Firms and the Gender Wage Gap: A Comparison of Eleven Countries

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Abstract

We quantify the role of gender-specific firm wage premiums in explaining the private-sector gender gap in hourly wages using a harmonized research design across 11 matched employer-employee datasets — ten European countries and Washington State, USA. These premiums contribute to the gender wage gap through two channels: women's concentration in lower-paying firms (sorting) and women receiving lower premiums than men within the same firm (pay-setting). We find that firm wage premiums account for 10 to 30 percent of the gender wage gap. While both mechanisms matter, sorting is the predominant driver of the firm contribution to the gender wage gap in most countries. We document three patterns that are broadly consistent across countries: (1) women's sorting into lower-paying firms increases with age; (2) women are more concentrated in low-paying firms with a high share of part-time workers; and (3) women receive about 90 percent of the rents that men receive from firm surplus gains.

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1. Introduction

Understanding what drives the gender wage gap remains a central question in the academic and policy debate. Despite some convergence, women continue to earn less than men in most developed economies (Blau and Kahn 2003; Goldin, Katz and Kuziemko 2006; Olivetti and Petrongolo 2016). Early explanations for the gender wage gap were grounded in the idea of competitive labor markets (Becker 1957; Mincer 1974; Polachek 1981). However, over the past decade, an active research agenda has emerged acknowledging that labor markets may not be competitive and that employers may be a source of male-female wage differences (Card, Cardoso, Heining and Kline 2018; Kline 2024). Specifically, in an influential paper, Card, Cardoso and Kline (2016) (hereafter CCK) document that a substantial portion of the gender wage gap stems from gender differences in firm-specific wage premiums, estimated using the Abowd, Kramarz and Margolis (1999) model (hereafter AKM).[1]

Applying the Kitagawa-Oaxaca-Blinder decomposition, CCK shows that the gender wage premium gap explains about 20% of the gender wage gap in Portugal. Subsequent work applying their approach finds considerable variation in the role of firms — ranging from 15 to 85 percent — in explaining gender wage gaps (see Table 1 for a summary of recent papers). This literature has shown that firms matter for the gender wage gap. Yet understanding why firms matter — and why the estimates are so different — is difficult because these studies differ in their sample selection (e.g., inclusion of public sector jobs), wage definitions (e.g., hourly vs. annual), and econometric methods. Because single-country studies differ in design, it is challenging to determine whether and to what extent cross-country patterns reflect differences related to the specific context

[1]Giving a full account of the literature on the gender wage gap is beyond the scope of this paper. Classic references include, e.g., Altonji and Blank (1999), Bertrand (2011) and Blau and Kahn (2017). See Goldin (2006); Kunze (2008, 2018) for reviews. Early studies on the role of firms in the gender wage gap include Blau (1977), Groshen (1991), Bayard, Hellerstein, Neumark and Troske (2003), and Babcock and Laschever (2003).

(e.g., market characteristics, policies). Single-country studies have made important contributions by identifying novel mechanisms specific to their institutional contexts.[2] However, since we lack a harmonized, cross-national perspective on how and why firms contribute to the gender wage gap, we have limited evidence on whether and why firm-based explanations hold up across different settings.[3]

This paper studies 11 advanced economies and applies the CCK framework in a standardized manner to compare how and why firm-specific wage premiums contribute to the gender wage gap in the private sector. We apply this harmonized research design to administrative matched employer-employee data for the United States (represented by Washington State) and ten European countries (Denmark, Finland, France, Germany, Hungary, Italy, the Netherlands, Norway, Portugal, and Sweden), for most countries covering the period 2010–2019. All data sets include high-quality information on work hours, ensuring that the measurement of the gender wage gap accounts for male–female differences in labor supply.[4] The harmonized research design allows us to make consistent comparisons across countries to answer the question of the extent to which firms matter for the gender wage gap and to quantify the relative importance of the mechanisms through which firms affect the wage gap. Moreover, by integrating harmonization into our research design from the outset, the paper contributes to the efforts to improve

[2]For example, the mechanisms explored include differential effects of parenthood by gender (Gallen, Lesner and Vejlin 2019), wage growth in firms and unionization (Bruns 2019), marital and family status (Li, Dostie and Simard-Duplain 2023), flexible wage components (Boza and Reizer 2024) or women seeking out high-amenity jobs (Morchio and Moser 2024).

[3]Some cross-country studies focus on gender wage inequality (e.g., Blau and Kahn 2003; Penner, Petersen, Hermansen, Rainey, Boza, Elvira, Godechot, Hällsten, Henriksen, Hou, Mrčela, King, Kodama, Kristal, Křížková, Lippényi, Melzer, Mun, Apascaritei, Avent-Holt, Bandelj, Hajdu, Jung, Poje, Sabanci, Safi, Soener, Tomaskovic-Devey and Tufail 2023); others examine the role of AKM firm fixed effects in explaining wage inequality (e.g., Bonhomme, Holzheu, Lamadon, Manresa, Mogstad and Setzler 2023; Criscuolo, Hijzen, Schwellnus, Barth, Bertheau, Chen, Fabling, Fialho, Garita, Gorshkov, Grabska-Romagosa, Haramboure, Kambayashi, Koelle, Lankester, Leidecker, Murakőzy, Nordström Skans, Nurmi, Peciar, Riom, Roth, Sandoval, Stadler, Upward and Zwysen 2023). However, none have examined both dimensions simultaneously.

[4]Washington State collects both hours and earnings, whereas the LEHD, which covers most US states, only collects earnings data. In some countries, we only observe contractual hours, not paid work hours. Further discussion is relegated to Appendix D.

both reproducibility and replicability in economics (Nosek et al. 2015; Brodeur et al. 2024; Dreber and Johannesson 2025).

To motivate our focus on firms, we start by showing that firm-specific wage premiums matter in explaining hourly wages of both men and women in all countries. If firm-specific wage premiums matter for wages, do they also affect the gender wage gap? To answer this question, we apply the CCK decomposition, which separates the gender wage premium gap into two distinct components: (i) that similarly skilled men and women work for employers with different wage premiums (the *sorting* channel) and (ii) that similarly skilled men and women are offered a different within-firm wage premium (the *pay-setting* channel). At least four findings stand out.

First, we find that firm wage premiums account for 10–30% of the gender wage gap. In the U.S., Hungary, and Germany, the premiums explain at least 30% of the wage gap, while in Denmark, Sweden, and Finland, they explain about 15%. Countries with large gender wage premium gaps also tend to have large gender wage gaps. This suggests that firm-level factors help explain cross-country differences in the observed gender wage gap. These countries are also those where firms matter more for overall wage setting; that is, the greater the firm-level pay inequality, the larger the gender gap in firm-specific wage premiums.

Second, we document substantial differences between countries in the relative importance in wage-premium gaps between firms *(the sorting channel)* and gaps in wage premiums within firms (*the pay-setting channel*). The pay-setting component ranges from less than 1% of the total gender wage gap in the Netherlands to 30% in Hungary. The sorting component varies from less than 3% in Denmark and Hungary to about 20% in the U.S. and Germany.

Third, in most countries, sorting increases over the life-cycle: men move up the job ladder, while women tend to stay behind.[5] High-quality information on hours allows us to investigate to what extent women trade off wages for greater workplace flexibility in terms of hours worked (Goldin 2014). Some firms might offer packages combining high wage premiums with long hours that may be less attractive to women than to men. We find that firms offer compensating differentials for long hours across countries, but these do not vary between men and women. However, we show that women are not only more likely to work part-time, but also sort into firms with a high share of part-time workers and low wage premiums. That women sort into low-wage firms in return for more flexibility is consistent with findings on the importance of non-wage employer amenities (see e.g., Goldin and Katz 2016; Sorkin 2017; Mas and Pallais 2017; Vattuone 2024; Morchio and Moser 2024; Burbano, Folke, Meier and Rickne 2024; Humlum, Rasmussen and Rose 2025; Lochner and Merkl 2025).

Fourth, we examine why women receive lower wage premiums than men within the same firms. Our findings indicate that pay-setting disparities are systematically larger in high-wage firms, which is consistent with evidence suggesting that individual wage bargaining is more prevalent in these firms (see e.g., Lachowska, Mas, Saggio and Woodbury 2022; Biasi and Sarsons 2022; Caldwell, Haegele and Heining 2025; Fredriksson, Gülümser and Hensvik 2025). To test whether this reflects differential rent-sharing, we estimate how firm productivity gains translate into wage premiums by gender. On average, across countries, women receive only 89% of the rent-sharing benefits that men receive, with the Netherlands being the only country where we cannot reject gender equality in rent-sharing.

We perform additional analyses and conduct several robustness checks. We show that including public-sector jobs substantially increases the sorting component in most countries where the information is available. Adjusting for occupational differences

[5]This is consistent with notions that motherhood slows the advancement of women up the job ladder (e.g., Bütikofer, Jensen and Salvanes 2018; Kleven, Landais and Søgaard 2019) or that women and men climb different job ladders (e.g., Le Barbanchon, Rathelot and Roulet 2021).

proportionally reduces both the gender wage gap and the wage premium gap, while leaving the share explained by firm-specific wage premiums roughly unchanged across countries. Our results are largely robust to various methodological choices and sample restrictions.

The remainder of the paper is structured as follows: Section 2 describes the datasets and sample selection criteria. Section 3 presents the empirical framework. Section 4 quantifies the role of firm-specific wage premiums to the gender wage gap across countries, Section 5 investigates the sorting component, and Section 6 analyzes the pay-setting component. Section 7 provides additional analyses and robustness checks. Section 8 concludes.

2. Harmonized Research Design

We use a harmonized cross-country dataset based on high-quality linked employer-employee data from the United States (Washington State), Denmark, Finland, France, Germany, Hungary, Italy, the Netherlands, Norway, Portugal, and Sweden. All the countries considered collect information on work hours needed to construct hourly wages.

Table 2 summarizes each country's dataset and its main characteristics in terms of coverage and variable availability. The data primarily cover the decade 2010–2019, with the exception of the U.S. and Germany (2010–2014). This period was chosen to focus on the most recent full decade up to the COVID-19 crisis. While some countries provide data covering the entire or nearly entire population of private-sector jobs (Denmark, France, Germany, the Netherlands, Norway, Portugal), others provide very large samples covering at least half of the population.[6]

We define the firm as an employer rather than an establishment (except for Germany), and construct hourly wage rates by dividing pre-tax annual labor earnings by annual hours worked.[7] We use paid hours where available and contractual hours otherwise (as in Germany, Hungary, Italy, and Sweden). Earnings include irregular payments such as overtime and bonuses in all countries. All wage rates are deflated using the OECD Consumer Price Index with 2015 as the base year.

Firm value-added data (defined as revenues minus intermediate inputs) are available for most firms in Denmark, Finland, France, Italy, Hungary, Norway, and Sweden. The U.S. data do not include financial information, for Germany the sample is relatively small. For Portugal, we observe only sales data rather than value-added. Throughout the paper, "productivity" refers to labor productivity, defined as value-added per person employed or, for Portugal, as sales per person employed.

More detailed information about country-specific data sources, institutional contexts, and variable definitions is provided in Appendix D.

2.1. Sample Selection

To ensure consistency across datasets, we apply uniform sample selection criteria. First, we focus on "prime-age workers" (ages 25-55). We restrict our analysis to workers employed in the private sector, specifically in industries where most firms are for-profit organizations. This leads us to exclude industries coded O through U in the NACE classi-

[6] For the U.S., the data from Washington State covers most private-sector jobs. However, demographic information is only available for workers who claimed unemployment insurance, which makes up about 51% of the sample. Italy uses a sample that is representative of 7% of firms. Sweden and Finland have samples that cover at least 50% of private-sector workers, though workers employed in large firms are overrepresented. Hungary uses a sample of 50% of employees. To improve representativeness, we construct appropriate sample weights for Washington State, Sweden, and Finland. All baseline results presented in this paper use weighted estimates. Detailed weighting procedures and comparisons between weighted and unweighted figures are provided in Appendix B and do not change the main results.

[7] Monthly labor earnings by monthly hours worked in the case of Hungary, Portugal, and Sweden.

fication (education, health, culture, other services, private households with employed persons, and extraterritorial organizations). The exclusion of the public sector addresses discrepancies in its coverage across administrative sources in different countries and the classification of semi-public companies, associations, and foundations.

Second, we annualize the data, regardless of the original collection frequency. For each worker, we identify their primary employer as the one from which they received the highest annual earnings, so that each final dataset contains one observation per worker per year in each country. We remove observations with hourly wages below 80% of the minimum hourly wage (or below 10% of the median hourly wage when minimum-wage information is unavailable). We also winsorize the top 0.1% of the hourly wage rate distribution within each country and year, and winsorize the bottom and top one percent of the productivity distribution.

The econometric framework described in Section 3 requires that we focus on firms that employ both men and women, connected through mobility of workers of both genders. In Appendix C, we document three progressively restricted samples: (1) the initial analysis sample after applying our selection criteria, (2) the dual-connected sample of firms that employ both men and women and are connected through worker mobility, and (3) the dual-connected sample with available productivity data. Throughout this paper, we refer to the dual-connected set as our main analysis sample for each country. The dual-connected set retains a very large and representative fraction of our initial sample, ranging from 75% of person-year observations in Hungary and the U.S. to 98% in Sweden.[8]

To address potential concerns about sample composition and examine whether limited mobility biases the estimated firm fixed effects (Andrews et al. 2008; Bonhomme et

[8]See Appendix C. Figure A1 compares the gender wage gap (measured as the difference between male and female average log hourly wages) across the three samples. The gender wage gap remains consistent when restricting to the dual-connected sample across all countries except Hungary, where it increases from 10 to 16 log points. This consistency suggests that our subsequent analysis based on the dual-connected sample accurately represents the broader population of private-sector workers aged 25–55.

al. 2023), we analyze two alternative samples. First, we include public-sector workers (these data are unavailable or only partly available for the U.S., Germany, Italy, Portugal, and Hungary) and workers in semi-public/not-for-profit firms to assess whether excluding these jobs affects our results. Second, we create a restricted sample of firms with at least ten movers of each gender over the observation period. Results from these alternative samples are presented in Section 7.

2.2. Descriptive Statistics of the Main Analysis Sample

Table 3 provides descriptive statistics of the main analysis samples based on the dual-connected set for each country and gender. In each country, women's hourly wages are lower than men's, with the gender wage gap ranging from 9 log points (9.4%) in Sweden to 26 log points (29.7%) in Germany.

We define part-time employment as an employment spell where the worker works, on average, less than 30 hours per week with the primary employer. Women are much more likely to work part-time than men in all countries. The Netherlands has the highest incidence of part-time work and the largest gender gap in part-time work (50.6% of women against 11.6% of men), followed by Italy (41.1% against 10.4%) and Germany (31.8% against 7.1%). In contrast, Portugal and Hungary have low overall part-time rates and smaller gender differences (6.4% against 1.7% and 11.3% against 5.2%, respectively).

For an accurate estimation of firm wage premiums, worker mobility is crucial. In all countries, the average number of movers per firm exceeds 10 for both sexes.

Table 3 reports the share of person-year observations in the analysis sample with non-missing log productivity data. These cover about 75 percent of observations for both men and women in most countries.

3. Estimating Firm-Specific Wage Premiums and Measuring Their Contribution to Gender Gaps

This section discusses the gender-specific AKM model and how we measure the contribution of firm-specific wage premiums to the gender wage gap.

3.1. Gender-Specific AKM Model

We estimate the two-way fixed effects AKM model separately for men and women as in CCK for each country:

$$\ln w_{it} = \alpha_i + \psi^{G(i)}_{J(i,t)} + X'_{it}\beta^{G(i)} + r_{(it)} \tag{1}$$

where $\ln w_{it}$ denotes the log hourly wage of worker i in firm $j \in \{1, \ldots, J\}$ in year t. α_i captures the worker fixed effect — the portable, time-invariant person-specific component of wage valued equally across employers. $\psi^{G(i)}_{J(i,t)}$ represents the *gender-specific* firm fixed wage effect, reflecting the wage premiums systematically associated with a particular employer j for gender G. X'_{it} contains observable time-varying characteristics, including a third-order polynomial in age and year effects. To identify age, time, and worker fixed effects separately, we follow CCK in restricting the age-wage profile to be flat at 40. $r_{(it)}$ denotes the error term.[9]

Firm fixed effects reflect between-firm wage premiums arising from differences in firm wage policies rather than differences in workforce composition (Card et al. 2018). Because we estimate Equation (1) separately by G, we can interpret $\hat{\psi}^{G(i)}_{J(i,t)}$ as systematic

[9] Our specification differs from Card et al. (2016) in that we take a more parsimonious approach to the covariates vector X. While Card et al. include interactions between year dummies, education levels, and age terms, we omit these education interactions because education data are unavailable for France, Hungary, and Italy. In Section 7, we show that including education interactions for countries with available data yields results similar results to our main specification.

differences in a firm's wage policy toward men and women.[10]

3.2. Measuring Firm Contributions to Gender Wage Gaps

Our main goal is to quantify how firm-specific wage policies contribute to the gender wage gap. We define the gender wage premium gap as the difference in average firm wage premiums between men and women: $E[\psi_j^M] - E[\psi_j^F]$.

To understand the channels through which firm wage premiums contribute to gender wage inequality, we further decompose the gender wage premium gap using the Kitagawa-Oaxaca-Blinder approach (Kitagawa 1955; Oaxaca 1973; Blinder 1973; Card et al. 2016):

$$E[\psi_j^M] - E[\psi_j^F] = \underbrace{E[\psi_j^M - \psi_j^F|M]}_{\text{Pay-setting}} + \underbrace{E[\psi_j^F|M] - E[\psi_j^F|F]}_{\text{Sorting}} \tag{2}$$

This decomposition separates the gender wage premium gap into two distinct components. The first component on the right-hand side is the *pay-setting* component, which measures the extent to which women receive lower wage premiums than men at the same employers. This captures within-firm gender gaps in wage premiums for similar workers, which may reflect differences in bargaining power or negotiation behavior (Babcock and Laschever 2003; Roussille 2024), potentially as a result of employer monopsony power (Manning 2021). The second component on the right-hand side is the *sorting* component, which measures the extent to which women are employed by firms that

[10] To identify firm fixed effects, we make the following assumptions. First, we assume log-additive worker and firm fixed effects with no complementarities between firm and worker types, meaning wage premiums apply equally to all workers of a given gender regardless of individual characteristics. Second, we require that, conditional on worker and firm fixed effects, workers' job transitions are uncorrelated with components of the error term (such as match-specific wage components). Third, we employ a static framework excluding lagged employment effects, assuming previous employers do not influence current wage premiums. Recent empirical work by Bonhomme et al. (2019), Card et al. (2013), and Di Addario et al. (2023) provides support for these assumptions.

offer lower wage premiums to all workers.[11]

Limited mobility bias does not affect estimates of the gender wage premium gap in Equation (2) because the Kitagawa-Oaxaca-Blinder method decomposes the differences of first moments.[12]

3.3. Normalization of Gender-Specific Firm Wage Premiums

To allow for comparisons between firm fixed effects estimated separately for men and women, a normalization is required. Because firm fixed effects are only identified up to a constant within each gender group, we need to establish a common reference point for meaningful cross-gender comparisons. The goal is to identify "low-surplus" firms and set their gender-specific firm fixed effects to zero, assuming that these firms pay, on average, zero wage premiums to both genders (Card et al. 2016). One approach to identifying "low-surplus" firms uses value-added data and relies on the economic intuition that low-productivity firms have limited resources to share with workers. Card et al. (2016) show that this intuition manifests itself empirically as a nonlinear relationship between firm productivity and wage premiums, a pattern that can be exploited to identify a set of low-surplus firms.

Figure A2 plots the relationship between firm productivity and gender-specific wage premiums for countries with value-added data. The figure shows mean estimated firm wage premiums from the AKM model for men and women, averaged across firms within centiles of log productivity. Gender-specific wage premiums and productivity are

[11] The decomposition in Equation (2) uses the distribution of jobs held by men as the reference. While this choice is conventional in the literature, it is ultimately arbitrary. As a robustness check, we also estimate the decomposition using the distribution of jobs held by women as the reference. The decomposition using women's jobs is given by $E[\psi^M] - E[\psi^F] = E[\psi^M - \psi^F|F] + E[\psi^M|M] - E[\psi^M|F]$. We report the results using this alternative reference in Section 7.

[12] This holds as long as limited mobility only induces classical measurement error in firm fixed effects. When we measure the standard deviation of firm fixed effects in Figure 2, we bias-correct the standard deviations. As an additional check, we also show that our results remain fairly consistent when we restrict the sample to firms with at least ten movers of each gender during the observation period (Section 7).

rescaled to improve readability. Across all countries, we observe a consistent hockey-stick pattern: firm fixed effects remain flat at low productivity levels and start increasing beyond a certain threshold. The normalization procedure sets male and female wage premiums to zero on average for all firms below this threshold, effectively defining these low-surplus firms as the reference group for measuring gender-specific wage premiums.[13] Only the pay-setting component is affected by the normalization procedure, while the sorting component remains invariant.

Productivity data are unavailable for the United States, cover only a limited set of firms in Germany, and after taking the log transformation significantly reduces the share of women in our sample for Norway.[14] For these countries, we follow the approach inspired by Morchio and Moser (2024), whose normalization selects firms at the bottom of a job utility ranking.[15] In practice, we define firms with high worker exit rates as low-rank firms. To do so, for each gender, we identify firms in the top ten percent[16] of the employment-weighted exit-rate distribution as the reference group, where the exit rate is defined by the share of workers who leave their employer between two consecutive years. The rationale for this is that high-exit rates are often regarded to be a negative employer attribute (e.g., Humlum et al. 2025). Other common measures of

[13]To formally identify the normalization threshold for each country, we follow CCK and estimate a bivariate regression model:

$$\begin{aligned} \hat{\psi}^M_{J(i,t)} &= \pi^M_0 + \pi^M \max\{0, S^o_{J(i,t)} - \tau\} + \nu^M_{J(i,t)} \\ \hat{\psi}^F_{J(i,t)} &= \pi^F_0 + \pi^F \max\{0, S^o_{J(i,t)} - \tau\} + \nu^F_{J(i,t)} \end{aligned} \tag{3}$$

where $S^o_{J(i,t)}$ is log labor productivity. We estimate this system for a range of potential τ values and select the threshold τ that minimizes the mean squared error of both equations. The vertical lines in Figure A2 represent these country-specific estimated thresholds.

[14]See Section 7 for further details.

[15]The Morchio and Moser (2024) approach is motivated by a noncompetitive model of compensating differentials for job amenities; see also empirical work on the relevance of amenities (e.g., Sorkin 2018; Bertheau and Hoeck 2025; Humlum et al. 2025). Another common normalization approach is to use low-rent industries such as the hotel-and-restaurant sector (e.g., Casarico and Lattanzio 2024; Palladino et al. 2025). We found the industry-normalization to be less robust than the exit-rate normalization when validating both against the productivity normalization.

[16]We tested alternative thresholds and found similar results (available upon request).

firm utility are the poaching index (Bagger and Lentz 2019) and the PageRank (Sorkin 2018) but these measures are not consistently implementable across countries due to differences in data frequency (e.g., daily in Denmark vs. annual in Portugal). We provide more details about normalization robustness and sample sensitivity in Section 7.

4. Contribution of Firm Wage Premiums to Gender Wage Gaps

This section decomposes gender differences in firm-specific wage premiums into the extent to which women receive lower wage premiums than men within the same firms (pay-setting) and the extent to which women are employed in firms that offer lower wage premiums to all workers (sorting).

