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Decomposing the finance wage premium: Contributions of technology and risk[☆]

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ABSTRACT

On average, wages in the finance industry are higher compared to the rest of the economy. Two explanations suggested for this finance wage premium are (1) the positive correlation between risk-taking and wages, and (2) industry differences in information technology intensity. Using a comprehensive worker-firm panel dataset for the Netherlands, we estimate wage models with additive worker and firm fixed effects, and compute the finance wage premium as the average of the firm fixed effects in an industry. We then relate the estimated cross-section of firm fixed effects to a range of firm characteristics, and find that information technology investment, the average level of educational attainment at a firm, and the complementarity of the two are the main drivers of the finance wage premium, while firm risk only makes a small contribution.

1. Introduction

Employee compensation in the finance industry has long attracted attention, especially after the Global Financial Crisis (Zingales, 2015). Concerns were raised about the size of remuneration in the financial sector in general (McQuaig, 2019) and about its implications for bank risk-taking in particular.[1] In the case of banking, there were some regulatory initiatives related to remuneration, trying to curb risk-taking incentives.[2] Beyond the compensation-risk-taking nexus, excess employee compensation in finance with respect to the rest of the economy, i.e., the finance wage premium, is crucial, because cross-industry and cross-firm

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[1] Regulators view compensation as potentially contributing to bank risk-taking (Wall, 2020).

[2] In 2014, for example, the EU introduced a bonus cap of 100% of fixed pay. Bonuses, i.e., variable pay, have been pervasive in the financial industry, but authorities in financial centers such as the U.K. have been critical of measures that limit such compensation (Jones, 2021).

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wage differences may drive wage inequality (Card et al., 2013; Song et al., 2019), and excessive wages in finance may engender a brain drain from other productive industries (Marin and Vona, 2022).[3] There is evidence that the finance wage premium has not decreased after the Global Financial Crisis (Bell and Van Reenen, 2014) and, to the contrary, continued to grow (Célérier and Vallée, 2019; Böhm et al., 2023).

In this paper, we provide additional evidence on the development and determinants of the finance wage premium in the Netherlands, using comprehensive administrative data from 2006–2018.[4] In previous literature, the finance wage premium is estimated from wage regressions including an indicator variable for whether the worker is employed at a firm in the finance industry or not (e.g., Célérier and Vallée, 2019; Böhm et al., 2023). We improve this estimation framework by using empirical models developed in Abowd et al. (1999a) that allow estimation of unobserved heterogeneity for both workers and firms. Since industry is a characteristic of the firm, the finance wage premium is then computed as the average of the estimated firm fixed effects in the finance industry relative to the rest of the economy. Comparing the industry-dummy variable versus our more flexible approach, we find that using an industry-dummy *underestimates* the finance wage premium by one-fifth. Specifically, we estimate a finance wage premium of 11.1% derived from firm fixed effects, compared to 8.8% using only a finance industry dummy variable.

To understand why the estimated finance wage premium is biased downward in the industry-dummy approach, note that in either estimation approach, the finance wage premium is inferred from the changes in the wages that are experienced by workers who switch between the finance and non-finance sectors (as worker fixed effects are included in either approach). In the finance industry dummy approach, these observed wage changes are relatively small (in absolute terms), giving rise to a downwardly biased finance wage premium. This is the case as workers who, for instance, switch out of finance primarily go to work at non-financial firms that pay relatively more (compared to other non-financial firms), to make up for the fact that, on average, non-financial firms pay less than financial firms. As a methodological contribution, we formally show that this selection effect can explain a downward-biased finance wage premium in the Appendix.

Using the estimated firm fixed effects allows us to explore explanations for the finance wage premium. Several explanations have been suggested in the literature, and we explore the relative importance of two in particular. One potential determinant is the relatively extensive use of information and communication technology (ICT) in finance compared to other industries (Philippon and Reshef, 2012; Lindley and McIntosh, 2017; Célérier and Vallée, 2019; Böhm et al., 2023). In this paper, we consider not only the role of ICT capital spending by itself, but also of the potential complementarity of ICT capital spending and human capital in the firm, which we proxy by average educational attainment at the firm level. That is in line with earlier work by Acemoglu and Autor (2011) and Autor et al. (1998) on complementarities between technology and human capital.[5] Another potential determinant of the finance wage premium we consider is firm risk, as proxied by leverage and the z-score.[6] Previously, Chemmanur et al. (2013) showed that wages are positively related to leverage in non-financial firms, reflecting a higher probability of job loss at more leveraged firms.[7]

Applying the statistical models of Abowd et al. (1999a), we obtain estimates of firm fixed effects for all firms in the economy. Firm fixed effects are time-invariant, and proxies for firm risk show little variation over time. Therefore, to estimate the impact of risk and other firm-level characteristics on the finance wage premium, we employ a two-step procedure. Specifically, after estimating the firm-specific wage premia, we relate these cross-sectionally to risk proxies and other firm-level variables, including ICT and education. We find that the firm component of wages is positively correlated with firm risk, and that the relatively higher leverage of firms (i.e., lower equity-to-assets ratio) in finance partly explains higher firm-specific wages in this sector. In addition, we show that the firm-specific wage component is positively correlated with ICT capital, average firm-level educational attainment, and their joint effect. This complementarity in part explains the finance wage premium, as both ICT capital and educational attainment are higher in the financial sector.

Given the variety of variables explaining the finance wage premium, we propose a decomposition that allows us to gauge the relative importance of risk and other firm-level variables. We take the estimated firm fixed effects from the AKM model and perform an Oaxaca-Blinder decomposition (see, e.g., Card et al. (2016) for an application using firm fixed effects, and Christelis et al. (2013) for an application in household finance) to decompose the finance wage premium into differences of characteristics of firms in finance versus other industries. We find that ICT and human capital measures, both separately and in their interaction, are the most important variables in explaining the finance wage premium; together, they account for 63% of the explained part of the finance wage premium.[8] In contrast, risk variables only account for 1% of the explanation of the finance wage premium. Other firm-level variables, in particular size and profitability, account for the remainder of the explained part.

The rich administrative data from the Netherlands allow us to estimate separate finance wage premia for the fixed contract wage and the full wage, which includes variable pay in the form of bonuses and overtime pay.[9] We find that the estimated finance wage

[3] The evidence on the finance wage premium leading to a brain drain is mixed. See, for example, Böhm et al. (2023) for talent allocation in Sweden and D'Acunto and Frésard (2018) for economic growth implications.

[4] The finance industry in the Netherlands constitutes an interesting case to study as it is relatively large compared to the size of the economy. The number of workers in finance represented 2% of the working population in 2018, while the share of gross value added in finance was 10%. The finance industry in the Netherlands is relatively large compared to the U.S., with a financial industry assets-to-GDP ratio of 11 in the Netherlands and 5 in the U.S. in 2018 (Statistics Netherlands).

[5] Our measure of ICT capital spending is the estimated cost of the inputs that flow to production from ICT capital assets (computers, communication equipment, software, and databases).

[6] The z-score is the sum of the equity-to-assets ratio and the rate of return on assets (ROA) divided by the standard deviation of the ROA, and it is a measure of how unlikely it is that a firm will become insolvent.

[7] Berk et al. (2010) examine optimal leverage in a model with risk-averse workers and tax benefits of debt.

[8] Overall, we can explain about half of the finance wage premium with the variables at our disposal.

premium is higher for the full wage (at 11.1%) than for the fixed wage (at 6.9%), consistent with the relative importance of variable pay in the finance industry. We further find that the finance full wage premium is higher for workers in higher income quartiles. Considering contract type, we show that the finance wage premium is higher for workers with regular employment contracts than for those with part-time or on-call contracts. For the Netherlands, we also observe that the finance wage premium has risen over time. Among financial institutions, we show that the finance wage premium is particularly pronounced for banks.

A growing literature documents the existence of a sizable wage premium in the finance industry and explores its potential sources. Early and influential work by Philippon and Reshef (2012) shows that periods of financial deregulation in the United States are associated with a higher finance wage premium, reflecting greater skill intensity and job complexity in finance. Subsequent studies, however, provide a more nuanced picture. Using Swedish data, Böhm et al. (2023) find no evidence that talent in finance has improved over time. For the United Kingdom, Lindley and McIntosh (2017) document a higher finance wage premium among more educated workers and also show that finance jobs exhibit greater computer intensity than jobs in other sectors. Evidence from France by Célérier and Vallée (2019) suggests that wages in finance increase more strongly with project size, consistent with a role for information technology in scaling financial activity. In contrast, using sector-level data across OECD countries, Boustanifar et al. (2018) find little evidence that higher ICT intensity in finance translates into higher relative wages.

Taken together, this literature points to a potential role for technology, skills, and firm characteristics in shaping the finance wage premium, but it leaves several key questions unresolved. First, existing studies typically rely on indirect proxies for technology and skills or sector-level measures, which limits the ability to assess complementarities between ICT capital and human capital within firms. Second, most estimates of the finance wage premium are based on industry dummy regressions, which abstract from firm-level heterogeneity and may confound industry effects with the sorting of workers across firms. Our paper contributes to this literature along both dimensions. Using comprehensive matched worker–firm panel data, we estimate the finance wage premium as the average firm-specific wage premium in finance relative to the rest of the economy, following the additive worker–firm fixed effects framework of Abowd et al. (1999a). This approach explicitly accounts for unobserved worker heterogeneity and firm-specific pay premia, and we show that standard industry-dummy regressions systematically understate the finance wage premium. Furthermore, leveraging data on ICT capital spending and educational composition, we directly test for complementarities between technology and human capital in wage setting. We find that these complementarities are a central driver of the finance wage premium, while firm risk plays only a minor role.[10]

More broadly, our analysis relates to the labor economics literature using matched employer–employee data to study wage determination. Seminal contributions by Card et al. (2013, 2018), and Song et al. (2019) demonstrate that firm-specific pay premia and worker sorting are central to understanding wage inequality. Building on this framework, we link estimated firm wage premia to firm characteristics, particularly ICT investment, workforce composition, and risk, to decompose the finance wage premium into its underlying sources. This allows us to quantify how much of the premium reflects technology–skill complementarities as opposed to compensation for firm risk.

Finally, our paper connects to the literature on inter-industry wage differentials. Classic studies by Krueger and Summers (1988) and Bartel and Sicherman (1999) document persistent wage differences across industries and relate them to technological change. While we treat all sectors symmetrically in the estimation, our contribution is to show that the finance industry stands out primarily because of its joint intensity of ICT capital and skilled labor, rather than risk alone.

The rest of the paper is structured as follows. Section 2 discusses the data. Section 3 outlines the empirical methodology. Section 4 presents initial estimates of the finance wage premium comparing different estimating approaches. Section 5 presents evidence of worker-level determinants of the finance wage premium. In Section 6, we relate firm-specific wage premia to firm-level characteristics and, in addition, we provide estimates of the finance wage premium using a propensity score matching approach where firms are matched on the basis of firm characteristics. Section 7 concludes.

2. The data

Our main data source for worker information is the SPOLIS/POLIS database provided by Statistics Netherlands (CBS). This administrative dataset provides monthly information on the employment and earnings history of all workers in the Netherlands. In particular, our dataset provides information on wage levels and composition, the type of labor contract, and whether the job is part-time. Unique firm identifiers are provided so that workers can be linked to firms. Employers are required to report this information so that the Dutch unemployment insurance agency can calculate unemployment benefits for unemployed workers. The Netherlands has a universal unemployment insurance system that covers all wage earners. We complete this labor market data with worker demographic information and firm data available at Statistics Netherlands. Our sample covers the period 2006–2018.[11]

We have information on a worker's total wage compensation, as well as on its fixed and variable components. The variable wage component includes overtime pay and bonuses that are prevalent in the financial sector. Following Card et al. (2016) and Philippon

[9] The availability of separate information on the fixed wage and the variable wage enables us to consider these distinct parts of the overall wage compensation in finance, thereby adding to the literature on executive compensation in the finance industry (Kaplan and Rauh, 2010; Thanassoulis, 2012; Bivens and Mishel, 2013; Greenwood and Scharfstein, 2013; Lin and Tomaskovic-Devey, 2013; Bell and Van Reenen, 2014; Bolton et al., 2016; Glode and Lowery, 2016; Efing et al., 2019).

[10] Relatively high wages in finance may also reflect competitive assignment of talent (Acharya et al., 2016; Glode and Lowery, 2016) or compensation for moral hazard (Axelson and Bond, 2015). Our analysis quantifies the relative importance of these channels through firm-level wage premia.

[11] Firm and worker identifiers are unique and anonymized to the researcher. Statistics Netherlands has cleared our research output for distribution.

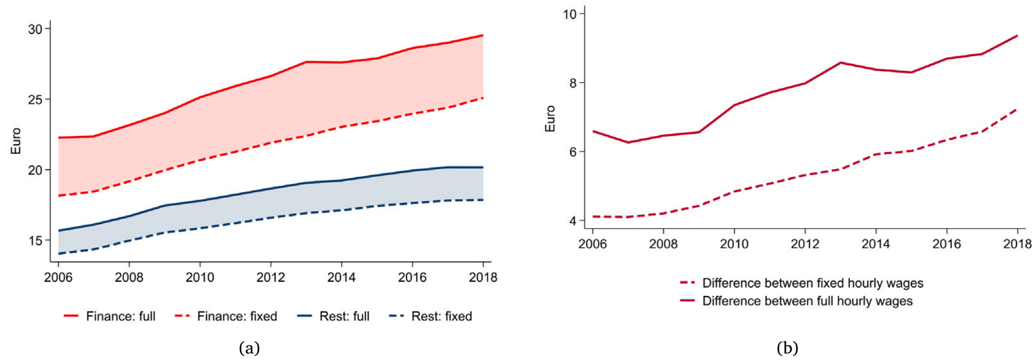


Fig. 1. Hourly wages in the finance industry and the rest of the economy (2006–2018).
Notes: Figure (a) reports the average fixed hourly wage and full hourly wage in the finance industry and the rest of the economy. Figure (b) reports the difference between finance and the rest of the economy for fixed and full hourly wages. The fixed hourly wage is the basic wage divided by basic hours. The full hourly wage is the gross wage divided by paid hours (basic hours plus paid overtime hours). The finance industry corresponds to NACE code 11. See Table A.1 for the industry classification used.

and Reshef (2012), we calculate a worker's hourly wage in a given year using monthly information on realized wages and hours of employment as specified in pertinent labor contracts during the year. We construct two measures of the hourly wage: (1) the fixed hourly wage, which is the contract wage divided by contract hours, and (2) the full hourly wage, which is all paid wages, including variable components, divided by all worked hours, including paid overtime hours. Fig. 1(a) displays time trends of the average fixed and full hourly wages both for the finance industry and the rest of the economy during the 2006–2018 period. The figure shows that average fixed and full wages in the financial sector exceeded average compensation in the rest of the economy throughout this period. Moreover, the implied finance wage premia based on fixed and full wages increased over time (Fig. 1(b)).

