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 explain the gender gap when women are less likely to work at high-paying firms (sorting) or receive lower premiums than men within the same firm (pay-setting). We find that firm wage premiums account for a substantial share of variation in gender wage gaps, ranging from 15 to 32 percent. While both mechanisms matter, sorting is the predominant driver of the firm contribution to the gender wage gap in most countries. Three patterns are broadly consistent: (1) women sorting into lower-paying firms becomes increasingly pronounced with age; (2) women are more concentrated in low-paying firms with a high share of part-time workers; and (3) pay-setting gaps are largest in high-wage firms, where women receive about 90 percent of the rents men receive from firm surplus gains.

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1. Introduction

The sources of the gender wage gap are a topic of great interest to both researchers and policy-makers. Despite some convergence, women 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) applied the Kitagawa-Oaxaca-Blinder decomposition of gender-specific employer wage premiums estimated using Abowd, Kramarz and Margolis (1999) model (hereafter AKM).[1]

CCK showed that about 20 percent of the gender wage gap in Portugal could be attributed to the firm wage premium gap. Subsequent work applying their approach has found considerable variation in the role of firms — ranging from 15 to 85 percent — in explaining the gender wage gaps; see Table 1 for a summary of recent papers. This literature has broadly concluded that "firms matter" for the gender wage gap, but understanding why firms matter and why the estimates are so different is difficult because these studies differ in sample selection (e.g., the inclusion of public sector jobs), wage definitions (e.g., hourly vs. annual), and econometric methods. Because single-country studies differ in design, it is hard to tell whether cross-country patterns reflect real differences or just specific context. Most single-country studies also aim to establish novel mechanisms to interpret the results, providing less evidence on whether

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

firm-based explanations hold up across settings.[2] As a result, we lack a harmonized, cross-national perspective on how and why firms contribute to the gender wage gap.[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 private-sector gender wage gap. This harmonized research design is applied 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. For these countries, the data include high-quality information on work hours, which allows the gender wage gap to account for male-female differences in work hours.[4] The harmonized research design is crucial because it 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.

We quantify the role of firms in the gender wage gap through two distinct mechanisms: (i) similarly productive men and women being employed by employers with different wage premiums (the *sorting* channel) and (ii) within-firm wage differences between similarly productive men and women (the *pay-setting* channel). We show that firm wage effects matter in explaining hourly wages in all countries. If firm wage effects matter for wages, do they also explain the gender wage gap? To answer this question,

[2] For example, the mechanisms explored have included 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 (2025)).

[3] Some cross-country studies have focused on gender wage inequality (e.g., Blau and Kahn (2003); Penner, Petersen, Hermansen, Rainey, Boza, Elvira, Godechot, Hällsten, Henriksen, Hou et al. (2023); others have focused on the role of AKM firm 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 et al. 2023, but not on both.

[4] Washington state collects hours and earnings, whereas the LEHD that covers most US states only collects data on earnings. In some countries we observe only contractual hours and not paid work hours. We relegate further discussion to the data appendix.

we apply the CCK decomposition. At least four findings stand out.

First, we find that firm wage premiums explain about 15 to 30% of the gender wage gap. In the U.S., Hungary, and Germany, the premiums explain about 30% of the wage gap, while in Denmark, Sweden, and Finland, they explain about 15%. Countries with larger gender wage premium gaps also tend to have large gender wage gaps.

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 channel ranges from less than 2% in the Netherlands and Finland to 30% in Hungary. The sorting component varies from less than 3% in Denmark and Hungary, about 16% points in the Netherlands and Portugal, to over 20% in the U.S. and Germany.[5]

Third, in most countries, the importance of sorting increases over the life-cycle. The role of sorting increases as men move up the job ladder, while women stay behind.[6] High-quality information on hours allows us to investigate to what extent women trade off wages for flexibility of part-time work (Goldin 2014). Across all countries, we show that women are more likely to work part-time and sort to firms with a high share of part-time work and low wage premiums. We do not, however, find that women are paid a greater compensating wage differential for long hours than men. That women sort to low-wage firms in return for more flexibility is consistent with the 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 2025; Burbano, Folke, Meier and Rickne 2024; Humlum, Rasmussen and Rose 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

[5]In an auxiliary exercise, we include public-sector jobs and show that the sorting channel increases by several orders of magnitude.

[6]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; Lochner and Merkl 2025).

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). 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 some countries showing even larger disparities. These gender differences in rent-sharing are positively correlated with the overall pay-setting component of the gender wage premium gap.

The remainder of the paper is structured as follows: Section 2 describes the datasets and sample selection criteria.[7] Section 3 presents the empirical framework. Section 4 quantifies the role of firm-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 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,

[7] We relegate a more detailed description of each country's data and institutional features to the appendix.

France, Germany, the Netherlands, Norway, Portugal), others provide very large samples covering at least half of the population.[8]

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. 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 are available for Denmark, Finland, France, Italy, Hungary, Norway, and Sweden. The U.S. data do not include financial information on firms, while for Norway (60% of female observations) and Germany (2%), productivity measures are available for smaller samples.[9] 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.

2.1. Sample Selection

To ensure consistency across datasets, we apply uniform sample selection criteria. First, we focus on "prime-age workers," defined as those between the ages of 25 and 55.[10] We restrict our analysis to workers employed in the private sector, specifically in industries

[8]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 C.

[9]In Norway more women tend to work in firms with missing productivity.

[10]See Créchet et al. (2024) for a recent cross-country analysis of employment trends.

where most firms are for-profit organizations. This leads us to exclude industries coded O through U in the NACE classification (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 exactly 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 and are linked by the mobility of workers of both sexes. In Appendices , we provide comprehensive tables summarizing 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.[11]

[11] Figure A.1 compares the gender wage gap (measured as the difference between male and female average log hourly earnings) across the three samples. With the exception of Hungary, where the gender gap increases from 10 log points in the full sample to 16 log points in the dual-connected sample, restricting to the dual-connected set yields remarkably similar gender wage gaps across countries. This consistency is reassuring, as it suggests that our subsequent analysis based on the dual-connected sample accurately

To address potential concerns about sample composition and examine whether limited mobility biases our firm effect estimates, 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 every country, women's hourly wages are lower than men's, with the gender wage gap ranging from 9 log points (9.42%) 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 considered irrespective of the overall incidence of part-time work. 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.[12]

Table 3 reports the share of person-year observations in the main analysis sample belonging to firms with available productivity data. Productivity data cover about 75

represents the broader population of private-sector workers aged 25–55.

[12] Finland and Sweden have particularly high numbers of movers per firm due to their sampling designs that oversample larger firms.

percent of observations for both men and women in most countries, with the exception of Norway (where the coverage of 59.5 percent of female person-year observations), Germany (2–4 percent coverage depending on gender), and the U.S. (productivity data not available).

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

This section discusses the gender-specific AKM model and how firm-specific wage premiums contribute to the gender wage gap.

3.1. Gender-Specific AKM Model

We estimate the AKM two-way fixed effects model separately for men and women as in CCK in 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 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.[13]

[13] 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

Firm wage 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 differences in a firm's wage policy toward men and women.[14]

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 effects between men and women: $E[\psi^M_j] - E[\psi^F_j]$.

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):

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

This decomposition separates the gender wage premium gap into two economically 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 (Babcock

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.

[14]To identify firm 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 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.

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 in firms that offer lower wage premiums to all workers. This component captures gender gaps in wage premiums between firms due to differences in women's preferences or in the availability of high-premium employers for similar workers by gender.[15]

Limited mobility bias will not affect estimates of the gender wage premium gap in Equation (2) because the Kitagawa-Oaxaca-Blinder method decomposes the differences of first moments.[16]

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 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 beyond their reservation wage. 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.

[15] 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.

[16] When we measure standard deviation of firm effects in Figure A.2, we biased-correct the standard deviation. 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).

Figure A3 illustrates the relationship between firm productivity and firm wage premiums for countries with available 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 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.[17] Note that only the pay-setting component is affected by the normalization procedure, while the sorting component remains invariant.

Productivity data are unavailable for the U.S. and only available for a limited sample for both genders for Germany and Norway. For these countries, we follow the approach inspired by Morchio and Moser (2025), whose normalization selects firms at the bottom of a job utility ranking.[18] In practice, we define firms with high worker exit rates as low-rank firms. To do so, for each gender, we normalize the bottom ten percent of employment-weighted firms by exit rate, where the exit rate is defined by the share of

[17]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 A3 represent these country-specific estimated thresholds.

[18]The Morchio and Moser (2025) 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 Latanzio, 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.

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). We test alternative thresholds and find similar results (available upon request). Other common measures of firm utility are the poaching index (Bagger and Lentz 2019) and the PageRank (Sorkin 2018) but this measure is not consistently implementable across countries due to differences in data frequency (e.g., daily in Denmark vs. annually in Portugal).

We provide more details about normalization robustness and sample sensitivity in Section 7.

4. Contribution of Firm-Wage Premiums to Gender Gaps

This section decomposes these 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).[19]

4.1. Firm-Specific Wage Premiums and the Gender Wage Gap

Figure 1 shows for each country, the results from the CCK decomposition, given by Equation (2). 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 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. The figure shows that firm-

[19] We begin by showing that countries with greater firm-pay heterogeneity tend to have larger gender wage gaps. Figure A.2 illustrates this by plotting, for each country, the standard deviation of women's firm wage premiums against the gender wage gap. This relationship suggests that firms play a role in pay differences, motivating a decomposition of the gender wage premium gap.

specific wage premiums explain cross-country differences in gender wage gaps and that countries with larger gender wage premium gaps tend to show larger overall gender wage gaps. In Sweden, France, Finland, the Netherlands, and Italy, these 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. Compared to other EU 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 et al. (2022); Dahl et al. (2013). 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.

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 Dynamics of Gender Gaps Across the Life Cycle

Figure 2, panel A plots, for every country, the change in the gender wage gap between older (50–55 years of age) and younger (25–29 years) workers against the corresponding change in the gender wage premium gap. Panel A shows a strong positive correlation between the widening of the gender wage gap and firm wage premium gaps by age. For example, Germany, Portugal, and Italy show substantial increases in both measures: an increase of about 4–8 log points in the gender wage premium gap is associated with a 20–30 log points increase in the gender wage gap.

Panel B plots the change in the gender wage gap between older and younger worker against the corresponding change in the sorting component. The pattern in Panel B closely align with that in Panel A, indicating that nearly all of the age-related expansion in firm wage premium gaps is explained by the sorting component. Confirming this, Panel C shows that there is essentially no relationship between the change in the gender wage gap between older and younger worker and the corresponding change in the pay-setting component.

Taken together, these patterns provide evidence that the widening gender wage gap over the life cycle is to an important extent related to changes in the sorting component; see, e.g., Kunze (2005), Goldin, Kerr and Olivetti (2022), Casarico and Lattanzio (2024), Card, Devicienti, Rossi and Weber (2025). A potential explanation is that women are less likely to progress in the career by moving to higher-wage firms (Bronson and Thoursie 2019).[20] 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. 2024).[21] In the next subsection, we

[20]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 dynamics 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.

[21]Figure A4 shows a positive association between the increase in sorting into low-wage firms and

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; see, e.g., Bolotnyy and Emanuel (2022). If some firms offer compensation packages that combine high wages with long hours and if long-hours/high-wage packages are more attractive to men than to women, especially as women take on more caregiving responsibilities, then compensating differentials for long hours could 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 hours firm effects as policies on hours, while accounting for the firm's workforce composition. We estimate the model separately by gender and then regress firm-wage effects on firm-hour effects to recover gender-specific elasticities of firm wage policies with respect to firm hour policies.[22] Figure 3 shows the elasticity of firm-wage premiums with respect to firm-specific hour policies, estimated separately by gender and restricted to countries where data on paid hours are available (and not solely contractual hours). Across most of these countries, we find a positive relationship between firm hours and firm-wage premiums: firms that require longer paid hours tend to offer higher wages. The magnitude of the elasticity varies across countries (from close to zero for France and Portugal, to about 0.2 for the U.S., Norway, and the Netherlands) but importantly, we mostly do not find gender differences in the

part-time workplaces over the life cycle.

[22] We estimate the elasticity of firm-wage premiums with respect to firm hour policies using firm-level regressions. Let ψ_j^g denote the AKM firm effect on wages and ϕ_j^g the firm effect on hours for gender $g \in \{m, f\}$. We estimate $\psi_j^g = \beta_g \hat{\phi}_j^g + \eta_j^g$, 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.

elasticities. The association between firm hours and firm wages is similar for both men and women, indicating that women are compensated similarly to men for working longer hours within firms. This suggests that the hours-wage relationship primarily influences gender wage gaps through women sorting to lower-paying and shorter-hours employers. The notable exception is Denmark, where the relationship between firm hours and firm-wage premiums is stronger for men (0.1) than for women (0.05).

Figure 4 provide direct evidence of this sorting by analyzing the relationship among firms' incidence of part-time work, their gender composition, and their wage-setting policies. In the top panel, firms are grouped by country-specific terciles based on the share of women in their workforce, and we plot the average share of male part-time workers for firms in the bottom tercile (low share of women, blue circles) and top tercile (high share of women, red triangles). We find that in all countries women are disproportionately employed in firms with high part-time incidence. The bottom panel sorts firms by country-specific terciles based on their within-firm share of male part-timers and shows the corresponding average firm-wage premium[23] for firms in the bottom tercile (low part-time intensity, blue circles) and top tercile (high part-time intensity, red triangles). A consistent negative relationship emerges across all countries except Germany: firms with high part-time intensity systematically offer lower wage premiums than those with low part-time intensity. Firms in the top tercile of part-time intensity offer, on average, wage premiums that are about 9 log points lower than those in the bottom quartile. It is not just that women are more likely to work 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.

These findings reveal that compensating differentials for longer hours exist and operate similarly for both men and women within firms. The sorting component of the

[23]The firm-wage premium is computed as the weighted average of gender-specific wage premiums.

gender wage premium gap partly reflect women's systematic concentration in firms offering shorter hours and lower wage premiums.[24]

6. Understanding the Pay-Setting Component

If women's labor supply is less responsive than men's — leading to fewer outside options and a weaker bargaining position — then the firm-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) does firm productivity affect pay-setting? We study these predictions below.

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

Figure 5 shows how the pay-setting component varies with firm-level wage premiums across countries.[25] There is a clear pattern: in all countries except Germany, the pay-setting component increases significantly with the firm's average wage premium, with elasticities ranging from approximately 0.1 to 0.3.

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

[24] Given the substantial cross-country variation in the sorting component, this Section raises the question of whether countries differ primarily in the allocation of workers across different types of firms or in the underlying dispersion of firm wage premiums. We explore this relationship and decompose their relative importance in Appendix B.

[25] We define the average firm-level premium as the weighted average of gender-specific wage premiums.

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.[26]

First, we estimate $\gamma_1 = \pi^F/\pi^M$, the relative rent-sharing parameter, which captures the share of male rent-sharing received by women. To study if firm productivity affects pay-setting, we estimate $\delta_1 = \pi^M - \pi^F$.[27]

Figure 6, panel A, 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.