Figure 1 presents the results from the CCK decomposition, given by Equation (2), for each country. Panel A plots the gender wage gap (y-axis)—the difference between male and female average log hourly wages—against the gender wage premium gap (x-axis)—the difference between male and female average firm-specific wage premiums. The figure includes diagonal reference lines marking where the gender wage premium gap accounts for 10% and 40% of the overall gender wage gap. Two key findings emerge. First, gender wage premium gaps are positive in each country. Second, there is a strong positive relationship between the gender wage and wage premium gap: countries with larger firm contributions in levels also tend to have larger overall gender wage gaps. This suggests that firm-level factors help explain cross-country differences in the observed gender wage gap. In Denmark, Sweden, France, Finland, the Netherlands, and Italy, firm-specific wage premiums account for 15–20% of the gap. In Norway and Portugal, they account for about 20–25%. In Germany, Hungary, and the U.S., firm-specific wage premiums account for about 30% of the gap. Hence, while firm-specific wage premiums play a role for the gender wage gap in all countries, their magnitude varies considerably across institutional and labor market contexts.

The cross-country variation in the sorting and pay-setting channels, shown in Figure 1, panel B, is even more pronounced. The figure decomposes the gender wage premium gap into sorting and pay-setting components, revealing different patterns across countries. In Hungary and Denmark, the gender wage premium gap is mainly driven by differences in within-firm pay-setting, that is, by women receiving lower premiums than men at the same employer.[17] In Finland, Germany, the Netherlands, Portugal, and the U.S., on the other hand, sorting is the dominant mechanism, as women are strongly concentrated in firms that offer lower wage premiums.

Are countries with high gender wage premium gaps also those where firms play a more important role in wage determination overall? The answer is yes, at least partly. Figure 2, Panel A, plots, for each country, the standard deviation of women's firm wage premiums against the gender wage premium gap. In countries where the dispersion of firm wage premiums is high, such as Germany and Hungary, the gender wage premium gap is also large. In contrast, in countries with much less dispersion in firm wage premiums, such as those in Scandinavia, the gender wage premium gap is substantially smaller.[18] The relationship is approximately linear: countries with greater firm-level pay heterogeneity also exhibit larger gender wage premium gaps. A bivariate regression shows that a one-standard-deviation increase in the dispersion of firm wage premiums is associated with a 0.26 log points increase in the gender wage premium gap. Panel B shows that women's and men's firm wage premium dispersions are similar in most countries.

[17] Compared to other European countries, wages in Denmark and Hungary are more likely to be negotiated either at the firm level or through employer-employee bargaining than at the industry level (Bhuller, Moene, Mogstad and Vestad 2022; Dahl, le Maire and Munch 2013; Larsen and Ilsøe 2022).

[18] See Kline (2024) for further discussion and cross-country comparisons of firm fixed effects.

5. Understanding the Sorting Component

The previous section showed that firm-specific wage premiums significantly contribute to the gender wage gap across countries, with variation in the relative importance of sorting and pay-setting channels. This section focuses on understanding the sorting component, while Section 6 examines the pay-setting component.

5.1. The Life Cycle Profile of Gender Gaps

Figure 3, panel A plots the change in the gender wage gap between older (50–55 years of age) and younger (25–29 years of age) workers against the corresponding change in the gender wage premium gap for each country. Panel A shows a strong positive correlation between the widening of the gender-wage and wage-premium gaps with age. For example, Germany, the Netherlands, Portugal, and Italy show substantial increases in both measures. A 4–8 log point increase in the gender wage premium gap is associated with a 20–30 log point increase in the gender wage gap.

Panel B plots the change in the gender wage gap between older and younger workers against the corresponding change in the sorting component of the gender wage premium gap. The patterns in Panels A and B closely align, indicating that the sorting component explains nearly all of the age-related expansion in gender wage premium gaps. Panel C confirms this by showing that there is essentially no relationship between the change in the gender wage gap between older and younger workers and the corresponding change in the pay-setting component, except in the United States.

Overall, these patterns show that the widening gender wage gap over the life cycle is associated with increased gender differences in firm sorting (Goldin et al. 2024; Casarico and Lattanzio 2024; Card et al. 2025). A potential explanation is that women are less likely to progress in their career by moving to higher-wage firms[19] (Bronson and Thoursie 2019). This suggests that constraints on job mobility — potentially related to motherhood and family responsibilities — play an important role in shaping gender wage disparities over the life cycle (Kleven et al. 2019).[20] In the next subsection, we investigate a potential mechanism behind the differential sorting.

5.2. Compensating Differentials and the Role of Part-Time Employment

Literature building on Goldin (2014, 2015) suggests that part of the gender wage gap arises due to compensating differentials for long work hours (Bolotnyy and Emanuel 2022). Some firms may offer compensation packages combining high wages and long hours. If these packages are relatively less attractive to women, especially when they take on family responsibilities, then compensating differentials for long hours could help explain the emergence of the sorting component over the life cycle.

We approach this question from two complementary angles. We start by estimating an AKM model of hours (Lachowska, Mas, Saggio and Woodbury 2023). This model allows us to interpret firm fixed effects in hours as firm policies on hours, while accounting for the firm's workforce composition. We estimate the model separately by gender and then regress firm wage premiums on firm hour effects to recover gender-specific elasticities of firm wage policies with respect to firm hour policies. We estimate the gender-specific elasticity of firm wage premiums with respect to firm hour policies using employment-weighted firm-level regressions. Let ψ_j^g denote the AKM firm fixed

[19] While we cannot fully disentangle cohort effects from age effects within cohorts, research by Arellano-Bover, Bianchi, Lattanzio and Paradisi (2024) indicates that cohort effects significantly influenced gender wage gap trends in several countries up to the mid-1990s, but have played a diminished role in the past two decades. Additionally, Casarico and Lattanzio (2024) find that similar age-specific patterns in sorting persist even when comparing different cohorts at the same age in Italy.

[20] Public spending on early childcare and education – potentially relaxing the time constraints of working mothers – is associated with a smaller contribution of sorting. This association is reported in Figure A13. Germany, the U.S., the Netherlands, and Portugal stand out as countries with a small share of GDP spent on public provision of childcare and a relatively large contribution from sorting.

effect on wages and ϕ_j^g the firm fixed effect on hours for gender $g \in \{m, f\}$. We estimate $\psi_j^g = \alpha + \beta_g \hat{\phi}_j^g + \eta_j^g$, where η is the regression error term. To correct for measurement error, we instrument ϕ_j^g with ϕ_j^{-g}, the firm hour effect estimated for the opposite gender. Figure 4 shows the elasticity of firm wage premiums with respect to firm-specific hour policies β_g, estimated separately by gender and excluding countries with solely contractual hours. In all countries except Portugal, we find a positive relationship between firm hour effects and firm wage premiums: firms that require longer paid hours tend to offer higher wages. The magnitude of the elasticity varies across countries, but, importantly, we consistently find no gender differences in the elasticities. Women are compensated similarly to men for working longer hours within firms. This suggests that the hours-wage relationship could primarily influence gender wage gaps through women sorting to lower-paying and shorter-hours employers.

Figure 5 provides direct evidence across countries of this sorting by analyzing the relationship among firms' incidence of part-time work, their gender composition, and their wage-setting policies. To construct this figure, we first calculate the country-specific quartiles based on the panel-specific x-axis measure, and then we pool these quartiles by taking the unweighted average across all countries. These steps are taken to more effectively show the general patterns.[21] The left panel shows the within-firm share of part-timers by gender against the share of women. We find that, in all countries, the share of part-time workers is larger in firms that disproportionately employ women. The right panel shows firm-specific wage premiums (computed as the weighted average of gender-specific wage premiums) against the within-firm share of part-timers by gender. A negative relationship emerges: firms with high part-time intensity systematically offer lower wage premiums than those with low part-time intensity. Firms in the top quartile of part-time intensity pay, on average, wage premiums that are almost 10 log points lower than those in the bottom quartile. It is not just that women are more likely to work

[21]Figure A3 reports country-specific relationships.

part-time, but also that women are more likely to work in firms where part-time work is more widespread, and the within-firm prevalence of part-time work is associated with lower firm-specific wage premiums.

Taken together, these findings reveal that compensating differentials for longer working hours exist and operate similarly for both men and women within firms. The sorting component of the gender wage premium gap partly reflects women's systematic concentration in firms offering shorter hours and lower wage premiums. In Figure A4, we link the increasing sorting of women into low-paying firms over the life cycle to the incidence of part-time work. We find a positive association between the rise in sorting into low-wage firms and the prevalence of part-time employment over the life cycle.

6. Understanding the Pay-Setting Component

If women's labor supply is less elastic with respect to wages than men's — leading to fewer outside options and a weaker bargaining position — then the gender wage premium gap will tend to be larger in high-wage and high-productivity firms because of employer market power. This leads to the following testable predictions regarding the pay-setting component: (i) do high-wage firms have a higher gap in pay-setting? (ii) do women receive a smaller share of rents than men at equally productive firms? (iii) do differences in rent-sharing across countries contribute to differences in the pay-setting component? We study these predictions below.[22]

[22] Unions might play a role in limiting inequalities within firms. In countries with high coverage of collective bargaining (France, Italy, Finland, Portugal, Sweden), the contribution of pay-setting to the gender wage premium gap is indeed lower than in countries with lower coverage (Hungary and the U.S.). This relationship is reported in Figure A13.

6.1. Is the Pay-setting Component Higher in High-Wage Firms?

Figure 6 shows how the pay-setting component varies with firm-level wage premiums across countries. We define the firm-level wage premium as the weighted average of gender-specific wage premiums. Specifically, the figure shows coefficients from firm-level regressions where the dependent variable is the pay-setting component (defined as the difference between male and female wage premiums) and the independent variable is the firm's weighted average wage premium across genders. The regressions are weighted by male employment at the firm level.

A clear pattern emerges. In all countries except Germany, the pay-setting component increases significantly with the firm's average wage premium. The elasticities range from approximately 0.07 to 0.25. We distinguish two groups of countries. The estimated elasticity is about 0.2 in Finland, Denmark, Portugal, the United States, Sweden, and Hungary, and about 0.1 in Norway, France, the Netherlands, and Italy.

6.2. Equal Rent-Sharing of Firm Wage Premiums Across Countries?

Card et al. (2018) show that more productive firms tend to pay higher wages and that firm wage premiums can be partially explained by rent-sharing, in which workers capture some of the firm-specific surplus. To test this mechanism, we estimate gender-specific rent-sharing equations:

$$\psi^G_{J(i,t)} = \pi^G_0 + \pi^G S^*_{J(i,t)} + \nu^G_{J(i,t)} \tag{4}$$

where $\psi^G_{J(i,t)}$ represents the gender-specific firm wage premium and $S^*_{J(i,t)}$ is the net surplus.[23] We show country-specific π^F and π^M in Figure A5. We estimate $\gamma_1 = \pi^F/\pi^M$, the relative rent-sharing parameter, which captures the share of male rent-sharing

[23] defined as $S^*_{J(i,t)} = \max\{0, S^o_{J(i,t)} - \tau\}$, the log firm-level productivity per worker in excess of the country-specific threshold τ estimated in Equation 3. Firms below the threshold are assigned zero net surplus.

received by women. We also estimate $\delta_1 = \pi^M - \pi^F$, the difference in rent-sharing coefficients, which directly quantifies how differential rent-sharing contributes to the pay-setting component of the gender wage premium gap.[24]

Women receive a smaller share of rents at equally productive firms. Figure 7 presents estimates of the relative rent-sharing parameter γ_1 across countries. The average ratio across countries is 0.89, indicating that on average, women receive 89% of the rent-sharing benefits that men receive. This result suggests that within the same firm, women capture a smaller share of productivity rents. The Netherlands comes closest to parity with a ratio close to 1, where we cannot reject equal rent sharing between men and women.

Firm surplus affects pay-setting. Figure A6 reports δ_1, the difference in rent-sharing coefficients, which quantifies how differential rent-sharing contributes to the pay-setting component of the gender wage premium gap in different countries. In Hungary, where the pay-setting component is the largest, a 10% increase in firm productivity is associated with an approximate 0.3% increase in the firm-level premium gap. In contrast, in the Netherlands, where the pay-setting component is nearly zero, there is virtually no change in the premium gap as firm net surplus increases.

7. Additional Analyses and Robustness

One aim of this paper is to provide a harmonized perspective on how and why firms contribute to the gender wage gap. With standardized estimates of sorting ad pay-setting, we can compare our estimates to previous research using the CCK decomposition and

[24]We estimate the relative rent-sharing parameter γ_1 via IV using firm productivity as an instrument: $\psi^F_{J(i,t)} = \gamma_0 + \gamma_1 \hat{\psi}^M_{J(i,t)} + e_{J(i,t)}$. We estimate δ_1 by regressing the within-firm gender gap in premiums directly on firm productivity: $\psi^M_{J(i,t)} - \psi^F_{J(i,t)} = \delta_0 + \delta_1 S^*_{J(i,t)} + e_{J(i,t)}$. All regressions are estimated at the firm level and weighted by male person-year observations.

comment on observable patterns. One important design difference is the inclusion or exclusion of public-sector workers (Table 1 summarizes variation across studies). Other considerations may include which gender is the reference group, normalization of firm fixed effects, sample cuts, limited worker mobility, and the role of education and occupation. We discuss these considerations below.

7.1. Public Sector and the Sorting Component

Thus far, the analysis has focused exclusively on private-sector jobs because public-sector jobs are not observed in Italy, and Portugal and only a subset of public-sector jobs are observed in Germany and the United States. However, it is well-documented that women are more likely than men to work in the public sector or in non-profit organizations (NPOs) (Gomes and Kuehn 2019). Therefore, given this gender difference in sector choice, it is important to examine how including public-sector and nonprofit jobs affects the contribution of firm-specific wage premiums to the gender wage gap.

Figure 8 contrasts the sorting component[25] of our baseline sample, which includes only private-sector jobs, with the results obtained when all jobs are included. The results show a clear pattern: when public-sector and nonprofit jobs are included, the sorting component increases substantially in five countries out of seven countries, with Norway and the Netherlands being the exceptions (Panel A). Including public-sector jobs makes our results for Denmark comparable to Gallen, Lesner and Vejlin (2019), who also included public-sector workers: the share of the gender wage gap explained by sorting (Panel B) is 17% in our extended sample, similar to their estimate of 16%. These findings suggest that studies focusing exclusively on private-sector jobs likely underestimate the true extent of gender-based sorting across types of firms.

[25] We focus on the sorting component for two reasons. First, productivity data are generally unavailable for public-sector employers, which prevents us from using our preferred normalization method. Second, the sorting component is invariant to normalization choices.

7.2. Robustness Checks

Alternative Decomposition. Figure A7 presents the results of an alternative CCK decomposition. In this alternative decomposition, the pay-setting effect is estimated using the distribution of jobs held by women (as opposed to men's jobs, as in the main analysis). The relative importance of the sorting and pay-setting components within countries remains consistent, though Denmark is a notable exception, where the sorting component becomes more prominent in the alternative specification. The cross-country ranking of components is also well-preserved, though the Netherlands shifts from having a relatively high sorting component to having average sorting while showing an above-average pay-setting component.

Alternative Normalization. Figure A8 reports the gender wage premium gap where, for each country, we normalize firm fixed effects using the exit-rate normalization described in Section 3.3. The key patterns from our baseline analysis remain: firm-specific wage premiums contribute positively to the gender wage gap in all countries, and there is a positive relationship between the overall gender wage gap and the gender wage premium gap across countries. Most countries show that firm-specific wage premiums explain between 10% and 30% of the gender wage gap. However, France and Sweden are notable exceptions: the normalization-induced reduction in the pay-setting component leads to a firm contribution below 10% in these two countries.

Different Sample Cuts and Econometric Specifications. Our analysis of the pay-setting component requires productivity data to apply our preferred normalization method. Figure A9 compares the sorting component between the dual-connected (DC) sample and the value-added (VA) sample to test whether limiting the sample to firms with productivity data affects representativeness. Because the sorting component does not depend on normalization choices, any differences between the two estimates would indicate that the VA sample is unrepresentative of the broader DC sample. Across most countries, the sorting component is similar in both samples. Germany shows some divergence, which is expected given its limited productivity data. Among countries with broad productivity coverage, Norway is the only case with a significant difference between estimates. As Table 3 shows, the share of women in that sample is relatively low. Therefore, for Norway, Germany, and the United States (which lacks productivity data), we use the alternative normalization method based on high-exit-rate firms.

In most countries, the data covers a ten-year panel of the entire private-sector workforce. However, in some cases, the data includes only a 50% random sample of workers. In the U.S. and Germany, we use a five-year panel. One concern is that low worker mobility could lead to greater sampling errors in firm fixed effect estimates, especially for firms with few job transitions. Figure A10 presents the sorting and pay-setting effects among workers employed in firms with at least ten gender-specific movers. This restriction ensures that firm fixed effects are estimated from a substantial number of worker transitions, thereby reducing potential measurement error. However, it is important to note that this sample is more selected and may be less representative of the studied population. Panel A shows that the sorting component generally remains stable when restricted to high-mobility firms, with most countries maintaining their relative positions. However, Hungary is an exception; its sorting component increases from 0.4 (Figure 1) to 2.3 log points. The ten-mover sample leads to significant reductions in the pay-setting component. Panel B of Figure A10 shows the same decomposition using firm fixed effects estimated from the baseline sample. The results in Panels A and B are very similar, indicating that the difference between this Figure A10 and Figure 1 is most likely driven by a different set of workers and firms rather than by the estimates.

Another potential concern is the limited set of observable worker characteristics included in our main specification, which accounts only for year effects and third-order polynomials in age.[26] Figure A11 presents the sorting and pay-setting effects estimated using a gender-specific AKM model with and without additional controls for worker characteristics. Specifically, we introduce four educational attainment categories (less than high school, high school or vocational training, some college, and master's degree or above) interacted with age. The results remain nearly identical, suggesting that our findings are robust to the inclusion of additional worker controls.[27]

Occupation. To account for differences in occupational structure between men and women, we apply a reweighting procedure following DiNardo, Fortin and Lemieux (1996) for countries with detailed occupation codes. We reweight men to match women's occupational distribution at the 1-digit ISCO level.[28] This isolates whether gender gaps reflect occupational segregation versus within-occupation mechanisms. Figure A12 presents the results. As expected, the gender wage gap decreases when we adjust for occupational differences. Interestingly, the gender wage premium gap also declines by a similar magnitude, primarily due to a reduction in the sorting component. Consequently, the share of the gender wage gap explained by firm-specific wage premiums remains roughly unchanged across countries.

[26] Actual labor market experience is not available in our datasets, either because employment history cannot be reconstructed or because the data only report point-in-time employment measures (e.g., payroll status in October). Moreover, employment gaps are generally non-random. Card et al. (2018) provide a detailed discussion of this issue.

[27] In a previous version, we also perform the same analysis incorporating broad occupational groups, following Casarico and Lattanzio (2024). Results were also similar.

[28] We reweight men to women's distribution rather than the reverse to preserve the interpretation of the pay-setting component, which is defined conditional on jobs held by men. Reweighting women would mechanically equalize pay-setting across genders, eliminating our ability to detect occupation-specific male pay advantages. The sorting component remains interpretable under this approach since it continues to measure differences in firm fixed effects between actual male and female employment distributions.

8. Conclusion

This paper studies how firm-specific wage premiums contribute to the gender wage gap using harmonized cross-country research design. Using matched employer-employee data from 11 developed economies, we establish that firms play a meaningful role in explaining both the level and cross-country variation in gender wage gaps. Firm-specific wage premiums account for 10–30% of the gender wage gap, and countries with larger overall gender gaps consistently show larger gaps in firm premiums. The decomposition into sorting and pay-setting channels shows significant cross-country variation.

Despite this heterogeneity, robust patterns emerge across countries. In most countries, women sort to lower-premium firms which also tend to be firms with a high part-time incidence. For the pay-setting component, we find that women receive only 89% of the rent-sharing benefits that men receive from firm productivity gains. By and large, our results supports the notion that the return to long working hours is a meaningful driver of the gender wage gap (see, e.g., Goldin 2014; Blau 2025). Women are more likely to sort into firms with higher rates of part-time work, which typically offer lower wage premiums—possibly reflecting a trade-off between working time arrangements and pay.

Overall, our findings highlight that firms play a role in shaping gender wage inequality. While factors like human capital and occupational segregation still matter, our results show that firm-specific wage premiums are an additional, separate, and important source of the gender pay gap. This suggests that policies should focus on addressing the causes of these firm-level wage premiums, rather than just their effects.

One possible avenue for further research is to examine the institutional conditions that shape these mechanisms. Cross-country variation in public investment in childcare and early education, or in collective bargaining coverage, may help explain differences in the relative importance of sorting and pay-setting. The correlations in Figure A13 point to promising directions for understanding how institutional contexts interact with firms' wage-setting practices and, in turn, shape gender wage gaps across countries.

References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

Addario, Sabrina Di, Patrick Kline, Raffaele Saggio, and Mikkel Sølvsten, "It Ain't Where You're From, It's Where You're At: Hiring Origins, Firm Heterogeneity, and Wages," *Journal of Econometrics*, 2023, *233* (2), 340–374.

Altonji, Joseph G. and Rebecca M. Blank, "Race and Gender in the Labor Market," *Handbook of Labor Economics*, 1999.

Andrews, Martyn J., Len Gill, Thorsten Schank, and Richard Upward, "High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 2008, *171* (3), 673–697.

Arellano-Bover, Jaime, Nicola Bianchi, Salvatore Lattanzio, and Matteo Paradisi, "One Cohort at a Time: A New Perspective on the Declining Gender Pay Gap," *NBER Working Paper*, 2024.

Babcock, Linda and Sara Laschever, *Women Don't Ask: Negotiation and the Gender Divide*, Princeton University Press, 2003.

Bagger, Jesper and Rasmus Lentz, "An Empirical Model of Wage Dispersion with Sorting," *The Review of Economic Studies*, 2019, *86* (1), 153–190.

Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet, "Gender Differences in Job Search: Trading off Commute against Wage," *The Quarterly Journal of Economics*, 2021, *136* (1), 381–426.

Bayard, Kimberly, Judith Hellerstein, David Neumark, and Kenneth Troske, "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data," *Journal of Labor Economics*, 2003, *21* (4), 887–922.

Becker, Gary S., *The Economics of Discrimination*, University of Chicago Press, 1957.

Bertheau, Antoine and Christian Philip Hoeck, "Firm Beliefs About Wage Setting," *IZA Discussion Paper*, 2025.

Bertrand, Marianne, "New Perspectives on Gender," *Handbook of Labor Economics*, 2011.

Bhuller, Manudeep, Karl Ove Moene, Magne Mogstad, and Ola Vestad, "Facts and Fantasies about Wage Setting and Collective Bargaining," *Journal of Economic Perspectives*, 2022, *36* (4), 29–52.

Biasi, Barbara and Heather Sarsons, "Flexible Wages, Bargaining, and the Gender Gap," *The Quarterly Journal of Economics*, 2022, *137* (1), 215–266.

Blau, Francine D., "Equal Pay in the Office," *Lexington Books*, 1977.

___ , "Gender Inequality in the Labor Market: Continuing Progress?," *ILR Review*, 2025, *78* (2), 275–303.

___ **and Lawrence M. Kahn**, "Understanding International Differences in the Gender Pay Gap," *Journal of Labor Economics*, 2003, *21* (1), 106–144.

___ **and** ___ , "The Gender Wage Gap: Extent, Trends, and Explanations," *Journal of Economic Literature*, 2017, *55* (3), 789–865.

Blinder, Alan S., "Wage Discrimination: Reduced Form and Structural Estimates," *Journal of

Human Resources, 1973, pp. 436–455.

Bolotnyy, Valentin and Natalia Emanuel, "Why Do Women Earn Less Than Men? Evidence from Bus and Train Operators," *Journal of Labor Economics,* 2022, *40* (2), 283–323.

Bonhomme, Stéphane, Kerstin Holzheu, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler, "How Much Should We Trust Estimates of Firm Effects and Worker Sorting?," *Journal of Labor Economics,* 2023, *41* (2), 291–322.