We expand this dataset in several dimensions, including workers' education, contract type, average education at the firm level, and job and industry tenure. We also incorporate firm-level information, including profits, assets, and risk measures, for a subsample of firms. Importantly, the dataset includes a measure of ICT capital. The measure of ICT capital spending corresponds to the estimated cost of the inputs that flow into production from ICT capital assets (computers, communication equipment, software, and databases).

Table 1 provides summary statistics for observations in finance and the rest of the economy. The average fixed and full hourly wages are Euro 21.75 and 26.53 in the financial sector, respectively, compared to Euro 17.8 and 20.27 in the rest of the economy. The shares of workers with low, middle, and high education in finance are 0.06, 0.32, and 0.62, and they are 0.14, 0.39, and 0.47 in the rest of the economy, confirming the importance of high education in the finance industry. The average firm-level shares of workers with these three levels of education are 0.06, 0.33, and 0.61 in finance, and 0.14, 0.40, and 0.45 for non-financial firms. Average worker ages in finance and other sectors are 41.22 and 42.22 years, respectively. In finance, the share of part-time workers is 0.36, compared to 0.51 elsewhere. The share of workers with regular employment contracts (i.e., those who are not temporary agency or on-call workers) in finance and other sectors is 0.99 and 0.95, respectively. On average, workers in finance have relatively short job and industry tenures of 5.02 and 6.15 years, respectively, compared to average job and industry tenures of 5.96 and 7.02 years in other industries.

ICT capital spending per worker in finance, with 8700 Euro, is more than double compared to spending on ICT capital per worker in the rest of the economy (3140 Euro).[12] Several firm-level variables are constructed using accounting information. For incorporated non-financial firms, we obtain this information from administrative tax records at Statistics Netherlands, and for financial firms, we supplement this with accounting information from Bank Focus. Comparing the two types of firms, we find that financial firms are relatively more profitable, and they are larger. We use two indices of firm risk: the ratio of equity to assets and the z-score. The z-score is constructed as the sum of the equity-to-assets ratio and the rate of return on assets (ROA) divided by the standard deviation of the ROA, and it is a measure of how unlikely it is that a firm will become insolvent (a higher z-score points to lower insolvency risk). Financial firms, on average, have a lower equity-to-assets ratio, suggesting that they are riskier. However, financial firms have a higher z-score and, by this measure, appear to be safer compared to non-financial firms. We show results using both measures of risk.

3. Estimation methods

This section first describes how we estimate the finance wage premium using an empirical framework that incorporates worker and firm fixed effects, following Abowd et al. (1999a,b), abbreviated as AKM. Next, we describe how we estimate financial wage

[12] Fig. A.1 shows that ICT capital per worker has increased substantially in finance relative to other sectors during 2006–2018.

Table 1
Descriptive statistics for the regression sample.

	Observations	Mean	SD	$p1$th	$p50$th	$p99$th
Finance industry						
Fixed hourly wage (Euro)	701,853	21.75	9.08	7.77	19.54	47.84
Full hourly wage (Euro)	701,853	26.53	16.50	8.43	23.27	65.61
LowEduc (worker)	454,824	0.06	0.24	0	0	1
MiddleEduc (worker)	454,824	0.32	0.47	0	0	1
HighEduc (worker)	454,824	0.62	0.49	0	1	1
ICT-K per worker (thousands, Euro)	701,853	8.70	2.07	6.01	8.87	12.77
Part-time contract	701,853	0.36	0.48	0	0	1
Type of contract						
-Regular contract	701,853	0.99	0.09	1	1	1
-Temporary agency worker	701,853	0	0.02	0	0	0
-On-call worker	701,853	0.01	0.09	0	0	0
Age	701,853	41.22	9.91	22	41	62
ShareLow (firm)	701,853	0.06	0.08	0	0.05	0.40
ShareMiddle (firm)	701,853	0.33	0.13	0	0.30	0.80
ShareHigh (firm)	701,853	0.61	0.18	0	0.64	0.96
Job tenure	701,853	5.02	3.45	1	4.45	13
Industry tenure	701,853	6.15	4.50	1	5.03	13
Profit per worker (thousands, Euro)	95,485	82.45	93.45	−49.02	80.00	214.23
Log assets	95,485	9.94	2.93	−0.61	11.42	12.76
Equity/Assets	95,485	0.09	0.14	−0.16	0.07	0.60
Z-score	95,485	11.70	17.56	−3.00	4.88	59.84
Firm fixed effects	95,485	0.24	0.09	−0.12	0.23	0.38
Rest of the economy						
Fixed hourly wage (Euro)	38,717,109	17.80	7.08	6.32	16.51	41.76
Full hourly wage (Euro)	38,717,109	20.27	8.85	6.76	18.66	49.42
LowEduc (worker)	24,698,087	0.14	0.34	0	0	1
MiddleEduc (worker)	24,698,087	0.39	0.49	0	0	1
HighEduc (worker)	24,698,087	0.47	0.49	0	0	1
ICT-K per worker (thousands, Euro)	29,821,172	3.14	2.61	0.95	2.52	16.56
Part-time contract	38,717,109	0.51	0.50	0	1	1
Type of contract						
-Regular contract	38,717,109	0.95	0.22	0	1	1
-Temporary agency worker	38,717,109	0.03	0.16	0	0	1
-On-call worker	38,717,109	0.03	0.17	0	0	1
Age	38,717,109	42.22	11.38	20	43	63
ShareLow (firm)	38,717,109	0.14	0.16	0	0.08	0.67
ShareMiddle (firm)	38,717,109	0.40	0.20	0.03	0.42	0.87
ShareHigh (firm)	38,717,109	0.45	0.28	0	0.42	0.95
Job tenure	38,717,109	5.96	4.59	1	4.87	13
Industry tenure	38,717,109	7.02	5.48	1	5.50	13
Profit per worker (thousands, Euro)	18,942,216	9.71	30.28	−45.75	2.10	209.20
Log assets	18,942,216	2.02	2.27	−2.85	1.71	8.00
Equity/Assets	18,942,216	0.17	2.15	−2.41	0.30	0.94
Z-score	18,942,216	9.01	74.02	−13.49	5.16	69.81
Firm fixed effects	18,942,216	0.00	0.11	−0.26	0.00	0.30
Total observations (N × T)	39,418,962					

Notes: There are fewer observations for education of the worker because education level is not available for the entire population. ICT-K is not available for the industries Real Estate, Public Administration and Education (NACE codes 12, 15, and 16). The Z-score is constructed as the sum of the equity-to-assets ratio and the rate of return on assets (ROA) divided by the standard deviation of the ROA, and it is a measure of how unlikely it is that a firm will become insolvent. Firm fixed effects are estimates of the firm fixed effects $\psi_{J(i,t)}$, from Eq. (2) that can be interpreted as firm-specific wage premia.

premium regressions in which firm fixed effects derived from the AKM estimation are the dependent variables, and we include a range of firm-level variables, particularly related to ICT capital investments and firm risk.

3.1. Estimation of the finance wage premium using the AKM framework

In the previous literature, the finance wage premium has been estimated by including a financial sector dummy variable in wage equations (see, e.g., Philippon and Reshef, 2012; Célérier and Vallée, 2019; Lindley and McIntosh, 2017) along the lines of the following specification

$$\ln w_{i,t} = \boldsymbol{X}_{i,t}\boldsymbol{\beta} + \alpha_i + \phi \mathbf{1}^F_{i,t} + \lambda_t + \epsilon_{i,t}, \tag{1}$$

where $ln(w_{i,t})$ is the log hourly wage for worker i in year t, $\boldsymbol{X}_{i,t}$ are a set of covariates, α_i are worker fixed effects, $\mathbf{1}^F_{i,t}$ is a dummy for employment in the finance industry, λ_t are year fixed effects, and ϵ_{it} is an idiosyncratic error term. $\hat{\phi}$ is the estimate of the finance wage premium.

A conceptual problem with specification (1) is that it omits unobservable firm heterogeneity that can be represented by firm fixed effects and that a recent literature has found to be substantial (Song et al., 2019; Haltiwanger et al., 2022). In practice, unobservable firm fixed effects can confound the estimated finance wage premium. To introduce firm fixed effects into the estimation, we follow the methodology developed by Abowd et al. (1999a) and estimate a model with additive worker and firm fixed effects:

$$\ln w_{i,t} = \boldsymbol{X}_{i,t}\boldsymbol{\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}. \tag{2}$$

In Eq. (2), firm fixed effects $\psi_{J(i,t)}$ incorporate a matching function J that assigns worker i in year t to firm j. Conceptually, in this framework, worker fixed effects are identified by observing the same worker in different time periods, while firm fixed effects are identified by observing the same worker at different firms. Thus, the estimation of firm fixed effects relies on worker mobility between firms, and Abowd et al. (2012) show that only fixed effects for those firms with some worker mobility can be identified, which make up the so-called largest connected set.[13] We follow the computational algorithm in Card et al. (2013) to construct the largest connected set of firms and associated workers.[14] In Appendix C, we provide a detailed discussion of the assumptions underlying the AKM framework, and we show that key assumptions on worker mobility patterns and sorting are satisfied in our dataset.

Importantly, the AKM framework allows for particular patterns of workers matching to firms. For example, it allows for the possibility that high-skilled workers are more likely to transition to high-wage firms (see Card et al., 2013). As a result, high-skilled workers (with larger worker fixed effects) are likely to be matched with high-wage firms (with more positive firm fixed effects).

However, there are three scenarios in which the assumptions of exogenous mobility in the AKM framework may be violated. First, there could be a link between firm-wide shocks and mobility if workers disproportionately leave negatively shocked firms and join positively shocked firms. Second, there potentially is selection based on idiosyncratic match effects, which would generate asymmetric wage changes for movers (e.g., gains for moves aligned with comparative advantage and losses for misaligned moves), contradicting the approximate symmetry implied by exogenous mobility. Third, there can be a correlation between the direction of mobility and transitory wage shocks, if promotions or stalls in wage trajectories induce moves that create differential pre-trends between movers to higher- versus lower-wage firms. In the Appendix, we examine each of these scenarios and find no evidence consistent with any of them in our data.

Abowd et al. (2012) show that in this framework, industry wage differentials can be computed as the differences of (weighted) averages of the estimated firm fixed effects across industries, where the weights are the number of employees at firms and their employment duration. In our setting, the finance wage premium is the weighted average firm effect in finance minus the weighted average firm effect in the rest of the economy, as follows:

$$\text{Finance wage premium} = \left(\frac{1}{N^f} \sum_{j=1}^{N^f} \bar{\psi}_j^{finance} - \frac{1}{N^r} \sum_{j=1}^{N^r} \bar{\psi}_j^{rest} \right), \tag{3}$$

where N^f is the number of firms in the finance industry; N^r is the number of firms in the rest of the economy; $\bar{\psi}_j^{finance}$ is the weighted firm fixed effect for firm j in the finance industry; $\bar{\psi}_j^{rest}$ is the weighted firm fixed effect for firm j in the rest of the economy. Practically, we estimate the finance wage premium by regressing the estimated firm fixed effects for each worker-year (to obtain a weighted average) on a dummy for the finance industry as follows:

$$\hat{\psi}_{J(i,t)} = \phi \mathbf{1}^F_{i,t} + \xi_{i,t} \tag{4}$$

where $\xi_{i,t}$ is an error term. This specification can easily be extended to apply to different sub-sectors of the finance industry. In particular, we will separately consider the banking sector and non-bank financial institutions.

Since we use estimated variables in Eq. (4), we bootstrap the standard errors at the firm-level with 200 repetitions (Hall and Wilson, 1991):

$$\hat{se} = \left\{ \frac{1}{k-1} \sum_{r}^{k} (\hat{\phi}_r - \bar{\phi})^2 \right\}^{1/2}, \tag{5}$$

where $r = 1, 2, \ldots, k$ denote the bootstrap samples and $\bar{\phi}$ is the average estimate of ϕ.

Specifications (1) and (2) both include worker fixed effects, which implies that in either approach, the finance wage premium is identified through worker mobility between industries.[15] More specifically, the finance wage premium is inferred from the average

[13] This concept is explained by Abowd et al. (2002) (page 3) as follows: "When a group of persons and firms is connected, the group contains all the workers who ever worked for any of the firms in the group and all the firms at which any of the workers were ever employed. In contrast, when a group of persons and firms is not connected to a second group, no firm in the first group has ever employed a person in the second group, nor has any person in the first group ever been employed by a firm in the second group".

[14] The connected set retains around 99% of the original sample.

[15] In fact, the two approaches would be identical if, in the AKM approach, we were to impose the restrictions of equal firm fixed effects in finance and equal firm fixed effects in the rest of the economy. These restrictions are rejected by our data, implying that specification (1) is likely to yield a biased estimate of the finance wage premium relative to the AKM approach.

wage increase experienced by workers who switch into the finance sector, and from the average wage loss experienced by workers who switch out of the finance sector. In the finance industry dummy approach, observed wage changes experienced by industry switchers are likely to be relatively small (in absolute terms), leading to a relatively small, downwardly biased estimate of the finance wage premium. The reason is a selection effect whereby workers who switch out of finance, in particular, primarily go to work at non-financial firms that pay relatively more (compared to other non-financial firms), to make up for the fact that, on average, non-financial firms pay less than financial firms. Similarly, workers who switch into the finance sector may accept a job at a financial firm that pays relatively less compared to other financial firms, as firms in finance generally pay more than non-financial firms. In Appendix B, as a methodological contribution, we formally show that these selection effects can explain a downwardly biased finance wage premium if the estimation includes a finance industry dummy but no firm fixed effects.