Figure 6, panel B, shows the how differential rent-sharing relates to the pay-setting component, δ_1. 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 productivity increases.

[26] Defined as $S^*_{J(i,t)} = \max\{0, S^o_{J(i,t)} - \tau\}$ where $S^*_{J(i,t)}$ is the firm-level productivity per worker and τ is the country-specific threshold estimated in Equation 3.

[27] We estimate the relative rent-sharing parameter γ_1 via IV using firm productivity as an instrument: $\psi^F_{J(i,t)} = \gamma_0 + \gamma_1 \hat{\psi}^M_{J(i,t)} + e_{J(i,t)}$. For the direct contribution parameter δ_1, we regress 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.

7. Additional Analyses and Robustness

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 2020). 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 7 contrasts the sorting component of our baseline sample, which includes only private-sector jobs, with the results obtained when all jobs are included.[28] The results show a clear and consistent pattern: the sorting component increases in all countries except Norway and the Netherlands when public-sector and nonprofit jobs are included. This increase is substantial. In Finland, France, Hungary, and Denmark, the sorting component ranges from close to zero to two log points in the private-sector sample, but increases to between two and five log points when all jobs are considered. The increases are large in relative terms: for example, in France the role of sorting increases from about 8 to 26%. These findings suggest that studies focusing exclusively on private-sector jobs likely underestimate the true extent of gender-based sorting across types of firms.

7.2. Robustness Checks

Alternative Decomposition. Figure A6 presents the results of an alternative CCK decomposition. In this alternative decomposition, the pay-setting effect is estimated using the

[28] We focus on the sorting component because, in the public sector, our preferred normalization based on productivity data is not feasible, which makes obtaining reliable estimates of the pay-setting component difficult for this extended sample.

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 A9 reports the firm effect gap where for each country, we normalize firm effects using the exit-rate normalization described in Section 3.3. By and large, we obtain similar results to those in Figure 1.

Different Sample Cuts and Econometric Specifications. In most countries, the data covers a ten-year panel of the entire private-sector workforce. However, in some cases, the data include 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 effect estimates, especially for firms with few job transitions. Figure A8 presents the sorting and pay-setting effects for a restricted sample of workers employed in firms with at least ten gender-specific movers. This restriction ensures that firm effects are estimated from a substantial number of worker transitions, thereby reducing potential measurement error. However, it is important to note that this this sample creates a more selected sample that may be less representative of the population studied. As in Figure 1, Panel A reports the gender wage gap against the gender wage premium gap. With the exception of Denmark, all countries still fall within the 10–40 percent range. Panel B 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, as the sorting component increases from

0.4 to 2.3 log points. This sample reveals more variation in the pay-setting component. While most countries have similar estimates to the baseline, Hungary, Denmark, Italy, and Portugal display significant reductions.[29]

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.[30] Figure A10 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. We also perform the same analysis incorporating broad occupational groups, following Casarico and Lattanzio (2024). In both cases, the results remain nearly identical, suggesting that our findings are robust to the inclusion of additional worker controls.

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 crucial role in explaining both the level and cross-country variation in gender wage gaps. Firm-specific wage premiums account for 15–32% 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.

[29] Figure A7 shows that the sorting component remains similar when focusing on the sample with productivity data (VA sample). Since the sorting estimate for Norway differs, the analysis uses the dual-connected (DC) sample instead.

[30] 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.

Despite this heterogeneity, robust patterns emerge across countries. The sorting component intensifies over the life cycle. Women's concentration in firms with high part-time incidence partly explains this sorting, as these firms offer systematically lower wage premiums. For the pay-setting component, we find that disparities are concentrated in high-wage firms where women receive only 89% of the rent-sharing benefits that men receive from firm productivity gains. By and large, our results support the notion that convexity in the returns to hours worked is a meaningful driver of the gender wage gap (Goldin 2014). Women value more flexible jobs and forego higher pay.

Taken together, our findings underscore the unequal role that firms play in shaping gender wage inequality. While traditional explanations such as human capital differences and occupational segregation remain relevant, firm-specific wage premiums emerge as a crucial factor in explaining persistent gender pay gaps. Our results suggest that policies aimed at reducing gender wage disparities should consider not only differences in bargaining power and wage-setting practices within firms but also the broader structural forces that shape gendered sorting across the firm wage distribution. Our findings highlight the need for future research on the mechanisms underlying firm-specific wage premiums, the role of labor market institutions in mitigating gender disparities, and the broader implications of firm pay policies for gender inequality.

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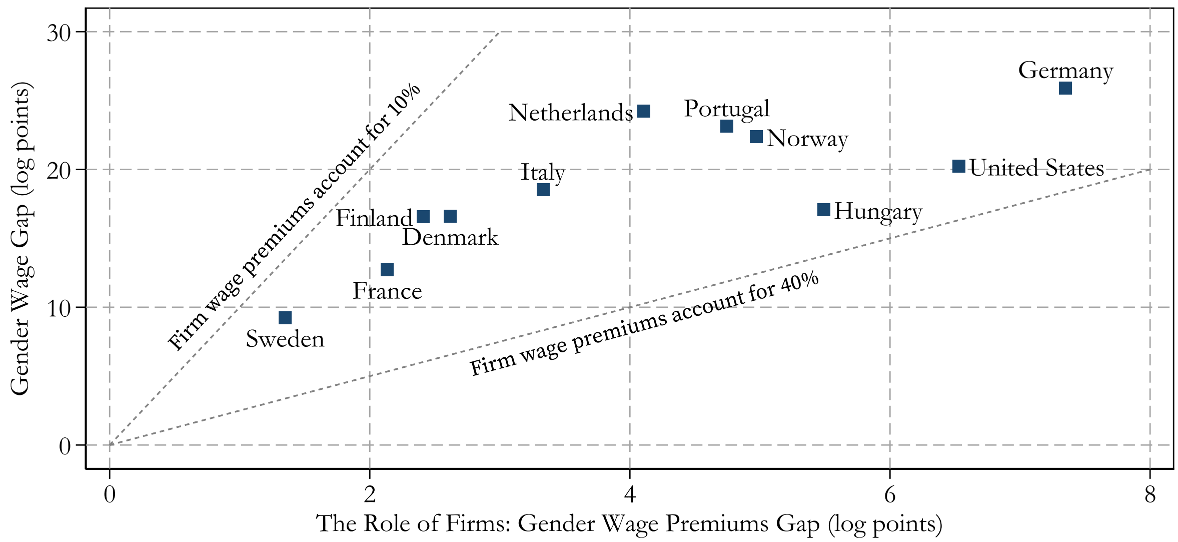
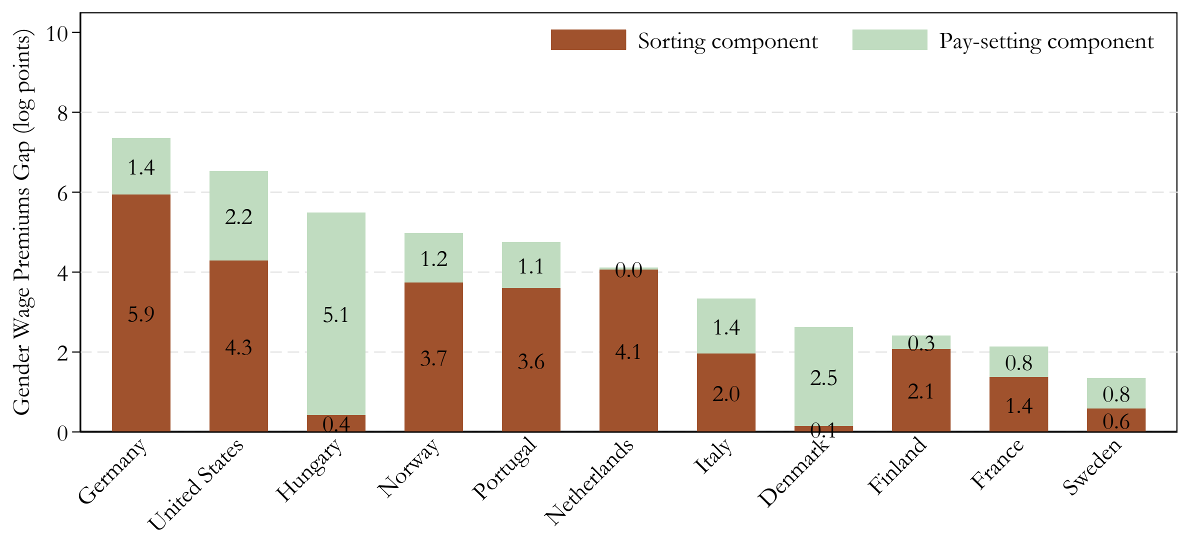
Figures and Tables

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

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

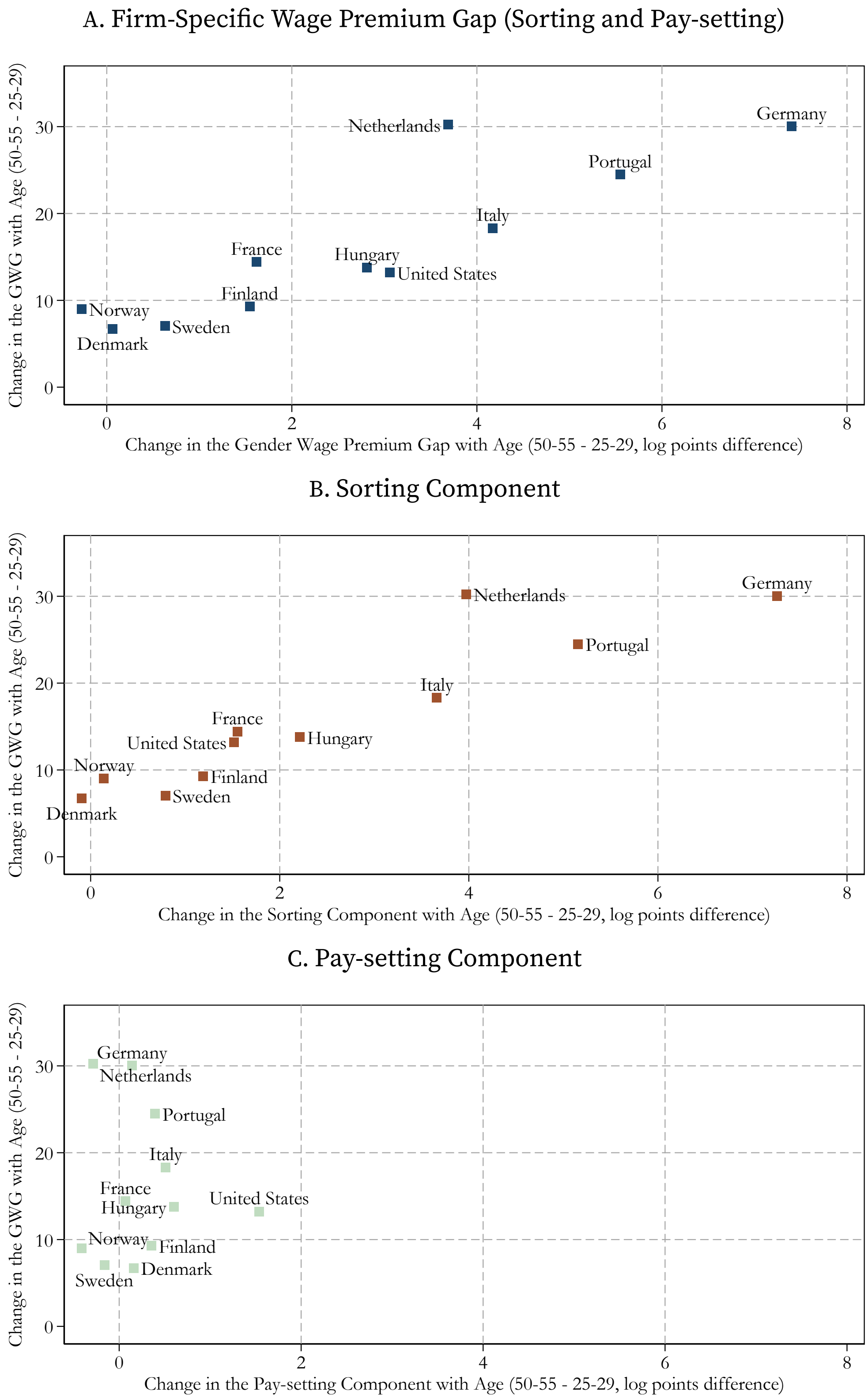


B. Decomposing the Gender Wage Premium Gap: Sorting vs Pay-setting



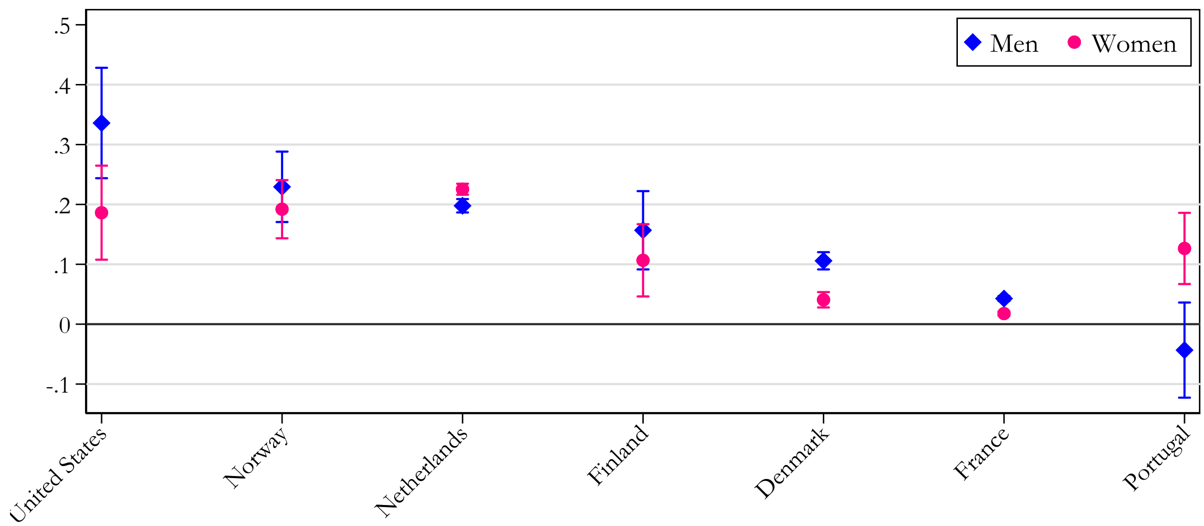
Notes: In Panel A, the y-axis shows the unconditional gender wage gap in log points in our main analysis sample. The x-axis displays the firm wage premium gap, calculated as the sum of sorting and pay-setting components. The diagonal lines represent scenarios where firm wage premiums account for 10% (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). For most countries (Denmark, Finland, France, Hungary, Italy, Portugal, and Sweden), we normalize the firm effects using a set of low-productivity firms, and for other countries we normalize using high-exit rate firms. The samples in Finland, the U.S., and Sweden are re-weighted based on worker characteristics to account for their sampling designs. See text for details.