___ **, Thibaut Lamadon, and Elena Manresa**, "A Distributional Framework for Matched Employer Employee Data," *Econometrica,* 2019, *87* (3), 699–739.

Boza, István and Balázs Reizer, "The Role of Flexible Wage Components in Gender Wage Difference," *IZA Discussion Paper,* 2024.

Brodeur, Abel, Derek Mikola, Nikolai Cook, Thomas Brailey, Ryan Briggs, Alexandra de Gendre, Yannick Dupraz, Lenka Fiala, Jacopo Gabani, Romain Gauriot, Joanne Haddad, Ryan McWay, Joel Levin, Magnus Johannesson, Edward Miguel, Lennard Metson, Jonas Minet Kinge, Wenjie Tian, Timo Wochner, and Sumit Mishra, "Mass Reproducibility and Replicability: A New Hope," *I4R Discussion Paper Series,* 2024.

Bronson, Mary Ann and Peter Skogman Thoursie, "The Wage Growth and Within-Firm Mobility of Men and Women: New Evidence and Theory," *Unpublished manuscript,* 2019.

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

Burbano, Vanessa C., Olle Folke, Stephan Meier, and Johanna Rickne, "The Gender Gap in Meaningful Work," *Management Science,* 2024, *70* (10), 7004–7023.

Bütikofer, Aline, Sissel Jensen, and Kjell G. Salvanes, "The Role of Parenthood on the Gender Gap among Top Earners," *European Economic Review,* 2018, *109,* 103–123.

Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining, "Bargaining and Inequality in the Labor Market," *NBER Working Paper,* 2025.

Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women," *Quarterly Journal of Economics,* 2016, *131* (2), 633–686.

___ **,** ___ **, Jörg Heining, and Patrick Kline**, "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics,* 2018, *36* (S1), S13–S70.

___ **, Francesco Devicienti, Mariacristina Rossi, and Andrea Weber**, "The Gender Gap in Career Trajectories: Do Firms Matter?," *Italian Economic Journal,* 2025, pp. 1–23.

___ **, Jörg Heining, and Patrick Kline**, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *Quarterly Journal of Economics,* 2013, *128* (3), 967–1015.

Casarico, Alessandra and Salvatore Lattanzio, "What Firms Do: Gender Inequality in Linked Employer-Employee Data," *Journal of Labor Economics,* 2024, *42* (2), 325–355.

Criscuolo, Chiara, Alexander Hijzen, Cyrille Schwellnus, Erling Barth, Antoine Bertheau, Wen-Hao Chen, Richard Fabling, Priscilla Fialho, Jonathan Garita, Andrei Gorshkov, Katarzyna Grabska-Romagosa, Antton Haramboure, Ryo Kambayashi, Michael Koelle, Valerie Lankester, Timo Leidecker, Balazs Murakőzy, Oskar Nordström Skans, Satu Nurmi, Vladimir Peciar, Capucine Riom, Duncan Roth, Catalina Sandoval, Balazs Stadler, Richard

Upward, and Wouter Zwysen, "Worker Skills or Firm Wage-Setting Practices? Decomposing Wage Inequality across 20 OECD Countries," *Working Paper*, 2023.

Dahl, Christian M., Daniel le Maire, and Jakob R. Munch, "Wage Dispersion and Decentralization of Wage Bargaining," *Journal of Labor Economics*, 2013, *31* (3), 501–533.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach," *Econometrica*, 1996, *64* (5), 1001–1044.

Dreber, Anna and Magnus Johannesson, "A Framework for Evaluating Reproducibility and Replicability in Economics," *Economic Inquiry*, 2025, *63* (2), 338–356.

Fredriksson, Peter, Dogan Gülümser, and Lena Hensvik, "Outside Job Opportunities and the Gender Gap in Pay," *RFBerlin Discussion Paper 71/25*, 2025.

Gallen, Yana, Rune V. Lesner, and Rune Vejlin, "The Labor Market Gender Gap in Denmark: Sorting out the Past 30 Years," *Labour Economics*, 2019, *56*, 58–67.

Goldin, Claudia, "The Quiet Revolution That Transformed Women's Employment, Education, and Family," *American Economic Review*, May 2006, *96* (2), 1–21.

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

___ , "Hours Flexibility and the Gender Gap in Pay," *Center for American Progress*, 2015.

___ **and Lawrence F. Katz**, "A Most Egalitarian Profession: Pharmacy and the Evolution of a Family-Friendly Occupation," *Journal of Labor Economics*, 2016, *34* (3), 705–746.

___ **,** ___ **, and Ilyana Kuziemko**, "The Homecoming of American College Women: The Reversal of the College Gender Gap," *Journal of Economic Perspectives*, 2006, *20* (4), 133–156.

___ **, Sari Pekkala Kerr, and Claudia Olivetti**, "The Other Side of the Mountain: Women's Employment and Earnings over the Family Cycle," *Oxford Open Economics*, 2024, *3*, 323–334.

Gomes, Pedro and Zoë Kuehn, "You're the One that I Want! Public Employment and Women's Labor Market Outcomes," *IZA Discussion Paper*, 2019.

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

Humlum, Anders, Mette Rasmussen, and Evan K. Rose, "Firm Premia and Match Effects in Pay vs. Amenities," *NBER Working Paper*, 2025.

Kitagawa, Evelyn M., "Components of a Difference between Two Rates," *Journal of the American Statistical Association*, 1955, *50* (272), 1168–1194.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard, "Children and Gender Inequality: Evidence from Denmark," *American Economic Journal: Applied Economics*, 2019, *11* (4), 181–209.

Kline, Patrick, "Firm Wage Effects," *Handbook of Labor Economics*, 2024, *5*, 115–181.

Kunze, Astrid, "Gender Wage Gap Studies: Consistency and Decomposition," *Empirical Economics*, 2008, *35* (1), 63–76.

___ , "The Gender Wage Gap in Developed Countries," in "Oxford Handbook on Women and the Economy," Oxford University Press, 2018.

Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A. Woodbury, "Wage Posting or Wage Bargaining? A Test Using Dual Jobholders," *Journal of Labor Economics*, 2022, *40* (S1), S469–S493.

——, ——, ——, and ——, "Work Hours Mismatch," *NBER Working Paper*, 2023.

Larsen, Trine Pernille and Anna Ilsøe, "Varieties of Organised Decentralisation across Sectors in Denmark: A Company Perspective," *Industrial Relations Journal*, 2022, *53* (4), 368–389.

Li, Jiang, Benoit Dostie, and Gaëlle Simard-Duplain, "Firm Pay Policies and the Gender Earnings Gap: The Mediating Role of Marital and Family Status," *ILR Review*, 2023, *76* (1), 160–188.

Lochner, Benjamin and Christian Merkl, "Gender-Specific Application Behaviour, Matching, and the Residual Gender Earnings Gap," *The Economic Journal*, 2025.

Manning, Alan, "Monopsony in Labor Markets: A Review," *ILR Review*, 2021, *74* (1), 3–26.

Mas, Alexandre and Amanda Pallais, "Valuing Alternative Work Arrangements," *American Economic Review*, December 2017, *107* (12), 3722–3759.

Mincer, Jacob, *Schooling, Experience, and Earnings* National Bureau of Economic Research, New York: Columbia University Press, 1974.

Morchio, Iacopo and Christian Moser, "The Gender Pay Gap: Micro Sources and Macro Consequences," *NBER Working Paper*, 2024.

Nosek, B. A., G. Alter, G. C. Banks, D. Borsboom, S. D. Bowman, S. J. Breckler, S. Buck, C. D. Chambers, G. Chin, G. Christensen, M. Contestabile, A. Dafoe, E. Eich, J. Freese, R. Glennerster, D. Goroff, D. P. Green, B. Hesse, M. Humphreys, J. Ishiyama, D. Karlan, A. Kraut, A. Lupia, P. Mabry, T. Madon, N. Malhotra, E. Mayo-Wilson, M. McNutt, E. Miguel, E. Levy Paluck, U. Simonsohn, C. Soderberg, B. A. Spellman, J. Turitto, G. VandenBos, S. Vazire, E. J. Wagenmakers, R. Wilson, and T. Yarkoni, "Promoting an Open Research Culture," *Science*, 2015, *348* (6242), 1422–1425.

Oaxaca, Ronald, "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 1973, pp. 693–709.

OECD, *The Role of Firms in Wage Inequality: Policy Lessons from a Large Scale Cross-Country Study*, Paris: OECD Publishing, 2021.

Olivetti, Claudia and Barbara Petrongolo, "The Evolution of Gender Gaps in Industrialized Countries," *Annual Review of Economics*, 2016, *8*, 405–434.

Palladino, Marco G., Alexandra Roulet, and Mark Stabile, "Narrowing Industry Wage Premiums and the Decline in the Gender Wage Gap," *Labour Economics*, 2025, *94*, 102693.

——, Antoine Bertheau, Cesar Barreto, Dogan Gülümser, Alexander Hijzen, Anne Sophie Lassen, Balázs Muraközy, and Oskar Nordström Skans, "The Role of Bargaining and Discrimination in the Gender Wage Gap in France: A Cross-Country Perspective," *OECD Social, Employment and Migration Working Paper*, 2024.

Penner, Andrew M., Trond Petersen, Are Skeie Hermansen, Anthony Rainey, István Boza, Marta M. Elvira, Olivier Godechot, Martin Hällsten, Lasse Folke Henriksen, Feng Hou, Aleksandra Kanjuo Mrčela, Joseph King, Naomi Kodama, Tali Kristal, Alena Křížková, Zoltán Lippényi, Silvia Maja Melzer, Eunmi Mun, Paula Apascaritei, Dustin Avent-Holt, Nina Bandelj, Gábor Hajdu, Jiwook Jung, Andreja Poje, Halil Sabanci, Mirna Safi, Matthew Soener, Donald Tomaskovic-Devey, and Zaibu Tufail, "Within-Job Gender Pay Inequality in 15 Countries," *Nature Human Behaviour*, 2023, *7* (2), 184–189.

Polachek, Solomon W., "Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure," *The Review of Economics and Statistics*, 1981, *63* (1), 60–69.

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

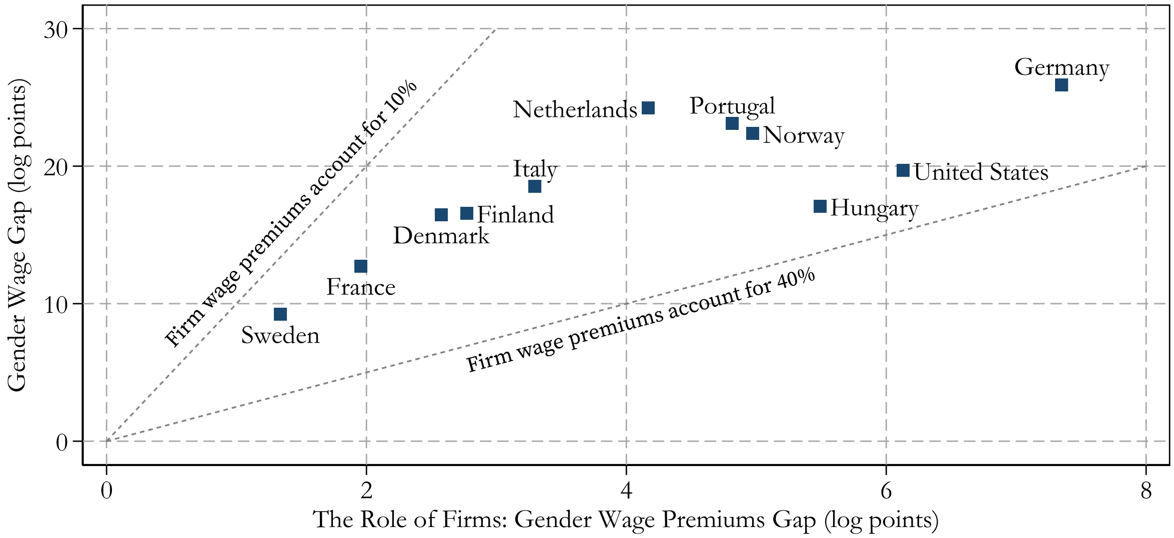
Sorkin, Isaac, "The Role of Firms in Gender Earnings Inequality: Evidence from the United States," *American Economic Review, Papers and Proceedings*, 2017, *107* (5), 384–387.

—, "Ranking Firms Using Revealed Preference," *The Quarterly Journal of Economics*, 2018, *133* (3), 1331–1393.

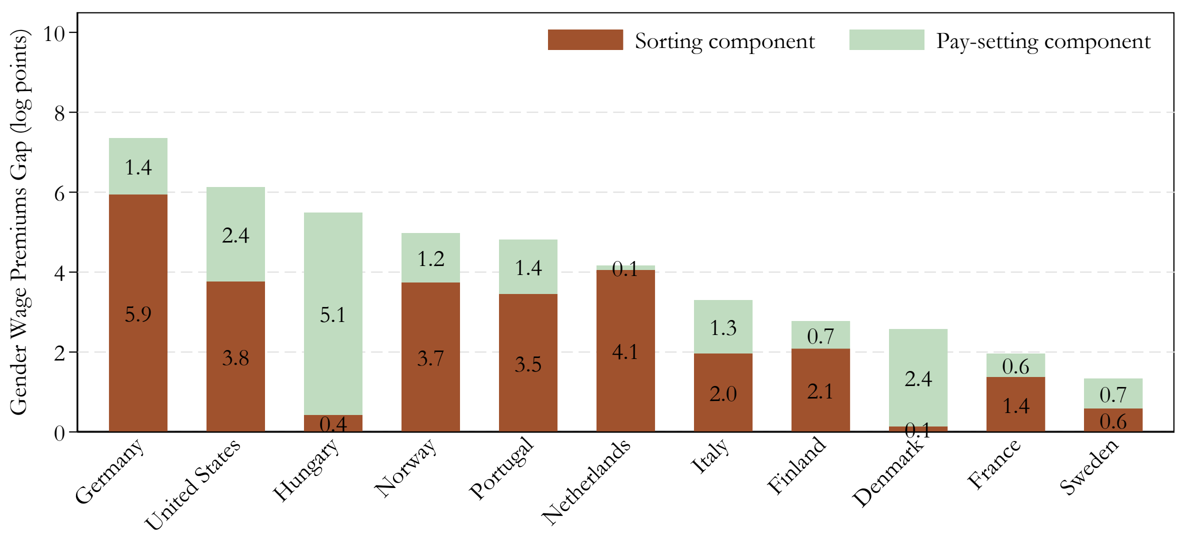
Vattuone, Giulia, "Worker Sorting and the Gender Wage Gap," *Working Paper*, 2024.

FIGURE 1. The Role of Firms in Gender Wage Gaps Across Countries

A. Relationship Between the Gender Wage and the Wage Premium Gap



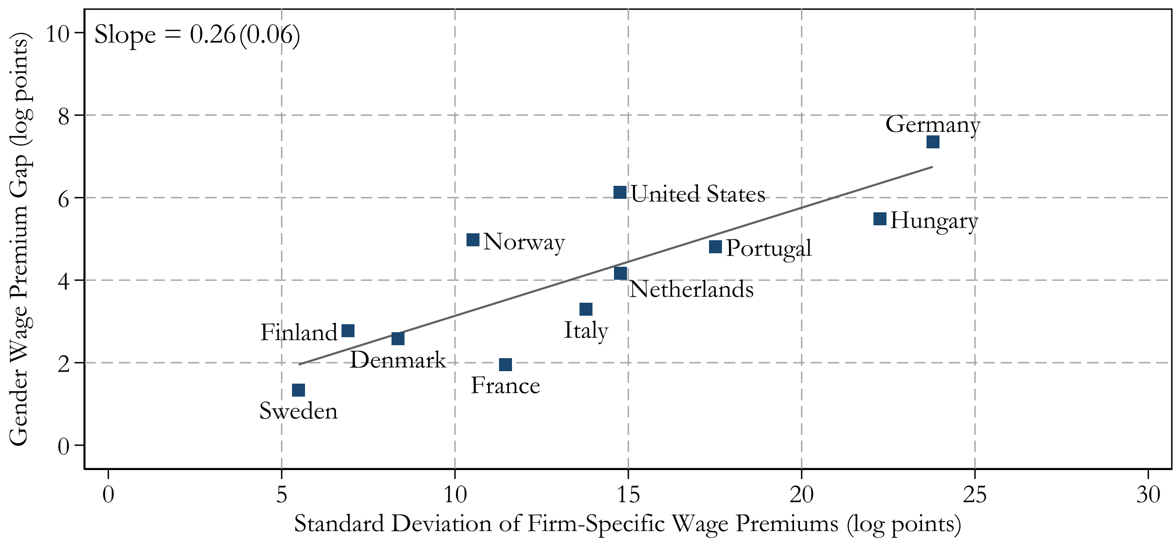
B. Decomposing the Gender Wage Premium Gap: Sorting vs Pay-setting



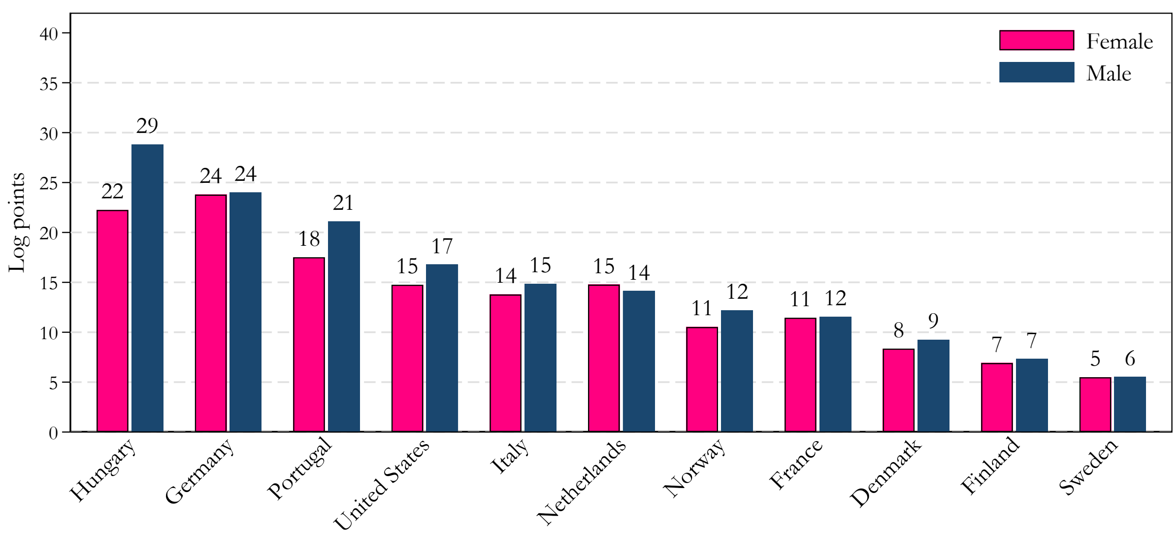
Notes: Panel A shows the gender wage gap (the difference in average log hourly wages between males and females) in log points in our main analysis sample (the dual-connected set sample) on the y-axis. The x-axis displays the gender wage premium gap, which is the sum of the sorting and pay-setting components. The diagonal lines represent scenarios in which firm wage premiums account for 10% (top line) and 40% (bottom line) of the total gender wage gap. Panel B decomposes the gender wage premium gap into sorting and pay-setting components using Equation (2). For most countries (Denmark, Finland, France, Hungary, Italy, the Netherlands, Portugal, and Sweden), we normalize the firm effects using low-productivity firms. For Germany, United States, and Norway, we normalize them using firms with a high exit rate (see Section 3.3). The samples in Finland, the U.S., and Sweden are reweighted based on worker characteristics to account for their sampling designs.

FIGURE 2. Gender Wage Premium Gap and Firm-level Pay Heterogeneity

A. Gender Wage Premium Gap and the Dispersion of Wage Premiums Across Countries



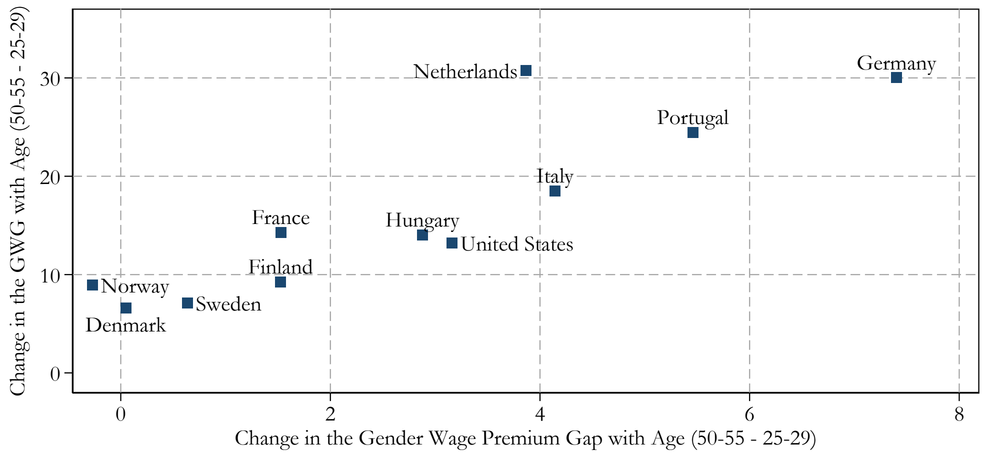
B. Standard Deviations of Firm-specific Wage Premiums by Gender Across Countries



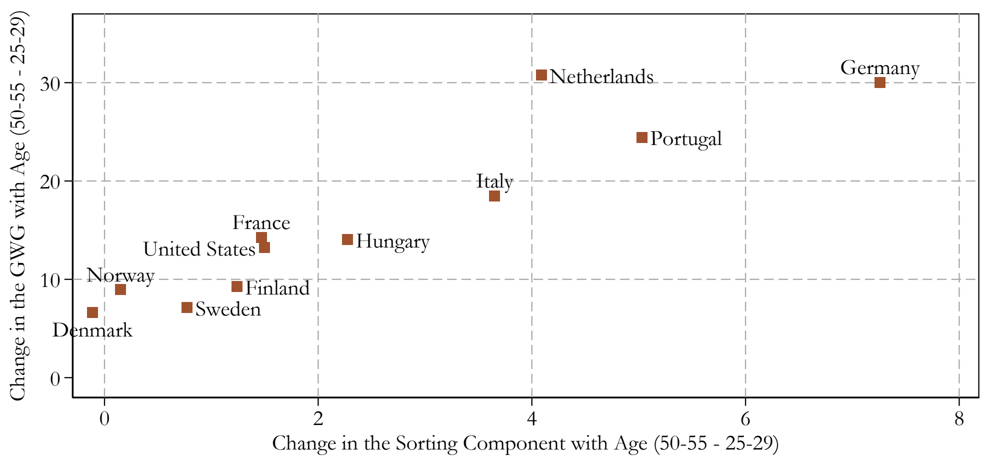
Notes: Panel A plots the gender wage premium gap in the main analysis sample against the standard deviation of the firm-specific wage premium for female workers. The standard deviations of the firm effects are bias-corrected using either the Kline, Saggio and Sølvsten (2020) method (for Germany, Italy, the United States, the Netherlands, Norway and Denmark) or Babet, Godechot and Palladino (2025) method (for France, Hungary, Sweden, Portugal, Finland). Panel B plots the standard deviations by gender.

