous employment spell. Coefficients in navy ($t = d-4, ..., d$) refer to log wages of the deceased worker, and coefficients in teal ($t = r, ..., r+4$) refer to log wages of the replacement worker. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure A5: 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



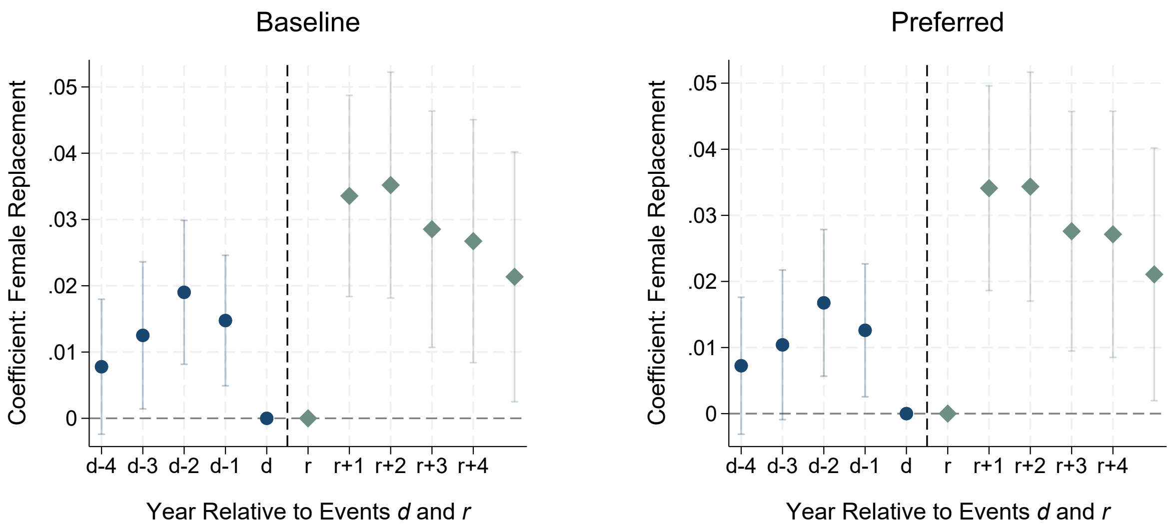
(b) Earnings from Full-time Job (EUR) per Year



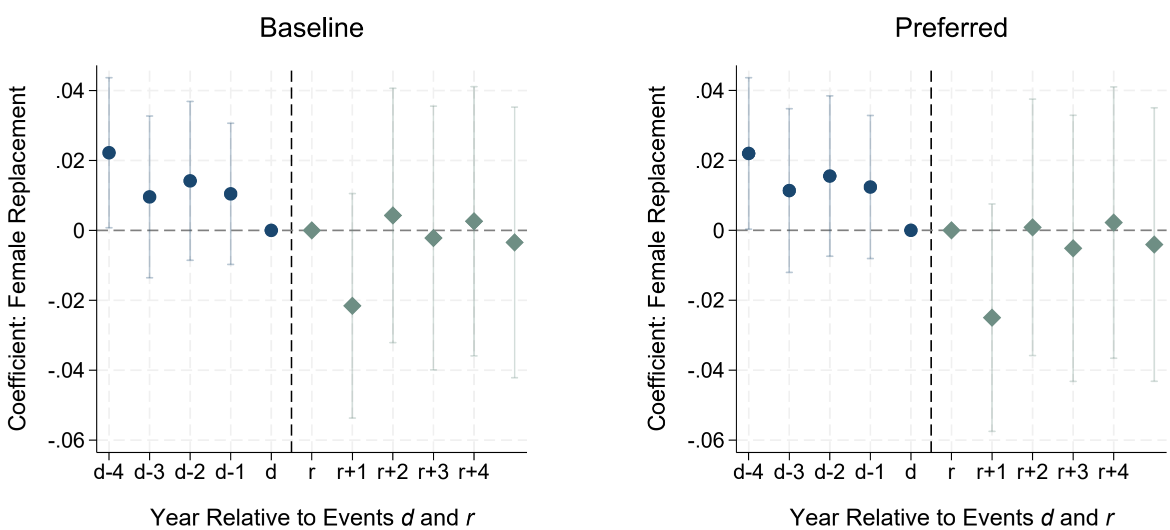
Notes: This figure shows the β_1 coefficients from Equation (11). The outcome variables are days worked in a full-time job per year (Panel a), and full-time earnings per year (Panel b). We restrict our sample to highly-attached replacement workers who work full-time from r to $r+4$. The left panel ("Baseline") corresponds to the baseline specification, while the right panel ("Preferred") shows coefficients from a specification which controls for vigintiles of the replacement worker's wage in the previous employment spell. Coefficients in navy ($t = d-4, ..., d$) refer to log wages of the deceased worker, and coefficients in teal ($t = r, ..., r+4$) refer to log wages of the replacement worker. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure A6: Employed at Hiring Firm