FIGURE 2. Gender Wage Gap and Its Components Over the Life Cycle



Notes: The y-axis reports the difference between the gender wage gap for workers aged 50–55 and workers aged 25–29. The x-scale in panel A reports the difference between the firm-specific wage premium gap for the same age groups. The x-scale in panel B reports the sorting component and the x-axis in panel C reports the pay-setting component.

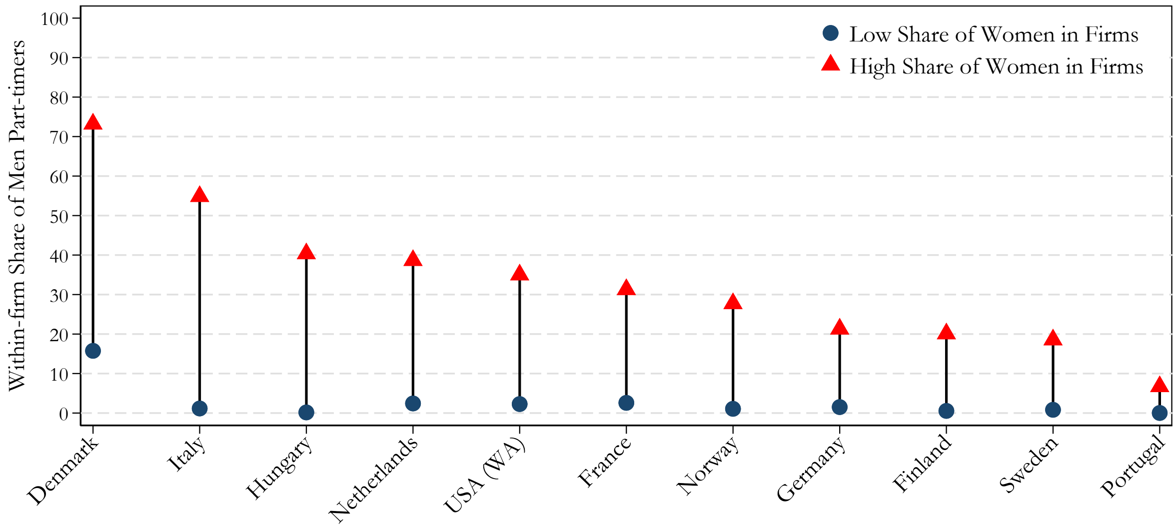
FIGURE 3. Elasticity of Firm-Wage Premiums with Respect to Firm-Hour Policies



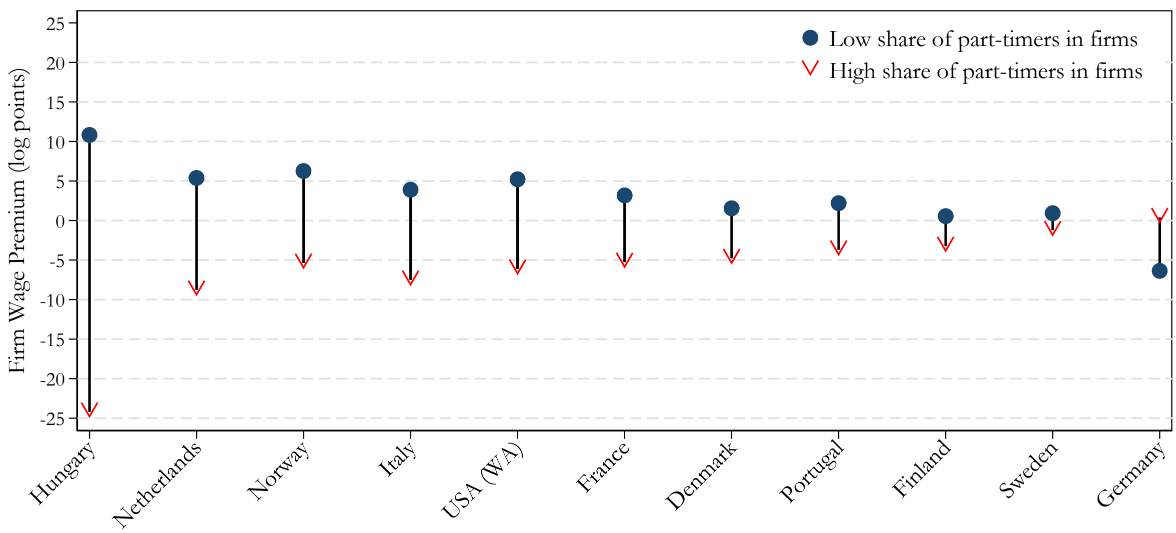
Notes: The figure plots the elasticity of firm-wage premiums with respect to firm-hour policies, estimated by an AKM model for hours, separately by gender. Each point represents the coefficient β_g from a firm-level regression. See Section 5.2. Vertical bars indicate 95% confidence intervals with standard errors clustered at the firm level. The analysis is restricted to countries where paid work hours are available.

FIGURE 4. Part Time Jobs and Firm Wage Premiums

A. Part-time Jobs and Female Employment

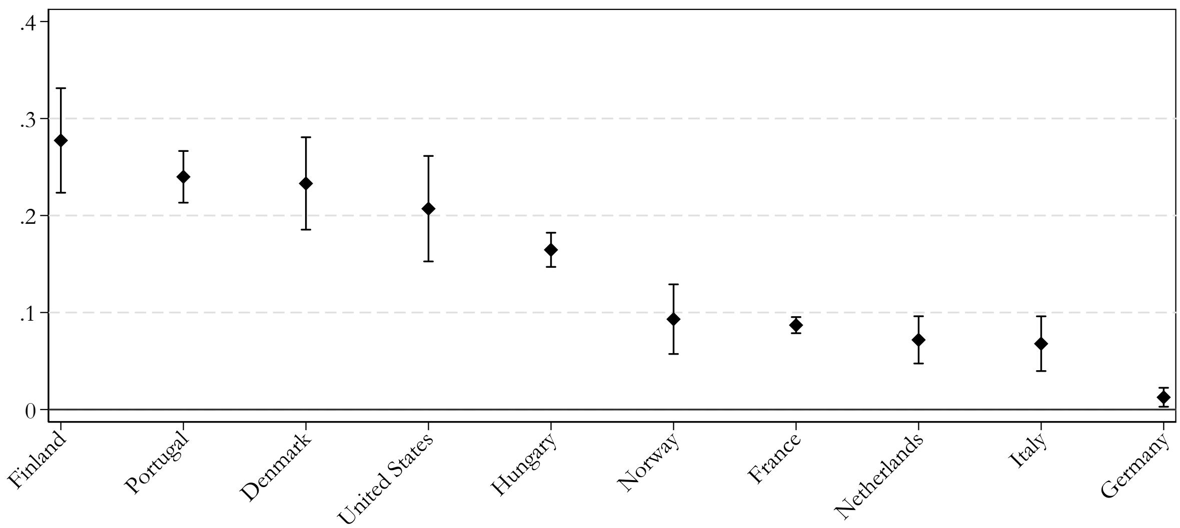


B. Part-time Jobs and Firm Wage Premiums



Notes: Panel A plots the share of part-time workers (men and women) for the lowest and highest terciles based on the share of women in their workforce. Women are disproportionately employed in firms with high part-time incidence in all countries. As shown in the Appendix, this pattern is not driven by the gender composition of part-timers within those firms. Panel B shows the average firm wage premium, with firms sorted into the lowest and highest terciles based on their share of part-time workers.

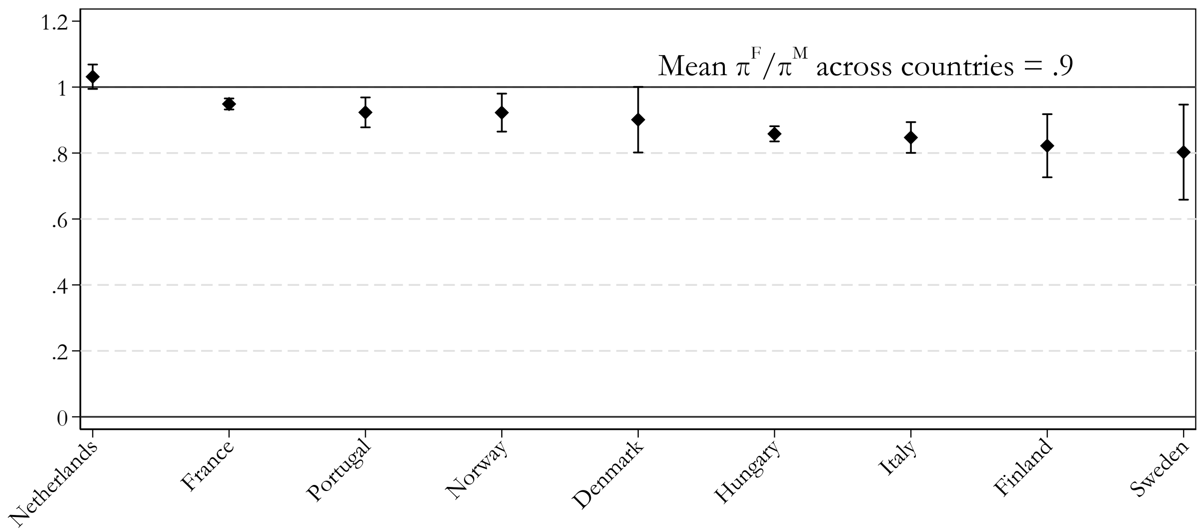
FIGURE 5. Pay-Setting Response to Average Wage Premiums



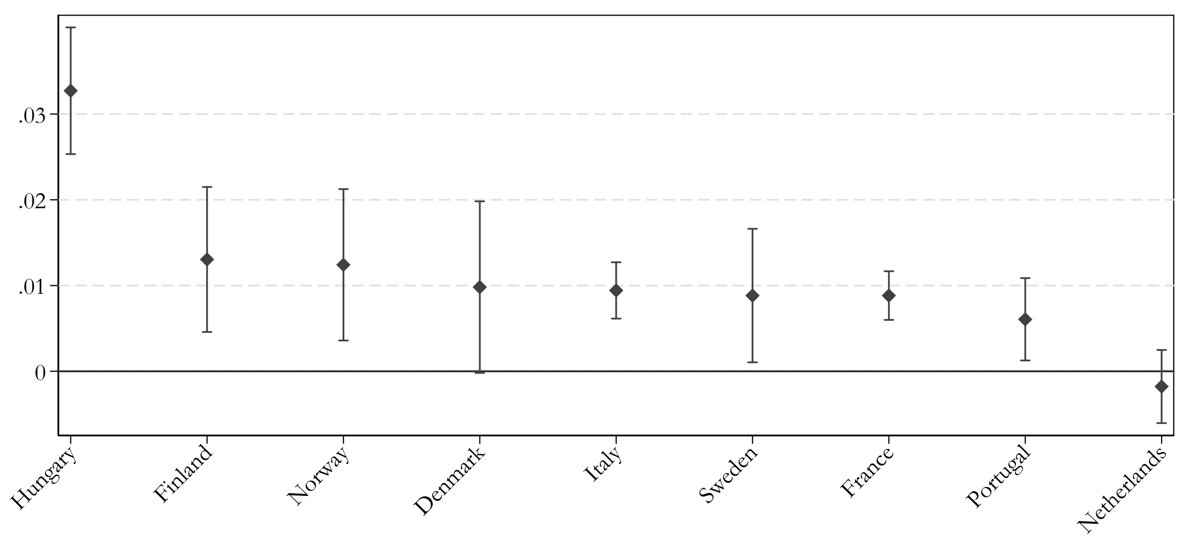
Notes: The figure shows coefficients from firm-level regressions where the dependent variable is the pay-setting component (defined as the difference between male and female wage premiums) and the independent variable is the firm's weighted average wage premium. Regressions are weighted by male employment at the firm level. The coefficients represent the percentage point change in the pay-setting component associated with a 1% increase in the average wage premium. Standard errors are clustered at the firm level.

FIGURE 6. Rent Sharing of Firm-Wage Premiums Across Countries

A. The Share of Male Rent-Sharing Captured by Women (%)

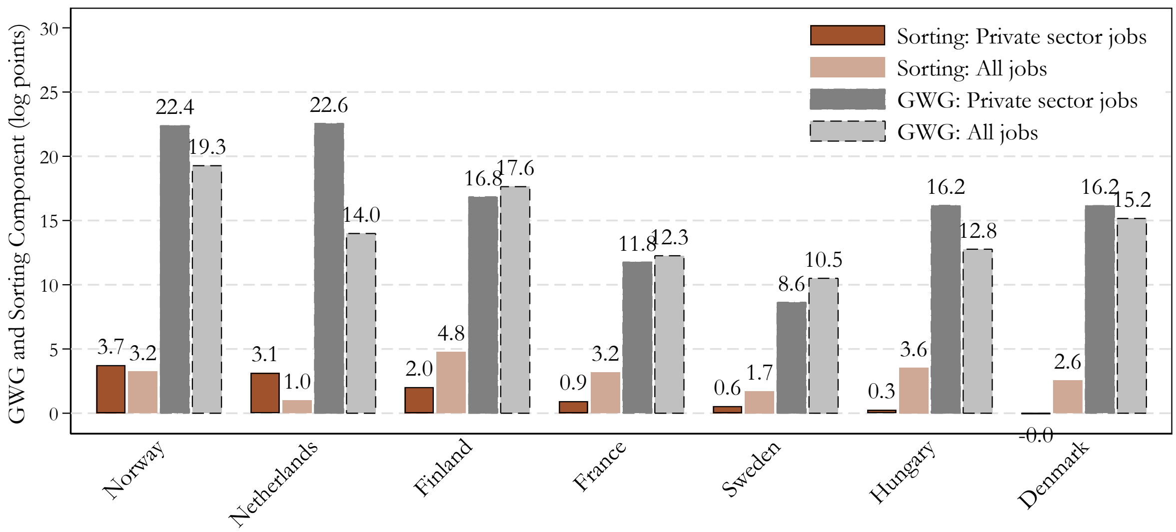


B. Direct Contribution to the Pay-Setting Component (ppt)



Notes: Panel A reports $\gamma_1 = \pi^F/\pi^M$, the relative rent-sharing parameter, which captures the share of male rent-sharing received by women. Panel B reports $\delta_1 = \pi^M - \pi^F$, the direct contribution of differential rent-sharing to the pay-setting component. π^F and π^M are estimated from a regression where the dependent variable is the gender-specific firm wage premium and the independent variable is the net surplus (defined as the max between the firm-level productivity per worker and the country-specific normalization threshold). Both regressions include a constant and are estimated at the firm level (weighted at the person-year level).

FIGURE 7. Gender Wage Gap and Sorting in Private Sector Jobs versus All Jobs



Notes: This figure compares the sorting component of the gender wage premium gap and the gender wage gap between private-sector jobs only (the baseline sample) and all jobs (including the public sector and non-profit organizations) across countries. Countries are ordered from left to right based on the magnitude of their private-sector sorting component, from highest to lowest. Only countries with representative information on the public sector 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)	.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)	.9 (7.1)	Industry	No
Bruns (2019)	W. Germany	Daily	24.7	6.4 (25.9)	6.3 (25.4)	.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 (2025)	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) Estimate AKM model including the public sector, and focuses on private sector with information on value added. (b) Normalizes only small firms in low-surplus industry (Hotel and Restaurant).