FIGURE 3. Gender Wage Gap and the Gender Wage Premium Gap Over the Life Cycle

A. Gender Wage Premium Gap (Sorting and Pay-setting)



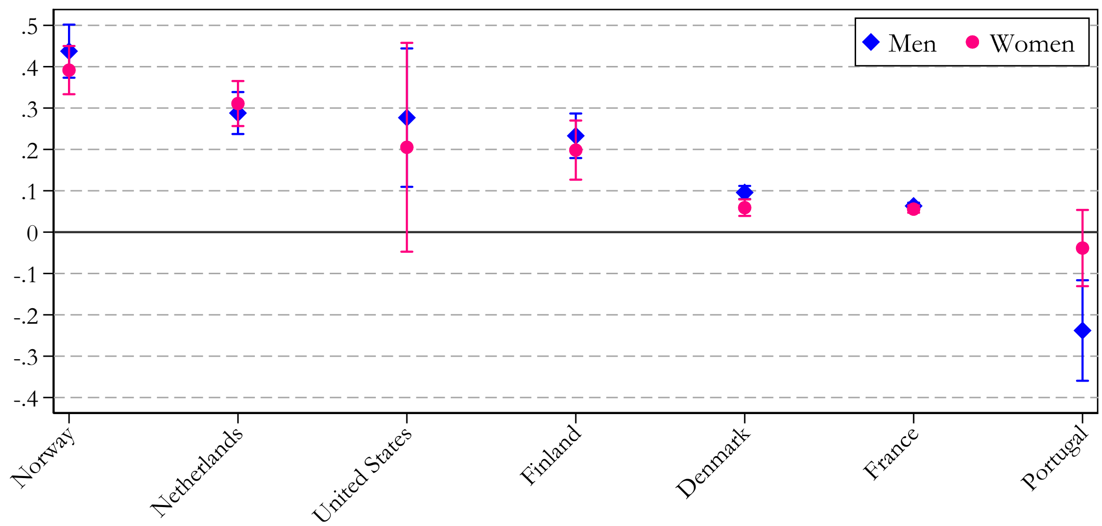
B. Sorting Component



C. Pay-setting Component

Notes: The y-axis reports the difference in gender wage gaps between workers aged 50–55 and workers aged 25–29. The x-axis reports the corresponding difference in: (A) the firm-specific wage premium gap, (B) the sorting component, and (C) the pay-setting component.

FIGURE 4. Elasticity of Firm Wage Premiums with Respect to Firm Hour Policies

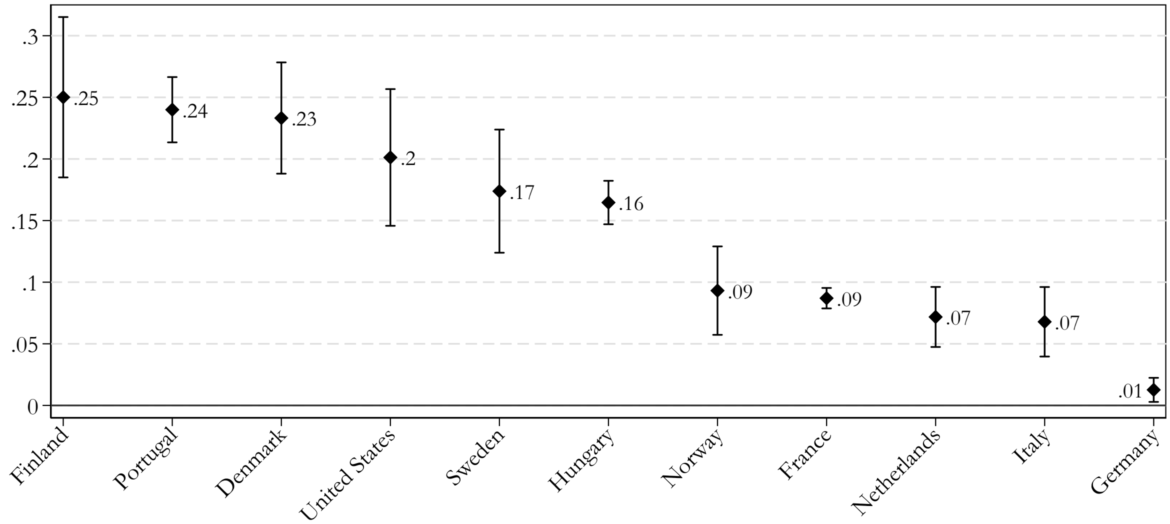


Notes: The figure plots the elasticity of firm-specific wage premiums with respect to firm-hour policies, estimated by gender using an AKM model for hours. Each point represents a coefficient from an employment-weighted, firm-level regression. Vertical bars indicate 95% confidence intervals with standard errors clustered at the firm level. This analysis is limited to countries with available data on paid work hours.

FIGURE 5. Part Time Jobs and Firm Wage Premiums

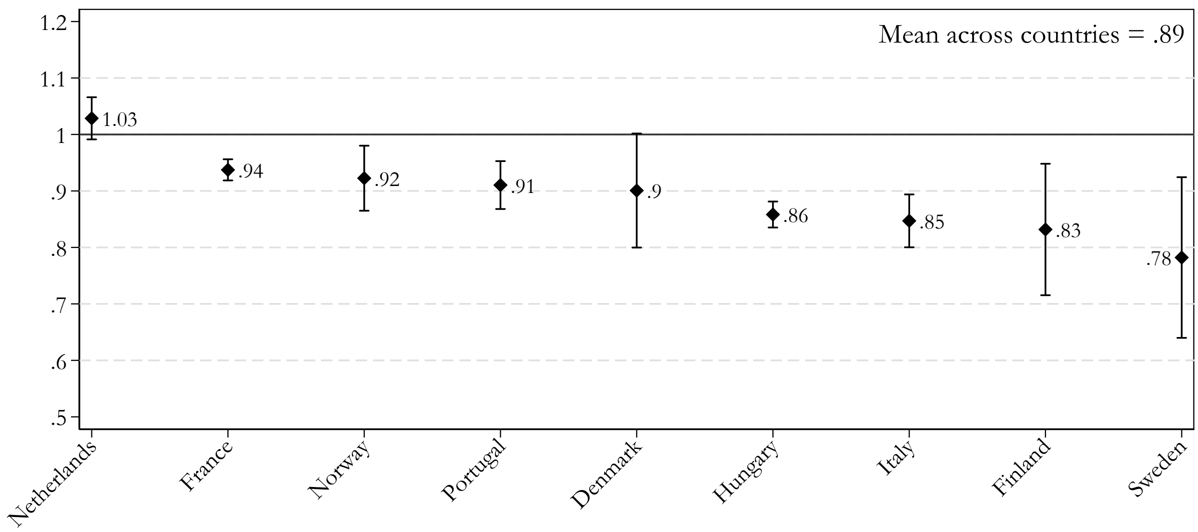
Notes: The left panel plots the relationship between the share of part-time workers and the share of women in the firm workforce. The right panel plots the relationship between arbitrarily normalized firm-specific wage premiums (computed as the weighted average of gender-specific wage premiums) and the within-firm share of part-time workers. Country-specific quartiles based on the x-axis measure are calculated first, then pooled across all countries. Country-specific relationships are available in Figure A3.

FIGURE 6. Pay-Setting Response to Average Wage Premiums



Notes: The figure shows coefficients from country-specific firm-level regressions where the dependent variable is the pay-setting component (defined as the difference between firm-specific male and female wage premiums) and the independent variable is the firm's weighted average wage premium. Regressions are weighted by male employment at the firm level. Standard errors are clustered at the firm level.

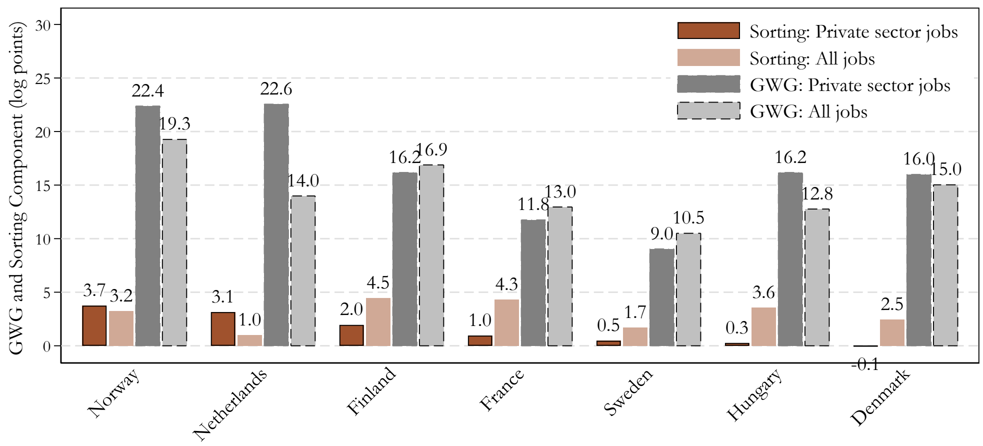
FIGURE 7. Relative Rent-Sharing Across Countries



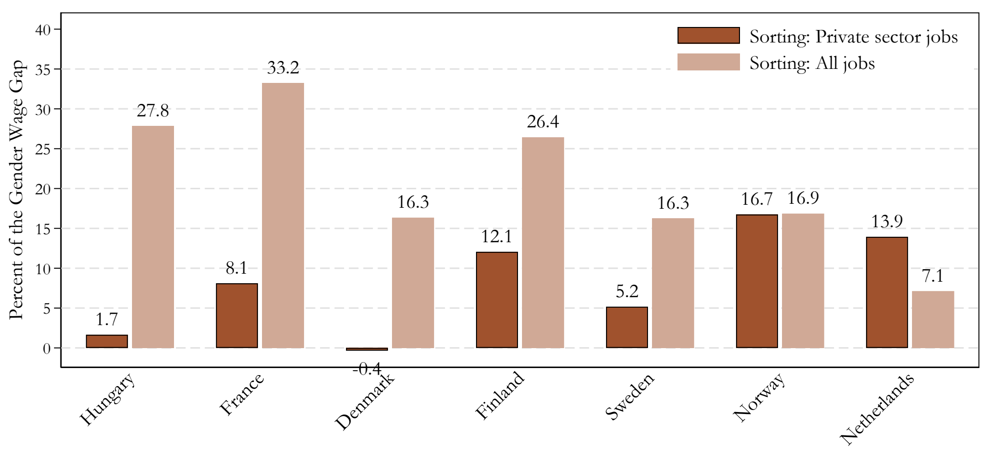
Notes: The figure reports $\gamma_1 = \pi^F/\pi^M$, the relative rent-sharing parameter, which captures the share of male rent-sharing benefits received by women. π^M and π^F are estimated from Equation (4). The relative rent-sharing parameter γ_1 is estimated via IV, regressing female wage premiums on male firm wage premiums using firm net surplus as an instrument. The regressions are weighted by male person-year observations. Standard errors are clustered at the firm level. Only countries for which firm-level productivity data is available for large samples are included.

FIGURE 8. Impact of Including Public-Sector Jobs on Gender Wage Gap and Sorting

A. Gender Wage Gap and Sorting Component (Log Points)



B. Sorting as Share of Gender Wage Gap (Percent)



Notes: This figure compares the sorting component of the gender wage premium gap and the overall gender wage gap between private-sector jobs (the baseline sample) and all jobs across countries. The "All jobs" sample includes, in addition to the private-sector sample, employment in the following sectors: education, health, culture, other services, private households with employed persons, and extraterritorial organizations. In Panel A, countries are ordered from left to right according to the magnitude of their private-sector sorting component, from highest to lowest. In Panel B, countries are ordered according to the percentage difference in the sorting component between the private-sector and all-jobs samples. Only countries with representative information on the public and semi-public sectors are included.

TABLE 1. Review of Research Designs and Estimates

Paper	Country	Wage Type	GWG	WPG (GWG %)	Sorting (GWG %)	Pay Setting (GWG %)	Norm. Method	Public Sector
Li et al. (2023)	Canada	Annual	26.8	6.1 (22.8)	2.9 (10.8)	3.2 (11.9)	Value Added	No
Sorkin (2017)	USA	Annual	33.5	—	9.3 (27.7)	—	—	Yes
Card et al. (2016)	Portugal	Hourly	23.4	4.9 (21.2)	4.7 (19.9)	0.3 (1.2)	Value Added	No
Casarico and Lattanzio (2024)	Italy	Weekly	20.4	6.9 (33.8)	4.2 (20.5)	2.7 (13.3)	Industry	No
Palladino et al. (2025)	France	Hourly	12.8	2.0 (15.8)	1.1 (8.7)	0.9 (7.1)	Industry	No
Bruns (2019)	W. Germany	Daily	24.7	6.4 (25.9)	6.3 (25.4)	0.1 (0.3)	Value Added	Yes
Gallen et al. (2019)	Denmark	Hourly	20.8	—	3.3 (15.8)	—	—	Yes
Masso et al. (2022)	Estonia	Monthly	27.1	10.9 (40.1)	7.7 (28.5)	3.1 (11.6)	Value Added	No
Boza and Reizer (2024)	Hungary	Hourly	23.6	9.8 (41.5)	4.4 (18.6)	5.4 (22.9)	Value Added	Yes[a]
Morchio and Moser (2024)	Brazil	Monthly	13.3	11.3 (85)	8.9 (66.9)	2.4 (18.0)	Rank[b]	Yes
Cruz and Rau (2022)	Chile	Monthly	21.0	9.6 (39.1)	8.8 (31.8)	1.7 (7.1)	Value Added	Yes

Notes: This table reviews papers studying gender wage gaps and firm-specific wage premium gaps in the Americas and Europe. The Gender Wage Gap (GWG) is the unconditional gender wage gap measured in log points. The Wage Premium Gap (WPG) is the sum of the sorting and pay-setting components (in log points). Norm. method refers to the normalization method of firm effects. Public sector indicates whether most public sector employees are included in the sample.
[a] Estimates the AKM model including the public sector and focuses on the private sector with information on value added.
[b] Normalizes with respect to small firms in low-surplus industries (Hotels and Restaurants).

TABLE 2. Characteristics of Data Sources by Country

Characteristic	USA	DNK	FIN	FRA	DEU	ITA	HUN	NLD	NOR	PRT	SWE
Time span and population											
Year coverage	2010–14	2010–19	2010–19	2010–19	2010–14	2010–19	2010–17	2010–19	2010–19	2010–19	2010–18
Reference month	No	No	Yes	No	No	No	Yes	No	No	Yes	Yes
Private sector jobs (%)	51	100	50	100	100	50	50	100	100	100	50
Public sector jobs	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Employee Information											
Hourly wage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hours information	P	P	P	P	C	C	C	P	P	P	P
Education	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes
Occupation	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes
Employer Information											
Labor productivity	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reference period spans 2010–2019 for most countries, except for Germany and the U.S. (Washington State) (2010–2014). While most countries have full coverage of private sector jobs, the data from the U.S., Sweden, Finland, Italy, and Hungary cover approximately 50% of jobs, for reasons explained in the data appendices. Reference month indicates whether the data represents a specific month snapshot (Yes) or contains information about all employment spells throughout the year (No). Hourly wage measures are available across all countries and include irregular payments (overtime and bonuses). Hours are measured as paid hours including overtime, except in Hungary and Italy where contractual hours are used. The resulting hourly wage measure in these countries reflects the base wage rate excluding overtime. P = Payroll-based hours; C = Contractual hours. Labor productivity is measured as value-added per person employed for Denmark, Finland, France, Italy, Hungary, Norway, and Sweden. For Portugal, productivity is calculated using sales per person employed instead of value added. No productivity data is available for the U.S. In Germany, productivity data is available for about 3 percent of person-year observations.

TABLE 3. Summary Statistics

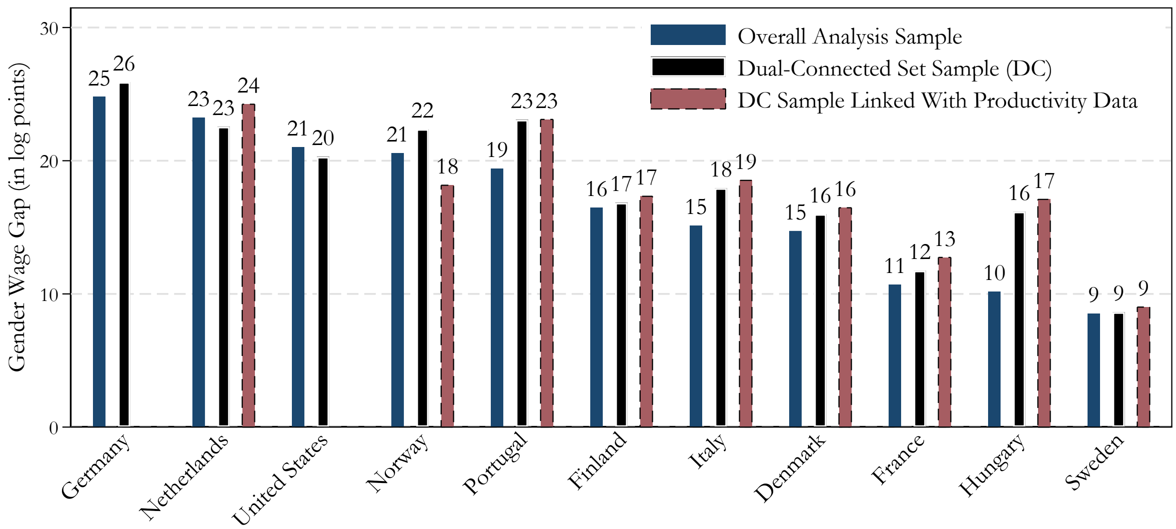
		Log Hourly Wage	Age	Part-time (%)	Separation (%)	Firm Size	Movers per Firm	Obs with log VA (%)	Person/Yr Obs	N of workers	N of firms
USA	Male	3.04 (0.54)	40.35	11.80	32.40	116	17	NA	1.06	350.28	17.27
	Female	2.84 (0.53)	40.18	18.13	34.57	132	12	NA	0.61	207.07	17.27
DEU	Male	3.05 (0.57)	40.81	7.09	19.45	45	26	3.86	38.59	10438.87	426.20
	Female	2.79 (0.54)	40.66	31.81	21.78	45	14	2.10	21.75	6336.21	426.20
DNK	Male	3.44 (0.41)	40.56	9.88	25.61	35	45	82.98	5.18	986.86	65.26
	Female	3.28 (0.35)	40.33	18.86	25.50	39	25	80.21	3.04	604.78	65.26
FIN	Male	3.03 (0.36)	40.17	4.40	21.21	80	51	93.91	2.58	526.47	9.04
	Female	2.87 (0.34)	40.28	14.57	23.51	81	33	88.43	1.63	361.12	9.04
FRA	Male	2.90 (0.46)	39.38	9.64	27.59	33	54	92.58	65.62	14848.22	548.84
	Female	2.79 (0.43)	38.94	20.85	29.26	34	33	88.14	42.17	10547.91	548.84
HUN	Male	6.84 (0.64)	38.85	5.24	25.79	44	24	90.11	2.90	640.06	56.91
	Female	6.67 (0.57)	39.52	11.33	26.97	46	18	90.23	2.26	522.59	56.91
ITA	Male	2.67 (0.45)	40.71	10.35	21.61	25	33	87.53	24.49	4050.51	376.27
	Female	2.49 (0.40)	40.02	41.09	23.74	26	23	85.09	15.83	2712.56	376.27
NLD	Male	3.05 (0.51)	39.95	11.66	24.45	62	61	82.19	19.33	3307.26	177.03
	Female	2.82 (0.44)	39.21	50.73	27.02	67	37	76.48	11.47	2180.69	177.03
NOR	Male	3.25 (0.46)	39.84	8.47	21.17	45	53	84.63	6.56	1130.21	62.71
	Female	3.03 (0.46)	40.01	26.62	22.36	51	33	59.66	5.01	961.04	62.71
PRT	Male	1.96 (0.58)	39.34	1.73	21.80	33	33	99.51	7.53	1483.68	92.96
	Female	1.73 (0.54)	38.92	6.37	22.25	34	24	99.37	5.69	1146.96	92.96
SWE	Male	3.11 (0.35)	40.26	19.45	26.71	72	28	90.61	3.93	904.82	6.53
	Female	3.02 (0.32)	39.74	26.99	29.8	76	16	86.11	2.19	547.84	6.53

Notes: This table presents summary statistics for the dual-connected sample across countries. The sample includes only private-sector jobs. Part-time employment is defined as working fewer than 30 hours per week. Separation is the percentage of workers who separate from their firm between consecutive years. Log VA observations are the share of person-years in the dual-connected sample with non-missing log productivity data. Mean firm size represents the average number of employees per firm, unweighted by the number of workers. The number of person-years is reported in millions. The number of workers and number of firms are reported in thousands. The samples in Finland, the U.S., and Sweden are reweighted based on worker characteristics to account for their sampling designs.

Appendix

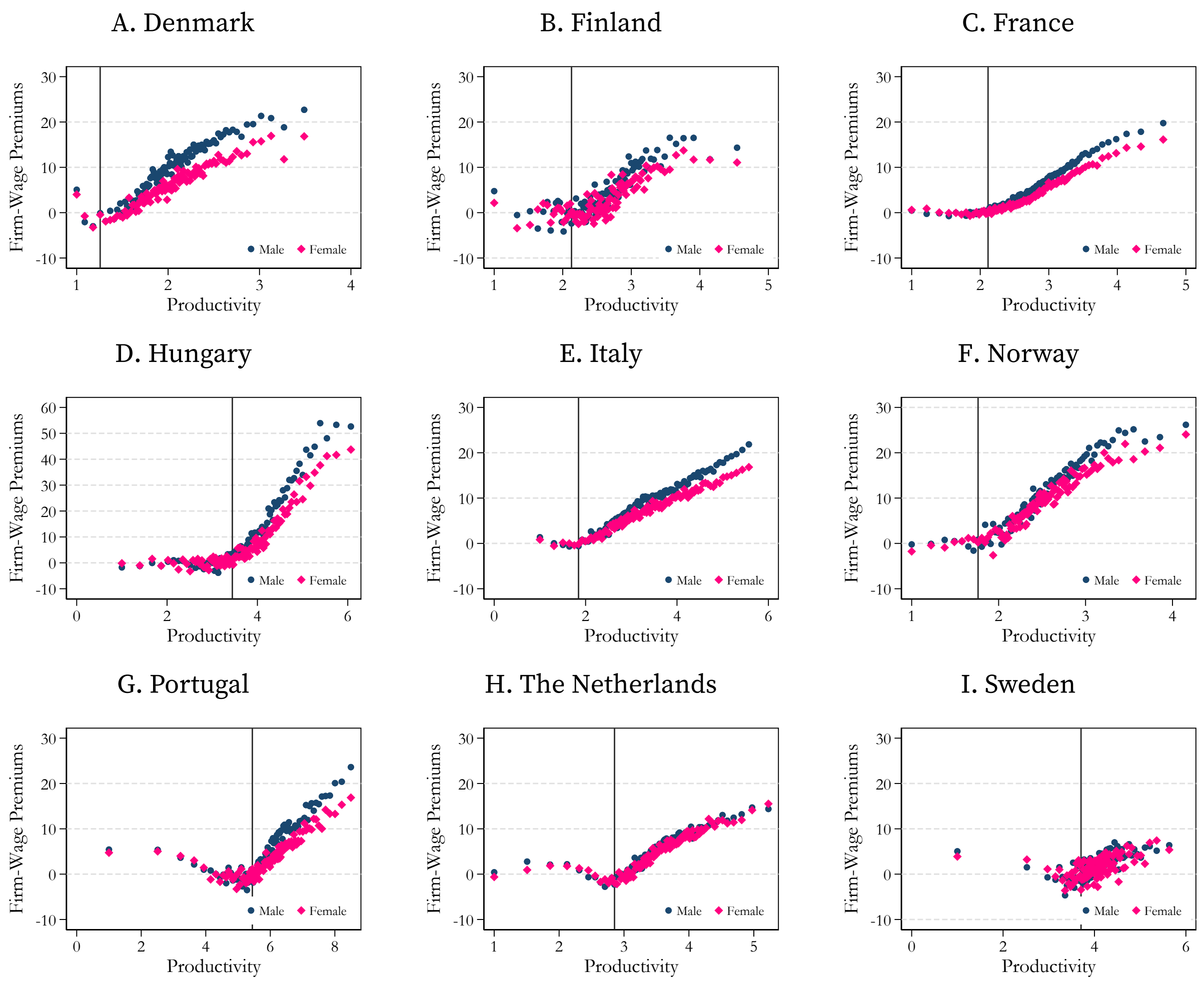
Appendix A. Additional Figures and Tables

FIGURE A1. The Gender Wage Gap Across Countries



Notes: The overall analysis sample includes paid workers aged 25–55 who are employed in the private sector. The private sector is defined as all sectors except education, health, culture, other services, private households with employed persons, and extraterritorial organizations. The dual-connected (DC) sample is a subset of firms that employ both men and women and are connected through worker mobility. The DC sample with productivity data is an additional subsample that contains productivity information, which is measured as value added (sales in the case of Portugal) per worker. Throughout this paper, we refer to the DC set as our main analysis sample for each country. Wages are measured in real (2015 = 100) euros per hour. The gender wage gap is the difference in log points between the average hourly wages of men and women, calculated across country-person-year observations.