(a) Baseline Sample



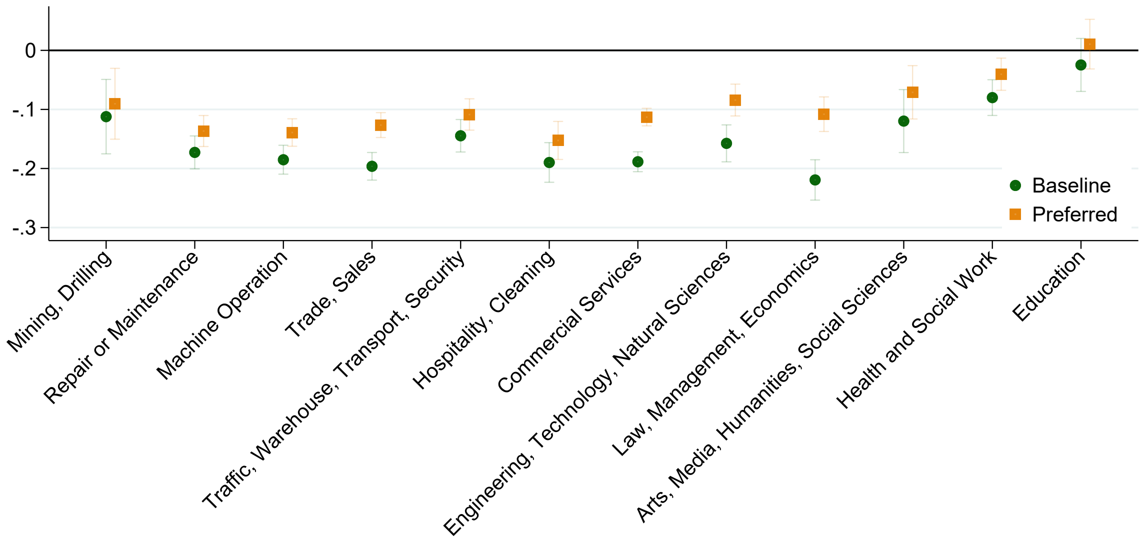
(b) Highly-Attached Worker Sample



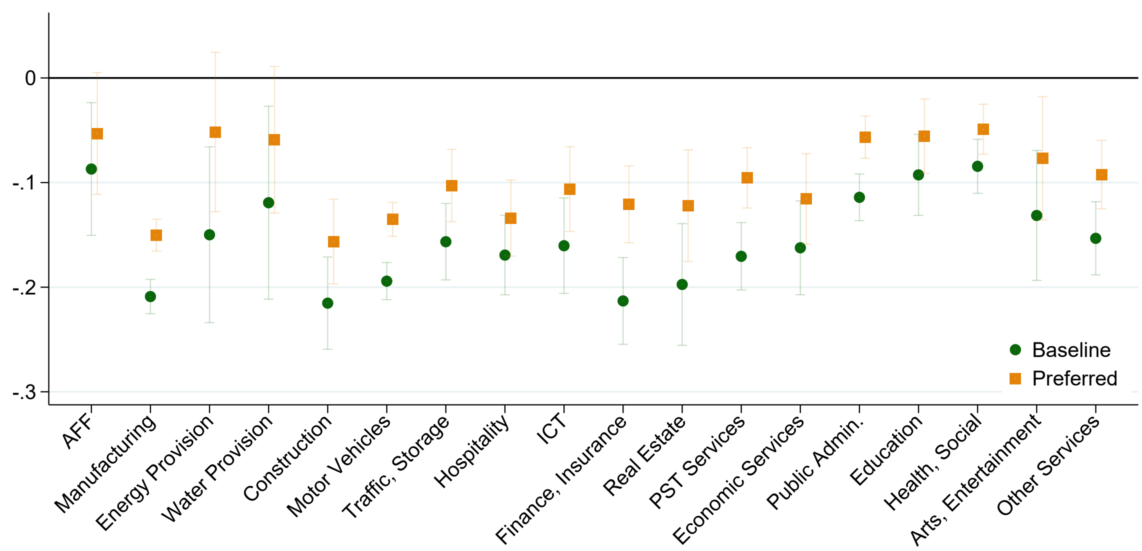
Notes: This figure shows the β_1 coefficients from Equation (11). The outcome variable is an indicator that equals 1 if the deceased worker (at d) or the replacement worker (at r) is employed at the hiring firm. Panel (a) shows results for the baseline sample of workers, Panel (b) shows results for the sample of highly-attached replacement workers who remain in full-time employed through $r+4$. The left panel ("Baseline") corresponds to the baseline specification, while the right panel ("Preferred") shows coefficients from a specification which controls for vigintiles of the replacement worker's wage in the previous employment spell. Coefficients in navy ($t = d-4, \dots, d$) refer to log wages of the deceased worker, and coefficients in teal ($t = r, \dots, r+4$) refer to log wages of the replacement worker. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure A7: The Gender Gap in Entry Wages by Occupation and Industry

(a) 1-Digit Occupations



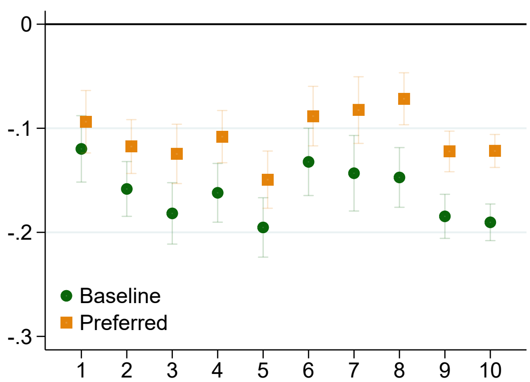
(b) 1-Digit Industries



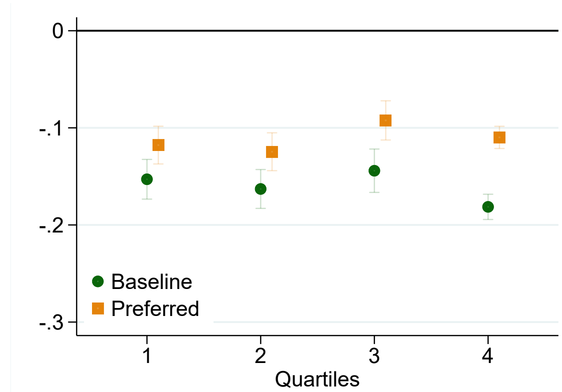
Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots the gender gap in entry wages by 1-digit occupation, and Panel (b) plots the corresponding gaps by 1-digit industry. Green dots correspond to the *baseline* specification, and orange squares correspond to the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021. To improve the graph's readability, we exclude three industries with a low number of women and thus large standard errors from Panel (b): Mining, NGOs, and private households. 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 A8: The Gender Gap in Entry Wages by Firm and Occupation Type