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	No	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	Yes	No	No	No	Yes	Yes	Yes	Yes
Occupation	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Employer Information											
Labor productivity	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: P = Payroll-based hours; C = Contractual hours. The reference period spans 2010–2019 for most countries, except for Germany and the U.S. (Washington state) (2010–2014). While most countries have comprehensive job coverage of private sector jobs, the data from the U.S., Sweden, Finland, Italy, and Hungary cover approximately 50% of jobs. 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. 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 US. In Germany, productivity data is available for about 3 percent of person-year observations. In Sweden, the sample overrepresents workers employed in large firms.

TABLE 3. Summary Statistics

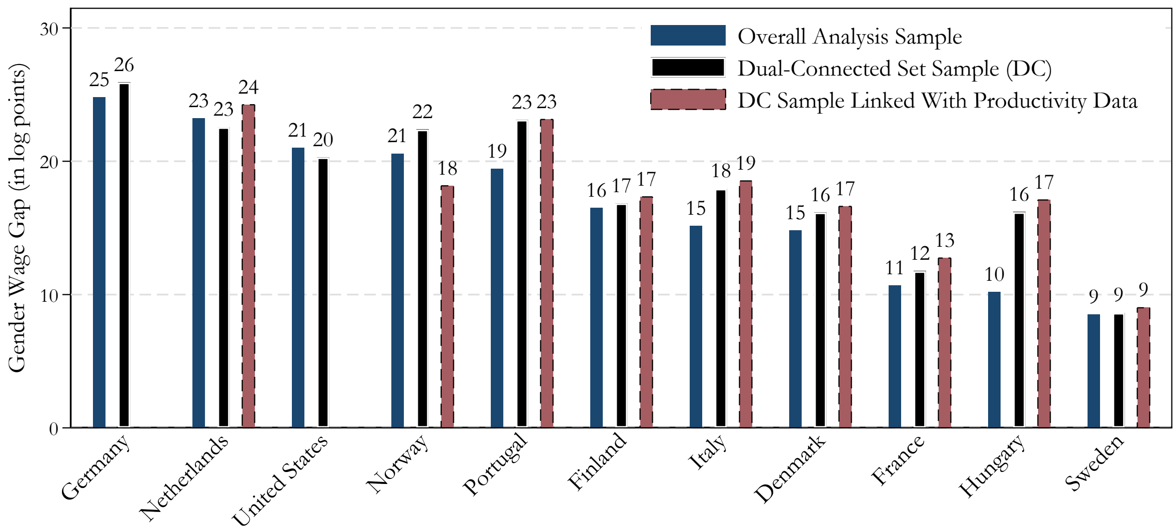
		Log Hourly Wage	Age	Part-time (%)	Separation (%)	Firm Size	Movers per Firm	Obs with VA (%)	Person/Yr Obs	N of workers	N of firms
USA	Male	3.00 (0.54)	39.46	11.56	30.85	120	19	NA	1.06	350.47	17.25
	Female	2.80 (0.53)	39.79	18.00	32.82	125	11	NA	0.61	207.15	17.25
DEU	Male	3.05 (0.57)	40.81	7.09	19.96	45	26	3.86	38.59	10438.87	426.20
	Female	2.79 (0.54)	40.66	31.81	22.95	45	14	2.10	21.75	6336.21	426.20
DNK	Male	3.44 (0.41)	40.59	25.92	27.66	36	41	82.61	4.58	930.03	59.26
	Female	3.27 (0.35)	40.35	32.01	26.75	40	23	79.80	2.70	567.42	59.26
FIN	Male	3.04 (0.36)	40.17	4.40	22.42	140	100	93.19	2.58	526.47	9.04
	Female	2.87 (0.34)	40.28	15.24	25.99	138	65	86.84	1.63	361.12	9.04
FRA	Male	2.90 (0.46)	39.38	12.68	27.79	42	54	92.58	65.62	14849.45	548.85
	Female	2.79 (0.43)	38.94	29.60	29.56	43	33	88.14	42.17	10549.49	548.85
HUN	Male	6.84 (0.64)	38.85	5.24	26.56	44	24	90.11	2.90	640.06	56.91
	Female	6.67 (0.57)	39.52	11.33	28.65	46	18	90.23	2.26	522.59	56.91
ITA	Male	2.67 (0.45)	40.71	10.35	22.03	25	33	87.53	24.49	4050.51	376.27
	Female	2.49 (0.40)	40.02	41.09	24.29	26	23	85.09	15.83	2712.56	376.27
NLD	Male	3.05 (0.51)	39.95	11.59	24.79	62	61	82.19	19.32	3306.77	176.87
	Female	2.82 (0.44)	39.21	50.59	27.33	67	37	76.48	11.47	2180.42	176.87
NOR	Male	3.25 (0.46)	39.84	8.47	21.94	45	53	84.63	6.56	1130.21	62.71
	Female	3.03 (0.46)	40.01	26.62	23.85	51	33	59.66	5.01	961.04	62.71
PRT	Male	1.96 (0.58)	39.34	1.73	23.62	33	33	99.51	7.53	1483.40	92.98
	Female	1.73 (0.53)	38.93	6.37	25.20	34	24	99.37	5.69	1146.84	92.98
SWE	Male	3.11 (0.35)	40.59	5.72	23.18	304	169	88.63	3.93	904.82	6.53
	Female	3.03 (0.32)	40.05	22.13	27.51	307	95	83.37	2.19	547.84	6.53

Notes: The table presents summary statistics of the main analysis sample for each countries. Workers are classified as part-time if they work less than 30 hours per week. The separation rate shows the percentage of workers who leave their firms between consecutive years. Mean firm size represents the raw count of employees per firm without weighting by workforce size. The last three columns are scaled: person-year observations are in millions, while the number of workers and firms are in thousands.

Appendix

A. Additional Figures and Tables

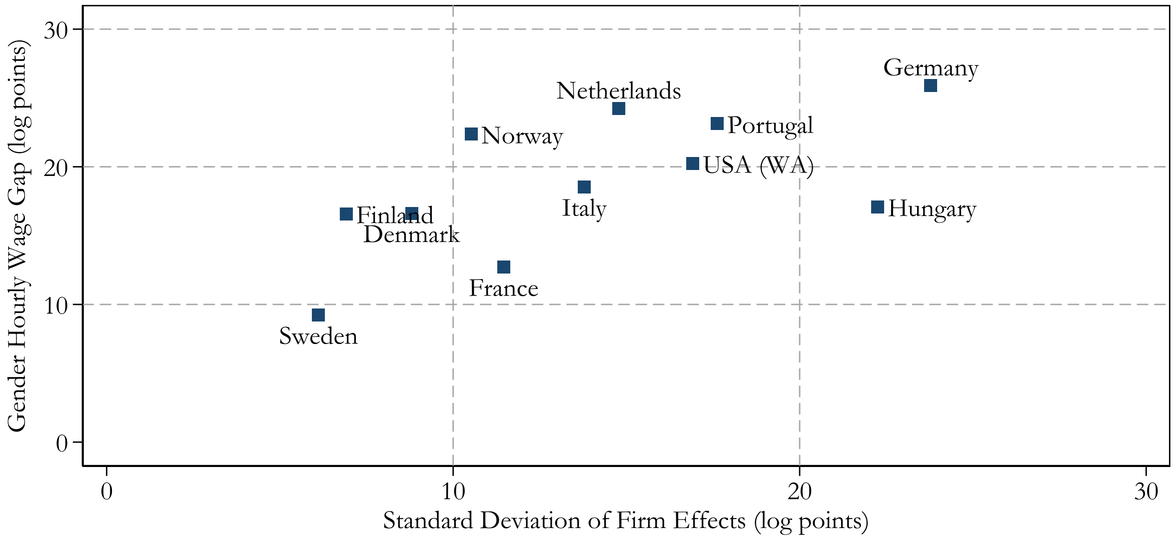
FIGURE A.1. The Gender Wage Gap Across Countries
Unconditional Gender Wage Gap For Various Samples



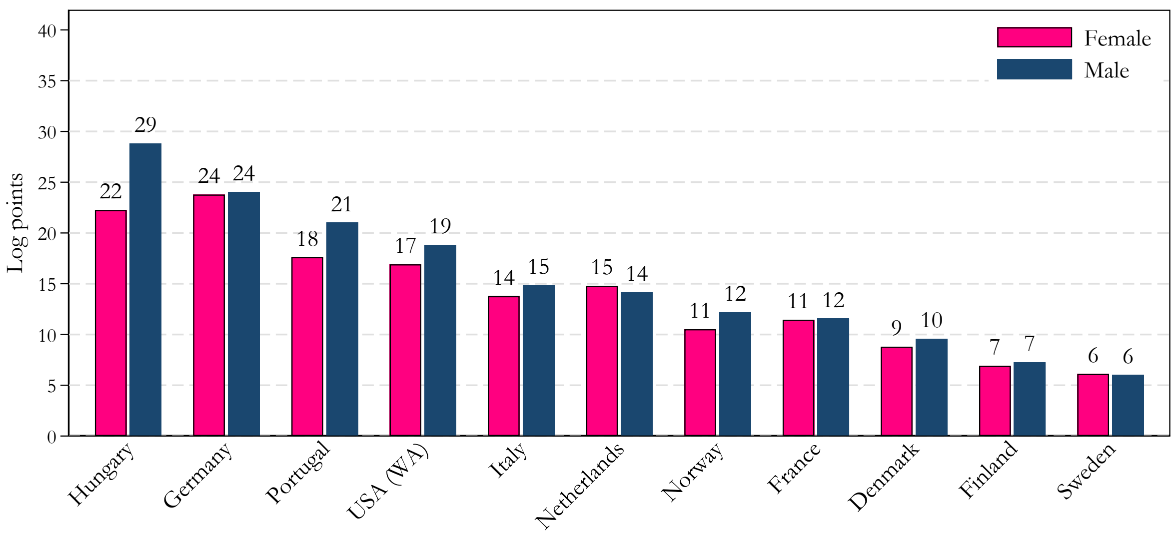
Notes: Overall analysis sample includes paid workers aged 25-55 employed in the private sector. Wages are measured in real (2015 = 100) euros per hour. The gender wage gap is calculated across country-person-year observations. See the text for details.

FIGURE A.2. The Role of Firms in Wage Inequality Across Countries

Panel (a) Gender Wage Gap and Firm-Wage Effects Across Countries

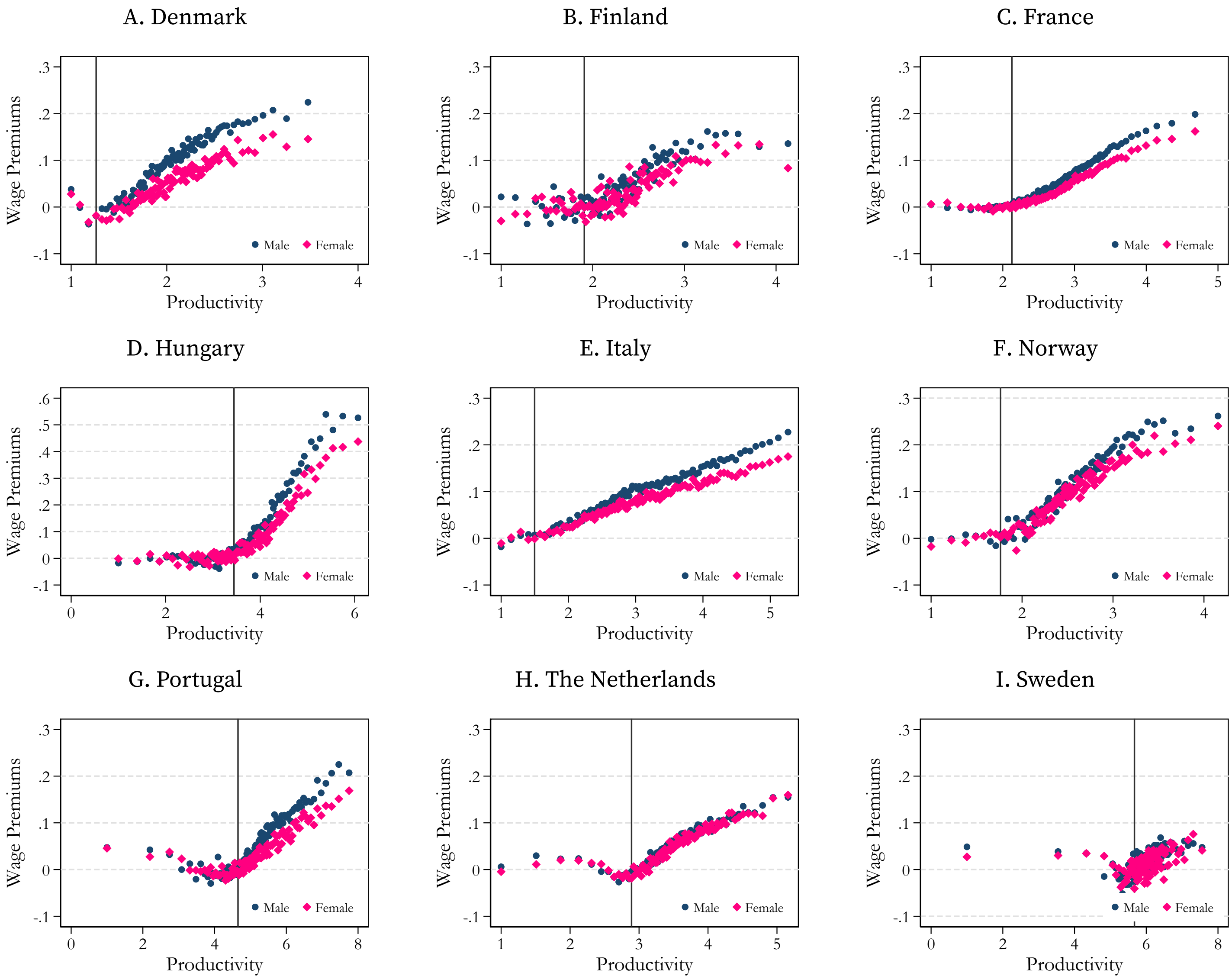


Panel (b) Firm Effects Standard Deviations



Notes: Panel A plots the gender wage gap in main analysis sample against the standard deviation of firm wage effects of female workers. We estimate firm wage premiums by estimating Equation (1) separately by gender for each country. Standard deviations of firm effects are biased-corrected using either the Kline, Saggio and Sølvsten (2020) or Babet, Godechot and Palladino (2025) methods. We bias-correct by leaving entire worker-firm matches out (i.e., spell level). Panel B plots the standard deviation by gender. The samples in Sweden and Finland oversample large firms. See the text for details.