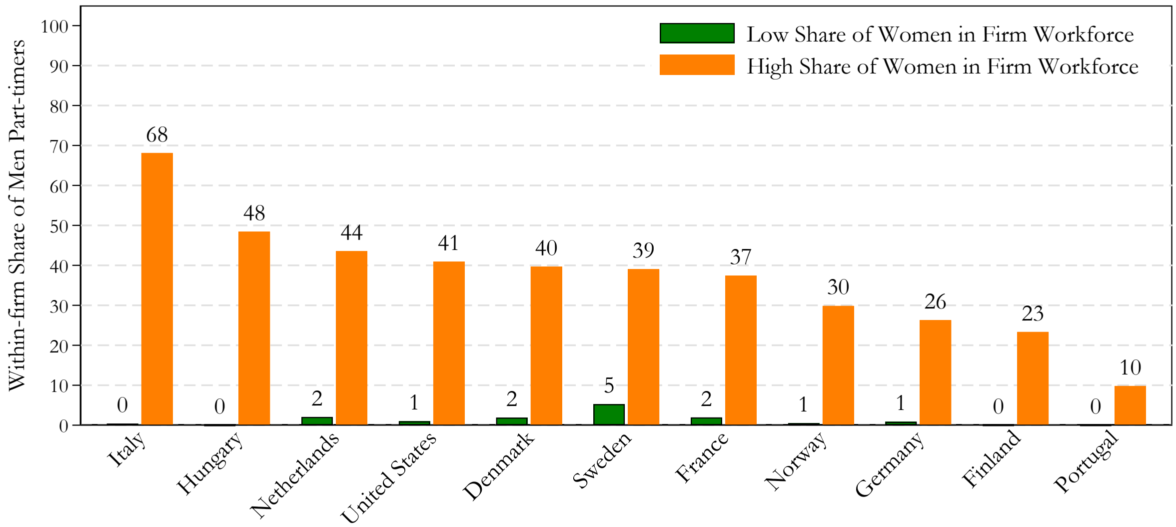
FIGURE A2. Firm Wage Premiums and Productivity Across Countries



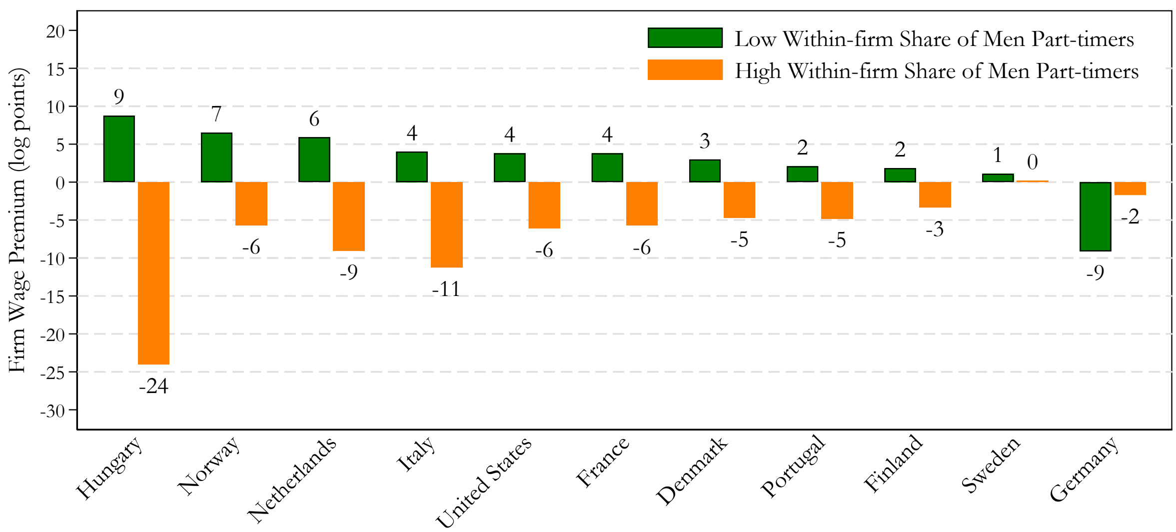
Notes: The figures represent the relationship between gender-specific firm wage premiums (arbitrary normalization) and firm-level labour productivity. Specifically, the points shown represent mean estimated firm wage premiums from the AKM models for men and women averaged across firms with 100 percentile bins of productivity (measured as mean log value-added — sales in Portugal — per worker). The vertical line marks a threshold in log value-added per worker used to normalize firm effects. For each country, firm wage premiums and productivity are rescaled. The first and last bins are omitted. For Sweden, percentiles 2 and 3 are additionally omitted for readability.

FIGURE A3. Part Time Jobs, Share of Women, and Firm-Specific Wage Premiums

A. Part-time Jobs and Share of Women



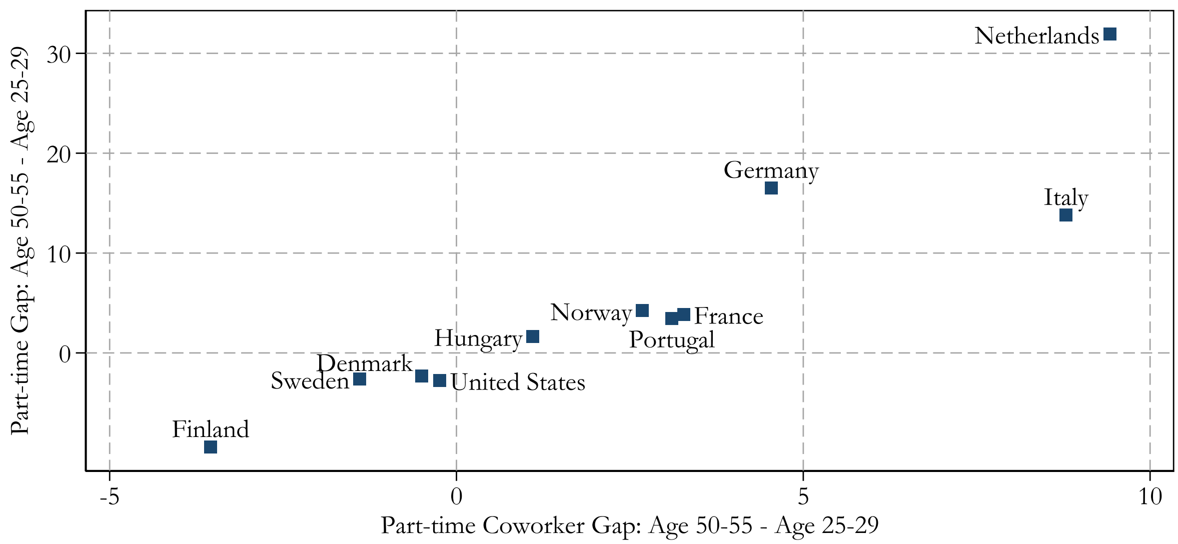
B. Part-time Jobs and Firm-Specific Wage Premiums



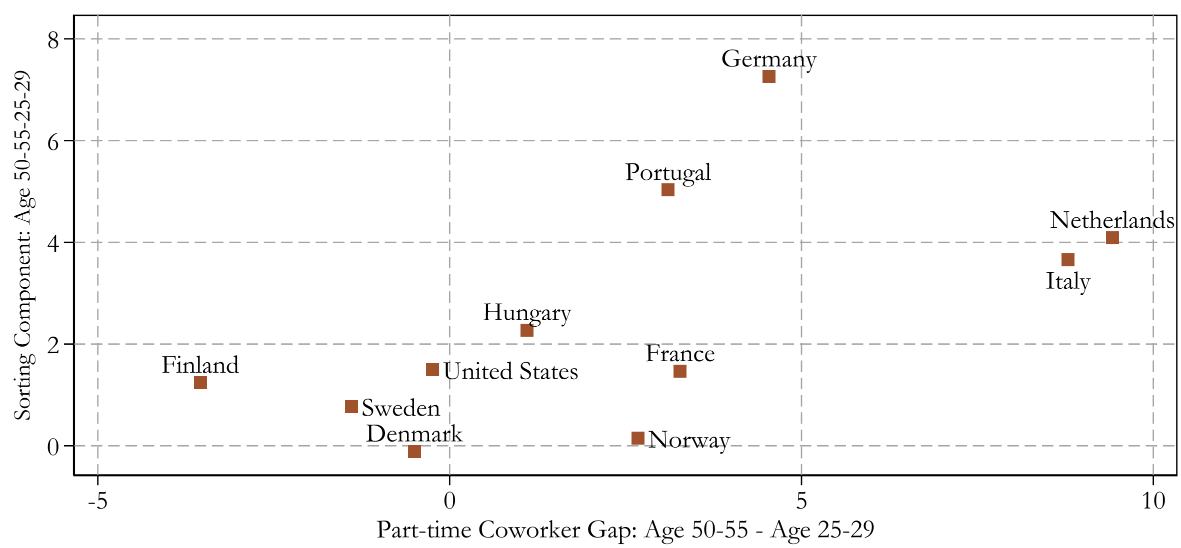
Notes: Panel A plots the share of part-time employment among men for firms in the lowest and highest quartiles of female employment share. Panel B plots the average firm-specific wage premium for firms in the lowest and highest quartiles of the share of part-time employment among men. Quartiles are calculated separately by country.

FIGURE A4. Sorting Over the Life Cycle: The role of Part-time Workplaces

A. Part-time Jobs and Part-time Workplaces Over the Life Cycle

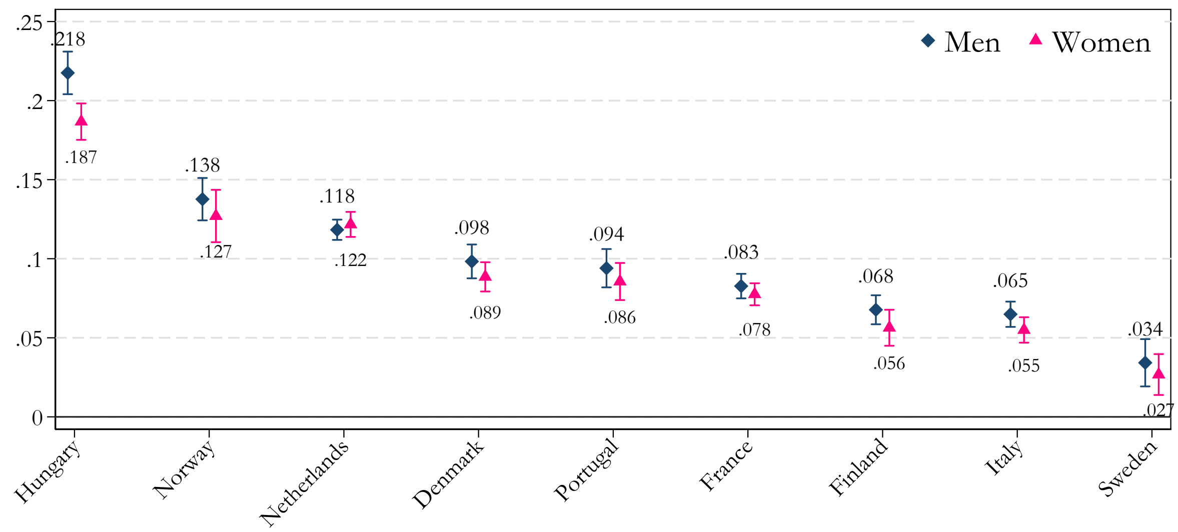


B. Sorting of Women to Low-Wage Firms and Part-time Workplaces Over the Life Cycle



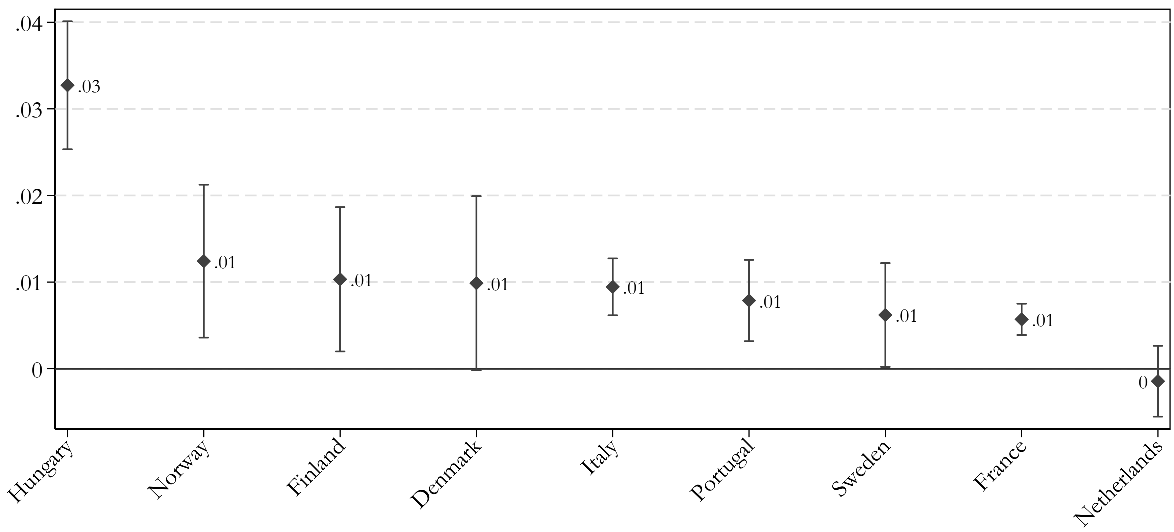
Notes: Panel A reports the difference in the part-time gap (the share of part-time workers among women minus men) between workers aged 50–55 and those aged 25–29 on the y-axis. The x-axis shows the difference in the part-time coworker gap (the extent to which women are more exposed to part-time coworkers than men) between the same age groups. Panel B reports the difference in the CCK sorting component between workers aged 50–55 and those aged 25–29 on the y-axis. The x-axis is identical to Panel A.

FIGURE A5. The Productivity Pass-Through to Wage Premiums



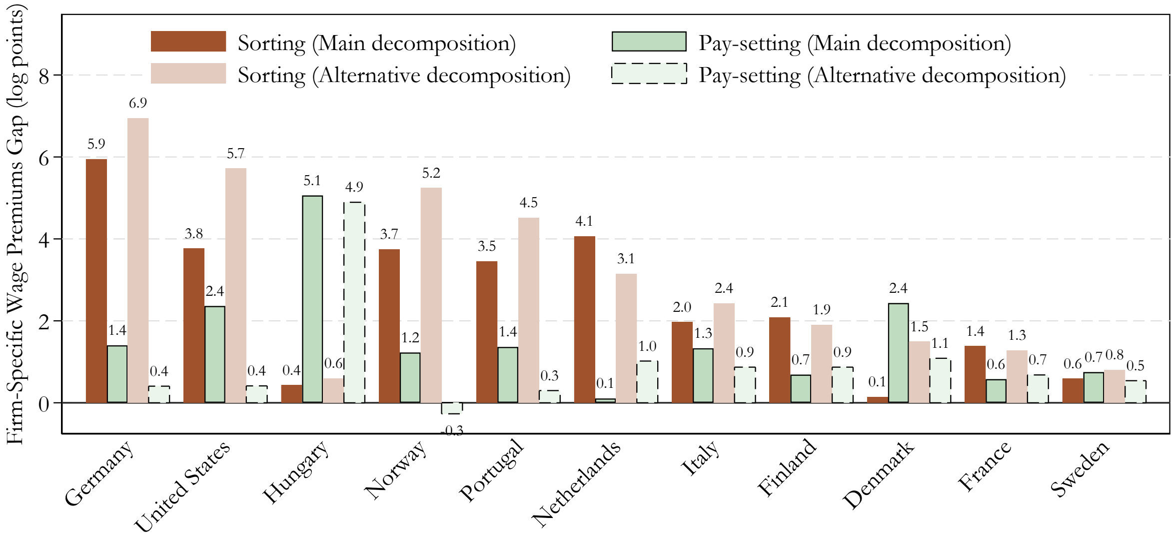
Notes: The figure reports π^M and π^F, the gender-specific rent-sharing parameters. π^M and π^F are estimated from Equation (4). The regressions are weighted by male person-year observations. Standard errors are clustered at the firm level. Only countries for which firm-level productivity data is available for large samples are included.

FIGURE A6. Differential Rent-Sharing and the Pay-Setting Component



Notes: The figure reports $\delta_1 = \pi^M - \pi^F$, the difference in rent-sharing coefficients. δ_1 is estimated by regressing the within-firm gender gap in wage premiums directly on firm net surplus. The regressions are weighted by male person-year observations. Standard errors are clustered at the firm level. Only countries for which firm-level productivity data is available for large samples are included.

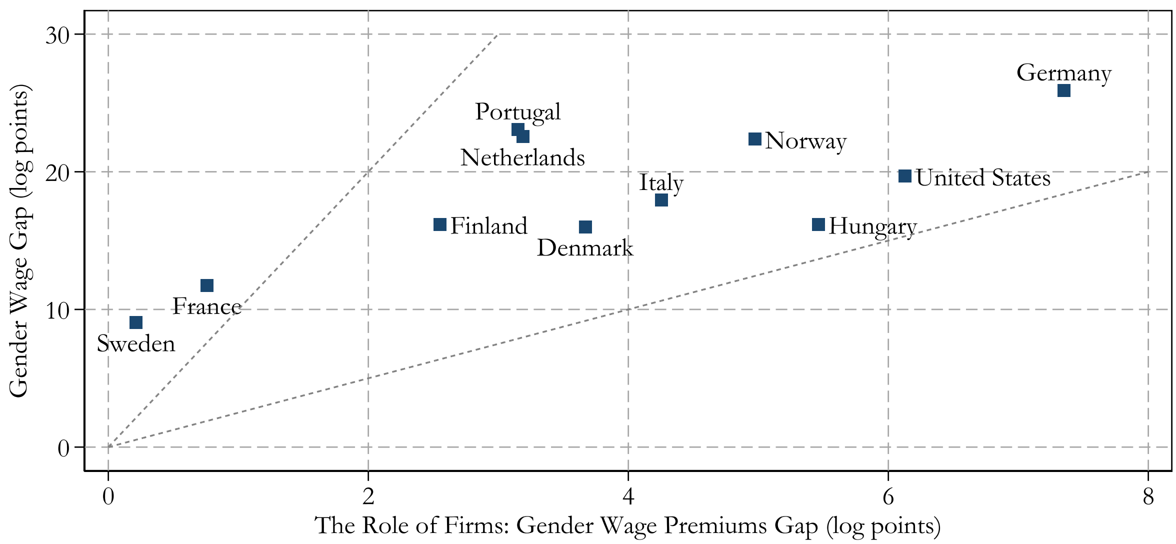
FIGURE A7. Gender Wage Premium Gap: Alternative Decomposition



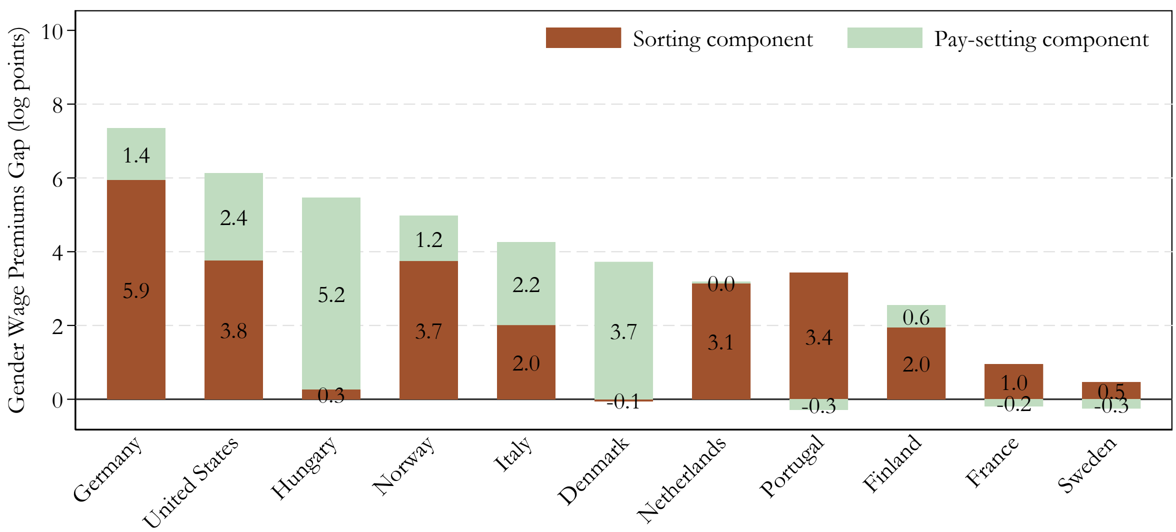
Notes: The figure shows an alternative decomposition of the sorting and pay-setting components. The pay-setting effect is calculated using the distribution of jobs held by women. The sorting effect is calculated by comparing the average male wage premium across jobs held by men versus women. Countries are ordered from left to right based on the magnitude of the baseline sorting component, from highest to lowest.

FIGURE A8. High-Exit Rate Normalization for All Countries

A. Relationship Between the Gender Wage and the Wage Premium Gap

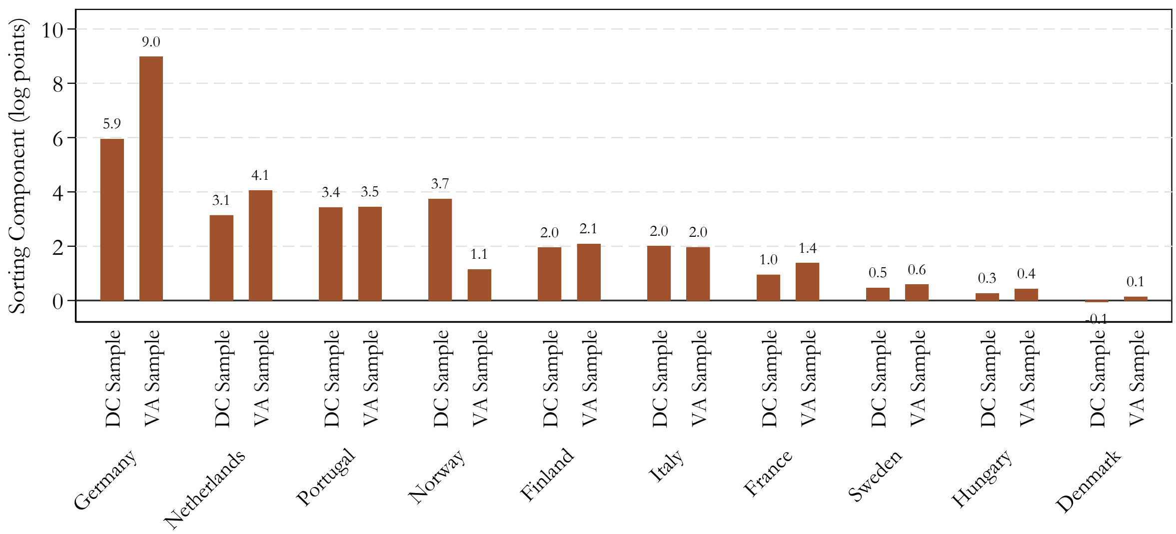


B. Decomposing the Gender Wage Premium Gap: Sorting vs Pay-setting



Notes: In Panel A, the y-axis shows the unconditional gender wage gap in log points in our main analysis sample. The x-axis displays the firm wage premium gap, calculated as the sum of sorting and pay-setting components. The diagonal lines represent scenarios where firm wage premiums account for 10% (top line) and 40% (bottom line) of the total gender wage gap. Panel B decomposes the gender wage premium gap into sorting and pay-setting components following Equation (2). Firm effects are normalized by selecting the bottom ten percent of employment-weighted firms by their high-exit rate. The samples in Finland, the U.S., and Sweden are re-weighted based on worker characteristics to account for their sampling designs.