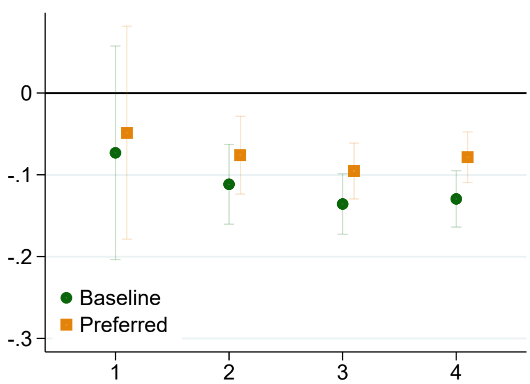
(a) 2-Digit Occupation's Share of Female Full-time Workers (Deciles)



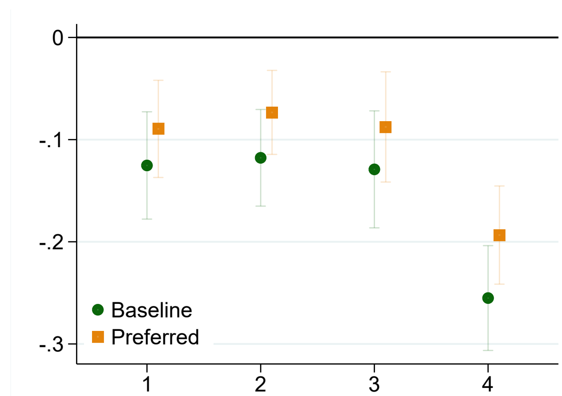
(b) 2-Digit Occupation's Working from Home Feasibility (Quartiles)



(c) AKM Firm Fixed Effect (Quartiles)