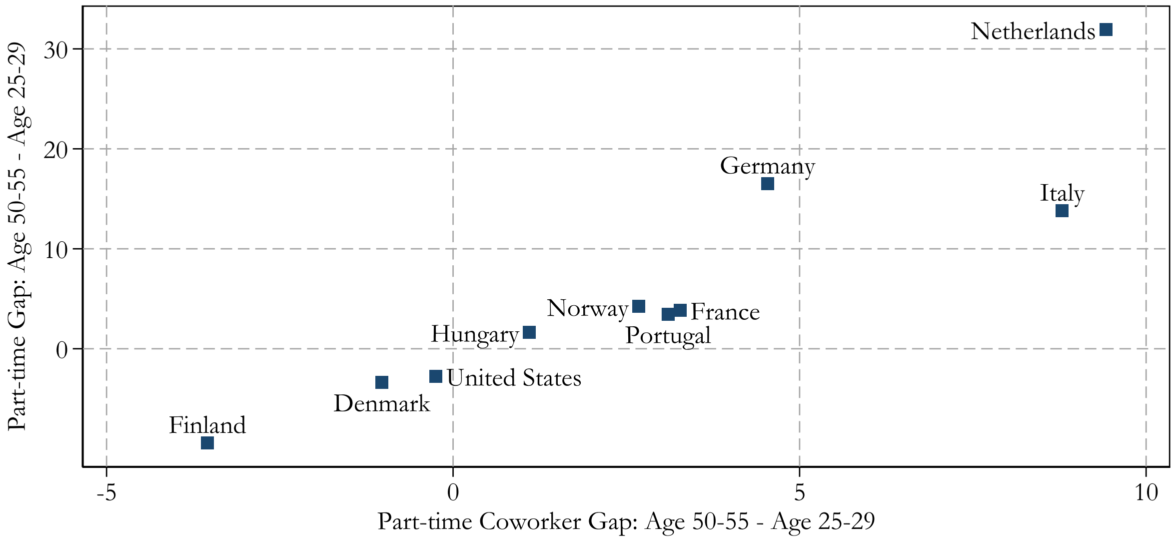
FIGURE A3. Firm Wage Premiums versus Productivity Across Countries



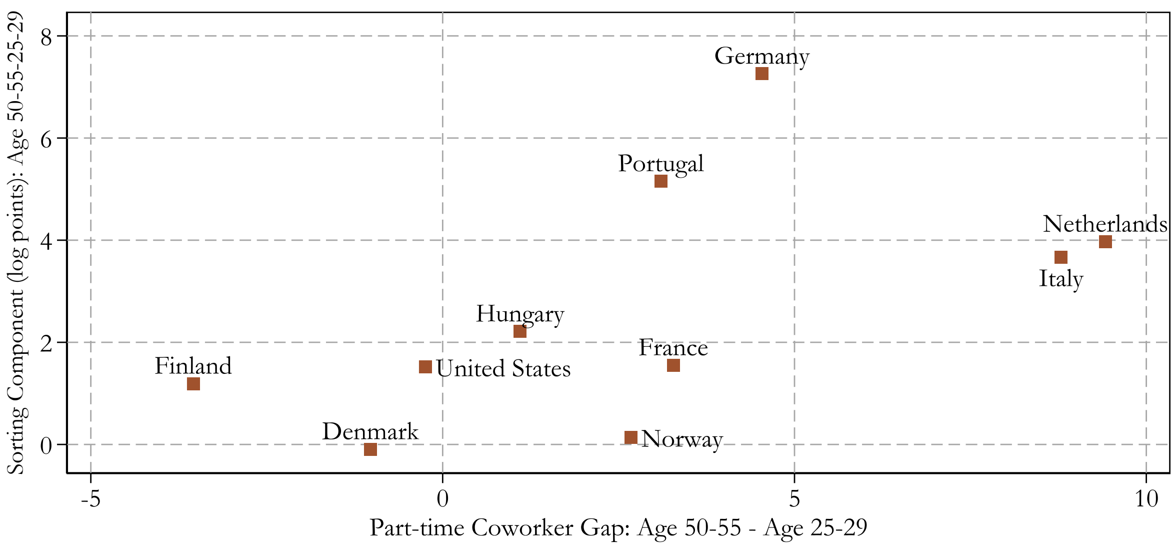
Notes: The figures represent the relationship between gender-specific firm wage premiums effects (arbitrary normalization) and firm-level productivity. Specifically, the points shown represent mean estimated firm wage premiums from the AKM models for men and women averaged across firms with 100 percentile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

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

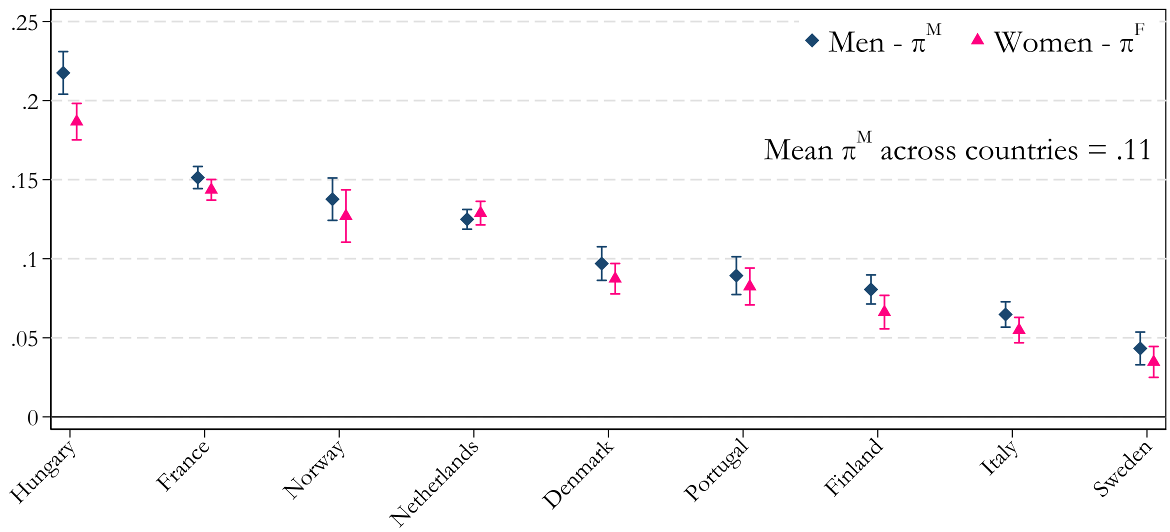


B. Sorting of Women to Low-Wage Firms and Part-time Workplaces Over the Life Cycle



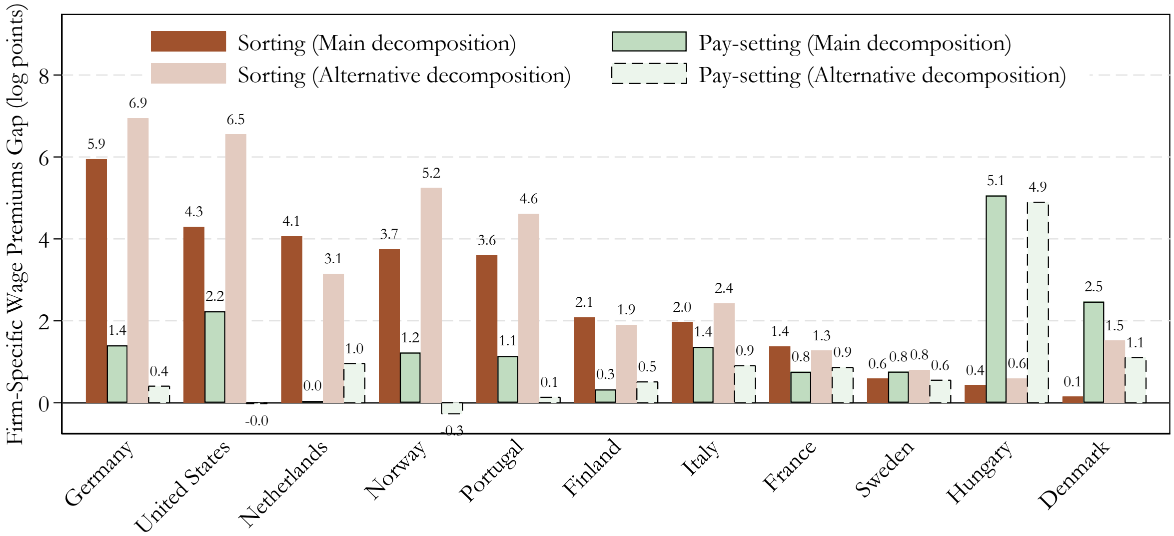
Notes: Panel A reports, on the y-axis, the difference in the prevalence of part-time jobs between workers aged 50–55 and those aged 25–29. On the x-axis, it shows the difference in the percentage of coworkers working part-time between the same age groups. Panel B reports, on the y-axis, the CCK component for the same age groups.

FIGURE A5. The Productivity Pass-Through to Wage Premiums



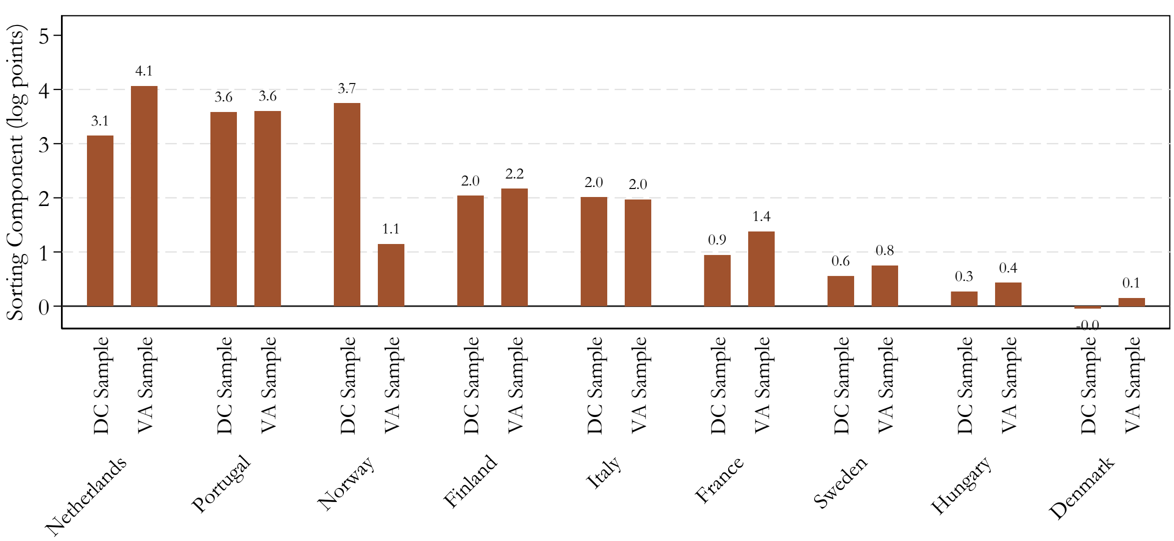
Notes: Panel A reports the elasticity of firm-level productivity to male and female wage premiums. The male and female models include a constant and are estimated at the firm level (weighted at the person-year level).

FIGURE A6. Gender Wage Premium Gap: Alternative Decomposition



Notes: The figure reports the alternative decomposition of the sorting and pay-setting components. The pay- setting effect is calculated using the distribution of jobs held by women, and the sorting effect is calculated by comparing the average value of the male wage premiums 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.

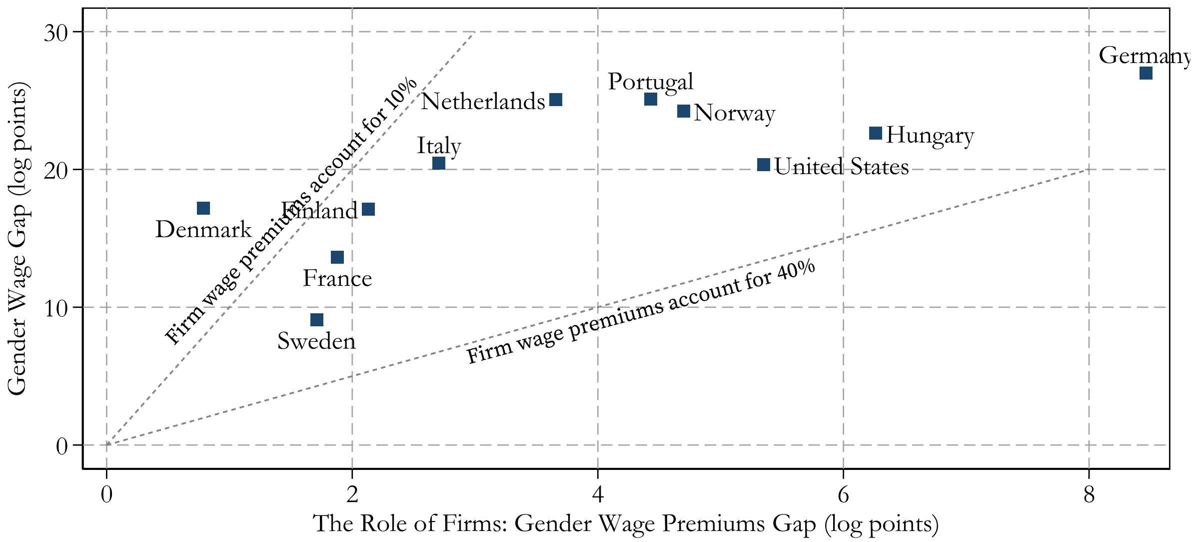
FIGURE A7. Sorting Component for the Sample With and Without Productivity



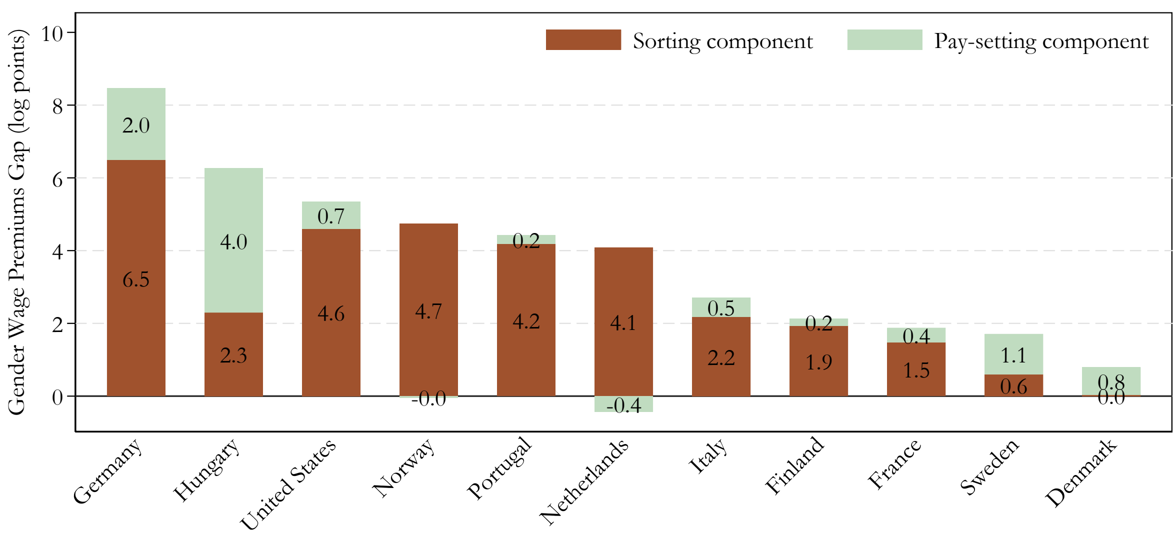
Notes: This figure compares the sorting component of the CCK decomposition for samples with and without value-added data.