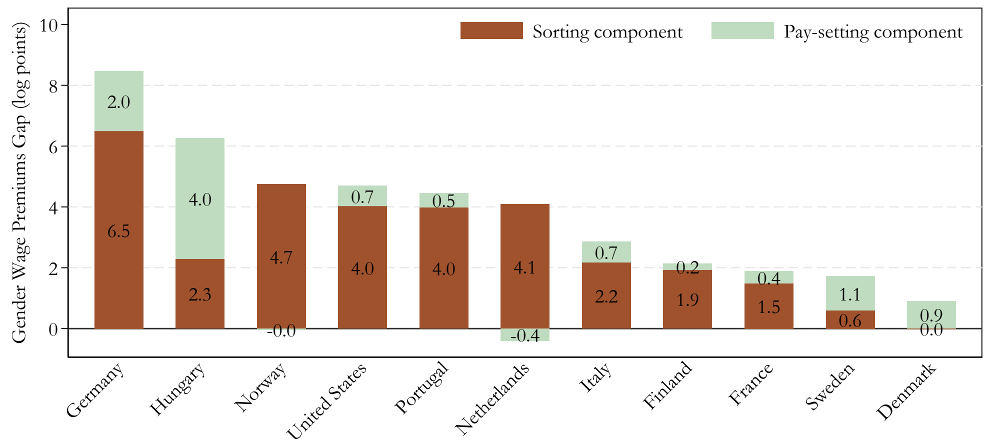
FIGURE A9. Sorting Component for the Sample With and Without Productivity



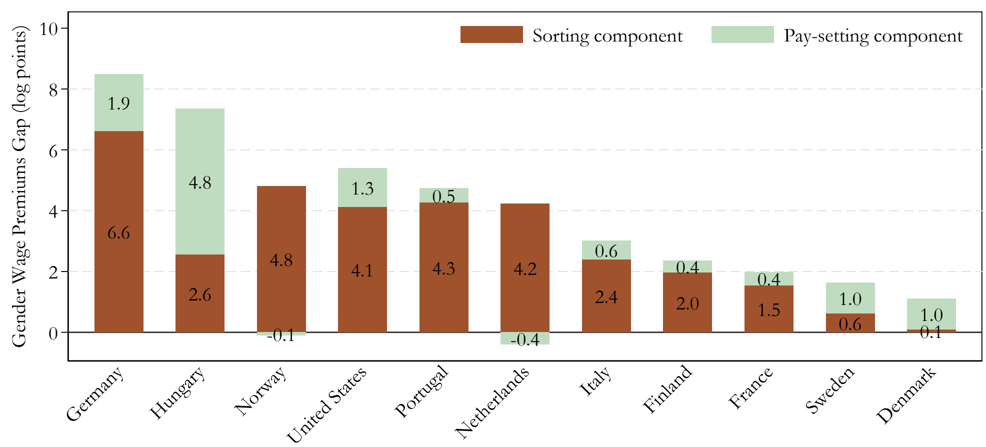
Notes: *Notes:* This figure compares the sorting component of the CCK decomposition between the dual-connected sample and the value-added sample (restricted to firms with value-added data).

FIGURE A10. Sample of Firms With at Least 10 Movers by Gender

A. 10+ Sample



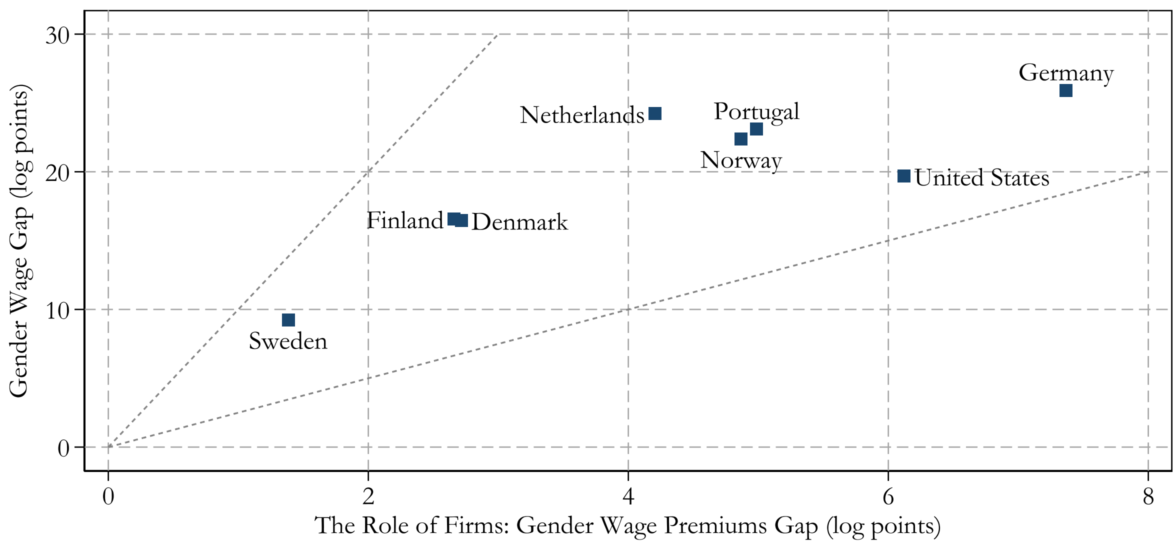
B. 10+ Sample with Firm Effects from the Baseline Sample



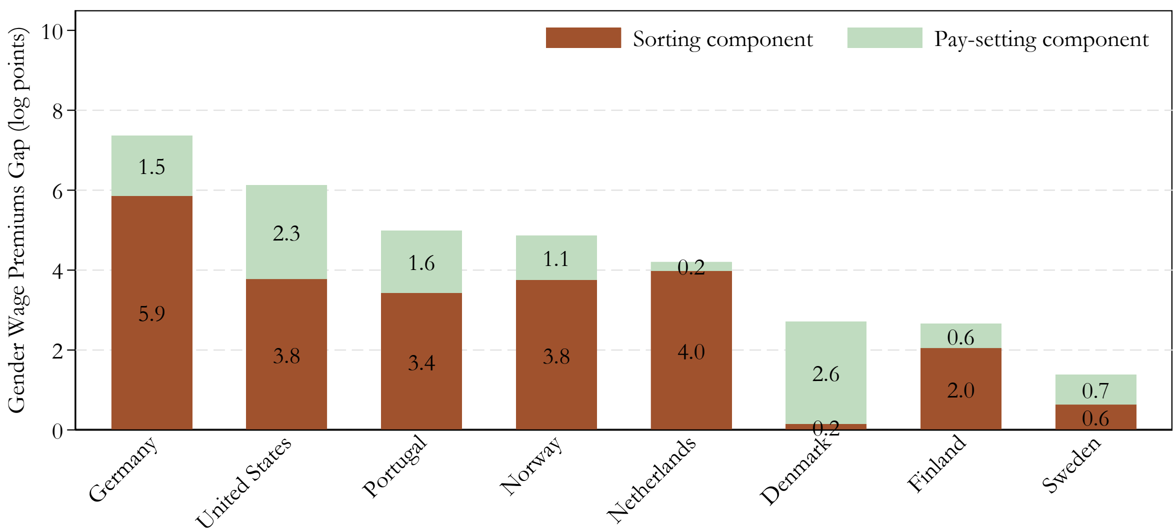
Notes: In Panel A we decompose the gender wage premium gap into sorting and pay-setting components following Equation (2) using the sample of at least 10 movers by gender. Panel B uses the sample of at least 10 movers by gender and the firm fixed effects estimated from the baseline sample.

FIGURE A11. Controlling for Education-specific Age Profiles

A. Relationship Between the Gender Wage and the Wage Premium Gap

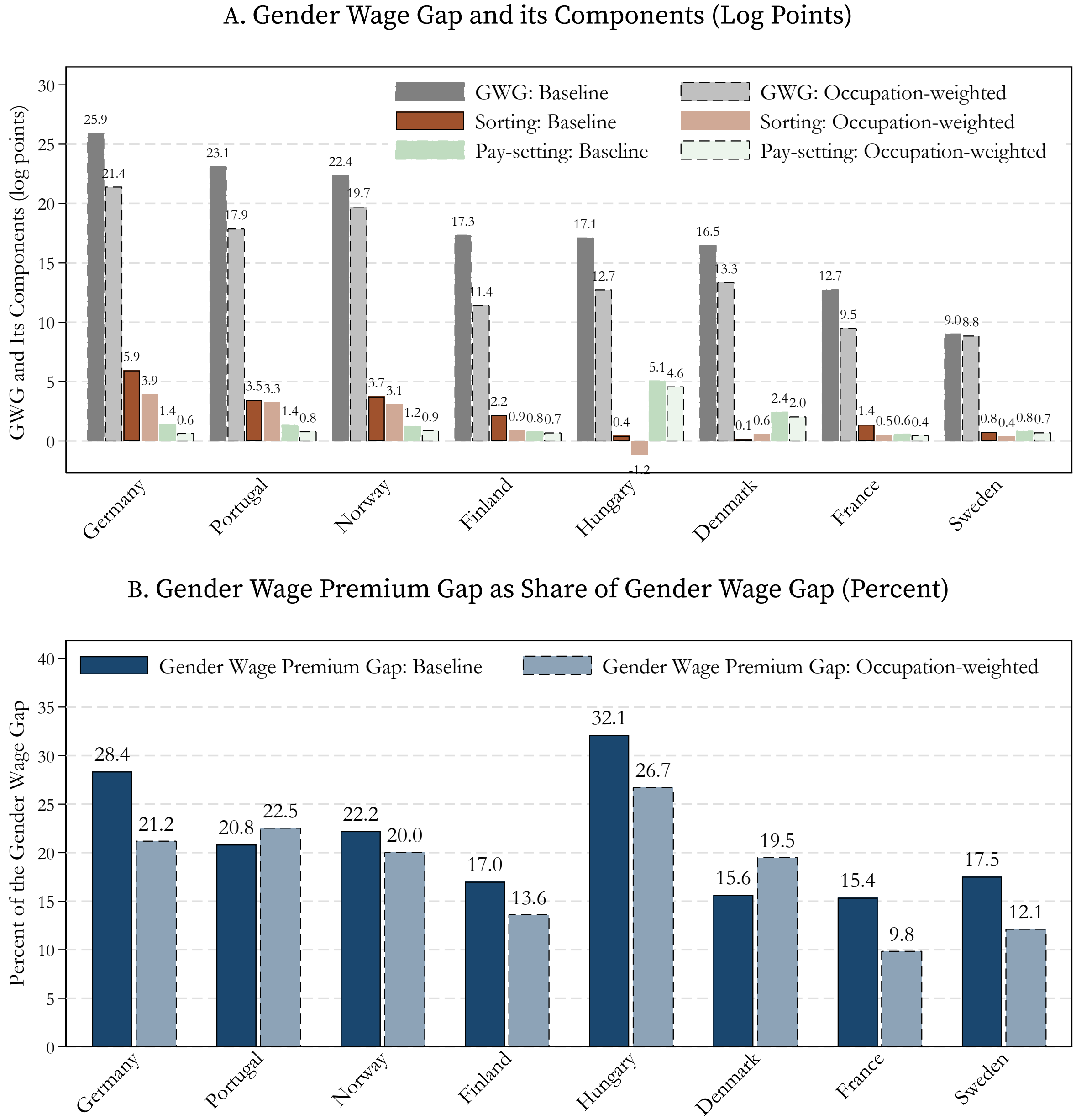


B. Decomposing the Gender Wage Premium Gap: Sorting vs Pay-setting



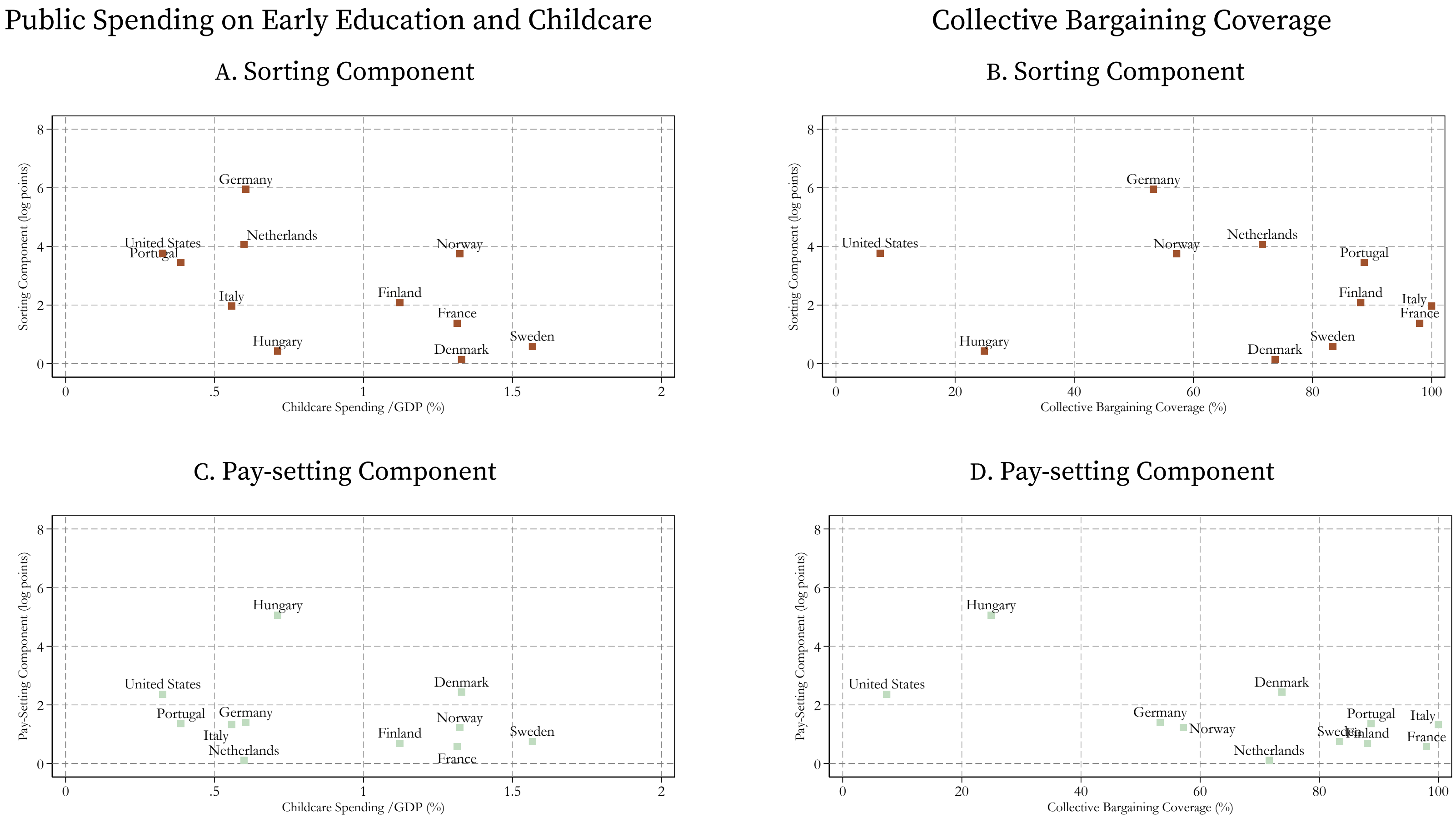
Notes: Compared to Figure 1, this figure presents results including education dummies in the AKM model.In Panel A, the y-axis shows the unconditional gender wage gap in log points in our main analysis sample. The x-axis displays the firm wage premium gap, calculated as the sum of sorting and pay-setting components. The diagonal lines represent scenarios where firm wage premiums account for 10% (top line) and 40% (bottom line) of the total gender wage gap. In Panel B, we decompose the gender wage premium gap into sorting and pay-setting components following Equation (2) Only countries for which worker-level education data is available are included.

FIGURE A12. The Role of Occupation on Gender Wage Gap and Its Components



Notes: This figure compares the gender wage gap, the gender wage premium gap, and its components (sorting and pay-setting) for both the baseline sample (Figure 1) and the reweighted sample. The reweighting procedure following DiNardo et al. (1996) adjusts the occupational distribution of men at the 1-digit level to match that of women. Only countries for which worker-level occupation data is available are included.

FIGURE A13. Association of the Gender Wage Premium Gap with Macro Indicators



Notes: In the left panel, the x-axis reports the share of GDP used on early education and child care (age 0–6) in 2015. Data Source: OECD Social Expenditure Database. In the right panel, the x-axis shows the share of private-sector workers reported to be covered by collective bargaining in 2015. Data Source: Visser (2019). The y-scale in panels A and B reports the sorting component, and the y-axis in panels C and D reports the pay-setting component.

Appendix B. Comparing Unweighted and Weighted Results

B.1. United States: Washington State

In order to make the Washington State data more representative of the U.S. workforce, we create weights from the 2013 Current Population Survey (CPS) Outgoing Rotation Group. First, using the CPS, we calculate sample proportion (p^{CPS}) for all possible interactions of age, gender, race/ethnicity, educational attainment categories, and sectors. In practice, these proportions are calculated by collapsing the data by values of these variables.[29] We then merge these proportions to the Washington State sample on age, gender, race/ethnicity, educational attainment, and sectors of industry. In the Washington sample, we create the analogous proportions (p^{WA}). Finally, for each worker, we compute an adjustment factor ω by dividing the CPS proportion by the proportion in the Washington analysis sample, $\omega = \frac{p^{CPS}}{p^{WA}}$. ω is then used in the analysis as a frequency weight intended to adjust the Washington State sample to better reflect the U.S. workforce.

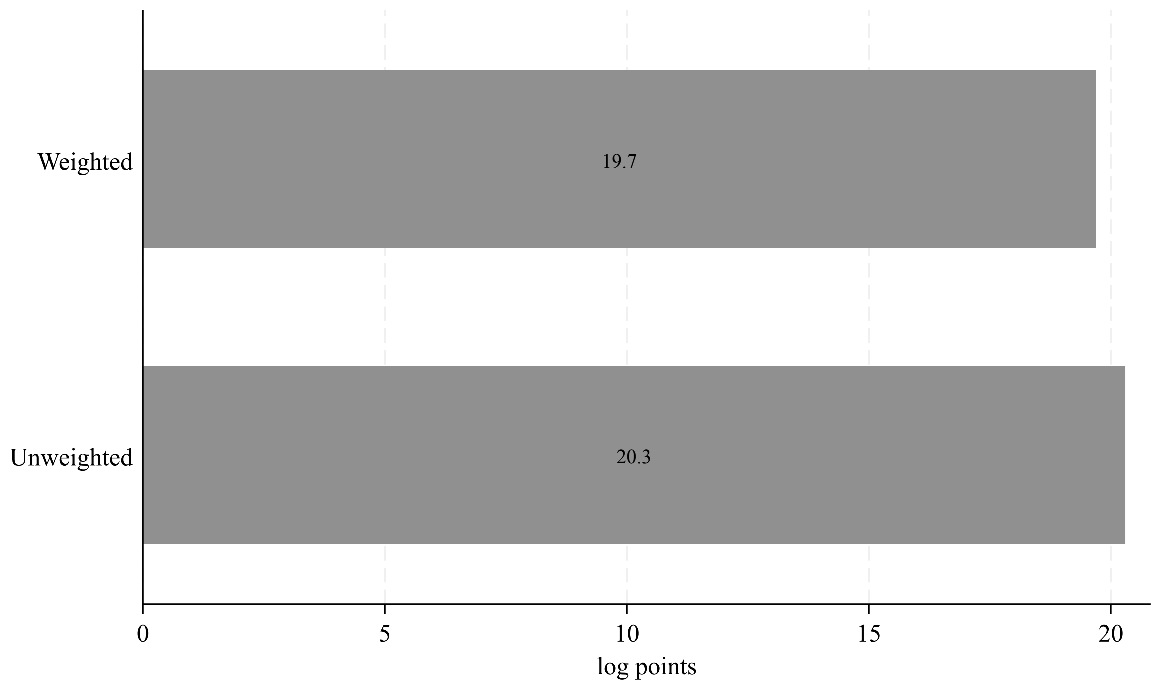
In practice, the results from unweighted data are very similar to their reweighed counterparts. For example, Figure B3, Panel A, shows that the weighted gender wage gap is slightly smaller (19.7 log points) compared to the unweighted gap (20.3 log points).

Figure B3, Panel B, shows that the sorting effect accounts for about 22.7% of the unweighted gender wage gender gap. When weighted, the sorting effect accounts for about 19.1% of the gender wage gender gap.

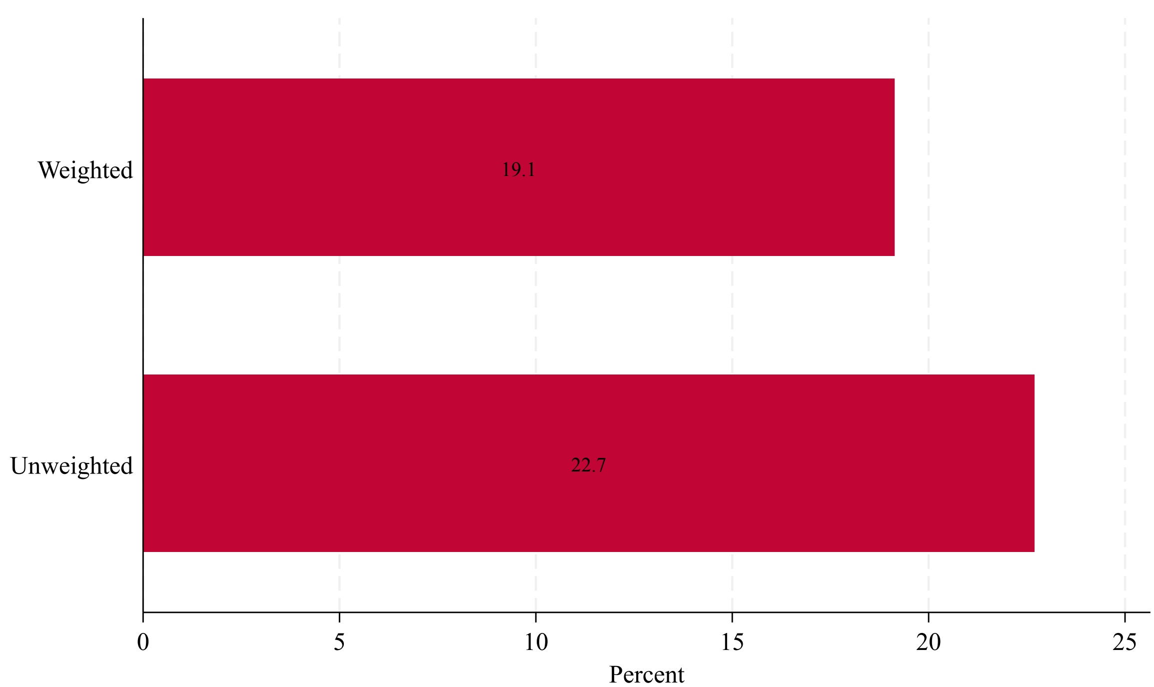
[29] When doing this, we use the associated CPS household weights.