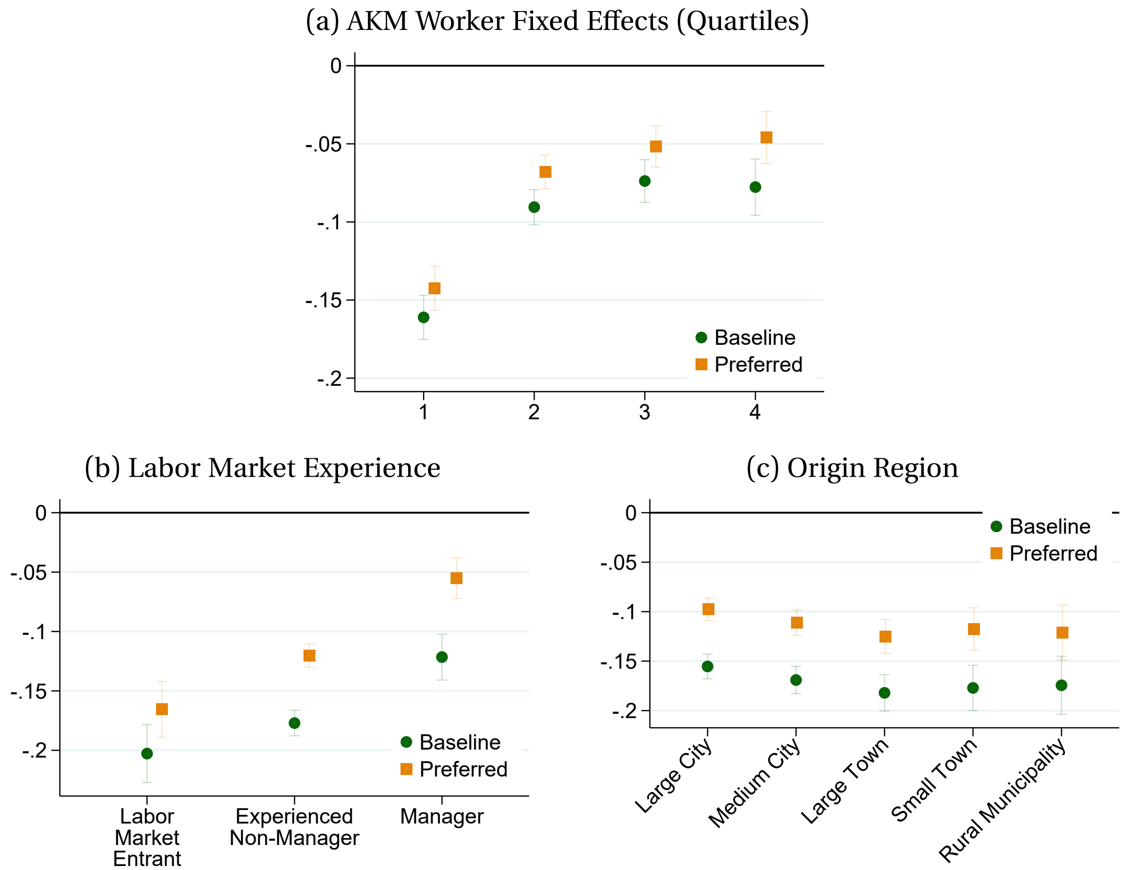


(d) Gender Wage Gap at Hiring Firm (Quartiles)



Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots the gender gap in entry wages by deciles of a 2-digit occupation's share of female full-time workers, based on a random 20% sample of German worker biographies in 1975-2022. Panel (b) plots the corresponding gaps by quartiles of a 2-digit occupation's working from home feasibility provided by Alipour et al. (2023), Panel (c) by quartiles of AKM firm fixed effects ($d-1$) provided by Lochner et al. (2023), and Panel (d) by quartiles of the hiring firm's gender wage gap ($d-1$). Green dots correspond to the *baseline* specification, and orange squares correspond to the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

Figure A9: The Gender Gap in Entry Wages by Replacement Worker Type



Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is replacement workers' log wages in the hiring spell (r). Panel (a) plots the gender gap in entry wages by AKM worker fixed effects ($r-1$) provided by Lochner et al. (2023). Panel (b) plots the corresponding gaps by labor market experience (r) following the definition by Caldwell et al. (2025), and Panel (c) plots the corresponding gaps by the replacement worker's origin region (workplace municipality type) in $r-1$ (classification provided by Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR), 2021). Green dots correspond to the *baseline* specification, and orange squares correspond to the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. Deceased and replacement workers are employed in full-time contracts in d and r, respectively, and the sample is further restricted to replacement workers with a full-time contract in $r-1$. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.

F Replication of Main Results for Alternative Sample

Table A12: 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]	91.8 [51.0]	94.1 [54.6]	70.8 [35.5]
Days Worked Full-time	332.1 [79.9]	337.3 [73.4]	338.4 [75.4]	330.9 [85.7]
Age (years)	38.7 [11.4]	45.1 [11.5]	45.4 [11.6]	42.7 [12.2]
Tenure in Firm (years)	5.87 [5.97]	6.46 [6.37]	7.45 [6.89]	6.53 [6.26]
Occ. Tenure (years)	8.19 [7.04]	9.56 [7.74]	10.0 [8.08]	9.10 [7.25]
Experience (years)	13.0 [8.54]	14.6 [8.82]	15.0 [8.94]	12.9 [8.38]
Education (years)	12.2 [1.93]	11.8 [1.43]	12.2 [1.92]	11.8 [1.48]
Mother	0.074 [0.26]	0 [0]	0.044 [0.20]	0.15 [0.36]
Panel B		*Replacement worker at the hiring event r*		
Daily Wage in EUR	91.7 [53.8]	81.4 [29.3]	75.1 [33.1]	64.0 [30.4]
Days Worked Full-time	332.1 [79.9]	315.6 [89.0]	314.5 [95.1]	315.3 [93.3]
Age (years)	38.7 [11.4]	33.9 [10.5]	32.4 [10.4]	32.2 [10.6]
Tenure in Firm (years)	5.87 [5.97]	0.43 [0.30]	0.45 [0.31]	0.44 [0.30]
Occ. Tenure (years)	8.19 [7.04]	3.56 [5.14]	3.23 [4.63]	3.53 [4.73]
Experience (years)	13.0 [8.54]	9.24 [7.21]	7.93 [6.86]	7.63 [6.54]
Education (years)	12.2 [1.93]	12.0 [1.57]	12.3 [2.11]	12.0 [1.59]
Mother	0.074 [0.26]	0 [0]	0.13 [0.34]	0.19 [0.39]
Number of Individuals	14,905,321	42,436	8,233	6,517