3.2. Explaining firm-specific wage premia by firm characteristics

Proxies for firm risk show limited variation over time, which precludes that they are jointly estimated with firm fixed effects in the AKM specification (2). Therefore, to estimate the impact of risk on firm-level wages and hence the finance wage premium, we employ a two-step procedure. First, we estimate firm-specific wage premia as represented by the firm fixed effects in the AKM model. Second, we relate these estimated firm-specific wage premia to risk measures and other firm-level variables. Previously, Lachowska et al. (2020b) and Bertheau et al. (2023) have used estimated fixed effects from AKM models as dependent variables in regressions to examine how firm-specific wage premia vary for workers around the time of job displacement. In our setting, the resulting regression is an extension of Eq. (4) as follows

$$\hat{\psi}_{J(i,t)} = \phi \mathbf{1}_j^F + \boldsymbol{X}_j \boldsymbol{\beta} + \epsilon_j, \tag{6}$$

where $\boldsymbol{X}_j$ are firm-level explanatory variables, consisting of ICT and education measures, risk measures, and indices of a firm's size, profitability, and location. In particular, we include interactions between ICT and education measures at the firm level to test their potential complementarity.[16] As risk measures, we examine the equity-to-assets ratio and the z-score. In specification (6), ϵ_j is the error term.

4. Benchmark estimation of the finance wage premium

In this section, we present estimates of the finance wage premium based on specifications (1) and (2) to analyze how the introduction of firm fixed effects in the AKM model affects the size of this premium. Panels A and B of Table 2 consider the finance wage premium in the fixed hourly wage and the full hourly wage, respectively. The estimation sample is the connected set of workers and firms. Column (1) shows the results of estimating the finance wage premium as a finance industry fixed effect in a specification that includes control variables and time fixed effects, but no worker and firm fixed effects. The estimated finance wage premium is 11.4% for the fixed hourly wage (Panel A) and 16.4% for the full hourly wage (Panel B). The relatively higher hourly full wage premium can be explained by the greater prevalence of variable compensation in the finance industry than in the rest of the economy. Column (2) includes worker fixed effects, which reduces both estimates of the finance wage premium by about one-half. This shows that unobserved worker productivity matters and suggests that the finance industry attracts relatively more productive workers than the rest of the economy.

In column (3), we present the results of a regression that includes firm fixed effects, but no worker fixed effects. A comparison of columns (1) and (3) reveals an interesting result: omitting firm fixed effects biases the finance wage premium downwards.[17] In other words, the finance wage premium needs to be estimated using firm fixed effects, not by an industry indicator. Therefore, the AKM regression in column (4), which includes both worker and firm fixed effects, is our preferred specification. Comparing columns (2) and (4) shows that omitting firm fixed effects in a specification with worker fixed effects also biases the finance wage premium downwards, similarly to the comparison between columns (1) and (3). In the AKM specification, the estimated finance wage premium is 6.9% for the fixed hourly wage and 11.1% for the full hourly wage.

To compare our results with the earlier findings, Célérier and Vallée (2019) and Lindley and McIntosh (2017) both estimate the finance wage premium as the coefficient of a finance sector dummy in regressions without worker or firm fixed effects, presenting benchmark estimates of the finance wage premium of 24.2% and 31.4%, respectively. Thus, their approaches correspond to column (1) in Table 2, where there is an upward bias in the estimated finance wage premium relative to the AKM approach of column (4). Böhm et al. (2023) estimate the finance wage premium as the estimated coefficient on a finance sector dummy while including job fixed effects, providing an estimated finance wage premium of 11.4%. Finally, Philippon and Reshef (2012) use the approach of estimating the finance wage premium as a finance industry dummy while including worker fixed effects, analogous to our column (2) in Table 2. Their benchmark estimate of the finance wage premium is 6.2%. Following our results, it appears that this estimate is biased downward relative to using the AKM methodology.[18]

[16] A positive coefficient on the interaction will imply that wages at a firm are higher in relative terms if the firm combines high-skilled labor with a higher ICT capital spending intensity, consistent with the theory of ICT capital-skill complementarity in production and in wage formation.

[17] We offer a formal proof of this result in Appendix B.

[18] Table A.2 reports finance wage premia separately for banks and for non-bank firms in finance, showing relatively large finance wage premiums of 15%–22% (for the fixed and full hourly wage measures) for banks.

Table 2
The finance wage premium in different specifications.

	OLS	Fixed effects		AKM		
		Worker	Firm	Worker & Firm		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fixed hourly wage						[older 30y]
Finance wage premium (FWP)	0.114***	0.0564***	0.145***	0.0693***	0.0580***	0.0699***
	(7.95)	(16.59)	(7.94)	(7.00)	(5.63)	(8.24)
FWP × 2011–2014					0.0120*	
					(2.33)	
FWP × 2015–2018					0.0298***	
					(3.72)	
Adjusted R-squared	0.381	0.903	0.564	0.911	0.911	0.911
Panel B: Full hourly wage						[older 30y]
Finance wage premium (FWP)	0.164***	0.0880***	0.198***	0.111***	0.102***	0.112***
	(10.26)	(19.79)	(9.33)	(8.70)	(7.74)	(10.10)
FWP × 2011–2014					0.00781	
					(1.38)	
FWP × 2015–2018					0.0247**	
					(2.72)	
Adjusted R-squared	0.390	0.894	0.579	0.902	0.912	0.901
Observations (N × T)	39,418,962					35,100,418
N workers	5,180,514					
N firms	83,077					
Fixed effects:						
-Worker	–	Yes	–	Yes	Yes	Yes
-Firm	–	–	Yes	Yes	Yes	Yes
-Year	Yes	Yes	Yes	Yes		Yes
-Type of contract	Yes	Yes	Yes	Yes	Yes	Yes
-Municipality	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All regressions include a polynomial term in age (normalized to 40 years old) and fixed effects for part-time contract, contract type (regular (baseline), temporary agency, and on-call), and municipality. Sample selections are described in the text. Columns (1)–(2) report *t*-statistics. Columns (3)–(6) report z-statistics from bootstrapped standard errors at the firm level (200 repetitions). $^{*}p < 0.05$, $^{**}p < 0.01$, *** $p < 0.001$.

In column (5), we test whether the finance wage premium has increased over time, as suggested by Fig. 1. In particular, starting from the AKM specification in column (4), we distinguish three sub-periods: 2006–2010 covering the Global Financial Crisis, 2011–2014 covering the Sovereign Debt Crisis in Europe, and the remainder period of 2015–2018. We find a slight increase in the finance wage premium during 2011–2014 for the fixed hourly wage, but no material change for the full hourly wage. For the years 2015–2018, we see that the finance wage premium is larger for both the fixed and full hourly wages compared to the periods before.[19] Fig. 2 visually confirms these time-trend results, showing an upward trend in the finance wage premium for both fixed and full hourly wages. In column (6), we restrict the sample to workers aged 30 and above so that the estimation relies on the labor mobility of relatively older workers. We find very similar estimates of finance wage premiums for fixed and full hourly wages of 7% and 11%, respectively.

5. Worker-level determinants of the finance wage premium

A natural question is how much the finance wage premium varies with observable worker characteristics. In this subsection, we address this question by estimating AKM specifications that additionally include interactions between firm fixed effects and various worker group or job type variables, which are subsequently aggregated to estimate the finance wage premium by worker group or job type.

To start, column (1) of Table 3 shows how the finance wage premium differs by gender. We find that women in finance earn about 2.6% less in fixed hourly wages than men (Panel A), and about 4.3% less for the full hourly wage (Panel B). Our finding of a smaller finance wage premium for women is consistent with lower firm-specific pay premia found by Card et al. (2016).

Next, we consider whether the finance wage premium varies with the sector-level income quartiles. To do this, in column (2) we include income quartile indices (based on the total gross wage) and their interactions with firm fixed effects, which are then aggregated to capture the finance wage premium across the income distribution. We find that the finance wage premium is higher for workers in higher sectoral income quartiles. This observation holds for both the fixed hourly wage in Panel A and the full hourly

[19] Given that the AKM methodology involves estimating a large number of worker and firm fixed effects, it is not straightforward to compare estimates from applying the AKM methodology to different sub-periods. Therefore, we estimate the finance wage premium for different sub-periods within the same regression by interacting it with sub-period dummies.

Table 3
Finance wage premium: observable heterogeneity.

	AKM regressions				
	Gender (1)	Income (2)	Top earners (3)	Hours (4)	Contract type (5)
Panel A: Fixed hourly wage					
Finance wage premium (FWP)	0.0825***	0.0769***	0.0823***	0.0701***	0.0671***
	(9.96)	(8.34)	(7.92)	(7.04)	(7.90)
FWP × Female	−0.0263***				
	(−4.23)				
Income Quartile II		0.183***			
		(54.72)			
Income Quartile III		0.312***			
		(80.44)			
Income Quartile IV		0.475***			
		(98.89)			
FWP × Income Quartile II		0.0307***			
		(3.52)			
FWP × Income Quartile III		0.0664***			
		(5.84)			
FWP × Income Quartile IV		0.0799***			
		(5.54)			
Top decile			0.229***		
			(70.30)		
FWP × Top decile			0.0131		
			(1.31)		
Part-time				−0.0167***	
				(−3.98)	
FWP × Part-time				−0.00662	
				(−0.86)	
Temporary agency					−0.0988***
					(−19.48)
On-call					−0.0882***
					(−19.22)
FWP × Temporary agency					0.0775
					(1.77)
FWP × On-call					−0.0932***
					(−5.75)
Observations (N × T)	39,418,962	39,418,962	39,418,962	39,418,962	39,418,962
Adjusted R-squared	0.912	0.945	0.918	0.912	0.910

	AKM regressions				
	Gender (1)	Income (2)	Top earners (3)	Hours (4)	Contract type (5)
Panel B: Full hourly wage					
Finance wage premium (FWP)	0.133***	0.100***	0.124***	0.117***	0.109***
	(11.16)	(8.66)	(9.11)	(9.55)	(9.23)
FWP × Female	−0.0425***				
	(−4.96)				
Income Quartile II		0.212***			
		(51.48)			
Income Quartile III		0.365***			
		(78.55)			
Income Quartile IV		0.565***			
		(99.82)			
FWP × Income Quartile II		0.0545***			
		(5.91)			
FWP × Income Quartile III		0.111***			
		(9.41)			
FWP × Income Quartile IV		0.159***			
		(9.39)			
Top decile			0.289***		
			(77.14)		
FWP × Top decile			0.0946***		
			(3.60)		

(*continued on next page*)

Table 3 (*continued*).

Part-time				−0.0185***	
				(−3.62)	
FWP × Part-time				−0.0206*	
				(−2.54)	
Temporary agency					−0.115***
					(−20.19)
On-call					−0.105***
					(−19.23)
FWP × Temporary agency					0.0297
					(0.61)
FWP × On-call					−0.143***
					(−7.89)
Observations (N × T)	39,418,962	39,418,962	39,418,962	39,418,962	39,418,962
Adjusted R-squared	0.903	0.945	0.913	0.903	0.901

Notes: All regressions include a polynomial term in age (normalized to 40 years old), year, and municipality. Sample selections are described in the text. For the finance wage premium coefficients, z-statistics are reported in parentheses from bootstrapped standard errors at the firm level (200 repetitions). For all other coefficients *t*-statistics are reported. *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$.

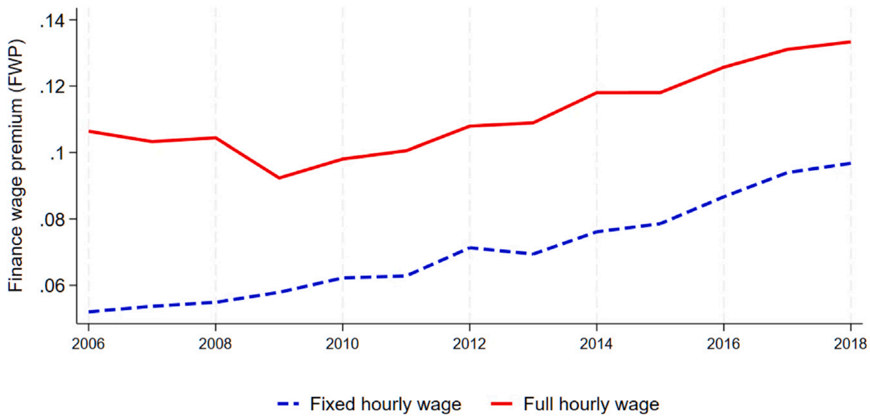


Fig. 2. Finance wage premium over time.
Notes: This figure shows the finance wage premium over time for the fixed hourly wage and the full hourly wage. The estimates follow from Eq. (2) after we introduce interactions with year fixed effects analogously to Column (5) of Table 2.

wage in Panel B. For example, finance workers in the lowest income quartile earn 7.7% more in fixed wages than workers in other industries, whereas workers in the highest income quartile in finance receive an additional 8.0% fixed wage premium, making the finance fixed wage premium almost 16% for the group of highest earners. Reflecting the importance of variable compensation in finance, finance wage premiums are even larger for the case of the full hourly wage. In particular, Panel B shows the full hourly wage premiums in finance for workers in the lowest and higher income quartiles, at 10% and 25.9%, respectively. In column (3), we focus on the subset of workers in the highest income decile. For the fixed hourly wage measure in Panel A, we find that the premium for finance workers in the top decile of the sectoral income distribution does not differ significantly from the finance wage premium estimated for the rest of the income distribution. However, in Panel B, we see that finance workers in the top decile earn a statistically significant additional finance wage premium of about 9.5% compared to the finance wage premium earned by other finance workers, consistent with relatively high flexible pay for the highest earners in finance.