FIGURE B1. Comparing Unweighted and Weighted Results

A. Gender Wage Gap



B. Sorting as a Share of the Gender Wage Gap



Notes: The figure compares the weighted and unweighted gender wage gap (panel A) and the contribution of sorting to the gender wage gap (panel B) in the Washington State baseline analysis sample. The weighted result uses weights calculated from the CPS.

B.2. Finland

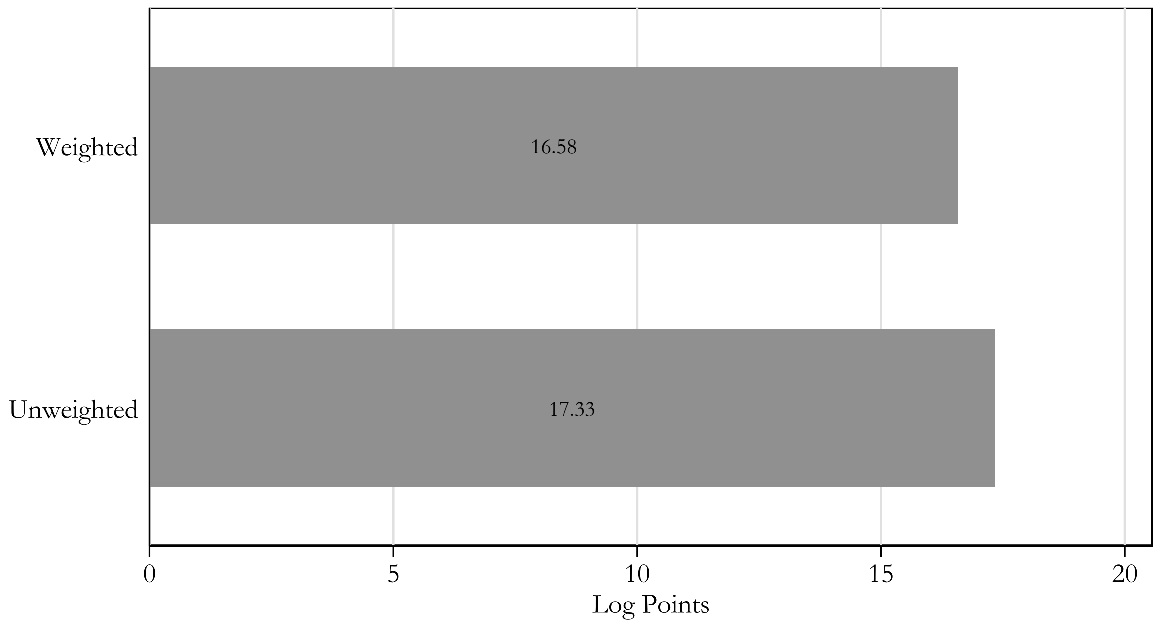
In Finland, hourly wages, hours worked, and related information is available from the Structure of Earnings registers, which cover the whole public sector and a 50% representative sample of the private sector. The overall sampling procedure is similar to the Swedish case. Each year the National Statistical Authority samples whole firms for statistical purposes, oversampling relatively large firms.

To correct for potential lack of representativeness in the sample of private firms, Statistics Finland computes and provides official employee weights that we apply to make the sample represenative of the underlying population. According to Statistics Finland's documentation, the weights have been tested to correct for the bias due to non-responding firms. There are on average 210 (depending on the observation-year) different strata (j) in the survey frame based on firm size and economic activity. For each stratum, the weight is defined as N_j/n_j, where N_j corresponds to the overall number of employees of (active) survey frame firms in stratum j, and n_j to the overall number of employees of responding firms in stratum j.

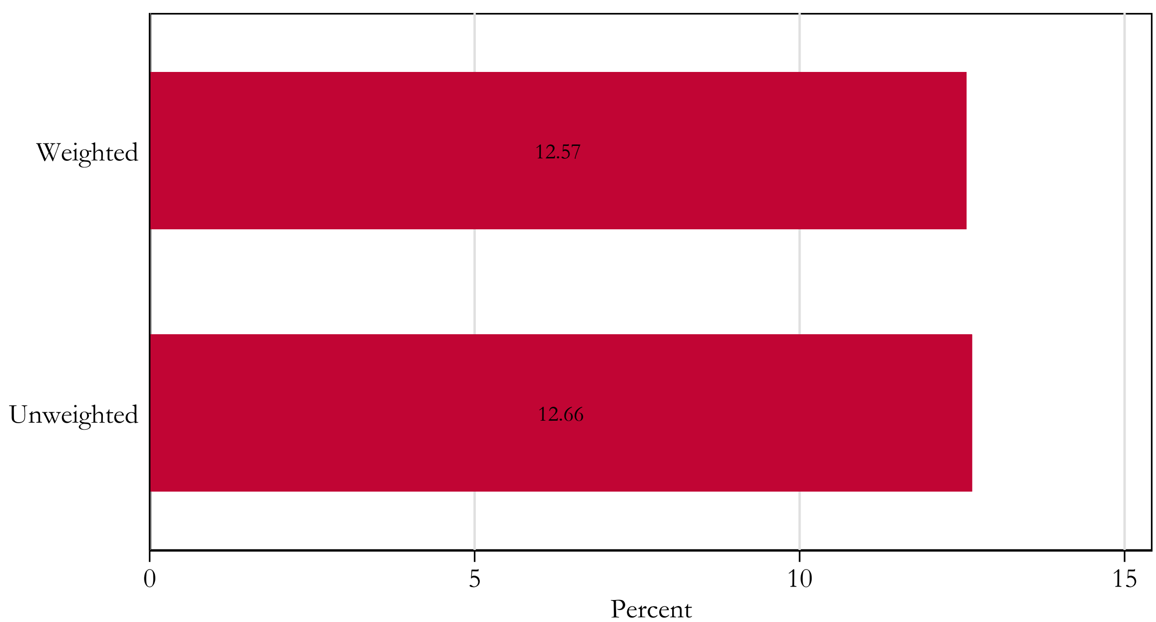
When using the weights, Figure B2 shows that the results are largely unaffected compared to the baseline analysis, both in terms of gender wage gap (panel A) and in terms of sorting as a share of the gender wage gap (panel B).

FIGURE B2. Comparing Unweighted and Weighted Results

A. Gender Wage Gap



B. Sorting as a Share of the Gender Wage Gap



Notes: The figure compares the weighted and unweighted gender wage gap (panel A) and the contribution of sorting to the gender wage gap (panel B) in the Finnish baseline analysis sample. The weighted result uses weights provided by Statistics Finland.

B.3. Sweden

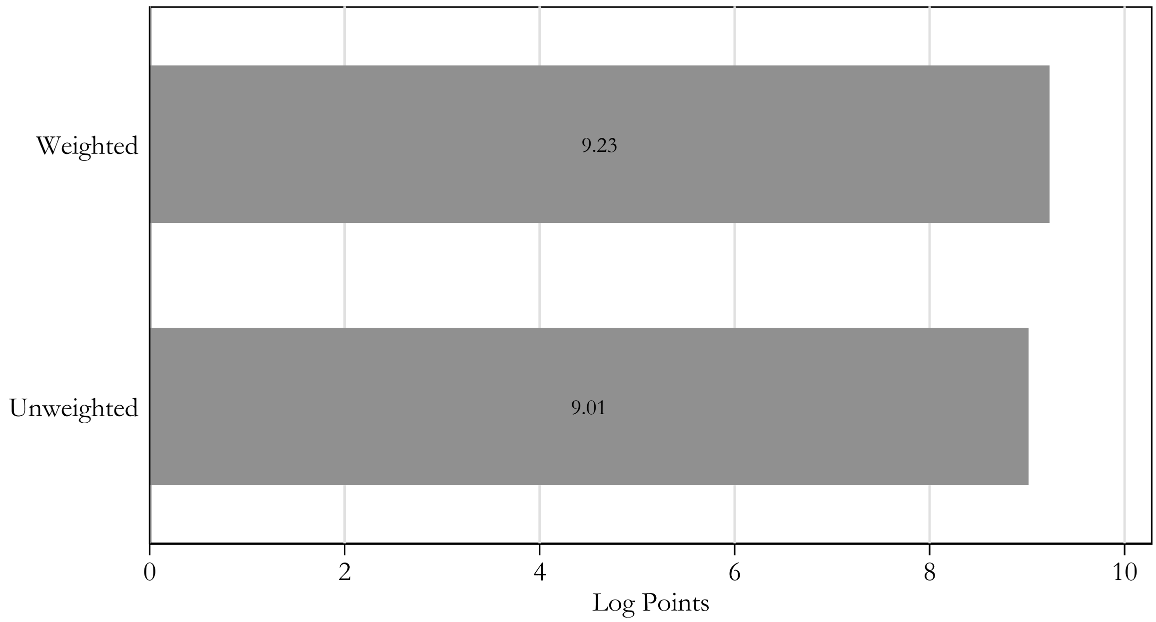
The data on hourly wages and occupations are drawn from the firm-level survey Wage Structure Statistics (WSS, Lönestrukturstatistik) conducted by Statistics Sweden. The survey provides a large-scale representation of the labor market, covering all public sector jobs and approximately 50% of private sector jobs. Sampling in the private sector is stratified by firm size, with sampling probabilities of 3, 12, 41, 70, and 100 percent for the firm-size intervals 1–9, 10–49, 50–199, 200–499, and 500 or more employees, respectively. Once a firm is sampled in a given year, all employees across all its establishments are included in the data. Larger firms are thus oversampled by design.

To address potential issues of non-representativeness resulting from this sampling procedure, Statistics Sweden computes and provides official firm weights that we apply to make the sample representative of the underlying population of firms.

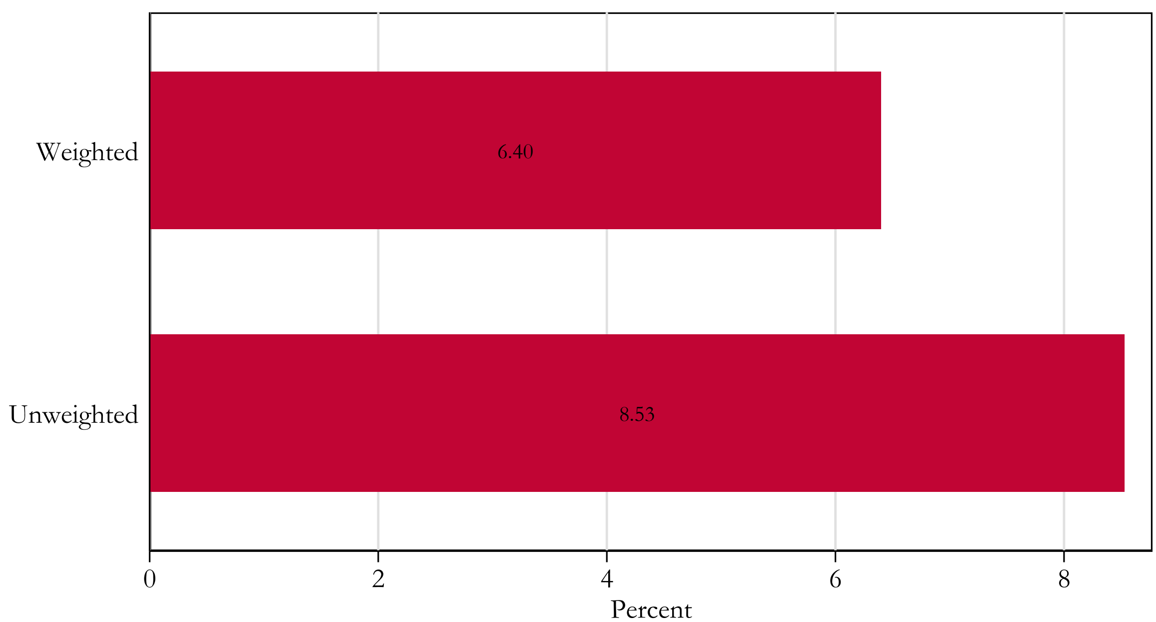
The results from the unweighted data are very similar to their reweighted counterparts. For example, Figure B3, Panel A, shows that the weighted gender wage gap is slightly larger (9.23%) compared to the unweighted gap (9.01%). Figure B3, Panel B, shows that the sorting effect accounts for about 8.5% of the unweighted gap. When weighted, the sorting effect accounts for about 6.4% of the gender wage premium gap.

FIGURE B3. Comparing Unweighted and Weighted Results

A. Gender Wage Gap



B. Sorting as a Share of the Gender Wage Gap



Notes: The figure compares the weighted and unweighted gender wage gap (panel A) and the contribution of sorting to the gender wage gap (panel B) in the Washington State baseline analysis sample. The weighted result uses weights calculated from the CPS.

Appendix C. Descriptive Statistics For Various Samples By Country

TABLE C1. Descriptive Statistics — Washington Administrative Data, 2010-2014

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.01	2.81	3.04	2.84	.	.
Std. dev.	0.53	0.52	0.54	0.53	.	.
Mean age	40	40	40	40	.	.
Part-time (%)	15	20	12	18	.	.
Separation (%)	33	35	32	35	.	.
Mean firm size	47	56	116	132	.	.
Movers per firm	7	5	17	12	.	.
Mean log VA/worker	.	.	.	.	.	.
Fraction females at firms	0.27	0.56	0.32	0.51	.	.
Number person-year obs.	1,465,034	766,800	1,063,829	612,565	.	.
Number of persons	464,424	257,061	350,283	207,068	.	.
Number of firms	70,967	52,918	17,269	17,269	.	.

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour. The sample is reweighted based on worker characteristics to account for the sampling designs.

TABLE C2. Descriptive Statistics — Danish administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.41	3.26	3.44	3.28	3.42	3.26
Std. dev.	0.41	0.36	0.41	0.35	0.39	0.35
Mean age	40	40	40	40	40	40
Part-time (%)	11	20	9	18	10	19
Separation (%)	26	25	25	25	26	26
Mean firm size	18	26	35	38	41	45
Movers per firm	20	15	44	25	43	23
Mean log VA/worker	11.32	11.31	11.35	11.33	11.35	11.33
Fraction females at firms	0.26	0.51	0.30	0.49	0.29	0.48
Number person-year obs.	6,161,017	3,349,989	5,181,461	3,038,597	4,299,574	2,437,320
Number of persons	1,112,425	662,743	986,864	604,779	900,532	539,312
Number of firms	180,404	122,181	65,264	65,264	51,900	51,008

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C3. Descriptive Statistics — Finnish Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.00	2.86	3.03	2.87	3.02	2.85
Std. dev.	0.36	0.34	0.36	0.34	0.35	0.34
Mean age	40	40	40	40	40	40
Part-time (%)	4	15	4	15	4	15
Separation (%)	24	25	21	23	21	24
Mean firm size	44	51	80	81	79	80
Movers per firm	20	16	51	33	47	27
Mean log VA/worker	11.12	10.91	11.15	10.94	11.15	10.94
Fraction females at firms	0.25	0.57	0.28	0.55	0.27	0.54
Number person-year obs.	2,749,168	1,741,972	2,575,431	1,633,772	2,400,042	1,418,842
Number of persons	584,789	391,758	526,467	361,115	507,296	330,855
Number of firms	24,483	20,335	9,038	9,038	8,458	8,461

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour. The sample is reweighted based on worker characteristics to account for the sampling designs.

TABLE C4. Descriptive Statistics — French Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.88	2.77	2.90	2.79	2.89	2.76
Std. dev.	0.46	0.42	0.46	0.43	0.45	0.42
Mean age	39	39	39	38	39	38
Part-time (%)	12	30	12	29	12	30
Separation (%)	28	29	27	29	28	30
Mean firm size	23	25	42	43	42	43
Movers per firm	24	16	54	32	54	31
Mean log VA/worker	4.20	4.12	4.24	4.13	4.24	4.13
Fraction females at firms	0.28	0.55	0.30	0.53	0.29	0.52
Number person-year obs.	74,657,286	46,663,660	65,622,545	42,171,308	60,752,972	37,170,277
Number of persons	17,061,367	11,656,165	14,849,448	10,549,494	14,010,689	9,628,806
Number of firms	1,411,500	1,196,096	548,851	548,851	503,020	501,994

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C5. Descriptive Statistics — German Administrative Data, 2010-2014

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.97	2.73	3.05	2.79	.	.
Std. dev.	0.57	0.54	0.57	0.54	.	.
Mean age	40	40	40	40	.	.
Part-time (%)	7	35	7	31	.	.
Separation (%)	20	22	19	21	.	.
Mean firm size	19	19	45	45	.	.
Movers per firm	10	6	25	14	.	.
Mean log VA/worker	11.29	11.13	11.31	11.16	.	.
Fraction females at firms	0.24	0.58	0.27	0.52	.	.
Number person-year obs.	49,563,213	28,257,241	38,587,140	21,750,570	.	.
Number of persons	13,155,660	8,168,368	10,438,866	6,336,209	.	.
Number of firms	1,428,388	1,358,133	426,196	426,196	.	.

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C6. Descriptive Statistics — Italian Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.62	2.47	2.67	2.49	2.68	2.50
Std. dev.	0.44	0.39	0.45	0.40	0.44	0.39
Mean age	40	39	40	40	40	40
Part-time (%)	11	43	10	41	8	40
Separation (%)	23	24	21	23	20	22
Mean firm size	13	15	24	26	34	37
Movers per firm	16	12	32	22	42	28
Mean log VA/worker	4.22	3.95	4.20	3.94	4.20	3.94
Fraction females at firms	0.26	0.58	0.30	0.54	0.29	0.54
Number person-year obs.	29,969,725	18,389,656	24,485,896	15,828,641	21,433,689	13,468,240
Number of persons	4,550,005	2,986,602	4,050,506	2,712,558	3,823,888	2,506,530
Number of firms	1,035,295	821,341	376,269	376,269	223,855	221,871

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C7. Descriptive Statistics — Hungarian Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	6.70	6.60	6.84	6.67	6.85	6.68
Std. dev.	0.63	0.56	0.64	0.57	0.64	0.57
Mean age	39	39	38	39	38	39
Part-time (%)	8	15	5	11	4	10
Separation (%)	27	27	25	26	25	27
Mean firm size	18	20	43	45	47	50
Movers per firm	10	7	23	18	22	17
Mean log VA/worker	8.61	8.50	8.78	8.64	8.78	8.64
Fraction females at firms	0.27	0.63	0.33	0.57	0.33	0.57
Number person-year obs.	3,989,959	2,878,313	2,900,496	2,255,559	2,613,539	2,035,183
Number of persons	825,401	644,898	640,062	522,594	597,932	487,862
Number of firms	205,098	176,353	56,910	56,910	49,672	49,290

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C8. Descriptive Statistics — Dutch Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.05	2.82	3.05	2.82	3.04	2.79
Std. dev.	0.51	0.44	0.51	0.44	0.49	0.42
Mean age	40	39	39	39	39	39
Part-time (%)	11	52	11	50	11	51
Separation (%)	24	26	24	27	25	28
Mean firm size	29	40	62	66	78	84
Movers per firm	24	21	60	36	73	41
Mean log VA/worker	4.10	3.93	4.09	3.91	4.09	3.91
Fraction females at firms	0.27	0.54	0.29	0.51	0.28	0.50
Number person-year obs.	21,966,061	12,679,870	19,334,176	11,472,728	15,890,253	8,774,172
Number of persons	3,625,666	2,354,253	3,307,262	2,180,686	2,983,035	1,893,558
Number of firms	505,334	344,220	177,033	177,033	113,892	113,076

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C9. Descriptive Statistics — Norwegian Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.23	3.02	3.25	3.03	3.26	3.08
Std. dev.	0.46	0.46	0.46	0.46	0.46	0.46
Mean age	39	40	39	40	39	39
Part-time (%)	8	27	8	26	7	20
Separation (%)	21	22	21	22	21	22
Mean firm size	22	33	44	50	36	40
Movers per firm	24	20	53	33	49	25
Mean log VA/worker	4.30	4.24	4.32	4.26	4.32	4.26
Fraction females at firms	0.27	0.62	0.30	0.61	0.26	0.52
Number person-year obs.	7,646,678	5,330,110	6,558,297	5,014,025	5,550,553	2,991,603
Number of persons	1,261,374	1,010,130	1,130,209	961,037	989,663	591,083
Number of firms	171,999	112,637	62,713	62,713	55,749	55,212

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C10. Descriptive Statistics — Portuguese Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	1.87	1.67	1.96	1.73	1.96	1.73
Std. dev.	0.57	0.52	0.58	0.54	0.58	0.53
Mean age	39	39	39	38	39	38
Part-time (%)	1	6	1	6	1	6
Separation (%)	22	22	21	22	21	22
Mean firm size	14	16	32	33	33	33
Movers per firm	14	10	32	24	32	24
Mean log VA/worker	13.53	13.39	13.64	13.49	13.64	13.49
Fraction females at firms	0.27	0.63	0.31	0.59	0.31	0.59
Number person-year obs.	9,973,068	7,166,943	7,529,303	5,688,521	7,492,529	5,652,432
Number of persons	1,909,148	1,421,120	1,483,676	1,146,956	1,481,294	1,144,793
Number of firms	309,880	280,294	92,959	92,959	92,160	92,147

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour.

TABLE C11. Descriptive Statistics — Swedish Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.07	2.99	3.11	3.02	3.09	3.00
Std. dev.	0.35	0.32	0.35	0.32	0.33	0.31
Mean age	40	40	40	40	40	40
Part-time (%)	19	28	19	27	20	28
Separation (%)	33	34	27	30	28	31
Mean firm size	26	32	72	76	68	73
Movers per firm	7	5	28	16	26	14
Mean log VA/worker	11.17	11.09	11.23	11.16	11.23	11.16
Fraction females at firms	0.25	0.50	0.29	0.48	0.28	0.47
Number person-year obs.	4,017,199	2,223,040	3,932,391	2,193,821	3,485,189	1,829,048
Number of persons	943,759	562,211	904,820	547,843	829,064	482,569
Number of firms	11,620	10,417	6,526	6,526	6,016	6,014

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55 employed in the private sector (defined as all sectors excluding education, health, culture, other services, private households with employed persons, and extraterritorial organizations). Wages are measured in real (2015 = 100) euros per hour. The sample is reweighted based on worker characteristics to account for the sampling designs.

Appendix D. Further Information on the Data

In this Section, we provide an overview of the data sources at firm and worker level for each country, as well as details on the definitions and construction of the variables.

D.1. United States: Washington State

Data sources. The data come from the wage and unemployment insurance (UI) claim records maintained by the Employment Security Department (ESD) of Washington State.[30] The purpose of collecting the data is to administer the state's UI system, which collects quarterly earnings records from all *UI-covered* employers in Washington and the UI claims records of all individuals who claimed UI in Washington. Government agencies and private non-profits are not required to report quarterly earnings. Also, self-employed workers do not file quarterly earnings reports, and underground earnings are not reported.

The wage records cover over 95% of all private sector employers in Washington State.[31] They include (a) a worker identifier, (b) a year-quarter identifier, (c) an employer identifier, (d) the NAICS industry code of the employer, (e) the worker's earnings from that employer in that quarter, and (d) the worker's paid work hours from that employer in that quarter.

Data source for information on workers. The information on workers comes from the wage records, which allow to track each worker's employment history in Washington State (earnings, work hours, and employer ID), and the claim records that include demographic information (date of birth, gender, level of education, and race/ethnicity) for workers who claimed UI.[32]

[30]This Section relies heavily on Lachowska et al. (2022).