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. Unlike the baseline sample, we do not restrict to replacement workers whose previous contract ($r-1$) was full-time. Column (1) shows characteristics for a random 2% sample of full-time workers in the German social-security data from 1981–2016. Columns (2)–(4) show characteristics for male–male, opposite-sex, and female–female transition pairs, respectively. In Panel A, columns (2)–(4) present characteristics of deceased workers in their last employment spell, and in Panel B, columns (2)–(4) present characteristics of replacement workers in their starting spell at the hiring firm (r). Here, d refers to the deceased worker's last employment spell. Deceased workers are employed in full-time contracts in d. Deaths occur between 1981 and 2016, and the baseline sample spans 1975–2021. Standard deviations are reported in brackets.

Table A13: Wages, Employment, and Adjustments Event Firms – No Additional Restrictions

	(1) Coefficient Female Replacement Baseline		(2) Coefficient Female Replacement Preferred		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Wages and Employment					
Log Wage	**-0.16**	[0.0043]	**-0.11**	[0.0040]	51,985
Days Worked Full-Time per Year	**6.49**	[1.16]	**8.12**	[1.22]	52,079
Log Hours Worked per Week	-0.0033	[0.0097]	-0.0059	[0.010]	4,066
Log Wage if in Hours Data	**-0.075**	[0.015]	**-0.042**	[0.014]	4,064
Wage Bill Replacement-Deceased Worker (EUR)	**-2919.8**	[128.3]	**-1733.4**	[130.4]	52,079
Panel B: Coworker Wage Bill					
Wage Bill All Coworkers (EUR)	4057.0	[5489.4]	3375.5	[5853.2]	52,079
Wage Bill Incumbents (EUR)	5183.6	[4941.3]	2280.6	[5260.5]	52,079
Wage Bill New Hires (EUR)	-559.4	[1592.5]	167.5	[1798.1]	52,079
Panel C: Firm-level Adjustments					
Sales/Worker	278.1	[347.0]	267.8	[362.3]	2,617
Firm Has Disappeared by r+4	0.0014	[0.0016]	0.0014	[0.0017]	43,132

Notes: This table reports gender differences in replacement workers' labor market outcomes and in firm outcomes by the replacement worker's gender, based on Equation (11). Unlike the baseline sample, we do not restrict to replacement workers whose previous contract $(r-1)$ was full-time. If not indicated otherwise, outcomes are measured in r, which refers to the replacement worker's starting spell at the hiring firm. Column (1) reports the β_1 coefficient for female replacement in the *baseline* specification, and column (2) reports the β_1 coefficient for female replacement in the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. 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 replacement worker. Incumbents are defined as all employees whose employment spell overlaps with the date of death, and new hires are defined as employees who worked at the firm in the post-death year t_1 but not in the calendar year of death t_0. Panel C reports firm-level adjustments. Sales come from the MUP-BHP dataset (see Gottschalk et al. (2025)) and are available for linked firms from 2010. Deceased workers are employed in full-time contracts in d. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975–2021. Coefficients in bold are statistically significant at the 5% level.

