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Technological Change and the Finance Wage Premium *

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Abstract

This paper utilizes a comprehensive worker-firm panel for the Netherlands to quantify the impact of ICT capital-skill complementarity on the finance wage premium after the Global Financial Crisis. We apply additive worker and firm fixed-effect models to account for unobserved worker- and firm-heterogeneity and show that firm fixed-effects correct for a downward bias in the estimated finance wage premium. Our results indicate a sizable finance wage premium for both fixed- and full-hourly wages. The complementarity between ICT capital spending and the share of high skill workers at the firm-level reduces the full-wage premium considerably and the fixed-wage premium almost entirely.

Keywords: finance wage premium, worker-firm panels, skill-biased technological change.

JEL Codes: G20, J24, J31, O33.

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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 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).

Despite the new regulations targeted to curtail worker's pay in the finance industry, 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, it continued to grow (Böhm et al., 2022; Célérier and Vallée, 2019). Using comprehensive administrative data for the Netherlands covering the period from 2006 to 2018, we estimate the finance wage premium and confirm its persistence after the Global Financial Crisis. Critically, we employ a state-of-the-art empirical framework to incorporate both unobserved worker- and firm-heterogeneity (Abowd et al. (1999a), henceforth AKM). Importantly, we find that restricting unobserved firm heterogeneity generates a downward bias in the estimates of the finance wage premium.

Extending prior literature (Böhm et al., 2022; Célérier and Vallée, 2019; Lindley and

[1]Employee compensation, both at the higher and lower levels, matters for banking outcomes such as risk-taking (Wall, 2020).

[2]In 2014, for example, the EU introduced a bonus cap of 100% of fixed pay. The bonuses, i.e. variable pay, have been pervasive in financial industry, and financial centers like the U.K. were critical of measures limiting such compensation (Jones, 2021).

McIntosh, 2017; Philippon and Reshef, 2012), we explore a new explanation for the finance wage premium: the relatively extensive use of ICT capital in the finance industry and, more specifically, its complementarity with human capital in wage formation. In recent decades, the financial industry has experienced rapid technological progress across the globe. Compared to other sectors, the digitalization of financial services induced financial institutions to invest more in ICT capital and to hire more high-skilled workers. The literature highlighted the role of matching ICT capital with high human capital workers in order to maximize its efficiency (Bell and Van Reenen, 2014; Kaplan and Rauh, 2010). Indeed, there has been a large increase in skill intensity in the finance industry (measured by the share of workers with a masters or Ph.D. degree) compared to other industries in the economy - accompanying the developments in ICT capital spending. This is in line with theories of skill-biased technical change as in Acemoglu and Autor (2011) and Autor et al. (1998), who argue that a main engine of economic growth is the complementarity between high technology capital and high human capital.

Based on the theory of capital-skill complementarity, we estimate firm-level average share of high, middle and low skilled workers in each year, proxied by their education level. We find that after the Global Financial Crisis firms in the finance industry obtain higher average skill levels compared to the rest of the economy. When ICT capital spending and the average share of high skilled workers at the firm-level are accounted for, the ICT-skill complementarity explains the finance wage premium to a large extent in the Netherlands. In particular, we find that the fixed-hourly wage premium largely disappears, and the full-hourly wage premium shrinks by two-thirds to around 4.2%. We perform an extensive list of checks and present further regression analyses to support the robustness of this key result.

The goal of our research is to explain the finance wage premium and quantify the importance of ICT capital's complementarity with human capital for finance wage premium. In this respect, our micro dataset offers several advantages in studying the finance wage premium. First, the data includes the universe of workers and firms in the Netherlands, and 19 industries (1-digit NACE). Second, it covers an important period with major changes in the structure of the finance industry resulting from the Global Financial Crisis, the European Debt Crisis, and the decline in interest rates to low and even negative levels (Buch and Dages, 2018).[3]

Our dataset also helps us to contribute to the literature in three additional dimensions. First, it provides separate information on the fixed wage and the variable wage, which includes bonuses and overtime pay. Unlike earlier studies, this enables us to consider the separate contributions of the fixed and variable wages to the overall wage compensation in finance, thereby adding to the literature on executive compensation in the finance industry (Bell and Van Reenen, 2014; Bivens and Mishel, 2013; Bolton et al., 2016; Efing et al., 2019; Glode and Lowery, 2016; Greenwood and Scharfstein, 2013; Kaplan and Rauh, 2010; Lin and Tomaskovic-Devey, 2013; Thanassoulis, 2012). Variable compensation has been an important, albeit declining part of overall labor compensation in the finance industry. Across different regression specifications, we find a higher finance wage premium when we take into account variable pay reflecting the importance of variable compensation in finance. Importantly, the impact of capital-skill complementarity on finance wage premium remains present with and without variable pay.

Second, our dataset allows to apply the additive worker and firm fixed-effects models of Abowd et al. (1999a), so that we can control for possible sorting of more productive

[3]The finance industry in the Netherlands also constitutes a great case to study as it is relatively large. The number of workers in finance represented 2% of the working population in 2018, while the share of gross value added value in finance was 10%. The finance industry in the Netherlands is relatively sizeable compared with the US, as the financial industry assets to GDP ratios are 11% in the Netherlands and 5% in the US in 2018.

workers into more productive firms as a determinant of the finance wage premium. Using this empirical framework, we estimate the finance wage premium as the difference of 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. Conceptually this amounts to imposing the restriction of equal firm fixed-effects within the finance industry, and equal firm fixed-effects within the rest of the economy. Comparing the two approaches, we estimate a finance full-wage premium of 11.1% derived from firm fixed-effects, compared to 8.8% as based on using only a finance industry dummy variable. This reflects that in the absence of a more flexible firm fixed-effects specification, some variation in firm-level contributions to wages is absorbed by worker fixed-effects– given that worker and firm fixed-effects are positively correlated in the data. Thus, as a methodological contribution, we show that disregarding firm fixed-effects in a worker fixed-effects specification *underestimates* the finance wage premium.

Finally, we estimate the finance wage premium by taking into account worker and job heterogeneity along several dimensions. Considering gender, we estimate a relatively large finance wage premium of 12.3% for men, compared to 10.0% for women. Furthermore, the finance wage premium is larger for workers with higher income, ranging from 3.1% for workers in the lowest income quartile, to 9.0% for workers in the highest quartile. For workers in the top decile of the income distribution, the finance wage premium consists primarily of variable pay including bonuses. Within the finance industry at large, we find that banks pay a relatively larger wage premium of 21.7%, compared to insurance companies and pension funds that pay wage premiums of 12.2% and 17.5%, respectively.

Our paper is closely related to three lines of research. The first one is the literature estimating the finance wage premium, taking into account varying measures of skills and ICT capital. For the case of the US, Philippon and Reshef (2012) find that the finance wage premium, at times of relatively stringent financial regulation, is associated with greater skill intensity and job complexity in the finance sector compared to other sectors. Using Swedish data, Böhm et al. (2022) do not find evidence that talent in finance improved, or that relative wage in the finance sector have increased faster for more talented workers. Using UK data, Lindley and McIntosh (2017) find a higher finance wage premium for workers with higher levels of education, and they present survey evidence that jobs in finance are characterized by greater computer complexity compared to non-finance jobs, although the gap appears to be smaller in 2012 than in 1997. For the case of France, Célérier and Vallée (2019) show that wages in the finance sector vary more positively with project size, which is consistent with a relatively positive impact of ICT on financial sector wages as ICT investments may enable larger project size. Using sectoral data for OECD countries, Boustanifar et al. (2018) do not find evidence that an increase in the relative share of ICT in the capital stock in the finance sector compared to other sectors leads to higher relative wages in the financial sector. Unlike these earlier studies, we do not only consider skill- or ICT-measures, but also their complementarity in explaining the finance wage premium.

Second, this paper is also related to the literature in labor economics that applied models with additive worker and firm fixed-effects of Abowd et al. (1999a). Card et al. (2013) use this model to show that a rise in the dispersion of firm pay premiums has substantially contributed to wage inequality in Germany. Card et al. (2018) find that the relative pay of women reflects relatively low firm fixed-effects for women, and the flow of women to firms with relatively low fixed-effects. Song et al. (2019) show that the rise in wage inequality in the US reflects increases in both within and between firm wage inequality, with the latter in part driven by the sorting of high-wage workers to high-wage firms.

Finally, our paper is related to the studies that consider inter-industry wage differences. Krueger and Summers (1988) find evidence for inter-industry wage differences that are similar for firms of different sizes and in different regions in the US. Bartel and Sicherman (1999) find a positive relationship between inter-industry wage differences and measures of technological change. Similar to these papers, we treat all sectors symmetrically in our estimation approach, although our main interest is in explaining the relative wages in the finance industry.