We further use the richness of the administrative data to examine the finance wage premium by job and contract characteristics. In column (4) of Panels A and B, we find that part-time workers, who are prevalent in the Netherlands, also enjoy a sizable finance wage premium both in their fixed and full hourly wages. The full hourly wage premium for part-time workers in finance is around 2.1% lower than for full-timers, who enjoy a 11.7% premium. In column (5) of Panels A and B, we report that on-call and temporary agency workers generally have lower wages than regular workers, and that temporary agency workers receive a wage premium for working in the finance industry that is not significantly different compared to the rest of workers in finance. On-call workers in finance sector, in contrast, receive a significantly lower finance wage premium compared to the rest of workers in finance. In fact, the estimated coefficients suggest that on-call workers actually receive a negative finance wage premium, as the coefficient on the interaction FWP × On-call is negative enough to reduce the finance wage premium for on-call workers below zero. Note, however, that the finance sector employs relatively few on-call workers (Table 1).

Wages generally rise with worker experience, but the return to experience may differ between finance and non-finance sectors, suggesting that the finance wage premium may depend on worker experience. To examine this, we consider a worker's job tenure

Table 4
Finance wage premium by job and industry tenure.

	AKM regressions			
	Job tenure (1)	Industry tenure (2)	Job tenure (3)	Industry tenure (4)
	Fixed hourly wage		Full hourly wage	
Finance wage premium (FWP)	0.0728**	0.0813***	0.122***	0.125***
	(4.87)	(7.54)	(5.94)	(7.97)
Tenure [2–5 years]	0.0312**	0.0150***	0.0497***	0.0193***
	(44.03)	(16.37)	(39.03)	(16.14)
Tenure [longer than 5 years]	0.0501***	0.0240***	0.0748***	0.0322***
	(22.24)	(12.50)	(24.82)	(12.97)
FWP × Tenure [2–5 years]	0.00196	−0.00283*	−0.00416	−0.000435
	(0.50)	(−2.03)	(0.68)	(−0.18)
FWP × Tenure [longer than 5 years]	0.000103	−0.0247**	−0.0167	−0.0311**
	(0.01)	(−2.91)	(−1.04)	(−2.64)
Observations (N × T)	39,418,962	39,418,962	39,418,962	39,418,962
Adjusted R-squared	0.912	0.909	0.906	0.901

Notes: Tenure measures either job or industry tenure. In each case, we classify tenure into three groups: 1–2 years (baseline), 2–5 years, and longer than 5 years. For each type of tenure, the latter two groups are represented by dummy variables in the regressions. All regressions include a polynomial term in age (normalized to 40 years old) and fixed effects for part-time contract, contract type (regular (baseline), temporary agency, and on-call), and municipality. Sample selections are described in the text. For the finance wage premium coefficients, z-statistics are reported in parentheses from bootstrapped standard errors at the firm level (200 repetitions). For all other coefficients t-statistics are reported. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}\ p < 0.001$.

and, alternatively, industry tenure. For the case of job tenure, we construct a dummy variable indicating that job tenure is between 2 and 5 years, and also a dummy variable flagging that job tenure exceeds 5 years. Analogously, we construct dummy variables indicating that industry tenure is between 2 and 5 years or more than 5 years. In Table 4, we report estimates of how job and industry tenure affect wages and, in particular, the finance wage premium. As expected, wages in non-finance sectors are generally higher for workers with longer job and industry tenure. Comparing finance to non-finance workers, we see that the finance wage premium is not significantly affected by job tenure, but that industry tenure is associated with a lower finance wage premium. Specifically, for workers with more than 5 years of industry experience, the finance fixed and full hourly wage premiums are 2.5% and 3.1% lower, respectively, indicating that finance workers receive a relatively low return on their industry experience.

6. Firm-level determinants of the finance wage premium

Several explanations have been suggested for the finance wage premium, and the role of ICT capital and risk-taking are two prominent factors. In this section, we present two complementary analyses to gauge the (relative) importance of these factors. We can perform these two analyses because we estimated firm-specific wage premia for each firm (rather than using a single industry dummy). First, we perform an Oaxaca-Blinder decomposition that attributes the relatively high wages firms in finance pay to differences in observable characteristics between firms in finance and other industries. The second analysis takes advantage of the fact that we observe the universe of firms in the Netherlands. Using a propensity score matching model, we find a non-financial firm for each financial firm with comparable observable characteristics. After matching, we measure the remaining wage gap between financial and similar non-financial firms.

6.1. Explaining firm-specific wage premia

From Eq. (2), we obtain estimates of the firm fixed effects $\psi_{J(i,t)}$ that can be interpreted as firm-specific wage premia.[20] Fig. 3 plots the distributions of these estimated firm fixed effects separately for non-financial firms, non-bank financial firms (insurance companies, pension funds, fund management, and auxiliary financial services firms), and banks. The figure shows that the distributions for non-financial firms and non-bank financial firms are similar, but that banks have distinctly higher estimated firm fixed effects. This evidence suggests that the finance wage premium is particularly a banking phenomenon. As a robustness check, Fig. A.2 replicates this analysis for alternative samples and reveals similar patterns.

Table 5 presents the results of estimating specification (6) that relates estimated firm fixed effects to a range of firm-level variables, with a focus on ICT-related variables and firm risk measures. Firm variables are median values. The first four columns of the table present unweighted results where one firm is one data point, and the last four columns convey results that are weighted by the number of workers in each firm to proxy for size. Columns (1) and (5) relate the firm fixed effects to a finance industry dummy to provide an estimate of the overall finance wage premium. The estimated coefficient of 0.229 is significant in column (5),

[20] Table C.1 in the Appendix presents a variance decomposition of log wages (Lachowska et al., 2020b; Lamadon et al., 2019), showing that worker and firm fixed effects account for 55% and 7% of this decomposition, respectively.

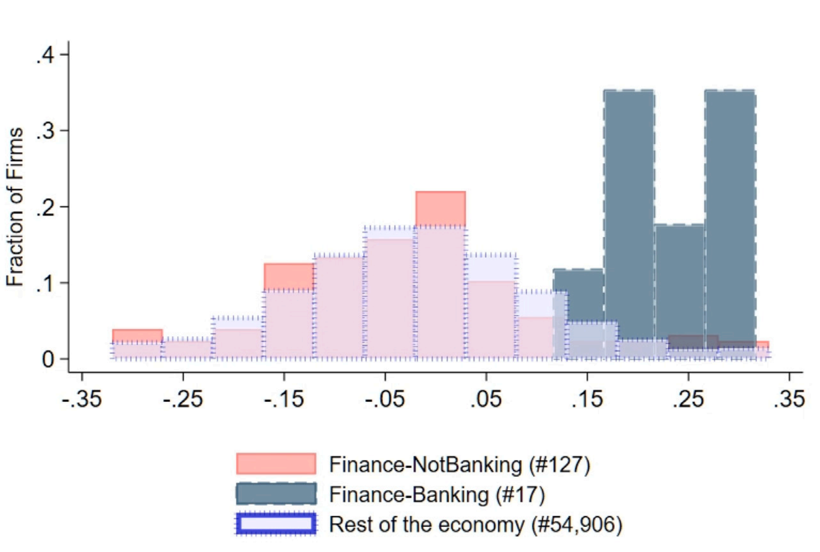


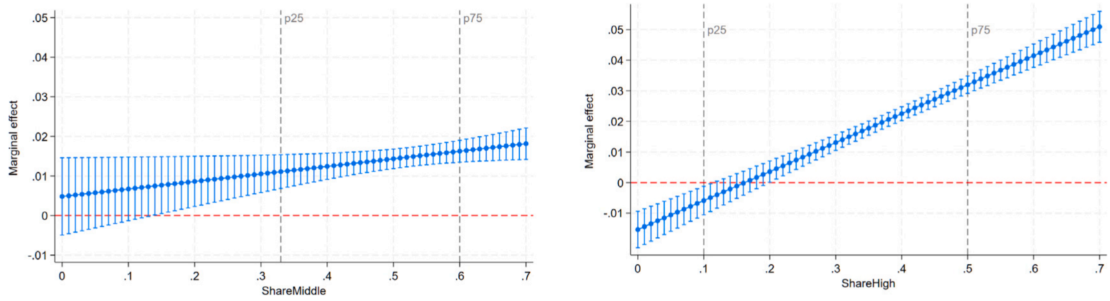
Fig. 3. Distribution of firm-specific wage premia (firm fixed effects).

Notes: This figure reports the firm fixed effects distribution for three groups of firms: firms in finance that are not part of the banking system, firms in finance that are part of the banking system, and firms in the rest of the economy. Firm fixed effects are estimated from Eq. (2).

Table 5
Explaining firm-specific wage premia.

	Firm-specific wage premia							
	Unweighted regressions				Weighted regressions (number of workers)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Finance	0.0233				0.229***			
	(1.88)				(5.60)			
-Finance-Non-banking		−0.00735	−0.0280*	−0.0160		0.0201	−0.0367	−0.0390*
		(−0.64)	(−2.33)	(−1.34)		(0.76)	(−1.66)	(−2.27)
-Finance-Banking		0.252***	0.177***	0.111***		0.282***	0.192***	0.144***
		(17.19)	(11.29)	(6.32)		(12.59)	(6.88)	(5.17)
Log ICT-K			−0.00869	−0.0245***			−0.0367*	−0.0451**
			(−1.24)	(−3.47)			(−2.32)	(−2.91)
ShareMiddle			0.0585	0.127*			0.642***	0.674***
			(1.13)	(2.45)			(5.07)	(5.42)
ShareHigh			0.461***	0.574***			0.549***	0.592***
			(11.30)	(14.03)			(5.59)	(6.24)
Log ICT-K × ShareMiddle			0.00636	0.0189*			0.107***	0.112***
			(0.69)	(2.05)			(4.92)	(5.27)
Log ICT-K × ShareHigh			0.0730***	0.0946***			0.0727***	0.0818***
			(10.01)	(12.93)			(4.20)	(4.91)
Equity/Assets				−0.00708***				−0.0168***
				(−5.31)				(−4.33)
Z-score				−0.000296***				0.0000169
				(−7.20)				(0.14)
Log assets				0.0113***				0.00281***
				(27.81)				(2.66)
Profits per worker (×1000)				0.366***				0.723***
				(12.96)				(5.74)
Observations (N × T)	55,050							
Adjusted R-squared	0.001	0.001	0.046	0.068	0.024	0.029	0.170	0.188

Notes: The dependent variable is the firm-specific wage premium. Finance-Non-banking is a dummy variable equal to one for firms in finance that are not part of the banking system. Finance-Banking is a dummy variable equal to one for firms in finance that are part of the banking system. ICT-K capital is spending on ICT capital assets per period. ShareMiddle and ShareHigh are the shares of workers in a firm with middle, respectively high level of education. The z-score is constructed as the sum of the equity-to-assets ratio and the rate of return on assets (ROA) divided by the standard deviation of the ROA, and it is a measure of how unlikely it is that a firm will become insolvent. T-statistics are reported in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}\ p < 0.001$.



(a) (b)

Fig. 4. Marginal effect of ICT capital spending on the firm-specific wage premium by level of education.
Notes: Figure (a) reports the marginal effect of ICT capital on the firm-specific wage premium by the education variable ShareMiddle, while assuming that ShareHigh is at its median value. Figure (b) reports the marginal effect of ICT capital on the firm-specific wage premium by the education variable ShareHigh, while assuming that ShareMiddle is at its median value. The used coefficients are obtained from Table 5, column (3). We report 95% confidence intervals. We also indicate the 25th and 75th percentiles of each variable with vertical dashed lines.

while the corresponding coefficient is insignificant in column (1). The implied finance wage premium of 22.9% from column (5) is considerably larger than the estimate of 11.1% from column (4) in Table 2, Panel B. The difference reflects that the sample for Table 5 only includes relatively large, incorporated firms for which we could obtain firm-level information from Statistics Netherlands. In columns (2) and (6), we replace the overall finance industry dummy with separate dummy variables for non-banking financial firms and for banks. In both columns, the dummy variable for non-bank financial firms is insignificant, while the bank dummy is significantly estimated at 0.252 and 0.282, respectively. This suggests that the banking sector is driving most of the finance wage premium, consistent with Fig. 3.

Columns (3) and (7) include variables related to ICT and education, while columns (4) and (8) additionally include risk variables (i.e., the equity-to-asset ratio and the z-score) and measures of firm size (log of assets) and profitability per worker. In columns (4) and (8), we see that these firm-level variables are similarly estimated. Specifically, we find that the interaction terms Log ICT-K×ShareMiddle and Log ICT-K×ShareHigh are estimated with positive and significant coefficients, consistent with a complementarity of ICT capital and firm-level educational attainment in productivity and in wage setting in line with Acemoglu and Autor (2011) and Autor et al. (1998). Fig. 4 plots the implied marginal effect of ICT-K on the firm-specific wage premium for different levels of ShareMiddle and alternatively ShareHigh, using estimated coefficients from Table 5, column (3). We report 95% confidence intervals and indicate the 25th and 75th percentiles of each variable with vertical dashed lines. The figure generally shows a higher marginal effect of ICT capital for higher levels of firm-level educational attainment, indicative of a complementarity between ICT capital and human capital.

Note that introducing firm-level education variables in the regressions of Table 5 does not re-introduce worker-level human capital effects that are already absorbed by the worker fixed effects in the underlying AKM framework: the second-stage regressions of Table 5 rather relate firm wage premia, conditional on worker fixed effects, to industry ICT capital and firm-level educational attainment shares. We interpret the estimated coefficients at this second stage as indicating associations rather than causal effects. Overall, the analysis provides evidence of a positive complementarity effect of ICT capital and firm-level education at the middle and higher levels.