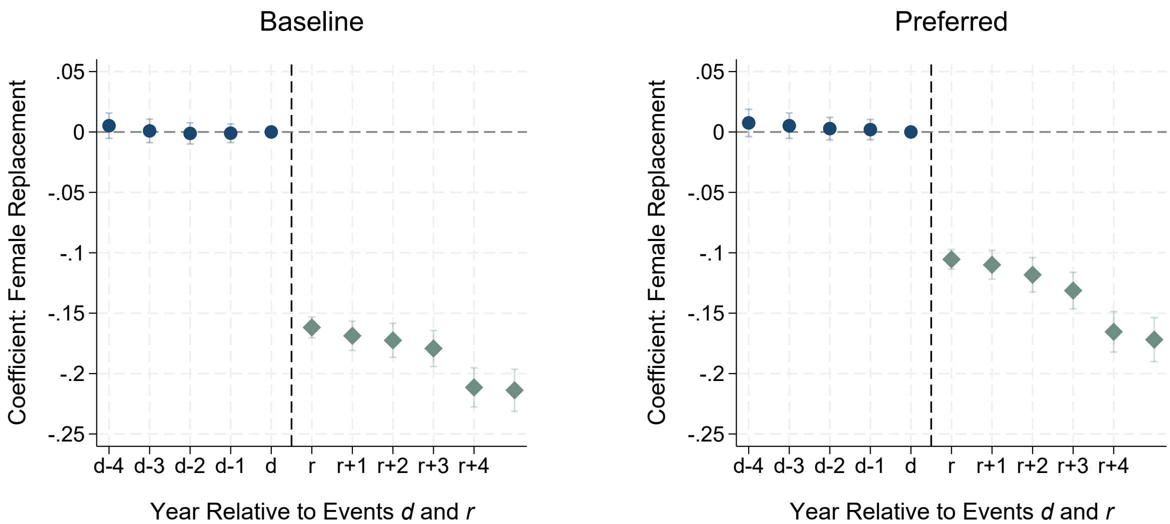
Table A14: Replacement Worker Characteristics, Amenities, Outside Options – No Additional Restrictions

	(1) Coefficient Female Replacement Baseline		(2) Coefficient Female Replacement Preferred		(3) Number of Observations
	Gap	Std. Err.	Gap	Std. Err.	
Panel A: Replacement Worker Characteristics in $r-1$					
Education (years)	**-0.13**	[0.025]	0.013	[0.025]	51,920
Experience (years)	**-0.73**	[0.082]	**0.19**	[0.080]	52,070
Tenure (years)	**-0.10**	[0.045]	**0.21**	[0.045]	52,053
Occupational Tenure (years)	**-0.27**	[0.068]	**0.46**	[0.067]	50,435
Worker Fixed Effect	**-0.16**	[0.0040]	**-0.095**	[0.0036]	49,828
Days Worked Full-time	**-5.92**	[1.19]	-1.45	[1.29]	52,079
Yearly Full-time Earnings (EUR)	**-965.4**	[72.2]	-14.4	[69.1]	52,079
Log Wage	**-0.24**	[0.0076]	0.0023	[0.0028]	52,079
Days Job Was Vacant	0.66	[0.70]	**1.90**	[0.75]	52,079
Panel B: Amenities					
Δ Commuting Distance (km)	2.35	[2.43]	1.70	[2.44]	20,358
Δ Gender Wage Gap in Firm	0.0020	[0.0054]	-0.0048	[0.0056]	35,345
Gender Wage Gap Other Workers (r)	-0.0025	[0.0038]	-0.0032	[0.0042]	52,079
Family Friendly Firm (r)	0.0018	[0.0045]	-0.0022	[0.0048]	52,079
Panel C: Outside Options in $r-1$					
Outside Option Index $\phi_{cz,occ,t,g}$	-0.00086	[0.0026]	-0.000099	[0.0025]	50,429
Pre-Hire Firm Median Full-time Wage	**-2.40**	[0.35]	**2.91**	[0.33]	50,385
Pre-Hire Firm FE	**-0.019**	[0.0032]	**0.035**	[0.0031]	49,740