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 the level and composition of wages, the type of labor contract, and the nature of the job. 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.[4]

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

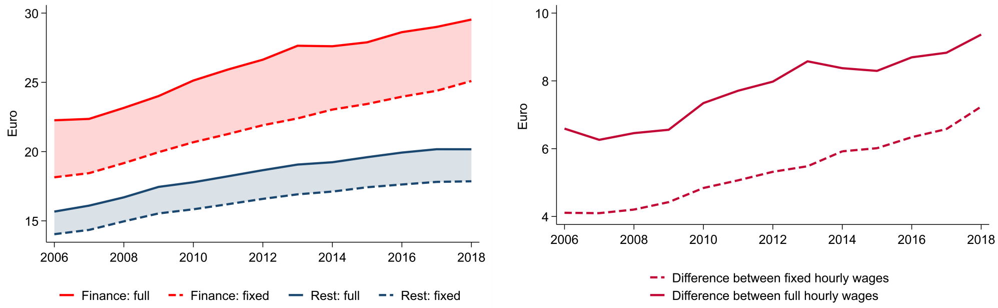
[4]Firm and worker identifiers are unique and anonymized to the researcher. Statistics Netherlands has cleared our research output for distribution.

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. Figure 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 full and fixed wages in the financial sector exceeded average compensation in the rest of the economy throughout this period. Moreover, the implied finance - full and fixed - wage premia increased over time (Figure 1(b)).

An important observable worker characteristic is the highest level of education obtained.[5] To represent worker educational attainment, we construct three dummy variables. First, *LowEduc* is a dummy that equals one if the highest level of education is primary education, practical education, or VMBO (preparatory secondary vocational education). Second, *MiddleEduc* is a dummy variable equaling one if the highest level of education is MBO (middle-level applied education) or any of two levels of secondary education, VWO (pre-university secondary education) and HAVO (higher general secondary education). Third, *HighEduc* captures that the worker has a bachelor's or a master's degree or a doctorate. Figures 2(a)-(b) show average educational attainment in finance and the rest of the economy during the sample period. The figures show a clear upward trend in the share of highly educated workers in finance, whereas this share is rather flat in the rest of the economy. Correspondingly, in finance the shares of workers with middle or low education declined, while in the rest of the economy only the share of low educated workers declined. In the empirical analysis, we use estimates of shares of workers with

[5] This information is missing for about 35% of the workers, with similar rates of missing data in finance and in other industries.

Figure 1: Hourly wages in the finance industry and the rest of the economy (2006-2018).



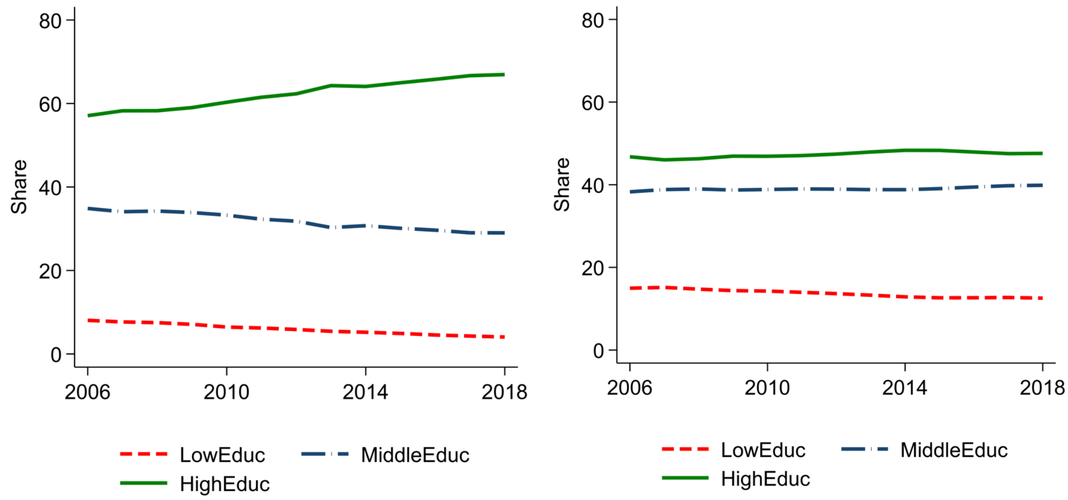
(a) (b)

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 the 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 A1 for the industry classification used.

low, middle, and high education for each firm in each year to capture to what extent firms use high skill labor (where we impute missing individual education levels with the firm average in a year).

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). We obtain this variable, which is available only at the industry level, from the harmonized European Union statistics database KLEMS, and we scale it by the number of workers in an industry in a given year. Figure 3 displays the time trends of ICT capital spending per worker in finance and the rest of the economy. ICT capital spending per worker has been relatively high throughout the period 2006-2018, and it increased at a higher rate in the finance industry than in the rest of the economy (7.2% vs 4.4%). Together, Figures 1, 2, and 3 demonstrate that increases in wages in the finance industry relative to the rest of the economy have coincided with relatively large increases in the employment of high skill labor and in ICT capital spending. This

Figure 2: Educational attainment in the finance industry and the rest of the economy (2006-2018).



(a) Finance (b) Rest of the Economy

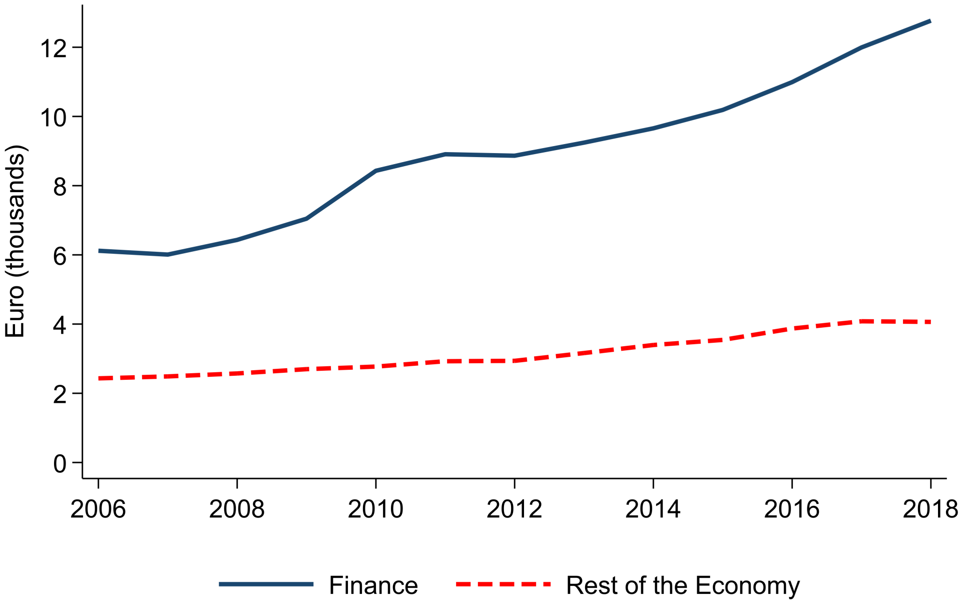
Notes: Figure reports the share of workers with a given educational attainment for finance (figure on the left) and the rest of the economy (figure on the right). Education corresponds to the highest educational attainment observed in 2018. We define three categories. "LowEduc" corresponds to primary education, practical education or VMBO (preparatory secondary vocational education) as the highest degree of education completed. "MiddleEduc" corresponds to MBO (middle-level applied education) or any of two streams of secondary education, VWO (pre-university secondary education) or HAVO (higher general secondary education), as the highest level of education completed. "HighEduc" corresponds to a bachelor's or master's degree ("HBO" and "WO") or a doctorate.

suggests that there could be a technology-skill complementarity in production, that we will formally analyze in the empirical section. In robustness checks, we will also use the wage bill of workers with an IT or ICT education as a proxy for the ICT intensity.[6]

In our empirical analysis, we include a polynomial term in age. In addition, we use a dummy variable indicating whether the labor contract is part-time rather than full-time, and controls for the type of job (regular, temporary agency, and on-call). At the level of the firm, we generate controls for firm size in categories as measured by employment, and we also construct municipality fixed-effects. For incorporated non-financial firms, we add balance sheet information provided by Statistics Netherlands. For financial firms,

[6] IT or ICT education includes degrees related to computer science, computer use, design and management of database and network, software development and system analysis, and IT others.

Figure 3: ICT capital spending per worker in the finance industry and the rest of the economy (2006-2018).



Notes: The figure reports the ICT capital spending per worker in the finance industry and the rest of the economy. ICT capital spending is the Euro value of productive inputs that flow to production from ICT capital assets (computers, communication equipment, software and databases).

we use balance sheet information from Orbis Banks Focus. We restrict the sample to workers between ages 18 and 65, and we drop all firms with fewer than 10 workers in a year. Furthermore, we winsorize extreme values of the hourly wages to the 1st and the 99th percentile. The resulting dataset contains 39,418,962 worker-year observations.