FIGURE A8. Sample of Firms With at Least 10 Movers by Gender

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



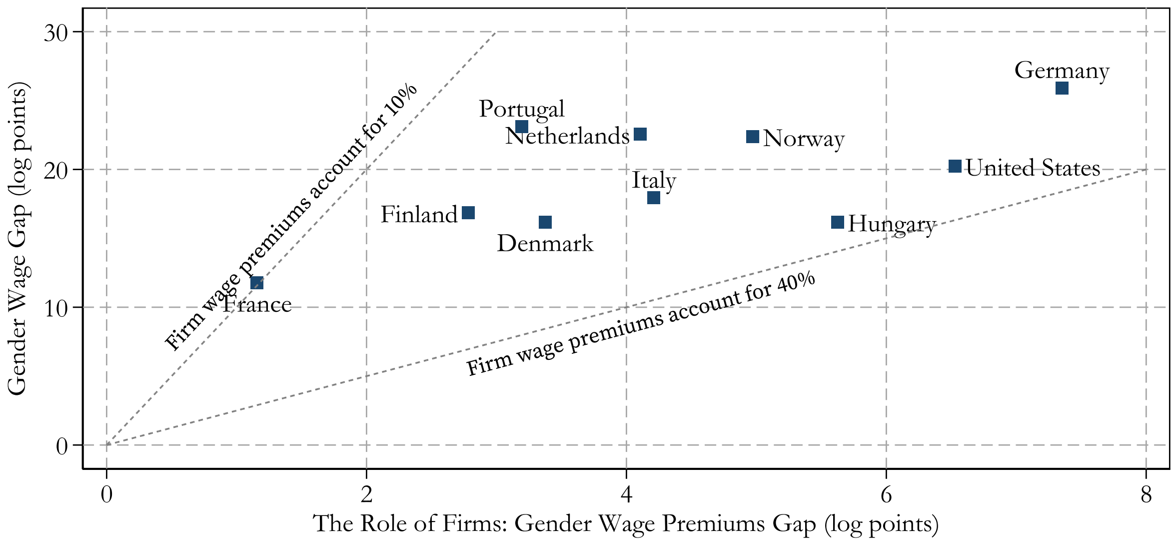
B. Decomposing the Gender Wage Premium Gap: Sorting vs Pay-setting



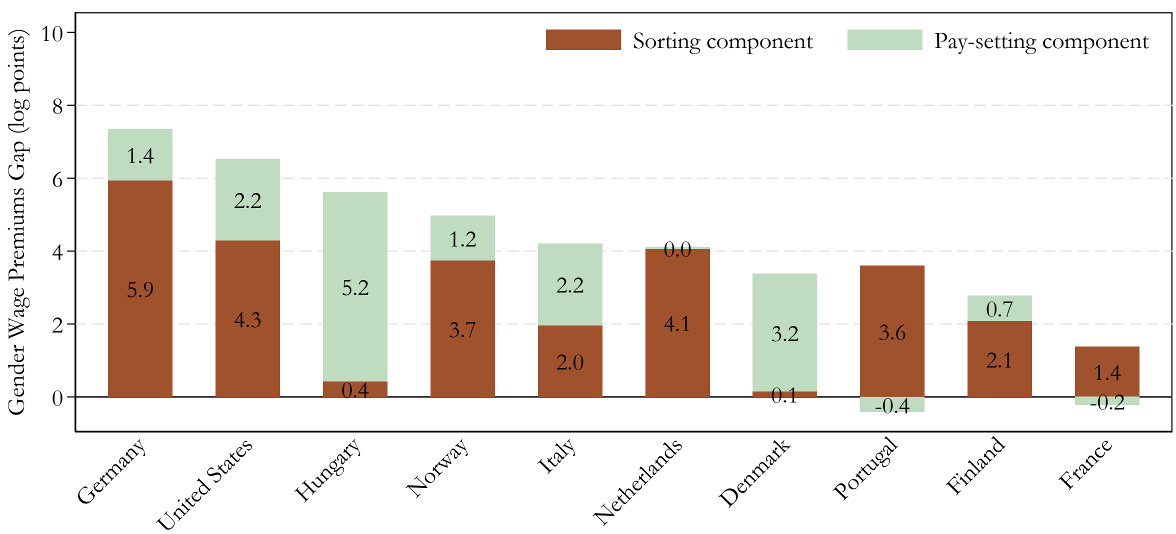
Notes: In Panel A, the y-axis shows the unconditional gender wage gap in log points in our main analysis sample. The x-axis displays the firm wage premium gap, calculated as the sum of sorting and pay-setting components. The diagonal lines represent scenarios where firm wage premiums account for 10% (top line) and 40% (bottom line) of the total gender wage gap. In Panel B, we decompose the gender wage premium gap into sorting and pay-setting components following Equation (2). For most countries (Denmark, Finland, France, Hungary, Italy, Portugal, and Sweden), we normalize the firm effects using a set of low-productivity firms, and for other countries we normalize using high-exit rate firms. The samples in Finland, the U.S., and Sweden are re-weighted based on worker characteristics to account for their sampling designs. See text for details.

FIGURE A9. High-Exit Rate Normalization for All Countries

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

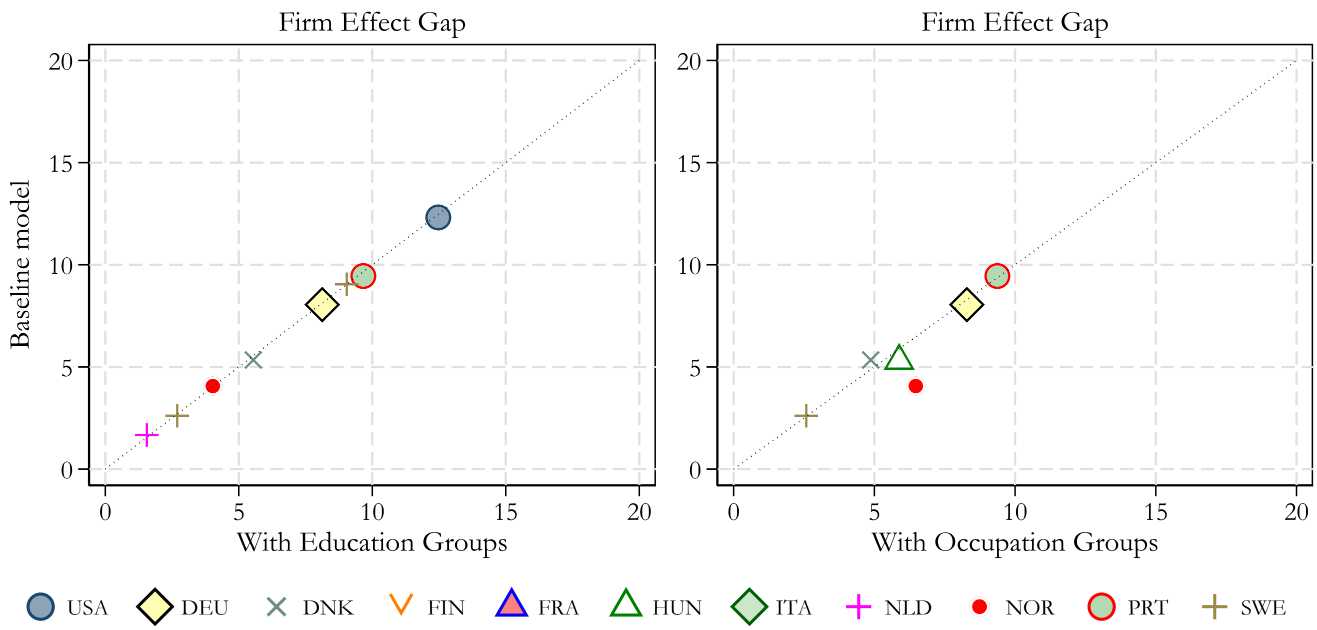


B. Decomposing the Gender Wage Premium Gap: Sorting vs Pay-setting



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. In Panel B, we decompose the gender wage premium gap into sorting and pay-setting components following Equation (2). We normalize firm effects by selecting the bottom ten percent 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. See text for details.

FIGURE A10. Gender Wage Premiums Gap: Model specification



Notes: The figure reports the firm wage premium gap using education groups and occupation groups in the AKM model.

B. Explaining Variation in the Sorting Component: Gender Allocation or Wage Premiums Dispersion?

As documented in Section 4.1, the sorting component ranges widely, from close to zero in Denmark to six log points in Germany. We explore the extent to which these differences arise from two channels: (1) differences in the allocation of men and women across firms' wage premiums (i.e., gender segregation across firms) and (2) differences in the dispersion of firms' wage premiums (i.e., the difference in premiums offered by high- and low-wage firms).[31] Since greater dispersion in firm wage premiums creates stronger incentives for sorting into different types of firms, these channels are likely interconnected. Figure A11 illustrates visually these two channels. Panel A plots the difference between the share of women and men employed in each quintile of the firm wage premium distribution.[32] In countries like Norway and Germany, women are overrepresented in low-paying firms and underrepresented in high-paying firms, with a gap of more than 12 and 8 percentage points in the top quintile respectively. By contrast, Denmark shows almost no gender imbalance across quintiles, consistent with its near-zero sorting component. Panel B shows the average firm wage premium by quintile. Dispersion is especially large in countries like Germany and Hungary, where the gap between the bottom and top quintiles exceeds 80 log points, compared to only 20 log points in Finland and Sweden.

To quantify the relative importance of these channels, we implement a percentile-based decomposition. We first divide firms into 100 percentiles based on their wage premiums (Ψ^F), assuming no differential sorting of males and females within percentiles. For each percentile p, we compute the share of female and male employed in that percentile relative to total female and male employment (S^F and S^M) and average

[31] Throughout this section, we consistently use female wage premiums in accordance with the baseline decomposition in Equation 2

[32] For each quintile i, we compute $(F_i/F - M_i/M) \times 100$, where F and M denote total female and male employment, respectively.

wage premiums. Each country *c*'s deviation from a benchmark can then be written as:

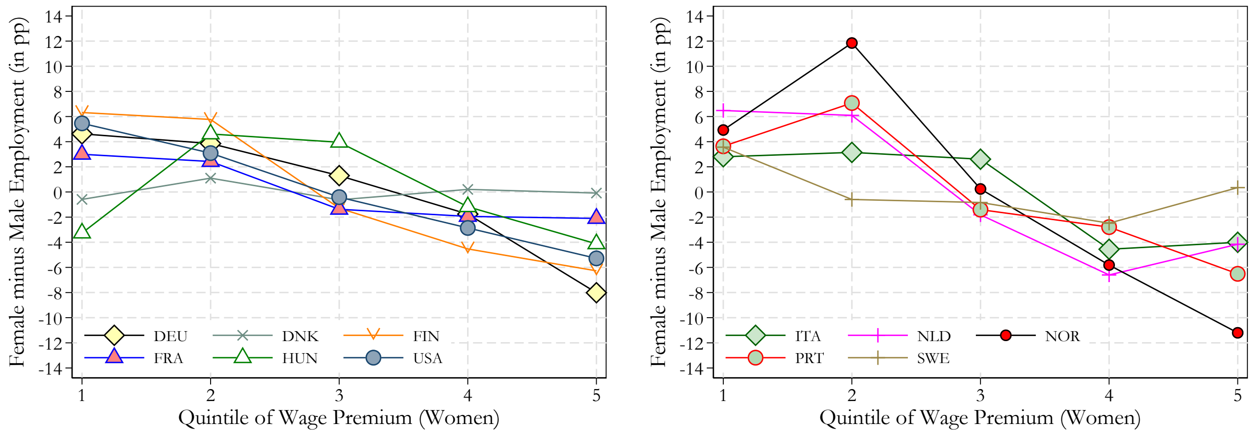
$$\underbrace{\sum_{p=1}^{100} S_{p,c} \cdot \Psi^F_{p,c} - \sum_{p=1}^{100} S_{p,\mathrm{b}} \cdot \Psi^F_{p,\mathrm{b}}}_{\text{Total Difference}} = \underbrace{\sum_{p=1}^{100} (S_{p,c} - S_{p,\mathrm{b}}) \cdot \Psi^F_{p,\mathrm{b}}}_{\text{Allocation}} + \underbrace{\sum_{p=1}^{100} (\Psi^F_{p,c} - \Psi^F_{p,\mathrm{b}}) \cdot S_{p,c}}_{\text{Dispersion}} \tag{A.1}$$

where $S_p = S^M_p - S^F_p$. As is common in Kitagawa-Oaxaca-Blinder decompositions an alternative formulation is possible, using different base periods for each component. In this case, since there is no prior as to which would work best *a priori*, we compute both versions and use their average as our baseline estimate. Figure A12 shows the results of decomposing the sorting component of the gender wage premium gap into two channels. Panel A uses Denmark — the country with the lowest observed sorting component — as the benchmark. For each country, we decompose the difference in the sorting component relative to Denmark into the gender allocation component and the dispersion component. Then, we sum the absolute value of each component across countries to measure their relative importance. Using Denmark as the benchmark, the gender allocation channel accounts for 79% of the total absolute variation, while dispersion explains the remaining 21%. Panel B repeats the decomposition, but uses the average sorting component across countries as the benchmark instead of Denmark. In this case, the dispersion component plays a larger role, accounting for 39% of the variation. This shift is expected because Denmark does not have the flattest firm wage premium distribution in the sample. Thus, comparing other countries to Denmark minimizes the role of dispersion by construction. Nevertheless, even under this more neutral benchmark, the gender allocation channel remains the dominant factor, explaining 61% of the absolute cross-country variation.