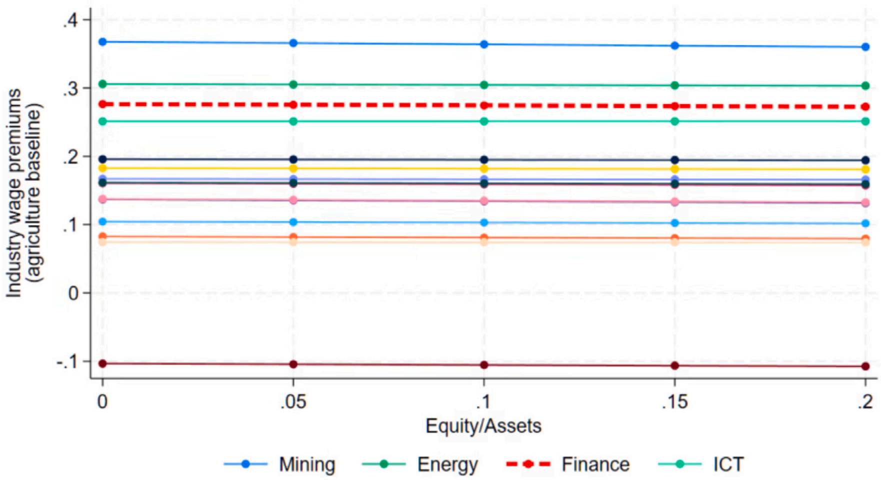
Turning to the proxies for firm risk, we see that wages are negatively and significantly related to the equity-to-assets ratio (in columns (4) and (8)) and the z-score (in column (4)), indicating that safer firms pay lower wages in line with Chemmanur et al. (2013). Furthermore, larger and more profitable firms are shown to offer higher wages (Card et al., 2014; Guiso et al., 2005). To investigate whether firm wage premiums in finance vary differently with profits per worker and the equity-to-assets ratio than in other sectors, we augment column (3) of Table 5 to include the profits per worker and equity-to-assets variables, and we interact them with sector dummy variables (using agriculture as the base category).[21] Using the estimated coefficients from this regression, we plot the implied average firm wage premiums by sector for different values of profits per worker and equity-to-assets in Fig. 5(a) and (b), respectively. These figures show that the average firm wage premium in finance is lower than in the mining and energy sectors but higher than in the ICT sector. Fig. 5(a) also shows that there is rent sharing, i.e., a positive relationship between the average firm wage premium and profits per worker, in finance consistent with Böhm et al. (2023) and that rent sharing in finance is more pronounced than in other sectors, and in particular in the mining, energy, and ICT sectors.[22]

The evidence of Table 5 implies that increases in ICT capital tend to give rise to higher firm wage premia. As an implication, variation in increases in ICT capital at the sector level could potentially explain different trajectories of wage premia across sectors.

[21] The results are very similar if we take the weighted regression in column (7) in Table 5 as the starting point.

[22] Fig. A.3 in the Appendix plots the time series of profits per worker in the finance industry, showing that these profits per worker did not exhibit an upward trend over the past decades.

(a)



(b)

Fig. 5. Industry wage premiums related to profits per worker and equity-to-assets.
Notes: Figure (a) reports industry wage premiums for different values of profits per worker. Figure (b) reports industry wage premiums for different values of the equity-to-assets ratio. To draw both figures, starting from column (3) of Table 5, we estimate a regression that includes interactions of sector dummies (NACE classification) with profits per worker and equity-to-assets. We then compute the industry wage premium (using agriculture as the base category) for different values of profits per worker and equity-to-asset from the 5th percentile to the 95th percentile. We do not report confidence intervals.

Next, we examine how variation in ICT capital increases across sectors explains variation in changes in sectoral wage premia, and in particular, in the finance wage premium. To do this, starting from column (3) in Table 5, we run a regression that replaces the interactions of log(ICT-K) with ShareMiddle and alternatively ShareHigh by sets of interactions of sector dummies with log(ICT-K) and ShareMiddle and alternatively ShareHigh. Using the estimated coefficients, we calculate the marginal effect of log(ICT-K) on firm wage premia at the median values of ShareMiddle and ShareHigh for each sector. To compute the effect of changes in ICT-K on sectoral wage premia over time, we multiply these calculated marginal effects of ICT-K per sector by the sectoral log change in ICT-K between 2006 and 2018. The resulting estimates of the contribution of changes in ICT-K over our sample period to sectoral wage premia are displayed in Fig. 6. In this figure, we can see that although the ICT marginal contribution to wage premiums is neither the largest for the finance sector (vertical axis) nor is the change in ICT over time (horizontal axis), the contribution of the increase in ICT-K to the average firm wage premium in finance is greater than in all other sectors including the ICT and mining sectors. This result supports the view that ICT capital has been an important determinant of the finance wage premium.

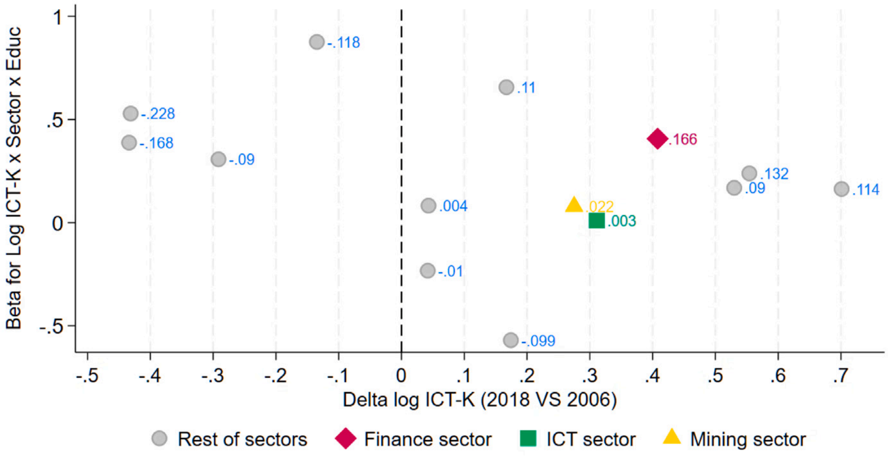


Fig. 6. ICT capital contributions to wage premiums by sector.
Notes: This figure shows the contribution of changes to ICT capital spending to wage premiums by sector. Starting from column (3) of Table 5, we estimate a regression that includes triple interactions between sector dummies, log(ICT capital), and the education shares ShareMiddle and ShareHigh. Using estimated coefficients, we calculate the marginal effect of log(ICT capital) at the median values of ShareMiddle and ShareHigh for each sector. This number represents the contribution of ICT capital to wage premiums by sector (vertical axis). We plot these contributions against the log change in ICT capital between 2006 and 2018 (horizontal axis). To calculate the overall contribution of ICT capital changes to changes in wage premiums per sector, we multiply the marginal effects of ICT capital by the log changes in ICT capital between 2006 and 2018. The resulting values are shown in the figure.

While the results of Table 5 indicate that a range of firm-level variables determine firm-level fixed effects in the AKM setting (and hence the finance wage premium), it is not immediately clear what their relative importance is in explaining the finance wage premium. To this end, we next perform an Oaxaca-Blinder decomposition of the difference in the average firm fixed effects between the financial and non-financial sectors, i.e., the finance wage premium, using differences in average explanatory variables. To do this, we first run two separate regressions of the estimated firm fixed effects in the financial and non-financial sectors, respectively, on firm-level variables as follows:

$$\hat{\psi}^F_{J(i,t)} = X'_F \beta_F + \epsilon_F,$$

$$\hat{\psi}^R_{J(i,t)} = X'_R \beta_R + \epsilon_R,$$

where F and R stand for financial sector and rest of the economy. Second, we estimate a pooled regression for all firms as follows:

$$\hat{\psi}_{J(i,t)} = X' \beta^* + \epsilon.$$

Using these three equations, we can decompose the difference in the expected firm fixed effects between the two sectors into explained and unexplained parts as follows

$$\underbrace{\mathbb{E}(\hat{\psi}^F_{J(i,t)}) - \mathbb{E}(\hat{\psi}^R_{J(i,t)})}_{\text{Finance Wage Premium}} = \underbrace{[\mathbb{E}(X'_F) - \mathbb{E}(X'_R)]\beta^*}_{\text{Explained}} + \underbrace{\mathbb{E}(X'_F)[\beta_F - \beta^*] - \mathbb{E}(X'_R)[\beta_R - \beta^*]}_{\text{Unexplained}}. \quad (7)$$

The explained part is the difference in firm characteristics between the finance industry and the rest of the economy weighted by a common coefficient β^*. The interpretation is that, for example, differences in risk between the finance industry and the rest of the economy can explain the higher wages in finance if the finance industry is, on average, riskier than the rest of the economy. The common coefficient β^* assumes that a unit increase in risk is associated with the same increase in wages in both the finance industry and the rest of the economy. The unexplained part allows for different compensations for risk, weighted by average risk in the finance industry and the rest of the economy, respectively. Thus, Eq. (7) decomposes the difference in average firm fixed effects, i.e., the finance wage premium, into a portion that is explained by cross-sectional differences in the explanatory variables, and a part that remains unexplained by these differences. The dependence of the unexplained part on both differences in the estimated effects of the explanatory variables and on differences in the values of these variables makes it difficult to interpret.

Table 6 shows the results of performing the decomposition. In particular, columns (1)–(3) show the decomposition for the case where the financial sector consists of all financial firms, while in columns (4)–(6) it is restricted to banks. The results in the two cases are very similar. In each instance, about half of the finance wage premium is explained by differences in average firm-level variables (see columns (2) and (5)). Of the explained part, 63% and 62% is attributed to education and ICT variables (columns (3) and (6)). In contrast, only 1% of the explained part of the finance wage premium is attributed to variation in risk measures in the two columns. This small contribution of risk variables in explaining the finance wage premium partly reflects that the financial

Table 6
Oaxaca-Blinder decomposition of the finance wage premium.

	Finance			Finance-Banking		
	FFE (1)	Explained (2)	Share (3)	FFE (4)	Explained (5)	Share (6)
Finance industry	0.220			0.273		
	(0.016)			(0.011)		
Rest of the economy	−0.010			−0.010		
	(0.002)			(0.001)		
Finance wage premium	0.229	0.125		0.282	0.138	
	100%	55%		100%	49%	
ICT and education measures:						
Log ICT-K		−0.061	−49%		−0.064	−46%
ShareMiddle		−0.123	−98%		−0.155	−112%
ShareHigh		0.178	142%		0.213	154%
Log ICT-K × ShareMiddle		0.156	125%		0.183	133%
Log ICT-K × ShareHigh		−0.071	−57%		−0.091	−66%
			63%			62%
Risk measures:						
Equity/Assets		0.002	2%		0.003	2%
Z-score		−0.001	−1%		−0.001	−1%
			1%			1%
Additional firm measures:						
Log assets		0.007	6%		0.008	6%
Profits per worker (×1000)		0.035	28%		0.041	30%
Firm municipality		0.000	0%		0.000	0%
			33%			35%

Notes: This table shows the Oaxaca-Blinder decomposition of the finance wage premium from Eq. (7). Column (1) and column (4) report the means of the firm-specific wage premia (FFE). Columns (2) and (5) report the explained part of the firm-specific wage premia, and columns (3) and (6) report the explained share. Standard errors are reported in parentheses.

sector, and banking in particular, has a lower equity-to-assets ratio (indicating more risk) but a higher z-score (indicating less risk). Other explanatory variables (log assets, profitability per worker, and firm municipality) collectively account for about a third of the explained portion of the finance wage premium. Overall, we conclude that differences in ICT capital spending, firm educational attainment, and their complementarity are most important in explaining the finance wage premium, while about half of the financial wage premium remains unexplained by our firm-level variables.

6.2. Propensity score matching

While the Oaxaca-Blinder decomposition of the finance wage premium allows us to attribute it to differences in firm characteristics, a complementary analysis is to compare the wages of financial firms with those of other firms with similar characteristics. In this subsection, we present a propensity score matching (PSM) model that matches financial and non-financial firms based on firm-level characteristics. In one specification, we match all financial firms with non-financial firms; in another, we match only banks with non-financial firms.

To implement the PSM model, we use a probit regression that estimates the likelihood that a firm is a financial firm (or only a bank) using the following variables: education shares, equity over assets, z-score, log of assets, profits per worker, municipality, and number of workers. To start, we apply a 1 : 1 nearest neighbor matching algorithm without replacement to assign one control firm to each firm in the finance sector. This matching algorithm maximizes comparability between financial firms and other firms, but in the case of banking, this results in a very small sample, as there are only 17 banks. Therefore, for banks, we also estimate a PSM model using 1:10 matching.

Table 7 presents the PSM results. Panel A displays the estimated wage differential (i.e., the finance wage premium) when we compare all firms in finance to matched non-financial firms, while Panel B shows the estimated finance wage premium for banks only. With 1:1 matching, the finance wage premia are estimated at 0.9% and 8.1% in the two panels, and they are both insignificant. Applying 1:10 matching to banks, we see that the finance wage premium in banking is estimated at 8.2%, and it is significant. These results indicate that the finance wage premium is primarily a banking phenomenon. As additional evidence, Fig. A.4 in the Appendix plots the firm-specific wage premium (from the AKM model) for each financial firm, including the 17 banks, against the firm-specific wage premium for the 1:1 matched non-financial firm in the PSM model, confirming that the finance wage premium is particularly prevalent in banking.

7. Concluding remarks

Using comprehensive administrative data, this paper provides evidence on the size and determinants of the finance wage premium in the Netherlands. Our dataset allows us to apply the additive worker and firm fixed effects model of Abowd et al. (1999a). Using this

Table 7
Estimates of the finance wage premium from propensity score matching.

	Finance wage premium (1)	Standard error (2)	t-Stat (3)
Panel A: Finance versus comparable firms			
Number of firms in finance	144		
1 : 1 nearest neighbor matching			
Average treatment effect (ATT)	0.009	0.0167	0.52
Panel B: Banking versus comparable firms			
Number of firms in banking	17		
Share of workers in finance	80%		
1 : 1 *nearest neighbor matching*			
-Average treatment effect (ATT)	0.081	0.045	1.76
1 : 10 *nearest neighbor matching*			
-Average treatment effect (ATT)	0.082	0.024	3.43

Notes: This table shows the results of comparing firm-specific wage premia for firms in finance to similar firms in the rest of the economy. We implement a propensity score matching using a probit model of the likelihood of a firm being in the finance industry. The model includes variables such as education shares, equity over assets, z-score, log of assets, profits per workers, municipality, and number of workers. We apply a 1 : 1 nearest neighbor matching algorithm without replacement to assign one control firm to each firm in the overall finance sector, and 1 : 1 and 1 : 10 nearest neighbor matching algorithms without replacement to assign one control firm to each firm in banking.

empirical framework, we estimate the finance wage premium as the difference in the average firm fixed effects in the finance industry compared to the rest of the economy. In previous studies, the finance wage premium is instead estimated as the coefficient on a dummy variable indicating that a firm belongs to the finance industry. As a methodological contribution, we show that disregarding firm fixed effects in a worker fixed effects specification leads to an underestimation of the finance wage premium.