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 finance industry. Similarly, the average firm-level shares

Table 1: Descriptive statistics.

	Observations	Mean	SD	p1th	p50th	p99th
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
Non-ICT-K per worker (thousands, Euro)	701,853	20.72	1.76	18.44	20.47	25.86
IT wage bill per worker (Euro)	701,853	1,643.25	279.97	1,200.65	1,726.94	1,963.78
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
Size firm						
-Less than 50 employees	701,853	0.34	0.47	0	0	1
-Between 50-250 employees	701,853	0.22	0.41	0	1	1
-More than 250 employees	701,853	0.44	0.50	0	1	1
share LowEduc (firm)	701,853	0.06	0.08	0	0.05	0.40
share MiddleEduc (firm)	701,853	0.33	0.13	0	0.30	0.80
share HighEduc (firm)	701,853	0.61	0.18	0	0.64	0.96
Profit per worker (Euro)	14,876	42.51	54.79	-30.61	21.36	202.70
Assets (thousands, Euro)	14,876	2,616,907	1,950,733	166	3,656,999	5,201,997
Equity to assets	14,876	0.16	0.19	0.03	0.09	0.86
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
Non-ICT-K per worker (thousands, Euro)	29,821,172	15.65	90.98	3.51	8.22	129.57
IT wage bill per worker (Euro)	38,717,109	515.83	963.44	85.57	333.32	6241.25
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
Size firm						
-Less than 50 employees	38,717,109	0.34	0.47	0	0	1
-Between 50-250 employees	38,717,109	0.24	0.43	0	0	1
-More than 250 employees	38,717,109	0.43	0.49	0	0	1
share LowEduc (firm)	38,717,109	0.14	0.16	0	0.08	0.67
share MiddleEduc (firm)	38,717,109	0.40	0.20	0.03	0.42	0.87
share HighEduc (firm)	38,717,109	0.45	0.28	0	0.42	0.95
Profit per worker (Euro)	14,834,547	9.13	20.64	-19.51	3.13	103.63
Assets (thousands, Euro)	14,834,547	78,888	244,591	162	6471	1,164,512
Equity to assets	14,834,547	0.39	0.23	0.02	0.37	0.91
Total observations (N×T)	39,418,962					

Notes: This table shows descriptive statistics for the main regression sample (worker-years). Fixed-hourly wage is the basic wage divided by basic hours. Full-hourly wage is the gross wage divided by paid hours (basic hours plus paid overtime hours). LowEduc denotes primary education, practical education or VMBO (preparatory secondary vocational education). MiddleEduc denotes MBO (middle-level applied education) or any of two levels of secondary education, VWO (pre-university secondary education), and HAVO (higher general secondary education). HighEduc denotes completion of a Bachelor's degree, a Master's degree, or a PhD. Education is missing for about 35% of the workers. ICT-K capital spending 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. Non-ICT-K spending is productive inputs that flow to production from a capital asset other than the ICT category per period. This aggregate also accounts for net subsidies and taxes. ICT-K and Non-ICT-K are not available for industries Real Estate, Public Administration and Education (NACE codes 12, 15, and 16). IT wage bill per worker is the total gross wage spending on workers with an IT education degree over the total number of workers. Part-time is a dummy variable equal to one if the contract is part-time. Regular contract, temporary agency worker, and on-call contract are dummy variable that signal the type of job. Age is worker age. There are three firm size dummies signaling firms with less than 20 employees, firms with between 20 and 250 employees, and firms with more than 250 employees. Profits per worker is profits before taxes divided by the number of workers of the firm. Assets is the total assets of the firm in thousands of euros.

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 in non-financial industries. 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 shares of workers with regular jobs in finance and in other sectors are 0.99 and 0.95, respectively. Employment of part-time or non-regular (on-call or temp agency) workers are less common in finance, which may have implications for the finance wage premium estimation unless they are accounted for. ICT capital spending per worker in finance, with 8,700 Euro, is more than double compared to what the rest of the economy spends on ICT capital per worker (3,140 Euro). We also observe that the shares of firms in different size categories by employment are similar in finance and the rest of the economy. Finally, we note that in relative terms the financial firms are more profitable, larger as measured by assets and relatively less capitalized.

3 Estimation Methods

This section 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 to AKM. We adapt this model to test for the existence of ICT capital-skill complementarity as a novel explanation of the finance wage premium.

3.a Estimation of the Finance Wage Premium

Equation (1) is a wage regression commonly used in the literature to estimate the finance wage premium (see e.g. Célérier and Vallée, 2019; Lindley and McIntosh, 2017; Philippon and Reshef, 2012).

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

where $ln(w_{i,t})$ is the log hourly wage for worker i in year t, which can be the fixed-hourly wage or the full-hourly wage; $\boldsymbol{X_{i,t}}$ are a set of covariates that includes a polynomial term in age (normalized to 40 years old) and fixed-effects for a part-time contract, the type of job, municipality and firm size. The α_i are worker fixed-effects, $\mathbf{1}^F_{i,t}$ is a dummy for employment in the finance industry, and λ_t are year fixed-effects; ϵ_{it} is an idiosyncratic error term clustered at the firm-level. $\hat{\phi}$ is the estimate of the finance wage premium.

A conceptual problem with specification (1) is that it omits unobservable firm heterogeneity, which recent literature has found to be substantial (Haltiwanger et al., 2022; Song et al., 2019). Moreover, the industry classification is a characteristic of the firm, and it follows that firm-level variation should be used to estimate an industry characteristic such as the finance wage premium. To allow for firm-level variation, we follow the AKM methodology developed by Abowd et al. (1999a) and estimate models with both additive worker and firm fixed-effects:

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

In equation (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. 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.[7]

We follow the computational algorithm in Card et al. (2013) to construct the largest

[7]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."

connected set of firms and associated workers.[8] In Appendix B, we provide a detailed discussion of the assumptions in the AKM framework, and we show that key assumptions on worker mobility patterns and sorting are satisfied in our dataset. Furthermore, in Appendix Table A2, we present the decomposition of the variance of log wages into the variances of worker, firm and covariates (Lachowska et al., 2020; Lamadon et al., 2019). Comparing our variance decomposition for the Netherlands with an analogous decomposition using US data (Song et al., 2019), we find similar results: most of the variance of wages is due to unobserved worker heterogeneity, while unobserved firm heterogeneity accounts for 7% of the variation in our data, compared to 9% for the United States. As we have more observable characteristics, 13% of the wage variability in our data is explained by covariates, compared to 6% for the United States. As a result, the wage residual variation in our data is considerably smaller (7% compared to 15%).

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 (as measured by the worker fixed-effects) could be more likely to be matched with high-wage firms (as measured by the firm fixed-effects) with important implications on finance wage premium estimation, which we discuss next.

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:

[8] We keep around 99% of the original sample.

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

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:

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

where $\xi_{i,t}$ is an error term. This specification can easily be extended to include all $(s-1)$ industries, or different levels of the NACE industry classification, e.g. 2-digit or 3-digit level NACE industry codes. We will use this when we look at sub-industries within finance and look at banking, insurance, pension funds and fund management.

Since we use estimated variables in equation (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 $r = 1, 2, ..., k$ denote the bootstrap samples and $\bar{\phi}$ is the average of the firm fixed-effects.

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. 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 in our data, which implies that specification (1) is likely to yield a biased estimate of the finance wage premium compared to the AKM approach. To see the likely direction of this bias, we can consider the scenario where higher productivity in finance gives rise to larger firm fixed-effects on average in the finance industry, and moreover worker and firm fixed-effects are positively correlated. Then, if we restrict firm effects in finance to be equal in the AKM setting, estimated worker fixed-effects for workers in finance will be upward biased to reflect the higher productivity of finance firms. This will leave a smaller part of the higher productivity in finance to be captured by the finance industry fixed effect in specification (2), which yields a lower estimated finance wage premium in specification (1) compared to the AKM approach.

3.b Capital-Skill Complementarity in the AKM Setting

In section 2, we observed that firms in finance employ more high skilled workers and make more intensive use of ICT capital than the rest of the economy. In this subsection, we expand the AKM approach to include variables that reflect average firm-level educational attainment and its interaction with industry-level ICT capital intensity to test for a possible ICT capital-skill complementarity as follows:

$$\ln w_{i,t} = \boldsymbol{X_{i,t}\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \delta_1 Educ_{j,t} + \delta_2 K_{s,t} + \delta_3 (Educ_{j,t} \times K_{s,t}) + \epsilon_{i,t}, \quad (6)$$

where $Educ_{j,t}$ is the share of workers with either middle or high education at firm j in year t, and $K_{s,t}$ measures log ICT capital spending per worker in industry s in year t. A positive coefficient estimate for δ_3 will imply that that wages at a firm are higher in relative terms if the firm combines high skill labor with a greater ICT capital spending intensity, consistent with the theory of ICT capital-skill complementarity in production and in wage formation.