[31]This number is based on the employment coverage estimate from the LEHD, which is based on UI wage records from over 40 states, see https://lehd.ces.census.gov/data/veo_experimental.html#employment-coverage.

[32]The demographic variables are available for the subset of workers who claimed UI between 2005 and 2013. For sample restrictions applied in this project, the wage-to-claim records match rate is about 51%. The incomplete match rate may raise concerns about the representativeness of the Washington sample for the Washington labor market as a whole. Analyses in Lachowska et al. (2022) show that UI claimants tend to have lower levels of educational attainment but somewhat higher earnings than Washington State workers overall, yet basic estimates from Mincer-style wage regressions suggest similar coefficients to those estimated using CPS from WA.

Data source for information firms. The information on employers comes from the wage records, which allow us to observe an employer's industry and to calculate employer characteristics such as employment or average employer hours or earnings. Typically, the employer is the set of establishments operating in Washington under a single owner, so for a company operating entirely in Washington (with a single or multiple addresses) the employer is a firm, and for a company with one address in Washington, the employer is also an establishment.

Definition of earnings and hours worked. Worker's earnings from a given employer in given quarter include the compensation earned for work, back pay, bonuses, commissions, royalties, severance pay, sick-leave pay, and tips.[33]

Work hours are the worker's paid work hours from a given employer in given quarter. When reporting hours, employers are asked to report the "number of hours worked in the quarter," including regular hours, overtime hours, hours of vacation and paid leave. For salaried, commissioned, and piecework employees, employers are instructed to report actual hours unless those hours are not tracked, in which case they are instructed to report 40 hours per week.[34] The data do not allow us to distinguish whether a worker is salaried or paid hourly.

The availability of quarterly earnings and quarterly hours allows to construct an hourly wage rate for each worker from each employer by dividing earnings by hours.

Data access. The data described in this Section are restricted administrative UI wage and claims records provided by the Washington State ESD. Because of the confidential information contained, the data cannot be shared or otherwise re-disclosed. An online data-sharing request form is available at: https://fortress.wa.gov/esd/file/datasharing#client.

D.2. Denmark

Data source for information on workers. We use several datasets to collect information on workers. The first dataset is called BEF. BEF contains information about the total population in Denmark. The status information for the individuals mainly refers to the beginning of the year (1 January). From this dataset, we retrieve information on worker age and gender.

[33] https://esd.wa.gov/employer-taxes/zero-hour-reports.
[34] https://www.esd.wa.gov/employer-taxes/reporting-requirements.

The second data set is called UDDA. UDDA contains information on the highest achieved education and an indicator for whether the person is currently enrolled in education. We exclude students.

The third dataset is called IDAN (*IDA ansættelser*). From this dataset, we retrieve information on occupation, earnings, hours worked, and firm identifier. We use information from this dataset to define the dominant job. Occupation classification follows the ISCO classification. This data set also contains information on whether individuals are self-employed. Hours worked are defined as paid hours worked: Include contractual and overtime hours. Earnings is defined as the near-universe of taxable income.

Data source for information firms. We use the General Company Statistics called the FIRM dataset, which annually lists active companies in Denmark. FIRM is built from several Statistics Denmark registers. FIRM covers economic and employment information on all sectors and industries. Active companies are defined as companies with at least 0.5 full-time hours of work. The firm identifier is the CVR number, the legal firm identifier in Denmark. We use this dataset to retrieve information about the industry classification (NACE) and the regional classification (NUTS).

The register that is used in FIRM for the variable value-added is the Accounts statistic for Non-Agricultural Private Sector (Regnskabsstatistikken for private byerhverv), abbreviated APB therefrom.[35] APB only includes market activity and does not contain agriculture, fishing, ports, banks, insurance, public housing companies, or public administration. There is a data break in 2014 in the population of firms considered in APB. Since 2014, firms in utilities, regional and long-distance trains, and radio and TV stations have been included. Value added is defined using several items from the income statement (*Resultatopgørelse*). Those items are: sales and other operating income minus cost of materials and equipment minus costs of energy and subcontractors minus rent paid minus payments for temporary workers and operational leasing of goods, and ordinary write-offs and other external charges.

Data access. All datasets can be obtained by contacting the Research service (*Forskningsservice*) of Denmark Statistics. To our knowledge, datasets provided by DST do not include a DOI, complicating replicability. The datasets that are used are recorded at a yearly frequency. Establishment identifiers are available, but our analysis focuses on

[35]This register is itself built from several sources: questionnaires, official annual accounts submitted in XBRL format to the Danish Business Authority (*Erhvervsstyrelsen*), the Danish tax authority (SKAT), Denmark's Statistics business register, and the Danish medicines agency (*Lægemiddelstyrelsen*).

the legal unit firm identifier (CVR number) and only changes due to firm restructuring. Individual identifiers are anonymized social security numbers (PNR number), and doesn't change over time. Contact Anne Sophie Lassen for questions.

D.3. Finland

Data Sources. We use several administrative registers to build the information used in the analyses. FOLK registers allow to follow the population of Finnish workers over time and include the link to the main employer at the end of the year. These registers also include detailed demographic and socioeconomic characteristics (including yearly earnings and employment information, occupation, sector, and industry), and employer-level spells. Earnings at the primary employer are computed by using TAX databases (and scaled by months worked at the employer level). The information on hourly wages, including overtime and bonuses, and of hours worked is retrieved for the private sector from the Structure of earnings (SES) database. The SES covers 55-75% of the private sector in the period considered.

D.4. France

Data sources. Our dataset is derived from the matched employer–employee registers in France known as BTS data.[36] This comprehensive dataset provides valuable information on workers' employment, including their earnings, hours worked, firm, and other administrative data for each of their jobs. The data are pseudonymized, with individuals assigned unique codes that change annually, allowing for cross-sectional analysis. However, it does not allow for long-term panel analysis of workers. Traditionally, panel analysis of employees in France has been carried out using the *DADS Panel*. This panel consists of a sample of individuals followed over time with a sampling frequency of 1/24 before 2002 and 1/12 after.

To enhance our analysis, we utilize a recently constructed and nearly exhaustive workers' panel based on the original dataset described in detail by Babet, Godechot and Palladino (2025). The DADS files for each year provide job variables at the individual level for the current and the previous year. This overlap allows for matching between yearly files at the worker level based on common information such as establishment ID, gender, number of hours worked, job duration, dates of employment, municipality of work and

[36] Formerly known as "DADS". DADS was the main source for the BTS, supplemented by other administrative sources (such as public sector data), and was gradually replaced by a new administrative source, the DSN ("déclarations sociales nominatives"), starting in 2016.

residence, earnings, and age. Using these matching procedures, Babet, Godechot and Palladino (2025) achieved a high matching success rate of 98% for individuals between 2002 and 2019.

To supplement the analysis, we incorporate exhaustive firm financial data from administrative sources (FICUS/FARE files), which are matched to the wage files and provide information on value-added per worker and total employment at the legal unit level.

Data access. Access to this data is restricted by statistical secrecy laws. Authorized researchers can request access via the Confidential Data Access Portal (CDAP) and perform computations through the CASD secure environment.

D.5. Germany

Data sources. We use data from the Institute for Employment Research (IAB) of the German Federal Employment Agency. The primary dataset is the Integrated Employment Biographies (IEB), which provides comprehensive records of employment and unemployment spells as documented by the German social security system. The IEB contains detailed information such as the start and end dates of employment spells, total earnings, occupation and industry codes, as well as individual worker characteristics like gender, age, and education.

Hours worked. Additionally, for certain years, the data includes information on working hours sourced from the German Social Accident Insurance. Between 2010 and 2014, employers reported individual total hours worked via the social security notification system, which can be linked to the administrative IEB data. Reporting work hours schemes vary across employers, that means some report actual hours, some report contractual hours, others report a “full-time worker reference value”. To mitigate these differences, we follow Dustmann et al. (2021) and correct reported hours, so that they uniformly reflect contractual hours (without overtime) across employers. See Vom Berge et al. (2023) for details.

Public sector jobs coverage. The Federal Office of Statistics (source: Statistisches Bundesamt: Personal des öffentlichen Dienstes, www.destatis.de) reports that in 2010 civil servants who are not in our data (because they are not subject to social security contributions) sum up to around 36.8 % (1,69 out of 4,59 million employees in the public sector).

Imputations of hourly wages. On average roughly 6 % in the IEB are top-coded. To compute hourly wages, we follow a two-step process. First, we calculate gross daily wages using total earnings and the total duration of each worker's employment spell, then deflate these wages using the CPI. We also follow standard procedures to impute censored wages above the social security contribution limit. Second, we divide earnings by hours worked, leveraging the significant advancement in data availability by linking our dataset with hourly wage data from 2010-2014 (see Dustmann et al. (2021)). Annual earnings are right-censored at the contribution assessment ceiling ("Beitragsbemessungsgrenze"), which is determined by the statutory pension fund and may be adjusted annually. We define a wage observation as censored whenever the reported wage exceeds 99% of the censoring thresholds. Following Dustmann et al. (2009) and Card et al. (2013), we fit a series of tobit regressions to impute the right tail of the wage distribution.[37] Assuming the error term is normally distributed but with different variances for each education and age category, we impute censored wages for each year as the sum of the predicted wage and a random component, drawn from separate normal distributions with mean zero and variances specific to each education and age category.

Data access. The data outlined in our article are social insurance data of administrative origin, which are processed and kept by the Institute for Employment Research (IAB) according to German Social Code III. There are certain legal restrictions due to the protection of data privacy. The data contain sensitive information and therefore are subject to the confidentiality regulations of the German Social Code (Book I, Section 35, Paragraph 1). The data are held by the IAB, Regensburger Str. 104, D-90478 Nurnberg, iab@iab.de, phone: +49 911 1790. Our data, computer programs, and results will be archived by the IAB to meet the objective of good scientific practice. This approach also extends to all data that cannot be shared directly. Interested researchers can access the data through the Research Data Centre (FDZ) of the German Federal Employment Agency at the IAB. The FDZ of the German Federal Employment Agency (BA) at the IAB is intended mainly to facilitate access to BA and IAB micro data for noncommercial

[37] We estimate tobit regressions by year, sex, education, and age group, controlling for variables such as worker age, average log wage in other years, the fraction of censored wages in other years, the number of full-time employees at the current establishment and its square, an indicator for large firms, average years of schooling and the fraction of university graduates at the current establishment, the average log wage of coworkers, the fraction of coworkers with censored wages, an indicator for individuals observed in only one year, an indicator for employees in one-worker establishments, and an indicator for region.

empirical research using standardized and transparent access rules. The FDZ mediates the relationship between data producers and external users. For this purpose, the FDZ provides separate workplaces for guest researchers at different locations. Access can be granted only after successful application and approval.

D.6. Italy

Data sources. We use a representative sample of 7 percent of firms from 2005 to 2019 in the non-agricultural private sector, available through an agreement between the Italian Social Security Institute (INPS) and the Bank of Italy. The firm-level data are matched with information on all workers ever employed by these firms. This includes the entire workforce of the sampled firms, as well as the complete employment histories of individuals who passed through these firms.

The data include detailed information on work contracts (annual earnings, weeks worked, contract and work schedule type, broad occupation, contractual hours, municipality of work, hiring and separation dates, and reasons for separation), worker demographics (gender, year of birth, province of residence), and firm characteristics (6-digit industry, opening and closing dates, and balance sheets for a sub-sample).

Earnings are measured as full net annual earnings, including all forms of cash compensation, grossed up for income taxes and social security contributions.

D.7. Hungary

Data sources for information on workers. The main datasource on workers is linked administrative data (admin3) based on social security records, collected by the Social Security Administration. It covers a random 50% of the population and records earnings from different employers each month as well, as well as occupation, days worked and contracted hours. At the same time, the data does not include information on the education for most of the workers. The linked administrative data collection (Admin3) is the property of the data owners and their legal successors: NEAK, MÁK, NAV, ITM, and OH. The data used was processed by the Centre for Economic and Regional Studies (KRTK) Data Bank.

Data sources for information on firms. The main data source on firms comes from Corporate Tax Declarations, collected by the Hungarian Tax and Customs Authority (NAV). Firms conducting double bookkeeping are obliged to submit these declarations each year. These data include financial information, number of employees and the firm's industry code. This data was also processed by the Centre for Economic and Regional Studies (KRTK) Data Bank.

Definition of earnings and hours worked. We use the social security data to calculate gross earnings for the workers main job, by following the harmonized guidelines of this project. The number of hours worked is contracted hours.

Data access. These confidential datasets are managed by the Databank of Centre for Economic and Regional Studies.

D.8. Netherlands

Data source for information on workers. The administrative data from Statistics Netherlands cover the entire population of Dutch individuals. Demographic, household and job characteristics are observed based on several datasets. *GBPERSOONTAB* contains an individual identifier ('rinpersoon') and individuals' demographic characteristics including gender, birth date and nationality, for the universe of individuals. *HOOGSTEOPLTAB* contains information on a person's highest level of educational attainment. As information on educational information is unobserved for those who graduated before 1995, for the Netherlands five categories are used: missing information, and four categories based on ISCED: less than high school (ISCED 0 to 2), high-school/vocational (ISCED 3 and 4), short-run tertiary and bachelor (ISCED 5 and 6); and Master, Phds or similar (ISCED 7 and 8). *GBAADRESOBJECTBUS* contains an individual identifier ('rinpersoon') and the anonymized individuals' home address identifier ('rinobjectnummer') for the universe of housing spells including start and end dates. *VSLGWBTAB* contains the home address ('rinobjectnummer') and regional identifiers for the universe of house addresses. *SPOLISBUS* contains an anonymized individual identifier ('rinpersoon') and monthly information on gross wages components (including 'basisloon'), hours worked ('aantverlu'), type of contract, full-time/part-time status, and a firm identifier ('beid'), for the universe of employment spells including start and end dates (both dates are measured from January 2006 onwards, so job tenures are counted from this point onwards). Hourly wage is computed by dividing total gross wages by the number of paid working hours. The number of weekly days worked is not observed in the data. We use data from 2010 until 2019, and aggregate the monthly data from the dataset *SPOLISBUS* based on (predominantly) monthly income statements to an annual level. For employees who worked shorter than a calendar year, we compute annualized variables based on the length of the job spell in the given calendar year. The main limitation of the Dutch administrative data on employees is that occupational information is not available.

Data source for information firms. At the firm-level, we use the datasets *Betab* and *ABR*. These annual datasets contains an anonymized firm identifier ('beid') and information on economic sector and firm size for the universe of firms. Firms are defined as entities, and each entity has control with legal basis over its own activities, as defined by Statistics Netherlands consistent with the Eurostat recommendations manual on business registers. Note that large firms could consist of multiple entities, i.e. an organization, but this depends on the control with legal basis of activities across these entities. The dataset *NFO* contains data on the organization's net sales ('r01') and the cost of raw and auxiliary materials, purchases and other operating expenses ('r02'). Value added is equal to the sum of r01 and r02. The variable productivity is defined based on the organization's value added divided by the organization's number of full-time equivalent workers, where the organization's number of full-time equivalent workers equals the total organization's paid working hours divided by 1924.

Definition of earnings and hours worked. Hours worked refer to monthly actual paid working hours and do include overtime. In addition, in the case of unpaid leave, working hours decrease, whereas in the case of paid leave and holidays, working hours and monthly wages are unaffected. Hourly wage is defined as the ratio of monthly gross wages divided by monthly working hours. Earnings are defined as monthly earnings from employment, unaffected by paid leave but affected by unpaid leave. Observations are retained for the individual-year observations where the hourly wage is over 0.2 of the median hourly wage, by year, and if the observations correspond to fewer than 60 paid working hours.

Disclaimer. We are grateful to Statistics Netherlands (Centraal Bureau voor de Statistiek, CBS) for providing access to the administrative data. Results are based on calculations using non-public microdata from Statistics Netherlands. Under certain conditions, these microdata are accessible for statistical and scientific research. For further information: microdata@cbs.nl and https://www.cbs.nl/en-gb/our-services/customised-services-microdata/microdata-conducting-your-own-research.
For questions: j.meekes@law.leidenuniv.nl

D.9. Norway

This study uses employer-employee matched data for the population of workers and firms for Norway for the period 2010 to 2019 which we constructed by merging several registers of the Norwegian administrative data at the individual and enterprise level.

Data sources. We have constructed a yearly employer-employee matched panel data set for the population of employees and firms. From the employment registers, we extract yearly information on the main job during a calendar year and earnings paid for work and all related characteristics of the employer (establishment identifier, enterprise identifier, industry, institutional sector) and the job characteristics incl. hours of work and occupation. Using the unique person identifier, we further merge information on gender and year of birth that is used to construct age from the population registers. We further merge education categories from the education registers based on the constructed highest level of education an individual has achieved. For generating tenure within establishment we use the individual time series data since 2000. Using the unique enterprise that is organisation number, we merge selected enterprise-level variables collected by the *Brønnøysund register center* through the cleaned and documented version by Berner et al. (2022). We calculate establishment and enterprise size as the number of employees per year.

We use the annual and monthly wage paid by the main employer. It includes the agreed monthly wage, irregular additional payments and bonus payments. Pay for overtime is not included. We measure hours as the total hours of work during a year in the main job. The hourly wage is then defined as the ratio of total earnings in year t divided by the total hours in year t. We also keep weekly hours that are agreed in the contract of an employee.

D.10. Portugal

Data sources. The data source is the Quadros de Pessoal (referred to as QP) from 2010 to 2019. This dataset is gathered annually by the Portuguese Ministry of Employment. Each October, it is legally required that firms with at least one salaried employee provide workforce information. The dataset encompasses virtually the universe of firms and establishments, along with information on their respective workforce as of October each year. Consequently, it only contains information on jobs for employed individuals during October. The dataset excludes the public administration and independent contractors.

Data source for information on workers. The QdP data contains worker-level information reported by firms on each employee's gender, education, occupation, date of hire, earnings and hours worked.

Data source for information firms. At the firm-level, the QdP data contains information on industry (NACE), regional location (NUTS), firm size (number of employees) and sales per worker. We use sales per full-time equivalent employment at the firm level to measure firm productivity. Our focus on the legal unit firm identifier, although establishment identifiers are available.

Definition of earnings and hours worked. The hourly wage at the main employer in October is defined as the ratio between total monthly earnings and total hours worked. Total monthly earnings include the individual's monthly base salary, regular salary supplements (e.g. tenure-related premiums), overtime and bonuses. Total hours worked refer to monthly contractual hours and overtime hours.

D.11. Sweden

Data sources. We use a comprehensive RAMS matched employer-employee database from Statistics Sweden (SCB), encompassing labor earnings of all workers linked to firms and employees from 2010 to 2018. We complement the employment information with socioeconomic characteristics from the LOUISE dataset. The data on wages and occupations come from a firm level survey Wage Structure Statistics (WSS, Lönestrukturstatistik) conducted by Statistics Sweden.

Data source for information on workers. Demographic data are collected from Statistics Sweden's LOUISE register, including the entire Swedish population aged 16 to 74. These data include demographic information such as the year of birth, gender, and the highest completed education level.

Data source for information firms. The information on employers comes from RAMS and WSS, all linked through anonymized firm and establishment identifiers. We can observe an employer's industry and calculate employer characteristics such as employment or average earnings.

Definition of earnings and hours worked. The earnings-spells include the first and last month of employment, so we can calculate monthly gross labor earnings using RAMS. These data are collected from tax registers, and the reporting is mandatory. However, they do not include hours worked. Instead, we use Wage Structure Statistics data (WSS, Lönestrukturstatistik), very large sample at the firm level. WSS data are collected during a measurement week in September for private sector and in November for public sector, including workers who have worked at least one hour with pay. All public sector employees are included. However, the sampling of private sector firms is stratified by firm size with the sampling probabilities 3, 12, 41, 70, and 100 percent for the firm size intervals 1–9, 10– 49, 50–199, 200– 499, and 500–, respectively. Approximately 50% of private sector workers is included every year. If a firm is sampled in a given year, all workers belonging to all establishments are included. The wage measure reflects the employee's wage during the sampling month expressed in full-time monthly equivalents. All wage components, e.g., piece-rate and performance pay, except overtime pay, are included. All salaries are calculated for full-time in order to be able to make comparisons for the time unit month. Thus, we compute hourly wages and daily wages using this full-time equivalent wages. In practice, we divide full-time equivalent monthly wages by 165 to get hourly wages.

Data access. Data is accessed through an online portal provided by Statistics Sweden. Other researchers can purchase the data from Statistics Sweden, conditional on the same protocol as the research group. We can provide access to the data for replication purposes.

References

Babet, Damien, Olivier Godechot, and Marco G. Palladino, "In the Land of AKM: Explaining the Dynamics of Wage Inequality in France," *Banque de France Working Paper*, 2025.

Berge, Philipp Vom, Matthias Umkehrer, and Susanne Wanger, "A Correction Procedure for the Working Hours Variable in the IAB Employee History," *Journal of Labour Market Research*, 2023, *57*, 10.

Boza, István and Balázs Reizer, "The Role of Flexible Wage Components in Gender Wage Difference," *IZA Discussion Paper*, 2024.

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

Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women," *Quarterly Journal of*

Economics, 2016, *131* (2), 633–686.

—, **Jörg Heining, and Patrick Kline**, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

Casarico, Alessandra and Salvatore Lattanzio, "What Firms Do: Gender Inequality in Linked Employer-Employee Data," *Journal of Labor Economics*, 2024, *42* (2), 325–355.

Cruz, Gabriel and Tomás Rau, "The Effects of Equal Pay Laws on Firm Pay Premiums: Evidence from Chile," *Labour Economics*, 2022, *75*, 102135.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach," *Econometrica*, 1996, *64* (5), 1001–1044.

Dustmann, Christian, Attila Lindner, Uta Schönberg, Matthias Umkehrer, and Philipp vom Berge, "Reallocation Effects of the Minimum Wage," *The Quarterly Journal of Economics*, 2021, *137* (1), 267–328.

—, **Johannes Ludsteck, and Uta Schönberg**, "Revisiting the German Wage Structure," *The Quarterly Journal of Economics*, 2009, *124* (2), 843–881.

Gallen, Yana, Rune V. Lesner, and Rune Vejlin, "The Labor Market Gender Gap in Denmark: Sorting out the Past 30 Years," *Labour Economics*, 2019, *56*, 58–67.

Kline, Patrick, Raffaele Saggio, and Mikkel Sølvsten, "Leave-Out Estimation of Variance Components," *Econometrica*, 2020, *88* (5), 1859–1898.

Lachowska, Marta, Alexandre Mas, and Stephen A. Woodbury, "How Reliable Are Administrative Reports of Paid Work Hours?," *Labour Economics*, 2022, *75*, 102131.

Li, Jiang, Benoit Dostie, and Gaëlle Simard-Duplain, "Firm Pay Policies and the Gender Earnings Gap: The Mediating Role of Marital and Family Status," *ILR Review*, 2023, *76* (1), 160–188.

Masso, Jaan, Jaanika Meriküll, and Priit Vahter, "The Role of Firms in the Gender Wage Gap," *Journal of Comparative Economics*, 2022, *50* (2), 454–473.

Morchio, Iacopo and Christian Moser, "The Gender Pay Gap: Micro Sources and Macro Consequences," *NBER Working Paper*, 2024.

Palladino, Marco G., Alexandra Roulet, and Mark Stabile, "Narrowing Industry Wage Premiums and the Decline in the Gender Wage Gap," *Labour Economics*, 2025, *94*, 102693.

Sorkin, Isaac, "The Role of Firms in Gender Earnings Inequality: Evidence from the United States," *American Economic Review, Papers and Proceedings*, 2017, *107* (5), 384–387.

Visser, Jelle, "ICTWSS Database. Version 6.1," 2019. Amsterdam Institute for Advanced Labour Studies (AIAS), University of Amsterdam.