The rich administrative data allow us to estimate separate finance wage premia for the fixed wage and the full wage, which includes variable pay such as bonuses and overtime. We find that the estimated finance wage premium is higher for the full wage than for the fixed wage, consistent with the relative importance of variable pay in finance. Among financial institutions, the finance wage premium is particularly pronounced for banks.

Wages positively reflect a complementarity between ICT capital and average firm-level educational attainment. This in part explains the finance wage premium, as both ICT capital and educational attainment are higher in the financial sector. In addition, wages are positively associated with firm risk, and the relatively higher leverage of firms in the financial sector (i.e., lower equity-to-assets ratio) partly explains the higher wages in this sector.

To inform on the relative importance of risk and other firm-level variables in explaining the finance wage premium, we perform a decomposition of the difference in the average financial and non-financial firm-specific wage, i.e., the finance wage premium. We find that ICT and human capital measures, including their complementarity, are most important in explaining the finance wage premium, as they account for 63% of the explained part of the finance wage premium. In contrast, risk variables account for only 1% of the explanation of the finance wage premium. Other firm-level variables, in particular size and profitability, together account for the remainder.

CRediT authorship contribution statement

Ata Can Bertay: Writing – review & editing, Methodology, Investigation, Formal analysis. **José Gabriel Carreño:** Writing – original draft, Validation, Formal analysis, Data curation, Conceptualization. **Harry Huizinga:** Writing – review & editing, Supervision, Conceptualization. **Burak Uras:** Writing – review & editing, Supervision, Investigation. **Nathanael Vellekoop:** Writing – review & editing, Writing – original draft, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Tables and figures

See Figs. A.1–A.4 and Tables A.1–A.2

Appendix B. Proof of downward bias in finance industry dummy regressions

The argument has two steps. Step 1 shows that the finance-industry indicator in models with worker fixed effects is identified entirely by *industry switchers*. Step 2 shows that when in these models firm fixed effects are omitted, within-industry firm heterogeneity enters the residual and becomes systematically related to industry switching. This generates a bias in estimating industry effects in general, and we show that the bias is likely downward in the estimated finance premium.

Table A.1
NACE classification.

NACE	Section	Title
1	A	Agriculture, forestry and fishing
2	B	Mining and quarrying
3	C	Manufacturing
4	D	Electricity, gas, steam and air conditioning supply
5	E	Water supply; sewerage, waste management and remediation activities
6	F	Construction
7	G	Wholesale and retail trade; repair of motor vehicles and motorcycles
8	H	Transportation and storage
9	I	Accommodation and food service activities
10	J	Information and communication
11	K	Financial and insurance activities
		-Monetary intermediation services
		-Services of holding companies
		-Services of trusts, funds and similar financial entities.
		-Other financial services, except insurance, and pension funding
		-Insurance services
		-Reinsurance services
		-Pension funding services
		-Services auxiliary to financial services and insurances services
		-Services auxiliary to insurance and pension funding.
		-Fund management services
12	L	Real estate activities
13	M	Professional, scientific and technical activities
14	N	Administrative and support service activities
15	O	Public administration and defence; compulsory social security
16	P	Education
17	Q	Human health and social work activities
18	R	Arts, entertainment and recreation
19	S	Other service activities
20	T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
21	U	Activities of extraterritorial organizations and bodies

Notes: This table shows "sections", which we call industries, of the Standard Business Classification 2008 (SBI 2008) used by Statistics Netherlands. Firms are classified by Statistics Netherlands based on main activity. The SBI 2008 is the version used from 2008 onward (with a cross-over table for 2006 and 2007). The SBI 2008 has several levels, which are indicated by a maximum of five numbers. The first four levels correspond to the European Union (NACE) classification.

Table A.2
Finance wage premium for banks and non-bank financial firms.

	AKM regressions	
	(1) Fixed hourly wage	(2) Full hourly wage
Finance wage premium (FWP):		
Non-bank financial firms	0.0482***	0.0840****
	(6.00)	(8.13)
Banks	0.153***	0.217***
	(9.39)	(10.80)
Observations (N × T)	39,418,962	39,418,962
Adjusted R-squared	0.911	0.902

Notes: All regressions include a polynomial term in age (normalized to 40 years old) and fixed effects for part-time contract, contract type (regular (baseline), temporary agency, and on-call), and municipality. z-statistics are reported in parentheses from bootstrapped standard errors at the firm level (200 repetitions). $*p < 0.05$, $**p < 0.01$, $***\ p < 0.001$.

Step 1: Identification of the finance industry dummy

For the sake of the argument, suppose the true wage-setting equation follows an AKM-style model with both worker and firm effects:

$$w_{it} = \alpha_i + \delta_{f(i,t)} + \varepsilon_{it}, \tag{B.1}$$

so that, conditional on α_i and the firm effect $\delta_{f(i,t)}$, there are no remaining systematic wage determinants.

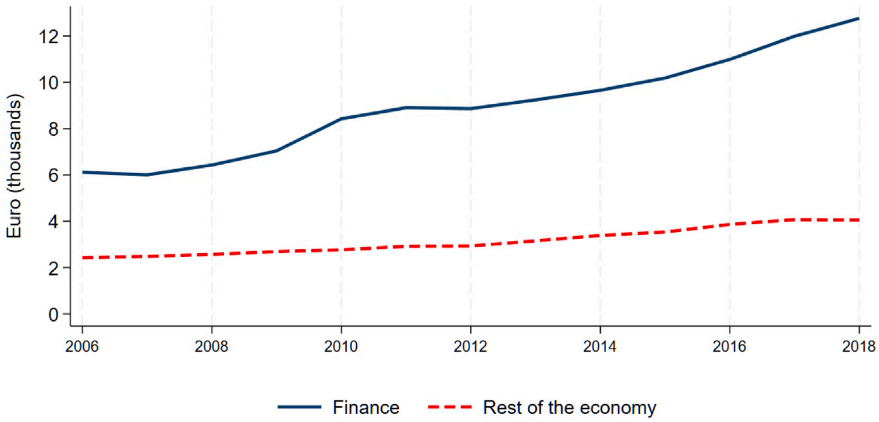


Fig. A.1. ICT-K per worker over time.
Notes: This figure shows the amount of ICT-K per worker over time. ICT-K is productive inputs that flow to the production from ICT capital assets per period. The ICT category consists of computers, communications equipment and software and databases. ICT-K is not available for the industries Real Estate, Public Administration and Education (NACE codes 12, 15, and 16).

To motivate the finance-industry dummy approach, ignore covariates and consider estimating the following worker fixed-effects regression:

$$w_{it} = \alpha_i + \phi\, 1_{it}^F + u_{it}, \tag{B.2}$$

where 1_{it}^F equals 1 if worker i is employed in the finance industry at time t. We interpret ϕ as the *finance wage premium* in this worker-FE specification, i.e., the average within-worker difference in log wages between finance and non-finance employment. Let $\widetilde{x}_{it} \equiv x_{it} - \bar{x}_i$ denote the within-worker (demeaned) transformation. The fixed-effects estimator can be written as

$$\hat{\phi}_{FE} = \frac{\mathrm{Cov}\left(\widetilde{w}_{it}, \widetilde{1}_{it}^F\right)}{\mathrm{Var}\left(\widetilde{1}_{it}^F\right)}. \tag{B.3}$$

Because 1_{it}^F is binary, $\widetilde{1}_{it}^F$ is identically zero for workers who never change finance industry status over time. Hence, both $\mathrm{Cov}(\widetilde{w}_{it}, \widetilde{1}_{it}^F)$ and $\mathrm{Var}(\widetilde{1}_{it}^F)$ are identified only by workers whose finance industry status changes (industry switchers).

Two-period, one-switch case. Suppose every switching worker is observed in exactly two periods (before and after the move) and switches industries once (to simplify the math). Let $\Delta w_i \equiv w_{i,2} - w_{i,1}$ denote the wage change at the move. Let p be the share of switchers who move *into* finance (so $1 - p$ move *out of* finance).[23] Then

$$\mathrm{Cov}\left(\widetilde{w}_{it}, \widetilde{1}_{it}^F\right) = \frac{1}{4}\left[p\,\overline{\Delta w}_{\text{into F}} - (1-p)\,\overline{\Delta w}_{\text{out of F}}\right], \tag{B.4}$$

and

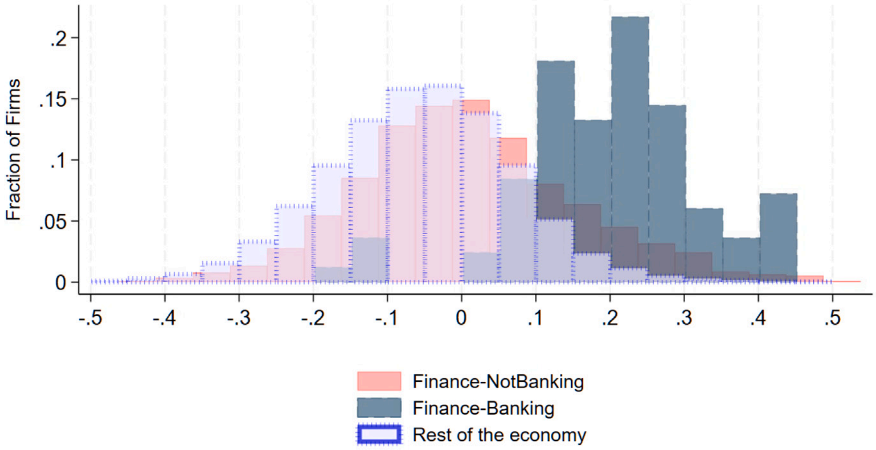
$$\mathrm{Var}\left(\widetilde{1}_{it}^F\right) = \frac{1}{4}. \tag{B.5}$$

Therefore, the estimated finance industry dummy in models with worker fixed effects simplifies to

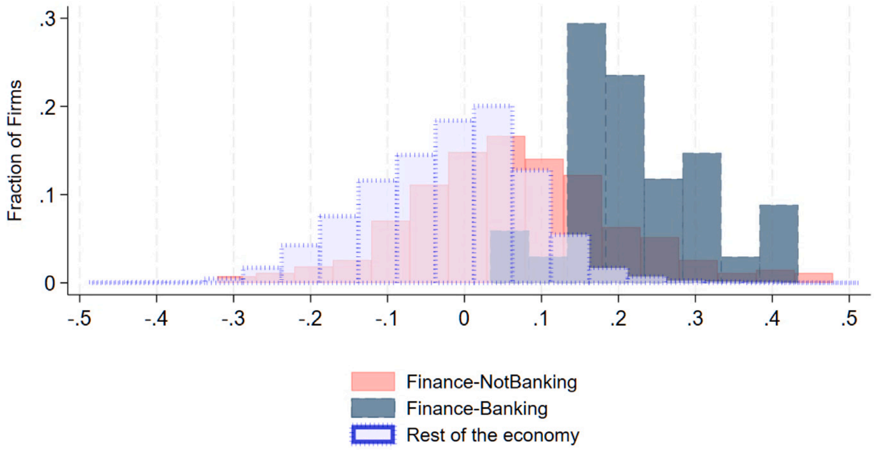
$$\hat{\phi}_{FE} = \frac{\mathrm{Cov}\left(\widetilde{w}_{it}, \widetilde{1}_{it}^F\right)}{\mathrm{Var}\left(\widetilde{1}_{it}^F\right)} = p\,\overline{\Delta w}_{\text{into F}} - (1-p)\,\overline{\Delta w}_{\text{out of F}}. \tag{B.6}$$

Step 1 shows that in models with worker fixed effects the finance industry dummy is identified by switchers in and out of finance. The estimated coefficient equals a mover-weighted average wage change associated with switching into finance versus out of finance. Under the maintained AKM model, this mover-weighted object can be interpreted as targeting the finance wage premium. Step 2 shows that the estimated finance industry coefficient is biased when firm effects are omitted from the estimated regression.

[23] The results are a consequence of the stylized two-period, one-switch setup in which each switching worker is observed exactly once before and once after the move. For instance, for an “into finance” mover, $(1_{i1}^F, 1_{i2}^F) = (0, 1)$ so $\bar{1}_i^F = \frac{1}{2}$ and $\widetilde{1}_{i1}^F = -\frac{1}{2}$, $\widetilde{1}_{i2}^F = \frac{1}{2}$. For an “out of finance” mover, $(1_{i1}^F, 1_{i2}^F) = (1, 0)$ and the demeaned values are $\widetilde{1}_{i1}^F = \frac{1}{2}$, $\widetilde{1}_{i2}^F = -\frac{1}{2}$. Hence $\mathrm{Var}(\widetilde{1}_{it}^F) = E[(\widetilde{1}_{it}^F)^2] = (\frac{1}{2})^2 = \frac{1}{4}$.



(a) Full sample.



(b) Firms larger than 50 workers.

Fig. A.2. Distribution of firm-specific wage premia (firm fixed effects).
Notes: Figure (a) shows the distribution of firm fixed effects for three groups of firms: (i) firms in finance that are not part of the banking system, (ii) firms in finance that are part of the banking system, and (iii) firms in the rest of the economy. Firm fixed effects are estimated from Eq. (2). Figure (a) presents the distribution for the full sample of firms including firms for which no firm-level data are available. Figure (b) reports the same distribution as Figure (a), but it excludes firms with an average number of workers lower than 50.

Step 2: Bias from omitting firm fixed effects

Step 1 shows that $\hat{\phi}_{FE}$ is identified by industry switchers and, under the maintained AKM environment, can be interpreted as targeting the finance wage premium. We now show that the estimated finance wage premium is biased when firm effects are omitted from the regression.

Decomposing the firm component. Using the maintained AKM wage-setting equation from Step 1,

$$w_{it} = \alpha_i + \delta_{f(i,t)} + \varepsilon_{it}, \tag{B.7}$$

decompose each firm fixed effect into an industry mean plus a within-industry deviation from the industry mean:

$$\delta_f = \psi_{j(f)} + h_f, \tag{B.8}$$

where $j(f) \in \{F, NF\}$ denotes the industry of firm f, ψ_j is the mean firm effect in industry j, and h_f captures how firm f differs from the industry mean (the "hierarchy" component). The object we would like ϕ to capture is the difference in industry means, $\psi_F - \psi_{NF}$.