4 Results

4.a Benchmark Estimate of the Finance Wage Premium

Table 2 shows the results of estimating the finance wage premium in specifications based on equations (1) and (2). The top panel has the log fixed-hourly wage as the dependent variable and the bottom panel the full-hourly wage. The 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 estimate of the finance wage premium is 11.4% for the fixed-hourly wage (Panel A), and 16.4% for the full-hourly wage (Panel B). The difference between the two estimated finance wage premia can be explained by the higher prevalence of variable compensation in the finance industry compared to the rest of the economy. Column (2) includes worker fixed-effects, reducing both finance wage premium estimates by one half. This is in line with the argument that unobserved worker productivity matters and that the finance industry attracts relatively more productive workers compared to the rest of the economy.

In column (3) we present the results of an auxiliary 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, such that we can reject the null hypothesis that all estimated firm fixed-effects are jointly zero. In other words, the finance wage premium is a firm characteristic that needs to be estimated off firm fixed-effects. 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

Table 2: The finance wage premium in different specifications.

	OLS	**Fixed-effects**		**AKM**
		Worker	Firm	Worker & Firm
	(1)	(2)	(3)	(4)
Panel A: fixed-hourly wage				
Finance wage premium	0.114***	0.0564***	0.145***	0.0693***
	(7.95)	(16.59)	(7.94)	(7.00)
Adjusted R-squared	0.381	0.903	0.564	0.911
Panel B: full-hourly wage				
Finance wage premium	0.164***	0.0880***	0.198***	0.111***
	(10.26)	(19.79)	(9.33)	(8.70)
Adjusted R-squared	0.390	0.894	0.579	0.902
Observations (N× T)	39,418,962			
N workers	5,180,514			
N firms	83,077			
Fixed-effects:				
-Worker	-	Yes	-	Yes
-Firm	-	-	Yes	Yes
-Year	Yes	Yes	Yes	Yes
-Type of contract	Yes	Yes	Yes	Yes
-Municipality	Yes	Yes	Yes	Yes
-Firm size	Yes	Yes	Yes	Yes

Notes: This table shows estimates for the finance wage premium. Column (1) reports $FWP = \hat{\phi}$, which we obtain from the regression ln $w_{i,t} = \boldsymbol{X_{i,t}\beta} + \phi\mathbf{1}_{it}^F + \lambda_t + \epsilon_{i,t}$, where $w_{i,t}$ may be the fixed-hourly wage (basic wage divided by basic hours) or the full-hourly wage (gross wage divided by paid hours); $\mathbf{1}_{it}^F$ is a dummy for employment in finance; λ_t are year fixed-effects; and $\epsilon_{i,t}$ is the error term; $\boldsymbol{X_{i,t}}$ includes a polynomial term in age (normalized to 40 years old) and the following fixed-effects: part-time contract, type of job, municipality, and firm size catergories. Column (2) reports $FWP = \hat{\phi}$, which we obtain from the regression ln $w_{i,t} = \phi\mathbf{1}_{it}^F + \boldsymbol{X_{i,t}\beta} + \lambda_t + \alpha_i + \epsilon_{i,t}$, where α_i are worker fixed-effects. Column (3) reports $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effect for the finance industry minus the average firm fixed effect for the rest of the economy weighted by the number of workers and employment duration. We get the FWP from the regression ln $w_{i,t} = \boldsymbol{X_{i,t}\beta} + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$, where $\psi_{J(i,t)}$ are firm fixed-effects. Column (4) reports $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effect for the finance industry minus the average firm fixed effect for the rest of the economy weighted by the number of workers and employment duration. We get the FWP from the regression ln $w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$. The period is 2006-2018. We exclude firms that are classified as belonging to other industries and firms with fewer than 10 employees. We limit the sample to workers from 18 to 65 years old. We drop extreme values. Sample includes only observations in the largest connected set. Standard errors are clustered at the firm-level. Columns (1)-(2) report t-statistics. Columns (3)-(4) report z-statistics from bootstrapped standard errors at the firm-level (200 repetitions). $^*p < 0.05$, $^{**}p < 0.01$, *** $p < 0.001$

with worker fixed-effects biases the finance wage premium downwards, which in part could reflect the positive correlation between worker and firm fixed-effects. Under the AKM specification, we report a benchmark estimate of the finance wage premium for the Netherlands of 6.9% for the fixed-hourly wage and about 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. (2022) estimate the finance wage premium as the estimated coefficient on a finance sector dummy while including job fixed-effects, which could partially model differential pay in the finance industry, 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.[9]

4.b The Finance Wage Premium by Worker and Job Characteristics and Over Time

A natural question that arises is whether workers in the finance industry earn the finance wage premium to different extents, based on observable worker and job characteristics. In this subsection, we address this question by estimating an AKM specification (with firm fixed-effects) that additionally includes a finance industry dummy that is interacted with personal or job characteristics.

Column (1) of Table 3 shows how the finance wage premium differs by gender. We find that women in finance earn about 1.98% less in fixed-hourly wages than men, and about 2.28% less for the full-hourly wage. Specifically, men and women are estimated to earn a

[9]Table A3 in the Appendix provides additional information on finance wages premium estimates in the literature compared to our estimation.

full-hourly wage premium in finance of 12.3% and 10.0%, respectively. Our finding of a lower finance wage premium for women is consistent with lower firm-specific pay premia found by Card et al. (2016).

Regarding heterogeneous finance wage premia with respect to income, in column (2) we include income quartiles (as measured by total gross wage) and the interaction with a finance industry dummy. Here we find interesting differences between the two wage measures, namely fixed and full wages. In the case of the fixed-hourly wage in Panel A, there is little wage differential between workers in finance versus the rest of the economy: the three interaction terms are each close to zero and not statistically significant. However, for the full wage in Panel B we find that workers in the fourth income quartile receive around 5.86% more in finance compared to other industries. In column (3) we focus on the subset of workers in the highest income decile. Here we find again different results for the two wage measures. Workers in the top decile in finance earn 2.5% lower fixed-hourly wages compared to workers in the top decile in other industries (Panel A). However, for the full wage measure, workers in the top decile earn about 6.25% more in finance compared to the rest of the economy (Panel B).

We also use the richness of the administrative data to examine the finance wage premium by contract and job characteristics. We find that part-time workers, who are prevalent in the Netherlands, earn about the same fixed and full-hourly wages in finance compared to other industries (column (4)). In column (5) we report that on-call and temp agency workers have generally lower wages compared to workers in regular jobs, but workers with either type of job still receive a premium for working in the finance industry. For temp agency workers, the interaction is not statistically significantly different from zero in both panels. For on-call workers, the interaction term is negative, but it is not large enough to drive down the finance wage premium to zero. In column (6), we examine

Table 3: Finance wage premium: observable worker and job heterogeneity.

	AKM regressions					
	Gender	Income	Top-Earners	Hours	Type-job	Education
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fixed-hourly wage						
Finance wage premium (FWP)	0.0797***	0.0164***	0.0849***	0.0684***	0.0700***	0.0853***
	(8.09)	(3.38)	(8.65)	(6.99)	(7.25)	(8.84)
FWP × Female	-0.0198***					
	(-7.93)					
Income Quartile II		0.204***				
		(129.91)				
Income Quartile III		0.347***				
		(134.53)				
Income Quartile IV		0.510***				
		(145.37)				
FWP × Income Quartile II		0.0051				
		(0.53)				
FWP × Income Quartile III		0.00684				
		(0.48)				
FWP × Income Quartile IV		0.0203				
		(1.22)				
Top-decile			0.196***			
			(64.66)			
FWP × Top-decile			-0.0251***			
			(-3.51)			
Part-time				0.00580***		
				(6.81)		
FWP × Part-time				0.00696		
				(0.66)		
Temporary agency					-0.0244***	
					(-6.18)	
On-call					-0.0327***	
					(-21.67)	
FWP × temporary agency					0.0913	
					(1.57)	
FWP × On-call					-0.0302***	
					(-3.52)	
FWP × MiddleEduc (worker)						-0.00963*
						(-2.48)
FWP × HighEduc (worker)						-0.0130*
						(-2.32)
Observations (N× T)	39,418,962	39,418,962	39,418,962	39,418,962	39,418,962	25,152,742
Adjusted R-squared	0.911	0.942	0.915	0.915	0.909	0.902

(*Table 3, Panel B next page*)

Table 3: Finance wage premium: observable worker and job heterogeneity (continued).