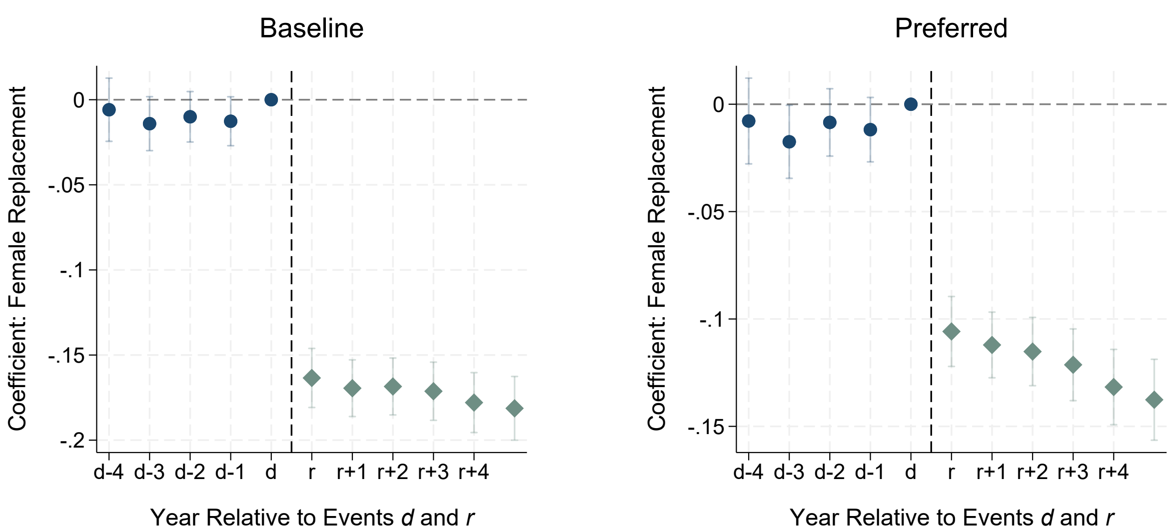
Notes: This table reports gender differences in replacement workers' characteristics in $r-1$, their amenities, and their outside options, based on Equation (11). Unlike the baseline sample, we do not restrict to replacement workers whose previous contract ($r-1$) was full-time. $r-1$ refers to the replacement worker's previous employment spell, and r refers to their starting spell at the hiring firm. Column (1) reports the β_1 coefficient for female replacement in the *baseline* specification, and column (2) reports the β_1 coefficient for female replacement in the *preferred* specification. The preferred specification controls for vigintiles of the replacement worker's wage in the previous employment spell. In Panel A, we report gender differences in replacement worker characteristics in $r-1$, as well as in the time it takes firms to fill a position, measured as the duration between the date of death and the start of the replacement's employment spell. In Panel B, we report four proxies for amenities: the change in commuting distance relative to the previous job (in km), the change in the firm gender wage gap, the gender wage gap among coworkers in the same 3-digit occupation at 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 fixed effects, as provided by Lochner et al. (2023), characterize the quality of workers' previous employers. Deceased workers are employed in full-time contracts in d. Robust standard errors are reported in brackets. Deaths occur between 1981 and 2016, and the sample spans 1975–2021. Coefficients in bold are statistically significant at the 5% level.

Figure A10: The Gender Gap in Entry Wages – No Additional Restrictions

(a) Baseline Sample



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



Notes: This figure shows the β_1 coefficients from Equation (11), where the outcome variable is log wages. Unlike the baseline sample, we do not restrict to replacement workers whose previous contract ($r-1$) was full-time. The left panel ("Baseline") corresponds to the baseline specification, while the right panel ("Preferred") shows coefficients from a specification which controls for vigintiles of the replacement worker's wage in the previous employment spell. Coefficients in navy ($t = d-4, ..., d$) refer to log wages of the deceased worker, and coefficients in teal ($t = r, ..., r+4$) refer to log wages of the replacement worker. Deceased workers are employed in full-time contracts in d. Vertical bars indicate 95% confidence intervals based on robust standard errors. Deaths occur between 1981 and 2016, and the sample spans 1975–2021.