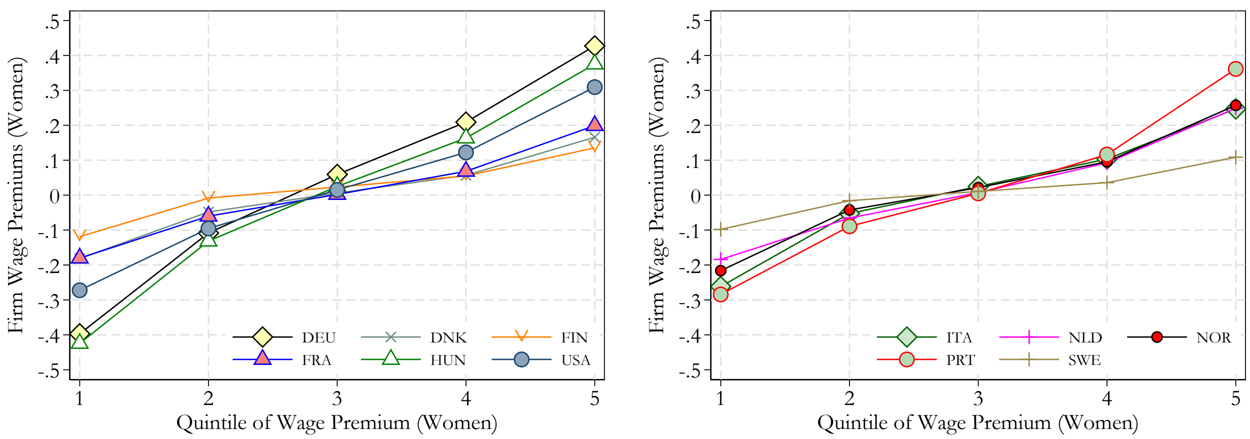
Together, these results suggest that cross-country differences in the sorting component are primarily driven by the segregation of men and women across different types of firms. However, the difference in how much high-paying firms pay relative to low-paying ones can amplify the effect of gender segregation. In countries with more dispersed firm wage premiums, similar levels of gender segregation result in significantly larger contributions to the gender wage gap from the sorting component.

FIGURE A11. Gender Allocation and Firm Wage Premium Dispersion

A. Gender Allocation Across Deciles of Firm Wage Premium



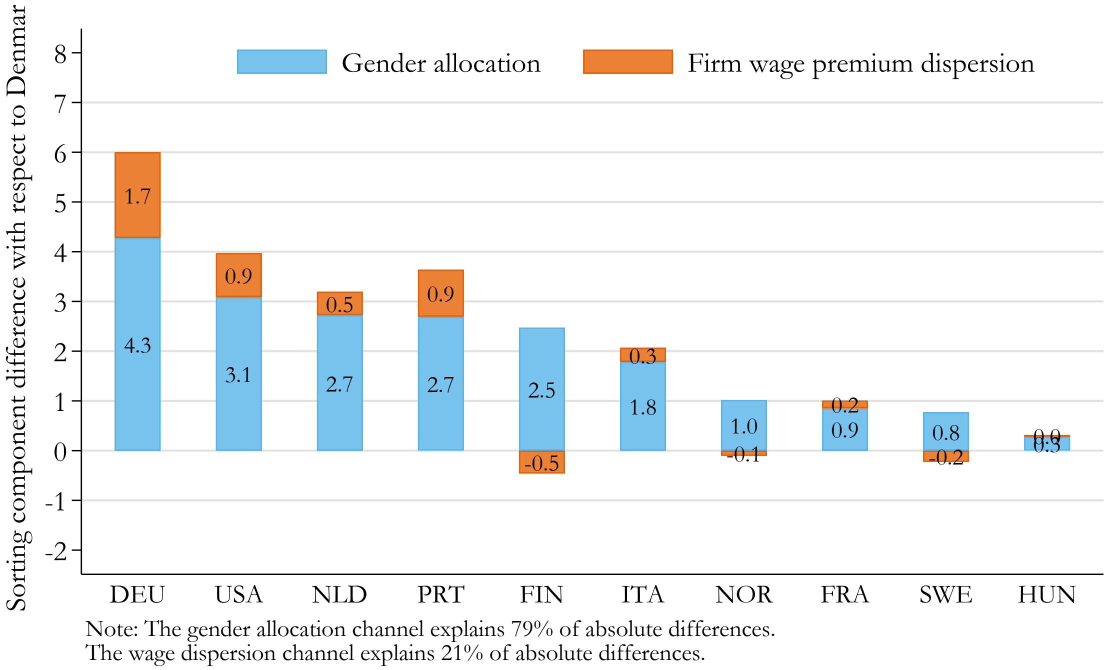
B. Firm Wage Wage Premium Dispersion



Notes: The top panel plots the relative gender composition of employment across rankings of firm wage effects (deciles of female firm fixed effects). For each firm wage decile, it shows the difference between the share of female employment and male employment (normalized by total gender employment). The bottom panel shows the average firm fixed effect by quintile for women.

FIGURE A12. Decomposition of the Sorting Component of the Gender Wage Gap

A. Using a given country as benchmark



Notes: The figure plots the Kitagawa-Oaxaca-Blinder (KOB) decomposition of the sorting component of the gender wage gap for each country with respect to a base category. Panel A uses as base category Denmark, the country with the lowest sorting component (0.1 log point). The KOB decomposition split the difference with respect to the category into a gender allocation and a firm wage premium dispersion components. The KOB decomposition can be performed by fixing gender allocation or firm wage premiums at the reference level. This figure reports the average of the two decompositions. See equation A.1 and text for details.

C. Comparing Unweighted and Weighted Results

C.1. United States: Washington state

To assess the bias due to this potentially selected sample, we create weights from the 2013 Current Population Survey (CPS) Outgoing Rotation Group in order to make the Washington state data representative of the U.S. workforce. 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.[33] 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.

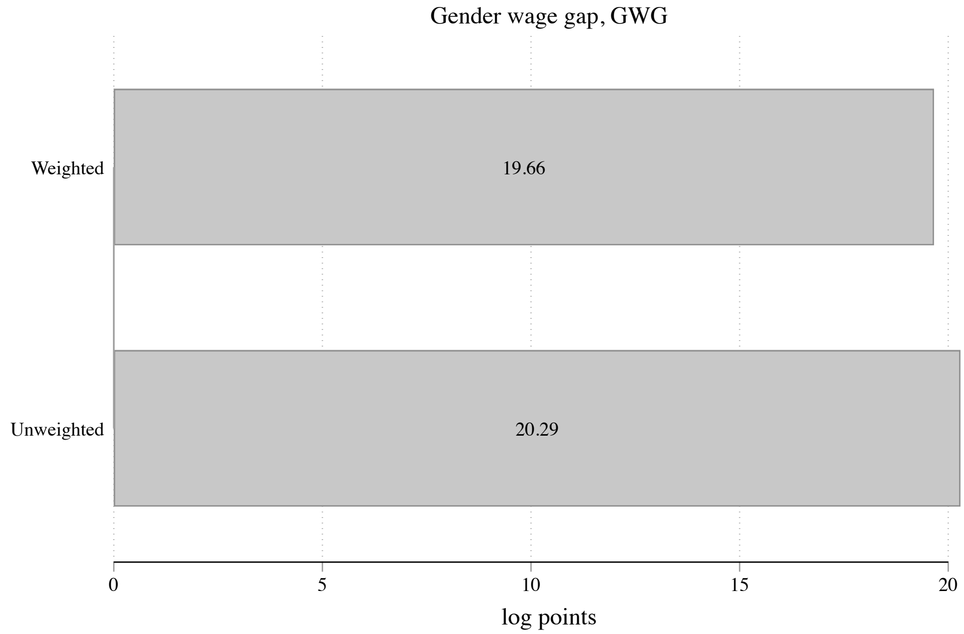
In practice,result from unweighted data are very similar to their reweighed counterparts. For example, Figure A13, Panel A, shows that the weighted gender wage gap is slightly smaller (19.66%) compared to the unweighted gap (20.29%).

Figure A13, Panel B, shows that the sorting effect accounts for about 21.5% of the unweighted gender wage gender gap. When weighted, the sorting effect accounts for about 19.3% of the gender wage gender gap.

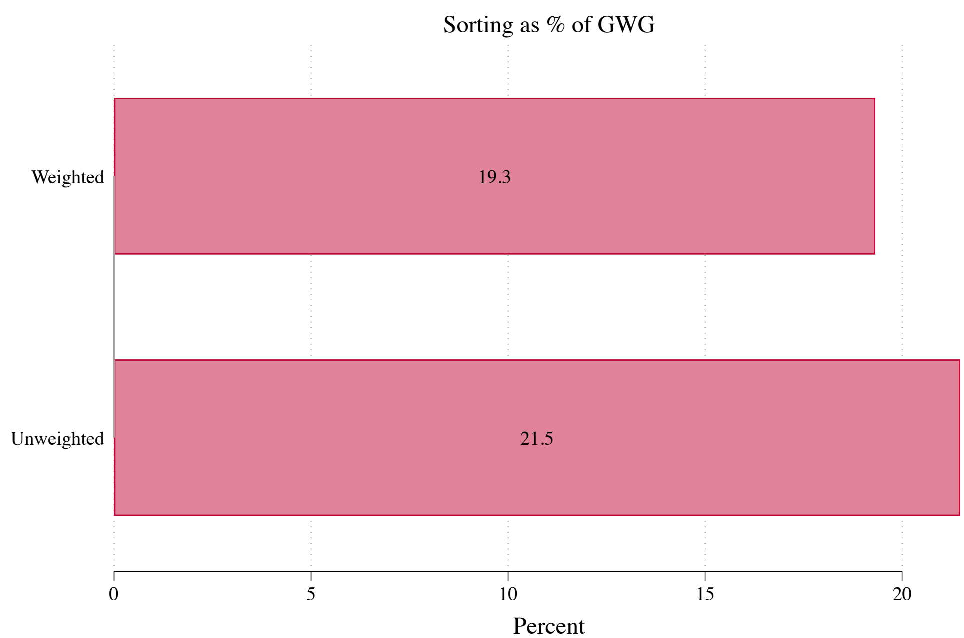
[33]When doing this, we use the associated CPS household weights.

FIGURE A13. 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 weighed result use weights calculated from the CPS. See Appendix for details.

C.2. Sweden

Throughout the paper, we use WSS data as we are interested in hourly wages. As noted above, the WSS data oversamples large firms. To determine whether the sampling weights effectively make the WSS sample representative of the population, we take two steps. First, we present summary statistics using these sampling weights and compare it to the full population sample. Second, to gauge the potential bias arising from a selected sample of firms, we produce both weighted and unweighted CCK decomposition results.

Table A.1 presents summary statistics across the two samples: the full population sample, and the WSS sample (unweighted versus weighted in columns 2 and 3, respectively). Overall, weighting makes sample statistics to be remarkably close to the full population sample. In the full sample, the monthly earnings gap is 21%, whereas in the WSS is around 20%.[34] Although the earnings levels differ somewhat, the gender earnings gap is similar across samples. Once we incorporate firm-level sampling weights, both the earnings level and the gender earnings gap become comparable to those in the full population. As expected, mean firm size and movers per firm is notably larger in the unweighted WSS sample. Once sampling probabilities are accounted for, mean firm size gets remarkably closer to firm size in the full population. Monthly earnings gap, age, firm size, movers per firm, fraction females at firms all look very similar to the full population sample when we use weights. This indicates that weighting compensates for the overrepresentation of large firms in the WSS data.

Table A.2 reports the main CCK decomposition for weighted and unweighted versions of the sample. The gender hourly wage gap, the contribution of the firm effects to the gap, and the CCK decomposition of unweighted data are very similar to their reweighted counterparts. For example, the weighted gender wage gap is slightly larger (9.23%) compared to the unweighted gap (9.01%). Total contribution of firm components is slightly larger for the unweighted. The sorting effect accounts for about 8.5% of the unweighted firm-wage gender gap (and pay-setting for about 10%, making the total contribution of firm effect sum to 18.5%). When weighted, the sorting effect accounts for about 6.4% of the firm-wage gender gap (and pay-setting for 8.2%, making the total contribution of firm effect sum to 14.6%).

[34] Since hourly wages are not observable in the full population sample, we provide monthly earnings gap.

TABLE A.1. Descriptive statistics of the Swedish Data, 2010-2018

	Full population sample		Sample with hourly wage info **Unweighted**		Sample with hourly wage info **Weighted**	
	Men	Women	Men	Women	Men	Women
Gender earnings gap	-0.21		-0.20		-0.20	
Log monthly earnings	8.11	7.89	8.21	8.01	8.16	7.96
Mean age	39.9	39.4	40.6	40.1	40.1	39.9
Mean firm size	24.5	32.0	224.1	242.8	25.6	32.3
Movers per firm	29.4	18.7	97.1	59.9	39.2	23.8
Mean log VA/worker	11.1	11.0	11.3	11.2	11.2	11.2
Fraction females at firms	0.25	0.50	0.29	0.47	0.25	0.50
Number person-year obs.	10611095	5235547	4017199	2223040	4017199	2223040
Number of persons	1833459	1028690	943759	562211	943759.0	562211
Number of firms	190857	142681	11620	10417	11620	10417

Notes: This table reports descriptive statistics for the Swedish matched employer–employee data over 2010–2018 under three alternative samples. The first, "Full population sample," includes all private-sector worker–firm observations. The second, "Sample with hourly wage info, unweighted," restricts to jobs for which hourly wages are observed but does not apply any sampling weights. The third, "Sample with hourly wage info, weighted," uses the same restriction on observed hourly wages and applies firm sampling weights to recover population-representative figures. Within each sample, the columns labeled "Men" and "Women" show gender-specific means of the following measures: the gender earnings gap, the log of gross monthly earnings (in SEK), worker age, firm size, movers per firm, the log of firm value added per worker, and the fraction of female employees at the firm. The final three rows report the total counts of person-year observations, unique persons, and unique firms in each sample.

TABLE A.2. Main CCK decomposition in the Swedish data for with and without firm sampling weights, 2010-2018

	Unweighted	**Weighted**
Gender Wage Gap	9.01	9.23
Means of Firm Premiums		
Male Premium among Men	0.044	0.035
Female Premium among Women	0.027	0.021
Total Contribution of Firms Components	1.67	1.35
%	18.5	14.6
Decompositions of Contribution of Firm Components		
Sorting		
Using Male Effects	0.77	0.59
%	8.53	6.40
Using Female Effects	0.85	0.80
%	9.40	8.67
Pay-setting		
Using Male Distribution	0.90	0.76
%	9.95	8.24
Using Female Distribution	0.82	0.55
%	9.08	5.97

Notes: This table presents the CCK decomposition in Swedish private-sector data with and without firm-level sampling weights. Column (1) reports results from the unweighted sample; Column (2) applies firm sampling weights to recover population-representative estimates. Gender wage gap shows the unconditional log-point difference in mean hourly wages. Means of Firm Premiums reports the average firm-specific wage effect for men and for women. Total Contribution of Firm Components is the sum of the sorting and pay-setting components. In the Sorting block, "Using Male Effects" (resp. "Using Female Effects") is the log-point gap explained by workers' sorting when applying the male (resp. female) firm-premium estimates to both genders. In the Pay-setting block, "Using Male Distribution" (resp. "Using Female Distribution") is the log-point contribution of within-firm pay-setting differences given the male (resp. female) distribution of workers across firms. The following "%" row expresses each contribution as a share of the overall gap.