	AKM regressions					
	Gender	Income	Top-Earners	Hours	Type-job	Education
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Full-hourly wage						
Finance wage premium (FWP)	0.123***	0.0310***	0.125***	0.111***	0.112***	0.130***
	(9.69)	(5.62)	(10.06)	(8.80)	(8.98)	(10.35)
FWP × Female	-0.0228***					
	(-7.90)					
Income Quartile II		0.239***				
		(125.20)				
Income Quartile III		0.411***				
		(136.16)				
Income Quartile IV		0.610***				
		(151.66)				
FWP × Income Quartile II		0.0109				
		(1.30)				
FWP × Income Quartile III		0.0203				
		(1.60)				
FWP × Income Quartile IV		0.0586***				
		(3.63)				
Top-decile			0.248***			
			(74.71)			
FWP × Top-decile			0.0625*			
			(2.49)			
Part-time				0.00381***		
				(4.23)		
FWP × Part-time				0.00441		
				(0.42)		
Temporary agency					-0.0253***	
					(-5.82)	
On-call					-0.0355***	
					(-22.05)	
FWP × Temporary agency					0.0954	
					(1.90)	
FWP × On-call					-0.0528***	
					(-7.05)	
FWP × MiddleEduc (worker)						-0.0129**
						(-2.97)
FWP × HighEduc (worker)						-0.0148*
						(-2.39)
Observations (N× T)	39,418,962	39,418,962	39,418,962	39,418,962	39,418,962	25,152,742
Adjusted R-squared	0.902	0.941	0.910	0.901	0.901	0.895

Notes: This table shows the finance wage premium for different groups of workers. It is calculated as follows $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effect for the finance industry minus the average firm fixed effect for the rest of the economy weighted by the number of workers and employment duration. We estimate the finance wage premium from the regression ln $w_{i,t} = \boldsymbol{X_{i,t}\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$, where $w_{i,t}$ is the full-hourly wage (gross wage divided by paid hours); $\boldsymbol{X}$ includes a polynomial term in age (normalized to 40 years old) and the following fixed-effects: part-time contract, type of job, 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; and $\epsilon_{i,t}$ is the error term. Column (1) considers worker by gender. Column (2) divides workers into quartiles by the total annual gross wage. Column (3) identifies workers at the top-decile of the total annual gross wage distribution. Column (4) identifies workers with part-time contracts as opposed to full time workers. Column (5) considers workers by their type of job: regular job (baseline), temporary agency worker, and on-call jobs. Column (6) considers workers by their level of education: LowEduc (baseline), MiddleEduc, and HighEduc. The sample size drops because education is missing for some workers. The period is 2006-2018. We exclude firms with less than 10 employees. We limit the sample to workers from 18 to 65 years old. We drop extreme values. Sample includes observations in the largest connected set. For the finance wage premium reports, z-statistics are reported in parentheses from bootstrapped standard errors at the firm-level (200 repetitions). Otherwise, t-statistics are reported. *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$

education as a worker characteristic and find the evidence that workers with middle and high education earn a lower but still positive finance wage premium, compared to the baseline of workers with low education.

The raw data represented in Figure 1 suggest that the finance wage premium has been increasing over time. We formally test whether this is the case in the empirical AKM framework. We define three sub-periods, 2006-2010 covering the Global Financial Crisis, 2011-2014 covering the Sovereign Debt Crisis in Europe, and 2015-2018. Table 4 illustrates that there is some increase in the finance wage premium for 2011-2014 for the fixed-hourly wage, but virtually no change for the full-hourly wage. For the years 2015-2018, we document that the finance wage premium is larger compared to the periods before, both for fixed- and full-hourly wages.[10]

So far, we examined the finance wage premium for the finance industry at the 1-digit NACE level. The finance industry is composed of five sub-industries (sectors) at the 2-digit level: banks, insurance firms, pension funds, fund management and auxiliary services. Using the AKM methodology, we can estimate separate wage differentials for the sectors of which the finance industry is composed. For this purpose, we modify equation (4) to introduce five finance sector dummies. In Table 4 panel B, we find that within the finance industry there is considerable heterogeneity in sector wage premia. Workers in banks earn a 15.3% higher fixed-hourly wage compared to the rest of the economy, and about a 21.7% higher full-hourly wage. Banks are followed by pension funds, with 14.2% higher fixed wages and 17.5% higher full-hourly wages. Though, there is wide variation in financial sub-industry wage premia, it is important to note that all sub-industries have

[10]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. We therefore estimate the subperiods within the same regression interacting the finance wage premium with sub-period dummies.

Table 4: Finance wage premium over time and by sub-industry.

	Fixed-hourly wage			Full-hourly wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Finance Industry						
Finance wage premium (FWP)	0.0693***	0.0580***	5.80%	0.111***	0.102***	10.20%
	(7.00)	(5.63)		(8.70)	(7.74)	
FWP × 2011-2014		0.0120*	7.00%		0.00781	10.98%
		(2.33)			(1.38)	
FWP × 2015-2018		0.0298***	8.78%		0.0247**	12.67%
		(3.72)			(2.72)	
Observations (N× T)	39,418,962	39,418,962		39,418,962	39,418,962	
Adjusted R-squared	0.924	0.911		0.902	0.912	
Panel B: Finance Sub-Industries (Sectors)						
-Banks	0.153***			0.217***		
	(9.39)			(10.80)		
-Insurance	0.0708***			0.122***		
	(7.11)			(11.24)		
-Pension Funds	0.142***			0.175***		
	(6.01)			(8.87)		
-Fund Management	0.0950*			0.121		
	(2.00)			(1.50)		
-Auxiliary Funds	0.0252**			0.0502***		
	(2.89)			(4.20)		
Observations (N× T)	39,418,962			39,418,962		
Adjusted R-squared	0.924			0.902		

Notes: This table shows AKM estimates of the finance wage premium by time period (Panel A) and by sub-industry (Panel B). The finance wage premium is calculated as follows $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effect for the finance industry minus the average firm fixed effect for the rest of the economy weighted by the number of workers and employment duration. We estimate the finance wage premium the regression $\ln w_{i,t} = \boldsymbol{X_{i,t}\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$, where $w_{i,t}$ is the full-hourly wage (gross wage divided by 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 job, municipality, and firm size catergories; α_i are worker fixed-effects; $\psi_{J(i,t)}$ are firm fixed-effects; λ_t are year fixed-effects; and $\epsilon_{i,t}$ is the error term. In Panel A, columns (1) and (4) report the baseline finance wage premium for the fixed-hourly wage and the full-hourly wage. Columns (2) and (5) report the finance wage premium for three periods: 2006-2010 (baseline), 2011-2014, and 2015-2018. Columns (3) and (6) report the implied finance wage premium by time period (i.e., baseline estimate plus interaction). In Panel B, column (1) reports the finance wage premium within the finance industry. We distinguish the following sub-industries within the finance industry as: banks, insurance companies, pension funds, fund management companies, and auxiliary funds. The time period is 2006-2018. We exclude firms with less than 10 employees. We consider workers from 18 to 65 years old. We drop extreme values. Sample includes only observations in the largest connected set. For the finance wage premium, z-statistics are reported in parentheses from bootstrapped standard errors at the firm-level (200 repetitions). Otherwise, t-statistics are reported. $*p < 0.05$, $**p < 0.01$, $***\ p < 0.001$

positive wage differentials compared to the rest of the economy.[11] Thus, the finance wage premium is more than only a "banking premium": it is an industry-wide characteristic.

Overall, from Tables 3 and 4, we learn that workers with varying observable characteristics earn a finance wage premium across a wide-spectrum of characteristics, the

[11] With the exception of the full wages in fund management, where the coefficient is still positive but not statistically significant.

finance wage premium is persistent over time, and that the finance wage premium is an industry-wide phenomenon that is not driven only by banking.

4.c Explaining the Finance Wage Premium with Capital-Skill Complementarity

In this sub-section, we present the main findings of the paper, using the specification (6), which investigates the role of ICT capital-skill complementarity in explaining the finance wage premium. We, first, re-estimate the finance wage premium as in column 4 of Table 2 for the smaller sample for which we have ICT capital spending data.[12] In column 1 of Table 5, we see that the premium for the fixed wage increases from 6.9% to 8.3%, and for the full-hourly wage from 11.1% to 12.9%. In columns (2) and (5), we introduce the firm-level shares of workers with middle and high education and the industry-level log of ICT capital spending per worker. The share of workers with middle education is negative and significant in column 2 and insignificant in column 5, while the share workers with high education is positive and significant in both columns. The latter result suggests that workers obtain higher wages if they are employed at a firm with a higher share of highly educated workers. To get a sense of the magnitude of this effect, increasing the share of highly educated workers in a firm by one percentage point raises the fixed-hourly wage on average by about $0.0160 \times 0.01 = 0.016$ percent *for all workers in the firm.* The ICT capital spending variable is positive and significant, consistent with the argument that ICT capital improves worker productivity.