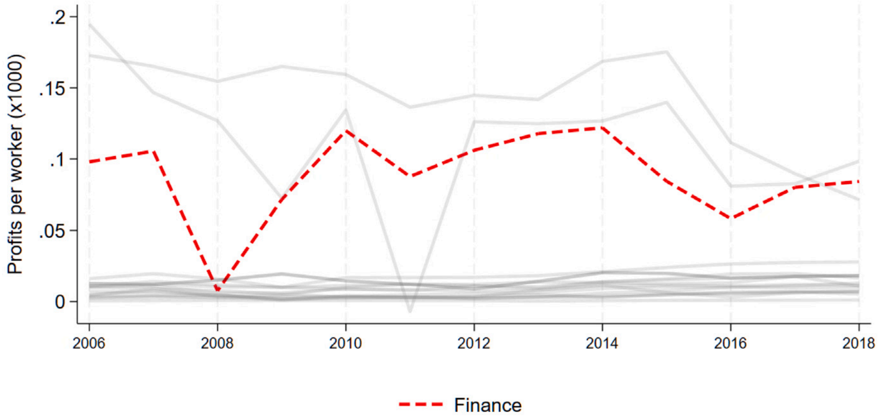


Fig. A.3. Profits per worker over time by industry.
Notes: This figure shows profits per worker over time (unweighted) by industry (NACE classification).

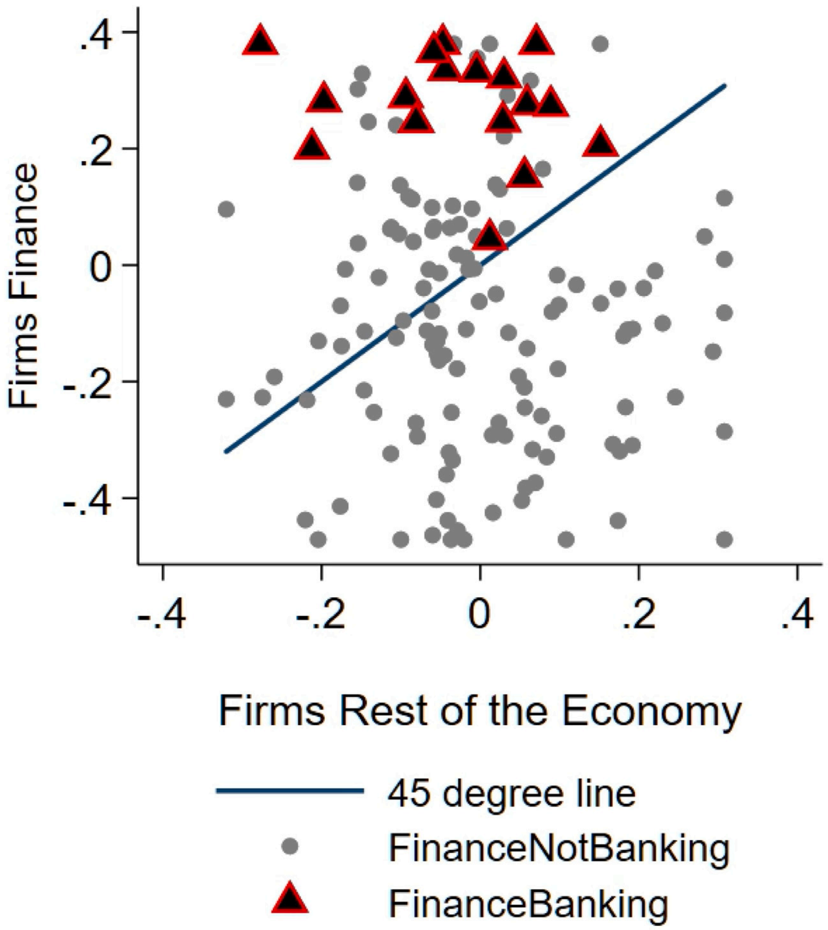


Fig. A.4. Firm-specific wage premia of financial firms and comparable non-financial firms.
Notes: Plot of firm-specific wage premium of firms in finance and of 1:1 matched non-financial firms. There are 144 pairs of matched financial and non-financial firms. We also include a 45-degree line. If a point is on the 45-degree line, it indicates that the two similar firms have the same firm-specific wage premium. If a point lies above the 45-degree line, the firm-specific wage premium is larger for the firm in finance. Firms in banking are shown in triangle-red.

If we estimate wage regressions with worker fixed effects and only the finance industry indicator,

$$w_{it} = \alpha_i + \phi\, 1^F_{it} + u_{it}, \tag{B.9}$$

then, using $\delta_f = \psi_{j(f)} + h_f$, the error term contains the omitted within-industry component:

$$u_{it} = \varepsilon_{it} + h_{f(i,t)}. \tag{B.10}$$

For a mover i, define $\Delta w_i \equiv w_{i,2} - w_{i,1}$, $\Delta 1^F_i \equiv 1^F_{i,2} - 1^F_{i,1} \in \{+1, -1\}$, and similarly $\Delta h_i \equiv h_{f(i,2)} - h_{f(i,1)}$. Using $\psi_{j(i,t)} = \psi_{NF} + \left(\psi_F - \psi_{NF}\right) 1^F_{it}$ and taking first differences of the true model, we get

$$\Delta w_i = (\psi_F - \psi_{NF})\, \Delta 1^F_i + \Delta h_i + \Delta\varepsilon_i. \tag{B.11}$$

Eq. (B.11) makes the bias transparent. The change in the mover wage reflects the industry-mean gap ($\psi_F - \psi_{NF}$) and the change in the hierarchy term Δh_i. Models with worker fixed effects and an industry fixed effect, but no firm fixed effects, attribute any systematic component of Δh_i that is correlated with $\Delta 1^F_i$ to the finance industry coefficient.

Direction of the bias. The direction of the bias follows from standard omitted-variable-bias logic applied to movers (Angrist and Pischke, 2009). In particular, using the movers representation in (B.11), the difference between the estimated coefficient and the industry-mean gap satisfies

$$\hat{\phi}_{FE} - (\psi_F - \psi_{NF}) = E\left[\Delta 1^F_i\, \Delta h_i\right], \tag{B.12}$$

under the condition $E[\Delta 1^F_i\, \Delta\varepsilon_i] = 0$.[24]

So $\hat{\phi}_{FE}$ is *downward biased* relative to $\psi_F - \psi_{NF}$ whenever

$$E\left[\Delta 1^F_i\, \Delta h_i\right] < 0. \tag{B.13}$$

We argue that $E\left[\Delta 1^F_i\, \Delta h_i\right] < 0$ is negative. The intuition is as follows. To leave finance (so $\Delta 1^F_i = -1$), a worker must typically receive a sufficiently good offer in non-finance to offset the lower industry mean. This selects moves with $\Delta h_i = h_{NF} - h_F > 0$. Symmetrically, to move into finance (so $\Delta 1^F_i = +1$), workers need not experience as large a positive hierarchy jump. This selection mechanism induces a negative relationship between $\Delta 1^F_i$ and Δh_i, implying $E\left[\Delta 1^F_i\, \Delta h_i\right] < 0$ and therefore satisfying (B.13). As a result, the finance dummy estimate in models with only worker fixed effects is biased downward relative to the industry-mean gap. Appendix C provides empirical evidence in our data consistent with this selection pattern.

Appendix C. AKM assumptions

This appendix describes in more detail the identifying assumptions of the AKM framework as well as the results of some diagnostic tests for our regression sample that have been proposed in the literature.

C.1. Log additive functional form in the AKM regression

From Section 3.1, the AKM specification we use is given by:

$$\ln w_{it} = \boldsymbol{X}_{i,t}\boldsymbol{\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{it}, \tag{C.1}$$

where w_{it} is the wage of worker i in year t, $\boldsymbol{X}_{i,t}$ are time-varying variables, α_i are worker fixed effects, $\psi_{J(i,t)}$ are firm fixed effects, λ_t are year fixed effects, and ϵ_{it} is the idiosyncratic error term. Firm fixed effects contain a matching function J that assigns worker i in year t at firm j.

The (log) additive functional form in the AKM specification implies that all workers who move from firm k to j will experience an average wage change of $\psi_j - \psi_k$, independent of the worker quality α_i, while those who move in the opposite direction will experience an average change of $\psi_k - \psi_j$. To assess the log additive structure, we perform an event study of the average wage change experienced by workers moving between different types of firms as in Card et al. (2018, 2016). The samples are restricted to workers who switch firms and have worked for at least two years at both the origin and destination firm. Similarly to their study, we define groups of firms based on co-worker pay quartiles (using data on male and female co-workers). Figs. C.1 and C.2 report the wage profiles of workers who move from jobs in quartile 1 and quartile 4, for male and female workers, respectively. Reassuringly, our results are in line with the log additive structure. Workers who move to firms with more highly paid co-workers experience a wage raise, while those who move in the opposite direction experience wage cuts of similar magnitude. As expected, the average wage does not change when workers move between firms with similarly paid co-workers. Furthermore, the wage profiles for all groups are all relatively stable in the years before and after a job move.

[24] In the two-period, one-switch case, the within-FE slope can be written as

$$\hat{\phi}_{FE} = \frac{\sum_i \Delta 1^F_i\, \Delta w_i}{\sum_i (\Delta 1^F_i)^2} = E[\Delta 1^F_i\, \Delta w_i],$$

since $(\Delta 1^F_i)^2 = 1$ for switchers. Using $\Delta w_i = (\psi_F - \psi_{NF})\Delta 1^F_i + \Delta h_i + \Delta\varepsilon_i$ yields

$$\hat{\phi}_{FE} = (\psi_F - \psi_{NF}) + E[\Delta 1^F_i\, \Delta h_i] + E[\Delta 1^F_i\, \Delta\varepsilon_i].$$

Assuming $E[\Delta 1^F_i\, \Delta\varepsilon_i] = 0$ gives $\hat{\phi}_{FE} - (\psi_F - \psi_{NF}) = E[\Delta 1^F_i\, \Delta h_i]$.

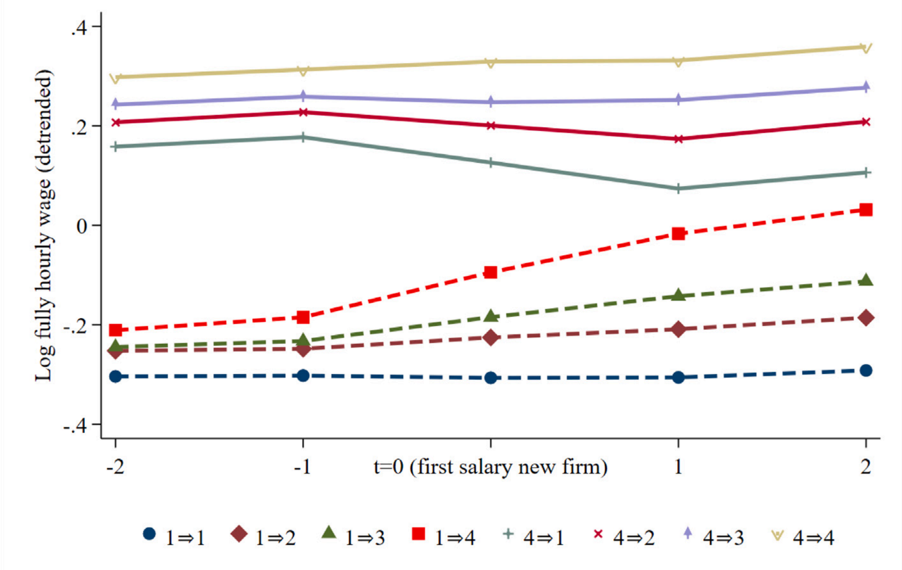


Fig. C.1. Event study of changes in earnings when male workers move between firms.
Notes: The figure shows the event study developed by Card et al. (2018, 2016). We consider male workers who switch firms and have worked for at least two years at both the origin and destination firms for the period 2006–2018. We define firms' groups based on co-worker pay quartiles (using data on all co-workers). We report the wage profiles of workers who move from jobs in quartile 1 and quartile 4, for male workers. Each line represents a different firm-to-firm movement, given by the firm group. We use the log full hourly wage (gross wage over paid hours) to describe the wage profile. To compare between different years, we detrend the log full hourly wage by using year fixed effects. We then plot the residuals from this regression. Since the first salary in the new firm does not represent a "real" annual wage (as the worker may have missed some variable compensation because he decided to change jobs in the middle of the year), the first full salary in the new firm is $t = 1$. Therefore, a proper comparison between firms is between $t = -1$ and $t = 1$.

Though the event study gives credence to a log-additive structure of the wage regression into worker and firm fixed effects, it is still possible to have interactions between worker and firm effects. Even if the functional form is non-additive, the gains and losses may look symmetric if workers making upward moves are of the same quality as those making downward moves (Bonhomme et al., 2019). Motivated by Lamadon et al. (2019), we classify firms and workers into ten types according to the average wage over the sample period. We then calculate the average wage for the combinations of worker–firm types. Fig. C.3 reports the results. Each point represents a worker–firm type ($10 \times 10 = 100$ points). While the figure shows evidence of worker heterogeneity (the vertical differences), we also observe that the gains for high-paid workers moving from low- to high-paying firms are similar to the gains for low-paid workers moving from low- to high-paying firms. This can be seen by visually moving on the top line (high worker type) from firm type 1 to firm type 10. Doing the same for the lowest worker type shows a similar difference. We conclude similarly to Card et al. (2013) that while firm-worker fixed effects may improve the statistical fit, the additive structure into separate worker and firm fixed effects is a fair assumption for our data.