D. Descriptive Statistics For Various Samples By Country

TABLE A.3. Descriptive Statistics in the Washington Administrative Data, 2001-2014

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.98	2.77	3.00	2.80	.	.
Std. dev.	0.53	0.52	0.54	0.53	.	.
Mean age	39	39	39	39	.	.
Part-time (%)	14	20	11	17	.	.
Separation (%)	31	33	30	32	.	.
Mean firm size	43	56	119	124	.	.
Movers per firm	7	4	18	11	.	.
Mean log VA/worker	0.00	0.00	0.00	0.00	.	.
Fraction females at firms	0.24	0.55	0.29	0.50	.	.
Social care sector	0.00	0.00	0.00	0.00	.	.
Number person-year obs.	1,465,309	766,738	1,064,690	612,622	.	.
Number of persons	464,506	257,079	350,469	207,147	.	.
Number of firms	71,012	52,893	17,246	17,246	.	.

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.96	2.75	2.97	2.78	.	.
Std. dev.	0.52	0.49	0.53	0.49	.	.
Mean age	39	39	39	39	.	.
Part-time (%)	15	22	12	20	.	.
Separation (%)	31	32	31	31	.	.
Mean firm size	53	57	133	137	.	.
Movers per firm	7	6	18	14	.	.
Mean log VA/worker	0.00	0.00	0.00	0.00	.	.
Fraction females at firms	0.27	0.62	0.32	0.57	.	.
Social care sector	0.10	0.33	0.13	0.32	.	.
Number person-year obs.	1,721,201	1,232,020	1,314,732	992,794	.	.
Number of persons	536,817	389,269	426,253	321,062	.	.
Number of firms	84,317	79,133	23,910	23,910	.	.

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour. The social care sector includes include public administration, education, human health activities, residential care activities and Social work activities without accommodation (i.e NACE code 84 to 88).

TABLE A.4. Descriptive Statistics in the German IAB 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	23	19	22	.	.
Mean firm size	19	19	45	45	.	.
Movers per firm	10	6	25	14	.	.
Mean log VA/worker	11.29	11.14	11.32	11.17	.	.
Fraction females at firms	0.24	0.58	0.27	0.52	.	.
Social care sector	0.00	0.00	0.00	0.00	.	.
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	.	.

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.97	2.74	3.04	2.80	.	.
Std. dev.	0.57	0.51	0.57	0.51	.	.
Mean age	40	41	40	40	.	.
Part-time (%)	8	37	7	34	.	.
Separation (%)	20	22	20	22	.	.
Mean firm size	20	18	45	44	.	.
Movers per firm	10	7	22	16	.	.
Mean log VA/worker	11.28	11.01	11.30	11.04	.	.
Fraction females at firms	0.27	0.66	0.30	0.60	.	.
Social care sector	0.06	0.29	0.07	0.28	.	.
Number person-year obs.	53,936,510	43,042,328	42,865,380	32,515,468	.	.
Number of persons	14,275,701	12,077,096	11,551,797	9,290,901	.	.
Number of firms	1,639,380	1,813,237	542,283	542,283	.	.

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour. The social care sector includes include public administration, education, human health activities, residential care activities and Social work activities without accommodation (i.e NACE code 84 to 88).

TABLE A.5. Descriptive Statistics in the 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	3.27	3.42	3.26
Std. dev.	0.40	0.36	0.41	0.35	0.39	0.35
Mean age	40	40	40	40	40	40
Part-time (%)	27	33	25	32	25	32
Separation (%)	28	27	27	26	30	29
Mean firm size	18	25	36	39	42	47
Movers per firm	18	13	41	23	39	21
Mean log VA/worker	11.32	11.30	11.34	11.32	11.34	11.32
Fraction females at firms	0.26	0.51	0.30	0.49	0.29	0.48
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
Number person-year obs.	5,513,301	2,997,736	4,581,129	2,698,865	3,784,425	2,153,791
Number of persons	1,061,348	626,533	930,026	567,421	846,657	504,013
Number of firms	169,372	114,603	59,257	59,257	47,008	46,254
	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.39	3.25	3.41	3.25	3.42	3.26
Std. dev.	0.39	0.31	0.39	0.30	0.39	0.35
Mean age	40	40	40	40	40	40
Part-time (%)	28	31	26	30	25	32
Separation (%)	27	23	26	23	30	29
Mean firm size	27	34	49	53	39	43
Movers per firm	21	25	43	42	35	19
Mean log VA/worker	11.32	11.30	11.34	11.32	11.34	11.32
Fraction females at firms	0.34	0.66	0.38	0.64	0.29	0.48
Social care sector	0.21	0.55	0.23	0.57	0.00	0.00
Number person-year obs.	7,205,081	7,188,861	6,351,049	6,779,244	3,893,770	2,191,938
Number of persons	1,307,802	1,247,303	1,200,522	1,194,530	866,601	514,744
Number of firms	190,521	143,987	80,122	80,122	53,213	52,256

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.6. Descriptive Statistics in the Finnish Administrative Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.03	2.87	3.04	2.87	3.03	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	16
Separation (%)	23	26	22	25	22	26
Mean firm size	80	86	139	138	139	138
Movers per firm	39	31	99	64	91	52
Mean log VA/worker	11.17	10.94	11.18	10.96	11.18	10.96
Fraction females at firms	0.27	0.57	0.28	0.55	0.27	0.54
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
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

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.02	2.85	3.03	2.85	3.02	2.84
Std. dev.	0.36	0.32	0.36	0.32	0.35	0.34
Mean age	40	41	40	41	40	40
Part-time (%)	4	12	4	12	4	15
Separation (%)	23	24	22	23	23	27
Mean firm size	116	115	180	174	128	126
Movers per firm	42	62	90	120	77	48
Mean log VA/worker	11.16	10.91	11.17	10.93	11.17	10.93
Fraction females at firms	0.37	0.71	0.39	0.71	0.28	0.57
Social care sector	0.23	0.61	0.24	0.62	0.01	0.10
Number person-year obs.	3,656,129	4,768,551	3,495,641	4,624,910	2,465,597	1,610,131
Number of persons	765,501	946,334	711,843	911,767	526,607	390,258
Number of firms	30,075	27,625	13,535	13,535	10,366	10,368

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.7. Descriptive Statistics in the 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
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
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

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.90	2.79	2.93	2.81	2.93	2.81
Std. dev.	0.46	0.39	0.46	0.39	0.47	0.43
Mean age	39	40	39	39	39	38
Part-time (%)	14	30	14	28	14	28
Separation (%)	29	26	28	26	31	32
Mean firm size	27	29	63	64	52	53
Movers per firm	9	9	24	22	22	14
Mean log VA/worker	4.50	4.34	4.59	4.38	4.59	4.38
Fraction females at firms	0.34	0.64	0.38	0.62	0.31	0.54
Social care sector	0.19	0.45	0.22	0.48	0.02	0.09
Number person-year obs.	39,758,505	37,667,337	33,635,520	33,340,390	24,494,556	16,486,098
Number of persons	14,336,036	13,237,298	12,124,020	11,756,204	9,297,592	6,602,822
Number of firms	1,245,419	1,136,655	416,386	416,386	321,130	320,714

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.8. Descriptive Statistics in the 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	28	26	28	27	29
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
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
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

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	6.72	6.64	6.82	6.70	6.83	6.67
Std. dev.	0.62	0.53	0.62	0.53	0.62	0.56
Mean age	39	40	39	40	39	39
Part-time (%)	8	12	5	9	5	11
Separation (%)	28	30	27	30	26	29
Mean firm size	24	25	57	59	47	50
Movers per firm	12	13	27	32	22	16
Mean log VA/worker	8.57	8.45	8.70	8.56	8.70	8.56
Fraction females at firms	0.31	0.68	0.37	0.64	0.33	0.57
Social care sector	0.22	0.41	0.28	0.46	0.13	0.12
Number person-year obs.	5,562,938	5,368,465	4,408,991	4,535,714	3,126,261	2,375,859
Number of persons	1,047,195	1,034,853	880,024	908,240	691,935	563,499
Number of firms	268,792	252,975	84,458	84,458	61,160	60,681

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.9. Descriptive Statistics in the 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	22	24	21	24
Mean firm size	13	15	24	26	34	37
Movers per firm	16	12	32	22	42	28
Mean log VA/worker	4.23	3.95	4.21	3.95	4.21	3.95
Fraction females at firms	0.26	0.58	0.30	0.54	0.29	0.54
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
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

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	2.62	2.46	2.66	2.48	2.68	2.49
Std. dev.	0.45	0.40	0.45	0.40	0.44	0.39
Mean age	40	39	40	39	40	40
Part-time (%)	11	43	10	41	9	41
Separation (%)	23	25	22	24	22	24
Mean firm size	12	14	24	25	33	35
Movers per firm	16	12	31	22	41	28
Mean log VA/worker	4.23	3.98	4.21	3.97	4.21	3.97
Fraction females at firms	0.26	0.60	0.30	0.55	0.29	0.54
Social care sector	0.01	0.05	0.02	0.05	0.01	0.03
Number person-year obs.	30,917,605	19,842,291	25,445,030	17,020,059	22,049,190	14,128,883
Number of persons	4,621,933	3,115,471	4,146,330	2,840,484	3,895,677	2,590,204
Number of firms	1,105,702	934,738	416,383	416,383	243,145	241,095

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.10. Descriptive Statistics in the 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	26	29
Mean firm size	29	41	62	66	78	84
Movers per firm	24	21	60	36	73	41
Mean log VA/worker	4.10	3.92	4.08	3.91	4.08	3.91
Fraction females at firms	0.27	0.54	0.29	0.51	0.28	0.50
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
Number person-year obs.	21,948,900	12,675,814	19,320,406	11,469,130	15,879,101	8,771,416
Number of persons	3,625,149	2,353,960	3,306,765	2,180,420	2,982,414	1,893,285
Number of firms	504,414	344,029	176,865	176,865	113,805	112,994

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.08	2.93	3.08	2.94	3.05	2.86
Std. dev.	0.49	0.40	0.49	0.40	0.48	0.41
Mean age	40	40	40	40	39	39
Part-time (%)	12	58	12	57	11	55
Separation (%)	23	22	23	22	26	29
Mean firm size	36	46	73	77	81	88
Movers per firm	27	34	62	60	69	50
Mean log VA/worker	3.84	3.15	3.81	3.10	3.81	3.10
Fraction females at firms	0.32	0.66	0.34	0.64	0.30	0.59
Social care sector	0.16	0.46	0.18	0.47	0.07	0.28
Number person-year obs.	26,923,621	25,212,917	24,363,699	23,326,236	17,489,820	12,762,316
Number of persons	4,241,322	3,914,235	3,941,949	3,702,089	3,307,729	2,685,861
Number of firms	564,024	430,795	219,918	219,918	132,161	131,317

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.11. Descriptive Statistics in the 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 (%)	22	24	21	23	22	24
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	4.33	4.26	4.33	4.26
Fraction females at firms	0.27	0.62	0.30	0.61	0.26	0.52
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
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

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.23	3.04	3.25	3.05	3.26	3.07
Std. dev.	0.45	0.44	0.45	0.43	0.46	0.45
Mean age	39	40	39	40	39	39
Part-time (%)	9	27	9	27	8	22
Separation (%)	22	22	21	22	22	24
Mean firm size	25	33	46	51	35	39
Movers per firm	27	35	56	59	45	28
Mean log VA/worker	4.29	4.18	4.31	4.20	4.31	4.20
Fraction females at firms	0.31	0.66	0.34	0.65	0.28	0.58
Social care sector	0.11	0.30	0.12	0.30	0.05	0.22
Number person-year obs.	8,786,763	8,000,396	7,719,998	7,512,805	6,028,149	4,000,621
Number of persons	1,366,264	1,239,053	1,243,807	1,180,878	1,063,466	763,312
Number of firms	194,161	143,358	79,327	79,327	66,850	66,331

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.12. Descriptive Statistics in the Portuguese QP Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	1.86	1.67	1.96	1.73	1.96	1.72
Std. dev.	0.57	0.52	0.58	0.53	0.58	0.53
Mean age	39	39	39	38	39	38
Part-time (%)	1	6	1	6	1	6
Separation (%)	24	25	23	25	23	25
Mean firm size	14	16	32	33	33	33
Movers per firm	13	10	32	24	32	24
Mean log VA/worker	11.26	11.12	11.39	11.22	11.39	11.22
Fraction females at firms	0.27	0.63	0.31	0.59	0.31	0.59
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
Number person-year obs.	9,970,313	7,166,548	7,527,280	5,688,495	7,490,537	5,652,437
Number of persons	1,908,803	1,420,885	1,483,404	1,146,844	1,481,018	1,144,674
Number of firms	309,921	280,358	92,984	92,984	92,186	92,173

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	1.87	1.68	1.96	1.74	1.96	1.74
Std. dev.	0.57	0.51	0.58	0.53	0.58	0.53
Mean age	39	39	39	39	39	39
Part-time (%)	2	6	2	6	2	6
Separation (%)	23	23	23	23	23	24
Mean firm size	15	15	32	33	33	33
Movers per firm	13	11	30	25	30	25
Mean log VA/worker	11.19	10.75	11.29	10.86	11.29	10.86
Fraction females at firms	0.29	0.68	0.33	0.64	0.33	0.64
Social care sector	0.04	0.21	0.05	0.20	0.04	0.19
Number person-year obs.	10,632,988	9,606,084	8,203,480	7,527,071	8,121,353	7,318,953
Number of persons	2,015,699	1,811,564	1,595,336	1,455,489	1,589,213	1,441,579
Number of firms	335,732	331,943	108,910	108,910	107,633	107,699

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

TABLE A.13. Descriptive Statistics in the Swedish Data, 2010-2019

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.11	3.03	3.11	3.03	3.10	3.01
Std. dev.	0.35	0.32	0.35	0.32	0.33	0.31
Mean age	40	40	40	40	40	39
Part-time (%)	5	22	5	22	5	22
Separation (%)	23	27	23	27	23	28
Mean firm size	224	242	304	307	292	295
Movers per firm	97	59	168	94	153	80
Mean log VA/worker	11.33	11.25	11.33	11.25	11.33	11.25
Fraction females at firms	0.29	0.47	0.30	0.47	0.28	0.46
Social care sector	0.00	0.00	0.00	0.00	0.00	0.00
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

	Overall Analysis Sample		Dual-Connected Sets		With Productivity	
	Men	Women	Men	Women	Men	Women
Log Hourly Wage	3.10	3.00	3.11	3.00	3.09	2.99
Std. dev.	0.35	0.31	0.35	0.31	0.33	0.31
Mean age	40	40	40	40	40	40
Part-time (%)	6	25	6	25	6	25
Separation (%)	24	29	23	29	24	30
Mean firm size	196	206	257	259	283	285
Movers per firm	84	61	139	94	139	87
Mean log VA/worker	11.31	11.19	11.32	11.19	11.32	11.19
Fraction females at firms	0.31	0.53	0.32	0.53	0.30	0.52
Social care sector	0.03	0.17	0.03	0.17	0.03	0.17
Number person-year obs.	4,275,569	2,866,186	4,188,149	2,821,643	3,649,375	2,289,875
Number of persons	1,017,959	754,556	978,235	734,129	881,185	630,646
Number of firms	14,401	13,412	8,553	8,553	7,002	7,001

Notes: Overall analysis sample in columns (1)–(2) includes workers age 25–55. Wages are measured in real (2015 = 100) euros per hour.

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