In columns (3) and (6) of Table 5, we include interactions of the firm-level education variables with the ICT capital spending intensity. In these columns, the education variables are all estimated to be positive and significant, indicating that wages increase with average firm-level education. The interaction variables are also positive and significant,

[12] ICT capital spending is not available for industries L (Real estate activities), O (Public administration), and P (Education) corresponding to NACE codes 12, 15 and 16, respectively.

Table 5: Finance wage premium including ICT capital spending.

	Fixed-hourly wage			Full-hourly wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Finance wage premium	0.0827***	0.0653***	0.0107	0.129***	0.0993***	0.0421***
	(10.23)	(8.27)	(1.50)	(12.26)	(9.59)	(4.28)
share MiddleEduc (firm)		-0.00967*	0.361***		-0.00762	0.433***
		(-2.25)	(5.88)		(-1.67)	(7.08)
share HighEduc (firm)		0.0160**	1.24***		0.0184**	1.33***
		(2.78)	(18.44)		(3.00)	(19.06)
ln(ICT-K)		0.0107*	-0.0843***		0.0209***	-0.0843***
		(2.05)	(-7.86)		(3.76)	(-8.20)
ln(ICT-K) × share MiddleEduc (firm)			0.0601***			0.0718***
			(5.71)			(6.84)
ln(ICT-K) × share HighEduc (firm)			0.208***			0.222***
			(17.90)			(18.38)
Observations (N× T)	30,440,561					
Adjusted R-squared	0.908	0.908	0.908	0.901	0.901	0.901

Notes: This table shows AKM estimates of the finance wage premium when we include ICT capital spending. The finance wage premium is calculated as follows $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effect for the finance industry minus the average firm fixed effect for the rest of the economy weighted by the number of workers and employment duration. We estimate the finance wage premium from the regression $\ln w_{i,t} = \boldsymbol{X_{i,t}}\boldsymbol{\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$, where $w_{i,t}$ is the full-hourly wage (gross wage divided by 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 job, 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; and $\epsilon_{i,t}$ is the error term. Share MiddleEduc (firm) is the share of workers with middle level of education at firm-level. Share HighEduc (firm) is the share of workers with high level of education at the firm-level. ICT-K capital spending is the productive inputs that flow to production from ICT capital assets per perios. The ICT category consists of computers, communications equipment and software and databases. The period is 2006-2018. We exclude firms with less than 10 employees. We consider workers from 18 to 65 years old. We drop extreme values. Sample includes observations in the largest connected set. For the finance wage premium, z-statistics in parentheses from bootstrapped standard errors at the firm-level (200 repetitions). Otherwise, t-statistics are reported. *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$

suggesting that wages increase with average firm-level education especially in industries with high spending on ICT capital. This result is consistent with ICT capital-skill complementarity in production. In both columns (3) and (6), the interaction of ICT capital intensity with the share of highly educated workers is greater than its interaction with the share of middle-education workers. This suggests that ICT capital is complementary especially with a highly educated work force.

The ICT intensity variable per se is estimated to be negative and significant. Thus, ICT capital is estimated to depress wages at firms with very high shares of lowly educated workers (and very low shares of workers with middle or high education). This could reflect that ICT capital replaces low skill labor, thereby depressing the wages of low educated workers. Allowing for ICT capital-skill complementarity leads to an estimated finance fixed wage premium close to zero in column 3. The estimated full wage premium is 4.2% and significant in column 6. This estimate is materially less than estimated financial wage premium of 9.9% in column 5, which includes the ICT capital spending and education share variables, but not their interactions. Thus, we find that ICT capital-skill complementarity is important in explaining the finance wage premium, more than the employment of ICT capital and skilled labor per se. Our sample contains firms in many industries and thus explains wage formation generally, and not just in finance. Our finding of a positive joint impact of ICT capital and high education levels on wages is important in explaining the finance wage premium, as financial firms employ ICT capital and highly educated workers relatively intensively (see section 2).

As a first robustness check for our ICT capital-skill complementarity results, we include in our regressions three balance sheet items: profits per worker, log of assets and the ratio of equity to assets. We conduct this robustness analysis because the literature had argued that rent-sharing could be one of the drivers of the finance wage premium, which is likely to be more prevalent in larger and more profitable financial institutions (Böhm et al. (2022)).

Statistics Netherlands provides balance sheet information for a subset of all incorporated non-financial corporations, and we add the same variables for financial institutions using Orbis Bank Focus. In columns (1) and (5) of Table 6, we re-estimate the finance wage premium using AKM regressions as in column (4) of Table 2 for the fixed-hourly wage and the full-hourly wage, yielding finance wage premia of 12.0% and 15.6%, respectively. Adding balance sheet variables in columns (2) and (6) reduces the finance wage premia to 10.7% and 13.3%. For the full-hourly wage, the balance sheet measures have similar signs as found in the literature: higher profitability, larger asset size and a larger leverage ratio give rise to higher wages, as documented by Chemmanur et al. (2013), albeit for non-financial firms. In columns (3) and (7), we add the shares of middle and

Table 6: Robustness l: Finance wage premium and firm balance sheet measures.

	Fixed-hourly wage					Full-hourly wage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Finance wage premium	0.120***	0.107***	0.116***	0.0411**	0.156***	0.133**	0.138***	0.0724***
	(4.10)	(4.15)	(4.61)	(2.99)	(4.02)	(3.96)	(4.21)	(3.49)
share MiddleEduc (firm)			-0.00916*	0.198*			-0.00822	0.272***
			(-2.22)	(2.53)			(-1.96)	(3.54)
share HighEduc (firm)			0.0141*	0.936***			0.0152**	0.886***
			(2.55)	(10.77)			(2.70)	(9.73)
ln(ICT-K)			-0.00879	-0.0736***			-0.00688	-0.0755***
			(-1.66)	(-5.61)			(-1.31)	(-5.86)
ln(ICT-K) × share MiddleEduc (firm)				0.0358**				0.0490***
				(2.61)				(3.64)
ln(ICT-K) × share HighEduc (firm)				0.166***				0.156***
				(10.86)				(9.76)
Profit per worker		-0.0230	-0.0235	-0.0217		0.0643*	0.0639*	0.0654*
		(-1.01)	(-1.03)	(-0.95)		(2.43)	(2.42)	(2.54)
ln(Assets)		0.00383**	0.00381**	0.00401**		0.00592***	0.00592***	0.00609***
		(2.96)	(2.94)	(3.19)		(4.51)	(4.51)	(4.65)
Leverage ratio		0.00576	0.00573	0.00536		0.00815*	0.00814*	0.00778*
		(1.77)	(1.76)	(1.65)		(2.41)	(2.41)	(2.29)
Observations (N× T)	14,438,171							
Adjusted R-squared	0.918	0.918	0.918	0.918	0.91	0.910	0.910	0.910

Notes: This table shows AKM regressions of the finance wage premium when we include ICT capital spending and firm balance sheet measures. The financial wage premium is calculated as follows $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effect for the finance industry minus the average firm fixed-effects for the rest of the economy weighted by the number of workers and employment duration. We estimate the finance wage premium from the regression ln $w_{i,t} = \boldsymbol{X_{i,t}\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$, where $w_{i,t}$ is the full-hourly wage (gross wage divided by 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 job, 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; and $\epsilon_{i,t}$ is the error term. Share MiddleEduc (firm) is the share of workers with middle level of education at firm-level. Share HighEduc (firm) is the share of workers with high level of education at firm-level. ICT-K capital is the productive inputs that flow to production from ICT capital assets per period. The ICT category consists of computers, communications equipment and software and databases. Ratio equity to assets is equity divided by total assets. Profits per worker is profits before taxes is the total number of workers of the firm. Assets is total assets of the firm in thousands of euros. The period is 2006-2018. We exclude firms with less than 10 employees. We consider workers from 18 to 65 years old. We drop extreme values. Sample includes observations in the largest connected set. For the finance wage premium, z-statistics are reported in parentheses from bootstrapped standard errors at the firm-level (200 repetitions). Otherwise, t-statistics are reported. *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$

highly educated workers at the firm-level, and ICT capital spending per worker. In both columns (3) and (7) we find similar to Table 5 that increasing the share of highly educated workers is associated with a higher wage. Industry ICT-capital spending per worker is not statistically significant. However, adding the ICT capital spending-skill interactions in columns (4) and (8) decreases the finance wage premium considerably, to 4.1% and 7.2%. Thus, our earlier finding that wages are higher in those industries which exhibit jointly high ICT capital spending and high worker education is robust to controlling for firm-level variables, profitability, asset size and leverage.