C.2. Finance and the exogeneity assumption

To estimate Eq. (C.1), the following orthogonality condition must hold:

$$E[(\epsilon_{it} - \bar{\epsilon}_i)(D^j_{it} - \bar{D}^j_i)] = 0 \quad \forall j \in [1, \dots, J] \tag{C.2}$$

for $D^j_{it} \equiv 1[J(i,t) = j]$ where D^j_{it} is an indicator for employment at firm j in period t and bars over variables represent time averages. While this assumption is generally supported by data, we show that this assumption also applies to the job-to-job movements of workers going into/leaving the finance industry, which is the main focus of this study.[25]

Following the decomposition of the residual in terms of the joiners and leavers by Card et al. (2016), we decompose the residuals in terms of joiners and leavers of the finance industry for all job-to-job movements involving workers going into/leaving the finance industry during the sample period 2006–2018. To do that, we calculate the change in the residual after a job-to-job movement. Fig. C.5 reports the results of the exercise. As expected, we do find the average residual of leavers is comparable in magnitude to joiners but with an opposite sign (after accounting for a rich set of controls).

[25] Fig. C.4 shows that the residual wage changes are centered around zero, indicating that worker mobility does not show systematic patterns beyond those already captured by the AKM specification.

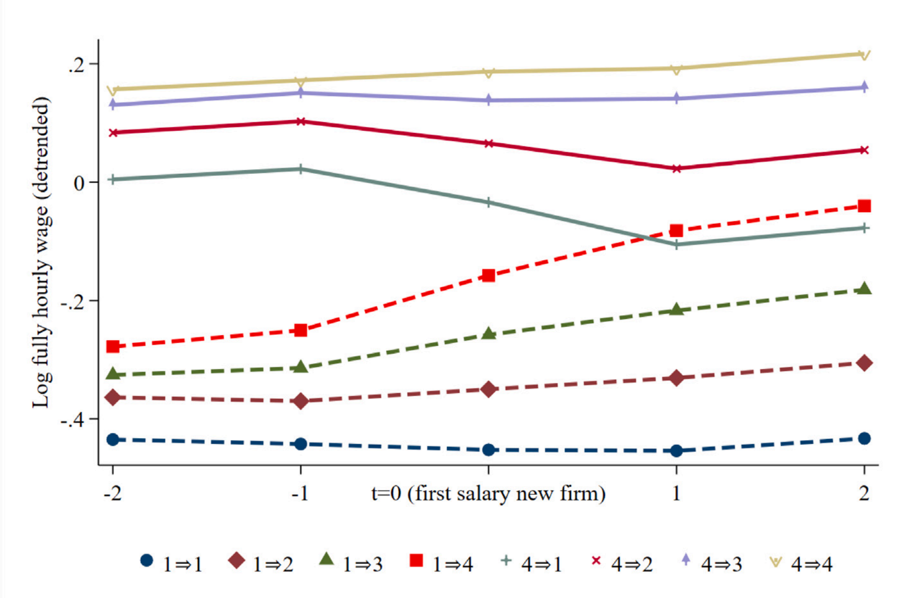


Fig. C.2. Event study of changes in earnings when female workers move between firms.
Notes: The figure shows the event study developed by Card et al. (2018, 2016). We consider female workers who switch firms and have worked for at least two years at both the origin and destination firms for the period 2006–2018. We define firms' groups based on co-worker pay quartiles (using data on all co-workers). We report the wage profiles of workers who move from jobs in quartile 1 and quartile 4, for female workers. Each line represents a different firm-to-firm movement, given by the firm group. We use the log full hourly wage (gross wage over paid hours) to describe the wage profile. To compare between different years, we detrend the log full hourly wage by using year fixed effects. We then plot the residual from this regression. Since the first wage in the new firm does not represent a "real" annual wage (as the worker may have missed some bonuses because she decided to change jobs in the middle of the year), the first full salary in the new firm is $t = 1$. Therefore, a proper comparison between firms is between $t = -1$ and $t = 1$.

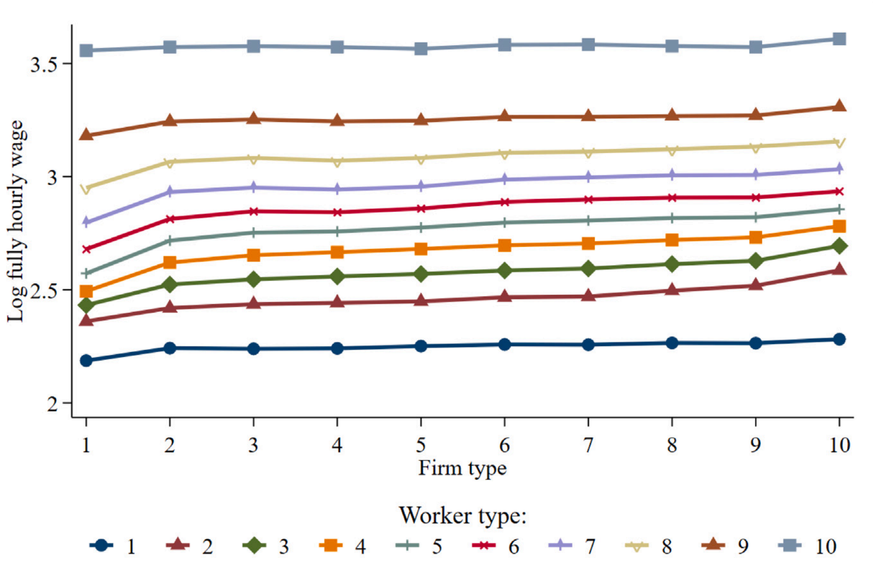
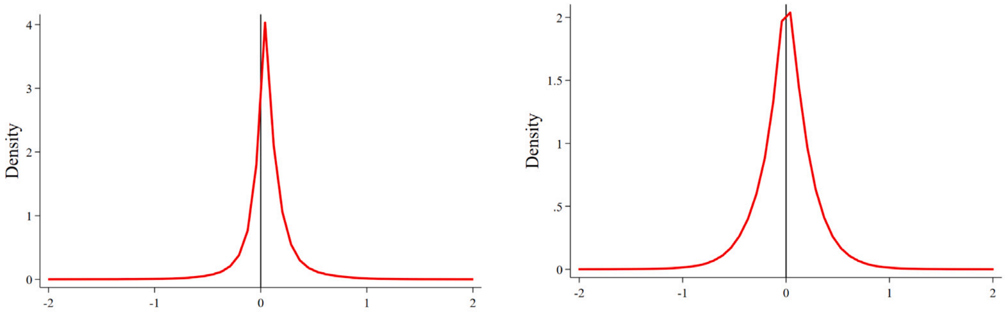


Fig. C.3. Earnings by type of workers and firms.
Notes: The figure shows the log full hourly wage for ten types of workers and firms. We classify firms and workers into ten types (i.e., deciles) according to the average log full hourly wage (gross wage over paid hours) over the years 2006–2018. We then calculate the average log full hourly wage for the combinations of worker–firm types (i.e., 100 combinations).



(a) Raw. (b) Residuals AKM regression.

Fig. C.4. Distribution of the log full hourly wage change for job-to-job movements over 2006–2018.
Notes: The figure shows the distribution of the change in log full hourly wage for workers changing jobs over the period 2006–2018. For each job-to-job movement observed in the dataset, we calculate the gains (or losses) for the log full hourly wage. Panel (a) plots this distribution. On the contrary, panel (b) cleans the data first. We run the regression $\ln w_{it} = \boldsymbol{X}_{i,t}\beta+\alpha_i+\psi_{J(i,t)}+\lambda_t+\epsilon_{it}$, where $w_{i,t}$ is the full hourly wage (gross wage over paid hours); $\boldsymbol{X}_{i,t}$ includes a polynomial term in age (normalized to 40 years old) and the following fixed effects: part-time contract, type of contract, municipality, and firm size categories; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; λ_t are year fixed effects; finally, $\epsilon_{i,t}$ is the error term. We then use $\hat{\epsilon}_{i,t}$ to calculate the gains (or losses) from job-to-job movements. Panel (b) plots this distribution. For the regression, we cover the period 2006–2018. We exclude firms that change industries and firms with fewer than 10 employees. We also consider workers aged 18 to 65. We drop extreme values. The sample includes only observations in the largest connected set.

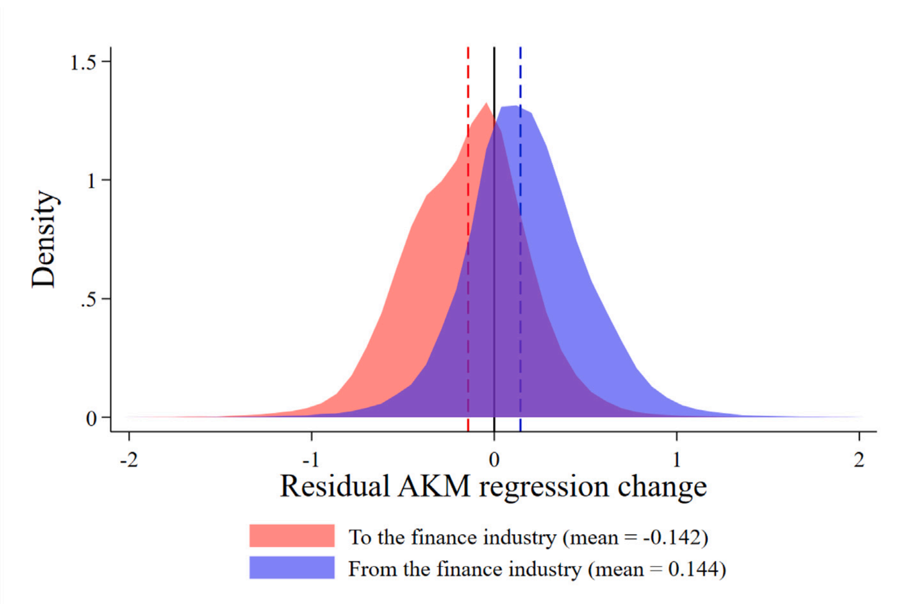


Fig. C.5. Distribution of the change in the residual of an AKM regression for job-to-job movements during 2006–2018.
Notes: The figure shows the distribution of the change in the residual of the wage regression for workers changing jobs from or to the finance industry during the period 2006–2018. For each job-to-job movement observed in the dataset, we calculate the gains (or losses) of the residual. We get the residual from the regression $\ln w_{it} = \boldsymbol{X}_{i,t}\beta + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{it}$ for the period 2006–2018, where $w_{i,t}$ is the full hourly wage (gross wage over paid hours); $\boldsymbol{X}_{i,t}$ includes a polynomial term in age (normalized to 40 years old) and the following fixed effects: part-time contract, type of contract, municipality, and firm size categories; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; λ_t are year fixed effects; finally, $\epsilon_{i,t}$ is the error term. We use $\hat{\epsilon}_{i,t}$ to calculate the gains (or losses) from job-to-job movements involving the finance industry. For the regression, the period is 2006–2018. The sample includes only observations in the largest connected set.

C.3. Limited mobility bias

The AKM estimates are sensitive to the limited mobility bias. According to Bonhomme et al. (2020) and Andrews et al. (2008), if firms are weakly connected to one another because of the limited mobility of workers across firms, AKM estimates of the contribution

Table C.1
Variance decomposition of the wage over the period 2006–2018.

	All		Interval	
	2006–2018		2007–2013	
	Comp. (1)	Share (2)	Comp. (3)	Share (4)
Total variance				
$Var(y)$	0.167		0.163	
Components of the variance				
$Var(WFE)$	0.091	55	0.099	61
$Var(FFE)$	0.011	7	0.011	7
$Var(Xb)$	0.025	15	0.021	13
$Var(residual)$	0.014	8	0.011	7
$2 * Cov(WFE, FFE)$	0.019	11	0.015	9
$2 * Cov(WFE, Xb)$	0.004	2	0.005	3
$2 * Cov(FFE, Xb)$	0.003	2	0.001	1
Observations (N × T)	39,320,449		21,484,422	

Notes: This table shows the following variance decomposition $Var(y) = Var(WFE) + Var(FFE) + Var(Xb) + Var(residual) + 2 * Cov(WFE, FFE) + 2 * Cov(WFE, Xb) + 2 * Cov(FFE, Xb)$ for the main regression sample and an alternative sample to compare with international evidence. We calculate the variance decomposition from the regression $y_{i,t} = \alpha_i + \psi_{J(i,t)} + Xb + \epsilon$, where $y_{i,t}$ is the log of the full hourly wage for worker i at time t; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; X corresponds to covariates, where we include a polynomial term in age (normalized to 40 years old) and the following fixed effects: year, part-time contract, type of contract, municipality, and firm size; ϵ is the error term. $Var(y)$ is the variance of the log full hourly wage, $Var(WFE)$ is the variance of worker fixed effects, $Var(FFE)$ is the variance of firm fixed effects, $Var(Xb)$ is the variance of covariates. $Var(residual)$ is the variance of the residual, $Cov(WFE, FFE)$ is the covariance between worker and firm fixed effects, $Cov(WFE, Xb)$ is the covariance between worker fixed effects and covariates, and $Cov(FFE, Xb)$ is the covariance of firm fixed effects and covariates. Sample includes only observations in the largest connected set.

of firms' effects to wage inequality are biased upwards, while AKM estimates of the contribution of the sorting to firms are biased downwards. For instance, Lamadon et al. (2019) show that the estimated variance of the firm fixed effects is several times larger if they only keep ten percent of the movers within each firm as compared to what they obtain if they were to keep all movers.

Although limited mobility bias may be more prominent in short panels according to Lachowska et al. (2020a), there is no formal test to check if the mobility observed in our dataset is sufficient to identify firm fixed effects. However, Bonhomme et al. (2020) give us a benchmark to compare our analysis to. To show how important the mobility bias may be, they compare the variance of firm fixed effects from a regular AKM with the bias-corrected estimates of the variance of firm effects. Importantly for us, they consider the United States and four European countries: Austria, Italy, Norway, and Sweden. They find that while the interquartile range of non-corrected estimates goes from 14% to 23%, the interquartile range of bias-corrected estimates of the variance of firm effects goes from 5% to 16%. As reported in Table C.1 column (2), the contribution of the variance of firm fixed effects in the Netherlands is 7%. While limited mobility bias may still be an issue, the consequences are likely to be small in our setting. A similar argument applies to bias-corrected estimates of sorting. While the interquartile range of non-corrected estimates goes from −1% to 8%, the interquartile range of the bias-corrected estimates of the contribution of sorting lies between 5% and 20%. As reported in Table C.1 column (2), in the Netherlands, the contribution of the variance of sorting is 11%.

Data availability

The data that has been used is confidential.

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