Table 7 Panel A shows results from a placebo test where we replace the variable ICT capital spending per worker with non-ICT capital spending per worker. In columns (2) and (5), we add the education and non-ICT capital spending variables, yielding coefficients for the education variables that are similar to Table 5, but we do not detect a decline in the size of the finance wage premium (and as a matter of fact we note that the finance wage premium increases slightly). In columns (3) and (6), we add the interactions, giving rise to insignificant coefficients that do not suggest a role for non-ICT capital-skill complementarity. This result prevails that only ICT capital spending's interaction with high human capital is relevant in explaining the finance wage premium.

Table 7 Panel B presents the results of a further robustness check where we replace the ICT capital spending variable with the log of the IT wage bill per worker in an industry, as an alternative measure of ICT capital. The ICT wage bill approximates the labor cost component of ICT spending, which is not included in the construction of our benchmark ICT capital measure. As a first observation we note that the two ICT variables are positively related, which suggests that labor and capital ICT spending complement each other in production (see Figure A1 in the Appendix). Furthermore, workers with an IT or ICT degree are likely to be employed in an ICT related job.[13] In columns (3) and (6), the interactions of the IT wage bill with firm-level education shares are positive and significant, consistent with a complementarity between IT labor spending and human capital. The finance wage premium is driven to zero for the full-hourly wage in column (6), and it even becomes negative for the fixed-hourly wage in column (3). These results again confirm a key role for the complementarity between ICT and a high-skilled labor in explaining the finance wage premium.

In a final robustness check, we simultaneously consider the complementarity of ICT capital with individual worker education and average firm-level education. Since we do not observe the level of worker education for each worker, we restrict our sample to workers with non-missing information on education. This results in a smaller sample of about 19 million worker-year observations. In columns (1) and (5) of Table 8 we re-estimate

[13] This robustness check utilizes the entire sample, as information on the IT wage bill is available for all industries.

Table 7: Robustness ll: Finance wage premium including non-ICT capital spending, and the IT wage bill.

	Fixed-hourly wage			Full-hourly wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Non-ICT capital spending						
Finance wage premium	0.0827***	0.0911***	0.0901***	0.129***	0.141***	0.141***
	(10.23)	(11.54)	(11.47)	(12.26)	(13.71)	(13.70)
share MiddleEduc (firm)		-0.00985*	-0.0408		-0.00784	-0.0669*
		(-2.28)	(-1.25)		(-1.70)	(-1.98)
share HighEduc (firm)		0.0166**	0.0259		0.0195**	0.00258
		(2.84)	(0.58)		(3.18)	(0.06)
ln(Non-ICT-K)		-0.0144***	-0.0121		-0.0193***	-0.0116
		(-3.30)	(-1.14)		(-4.27)	(-1.06)
ln(Non-ICT-K) × share MiddleEduc (firm)			-0.00709			-0.0136
			(-0.86)			(-1.59)
ln(Non-ICT-K) × share HighEduc (firm)			0.00179			-0.00423
			(0.17)			(-0.39)
Observations (N× T)	30,440,561					
Adjusted R-squared	0.908	0.908	0.908	0.901	0.901	0.901
Panel B: IT wage bill						
Finance wage premium	0.0693***	-0.0194*	-0.0484***	0.111**	0.0202	-0.0129
	(7.00)	(-2.03)	(-5.64)	(8.70)	(1.64)	(-1.14)
share MiddleEduc (firm)		-0.0135**	-0.299**		-0.0115**	-0.328***
		(-3.21)	(-3.22)		(-2.58)	(-3.58)
share HighEduc (firm)		0.00530	-0.915***		0.00838	-1.037***
		(0.83)	(-15.78)		(1.19)	(-16.57)
ln(IT wage bill)		0.0527***	-0.0394***		0.0537***	-0.0504***
		(3.97)	(-4.48)		(3.79)	(-4.92)
ln(IT wage bill) × share MiddleEduc (firm)			0.0529***			0.0589***
			(3.29)			(3.71)
ln(IT wage bill) × share HighEduc (firm)			0.160***			0.181***
			(15.64)			(16.74)
Observations (N× T)	39,418,962					
Adjusted R-squared	0.911	0.911	0.911	0.902	0.902	0.903

Notes: This table shows AKM estimates of the finance wage premium when we include non-ICT capital spending (Panel A) and the IT wage bill (Panel B). The finance wage premium is calculated as follows $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effect for the finance industry minus the average firm fixed effect for the rest of the economy weighted by the number of workers and employment duration. We estimate the from from the regression $\ln w_{i,t} = \boldsymbol{X_{i,t}\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$, where $w_{i,t}$ is the full-hourly wage (gross wage divided by 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 job, 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; and $\epsilon_{i,t}$ is the error term. Share MiddleEduc (firm) corresponds to the share of workers with middle level of education at firm-level. Share HighEduc (firm) is the share of workers with high level of education at firm-level. ICT-K capital spending corresponds the productive inputs that flow to production from ICT capital assets per period. The ICT category consists of computers, communications equipment and software and databases. Non-ICT-K spending is the productive inputs that flow to production from a capital asset other than the ICT category per period. This aggregate includes net subsidies and taxes on capital. IT wage bill is the total gross wage spending on workers with an IT or ICT education divided by the total number of workers. The period is 2006-2018. Sample includes observations in the largest connected set. For the finance wage premium, z-statistics are reported in parentheses from bootstrapped standard errors at the firm-level (200 repetitions). Otherwise, t-statistics are reported. $*p < 0.05$, $**p < 0.01$, $***\ p < 0.001$

the finance wage premium for this smaller sample, and find very similar estimates as the ones reported in Table 5. In columns (2) and (6), we include interactions of ICT capital spending with a dummy variable for the education level of the worker (the education level of the worker itself is subsumed by the worker fixed-effects). This reduces the estimates of the finance wage premium, from 8.3% to 4.9% for the fixed-hourly wage,

Table 8: Robustness lll: Finance wage premium and educational attainment at both firm and worker level.

	Fixed-hourly wage				**Full-hourly wage**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Finance wage premium	0.0834***	0.0493***	0.00516	0.000156	0.131***	0.0892***	0.0430***	0.0379***
	(9.85)	(5.91)	(0.65)	(0.02)	(12.41)	(8.48)	(4.21)	(3.69)
share MiddleEduc (firm)			0.465***	0.359***			0.502***	0.399***
			(7.20)	(5.64)			(7.53)	(6.09)
share HighEduc (firm)			1.507***	1.190***			1.567***	1.248***
			(21.68)	(17.30)			(21.10)	(17.13)
ln(ICT-K)		-0.0406***	-0.112***	-0.117***		-0.0353***	-0.112***	-0.117***
		(-7.10)	(-10.28)	(-10.48)		(-5.78)	(-10.37)	(-10.60)
ln(ICT-K) × MiddleEduc (worker)		0.0296***		0.0166***		0.0294***		0.0157***
		(17.77)		(11.33)		(17.26)		(10.42)
ln(ICT-K)× HighEduc (worker)		0.0960***		0.0653***		0.0976***		0.0658***
		(38.49)		(39.75)		(34.38)		(38.46)
ln(ICT-K)× share MiddleEduc (firm)			0.0766***	0.0591***			0.0824***	0.0653***
			(6.88)	(5.37)			(7.16)	(5.76)
ln(ICT-K)× share HighEduc (firm)			0.250***	0.197***			0.260***	0.206***
			(20.78)	(16.47)			(20.07)	(16.19)
Observations (N× T)	19,539,444							
Adjusted R-squared	0.901	0.902	0.902	0.902	0.895	0.896	0.896	0.896

Notes: This table shows AKM estimates of the finance wage premium when we include ICT capital spending and educational attainment at the person level. The is calculated as follows $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effect for the finance industry minus the average firm fixed effect for the rest of the economy weighted by the number of workers and employment duration. We estimate the finance wage premium from the regression $\ln w_{i,t} = \boldsymbol{X_{i,t}\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{i,t}$, where $w_{i,t}$ is the full-hourly wage (gross wage divided by 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 job, 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; and $\epsilon_{i,t}$ is the error term. MiddleEduc (worker) is MBO (middle-level applied education) or one of two levels of secondary education, VWO (pre-university secondary education, and HAVO (higher general secondary education). HighEduc (worker) is a bachelor's degree, a master's degree, or a PhD. Share MiddleEduc (firm) is the share of workers with middle education at the firm-level. Share HighEduc (firm) is the share of workers with high education at the firm-level. ICT-K capital spending corresponds is productive inputs that flow to production from ICT capital assets per period. The ICT category consists of computers, communications equipment and software and databases. The period is 2006-2018. We exclude firms with less than 10 employees. We consider workers from 18 to 65 years old. We drop extreme values. Sample includes observations in the largest connected set. t-statistics in parentheses. For the finance wage premium, z-statistics are reported in parentheses from bootstrapped standard errors at the firm-level (200 repetitions). Otherwise, t-statistics are reported

and from 13.1% to 8.9% for the full-hourly wage. The interpretation of the interaction terms is similar as in Table 5: workers with more advanced education earn higher wages especially in industries with high ICT capital spending, consistent with complementarity between ICT capital and individual education. In columns (3) and (7), we re-estimate specification (2) and (5) of Table 5, including only interactions of ICT capital spending with firm-level average education variables, for the smaller sample of workers with non-missing education information. The results remain the same to a good extent.

In columns (4) and (8), we jointly include interactions of ICT capital spending with individual and firm-level education variables. We find evidence of complementarities of ICT capital spending with both types of education measures. Specifically, from column (8) we see that a worker who acquires middle education (from low education) would see her wage go up by 0.0157×log(ICT-K) on account of the ICT capital spending complementarity with individual education. At the same time, all workers at her firm see their wages rise by 0.0653×log(ICT-K)×the change in the share of middle education workers at the firm due to the complementarity with firm-level average education (in addition to a positive effect due to a higher share of workers with middle education per se). The estimated coefficients of 0.0157 and 0.0653 imply that the ICT complementarity with firm-level average education is relatively important. To see this, we can consider the thought experiment where at a firm all workers transition from low education to middle education so that the share of middle education workers at the firm goes from zero to one. Then all workers' wages increase by $(0.0157 + 0.0653) \times \log(\text{ICT-K}) = 0.081 \times \log(\text{ICT-K})$ on account of the two complementarities. The complementarity effect related to average firm-level education is seen to be the larger one.

In Table 8, we also observe that accounting for firm-level education and its complementarity with ICT capital spending has a relatively large effect in reducing the estimated finance wage premium. Specifically, for the case of the full wage we see that including average education levels and their interactions with ICT capital spending reduces the estimated finance wage premium from 13.1% in column (5) to 4.3% in column (6), while the inclusion of interactions with individual level education variables reduces this premium to a lesser extent from 13.1% in column (5) to 8.9% in column (7). To conclude, we find that complementarities of ICT capital spending with individual and firm-average education are both important in explaining wages as well as the finance wage premium, with the complementarity with firm-average education being the more important one.

5 Concluding Remarks

In recent decades, advances in ICT technology have transformed the finance industry, giving rise to products and processes that are increasingly digitalized. To improve the efficiency of this transformation, financial institutions contemporaneously raised the demand for highly skilled workers. Using comprehensive data for the Netherlands, this paper finds that ICT capital spending and highly skilled labor are complementary in wage formation, and that this complementarity to a large extent explains the excess wages in finance relative to other industries, i.e. the finance wage premium.

ICT capital spending is found to be complementary to firm-level average educational attainment as well as to individual worker education. Thus, an individual worker's wage increases more with ICT capital spending, if she is working at a firm with higher average education and if she is better educated herself. We find the former complementarity, i.e. related to firm-level average education, to be empirically more important.

Our data source enables us to distinguish between fixed pay and variable pay, which includes bonuses. Variable pay is relatively important in the finance industry, and the ICT capital spending-skill complementarity explains a relatively larger part of the full-hourly wage premium compared to the fixed wage premium. To estimate the finance wage premium, we use the additive worker and firm fixed-effects model of Abowd et al. (1999a). Comparing different methodologies, we find that the inclusion of firm fixed-effects corrects for an otherwise downward bias in the estimation of the finance wage premium. We also conduct a battery of robustness checks and show that our key finding on ICT capital-skill complementarity continues to prevail across these specifications.

Our results are important for the policy-making as it suggests that the financial industry has become much more sophisticated compared to the pre-Global Financial Crisis period, when the industry was enjoying a wage premium despite lower education and less use of ICT capital. Thus, current high compensation in the finance industry can be attributed to the finance industry becoming a high-tech industry where skill-technology complementarities are driving compensations at the industry level.

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APPENDIX

A Tables and Figures

Table A1: 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 organisations 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 A2: Variance decomposition of the wage over the period 2006-2018.

	All 2006-2018		**Interval** 2007-2013		Song et al. (2019) 2007-2013	
	Comp.	Share	Comp.	Share	Comp.	Share
	(1)	(2)	(3)	(4)	(5)	(6)
Total variance						
$Var(y)$	0.167		0.163		0.924	
Components of the variance						
$Var(WFE)$	0.091	55	0.099	61	0.476	52
$Var(FFE)$	0.011	7	0.011	7	0.081	9
$Var(Xb)$	0.025	15	0.021	13	0.059	6
$Var(residual)$	0.014	8	0.011	7	0.136	15
$2 * Cov(WFE, FFE)$	0.019	11	0.015	9	0.108	12
$2 * Cov(WFE, Xb)$	0.004	2	0.005	3	0.036	4
$2 * Cov(FFE, Xb)$	0.003	2	0.001	1	0.027	3
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. 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 (gross wage over paid hours) 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, the type of job, 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. Song et al. (2019) do not use the hourly wage as information on hours worked is not available. Sample includes only observations in the largest connected set.

Table A3: Estimated finance wage premiums, selected studies.

Study	Country	Period	FWP	FWP (own estimation)
Célérier and Vallée (2019)	France	1983-2011	24.2%	31.4%
Böhm et al. (2022)	Sweden	2006-2017	10%	11.4%
Philippon and Reshef (2012)	US	2001-2005	6.2%	3.7%
Lindley and McIntosh (2017)	U.K.	1996-2011	31.4%	32%
Boustanifar et al. (2018)	Several countries	1970-2011	$> 30\%$	-
This study	The Netherlands	2006-2018	11.1%	-

Notes: This table shows the finance wage premium estimates from selected studies. Worker FE stands for worker firm effects. Firm FE stands for firm effects. FWP stands for the finance wage premium. In the last column, FWP - own estimation, we replicate the FWP of the selected studies by incorporating their sample restrictions as much as possible in our data. Célérier and Vallée (2019) estimate of the FWP corresponds to Table 3, column 1. Although this regression does not include worker FE, they use a measure of talent for each individual. If they do include worker FE, they find an FWP of 22.4% (column 7 same Table). The FWP is calculated by comparing finance (the log of yearly gross wage) against "virtually all" industries in France (48 industries). Controls include year dummies, a female dummy, a married dummy, a Paris area dummy, a working abroad dummy, experience level, squared and cubed, four hierarchic responsibility dummies, nine occupation category dummies, four firm size dummies, and four firm-type dummies. Böhm et al. (2022) estimate the FWP corresponds to around 10% for the years 2006-2017, taken from Figure 5b. The FWP is calculated by comparing finance (the log of earnings) against the private sector (i.e., they exclude agriculture and the public sector). They only include males in the estimation. Controls include education, work experience, age, and a measure of talent among others. They use firm-person fixed-effects instead of firm and worker fixed-effects. Philippon and Reshef (2012) estimate of the FWP corresponds to Table IV (period 2001-2005). The FWP is calculated by comparing finance (the log of hourly wage) against the private sector. They restrict the regressions to full-time full-year workers in the private sector, aged 15 to 65, who reported wages greater than 80% of the federal minimum wage. Controls include education, race, sex, marital status, urban residence, (potential) experience and its square; and industry-specific unemployment risk. The excess relative wage (finance against the non-farm private sector) was 51% in 2005. Lindley and McIntosh (2017) estimate of the FWP corresponds to Table 1 column 4. The FWP is calculated by comparing finance (the log of annual gross pay) against the private sector. Controls include gender, age, and its square, as well as the region of residence, and year fixed-effects. Boustanifar et al. (2018) estimate of the FWP corresponds to Figure 2. We report the finance relative wage (hourly wage), which is the average wage in finance divided by the average wage in the non-farm, non-finance private sector. This study corresponds to Table 2 (Panel B, regression 4).

Figure A1: Relationship between ICT capital spending and the IT wage bill.

Notes: The figure shows the relationship between (log) ICT capital spending per worker (ICT-K) and the (log) IT wage bill per worker for each industry. We calculate the average IT wage bill per worker as the total gross wage spending on workers with an ICT or IT degree obtained divided by he total number of workers. ICT-K capital spending is the productive inputs that flow to production from ICT capital assets per period. ICT capital consists of computers, communications equipment and software and databases. We also plot the best fit of a regression ln(IT wage bill) on ln(ICT-K). We plot the resulting line and confidence interval.

B 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.

B.a Log Additive Functional Form in the AKM Regression

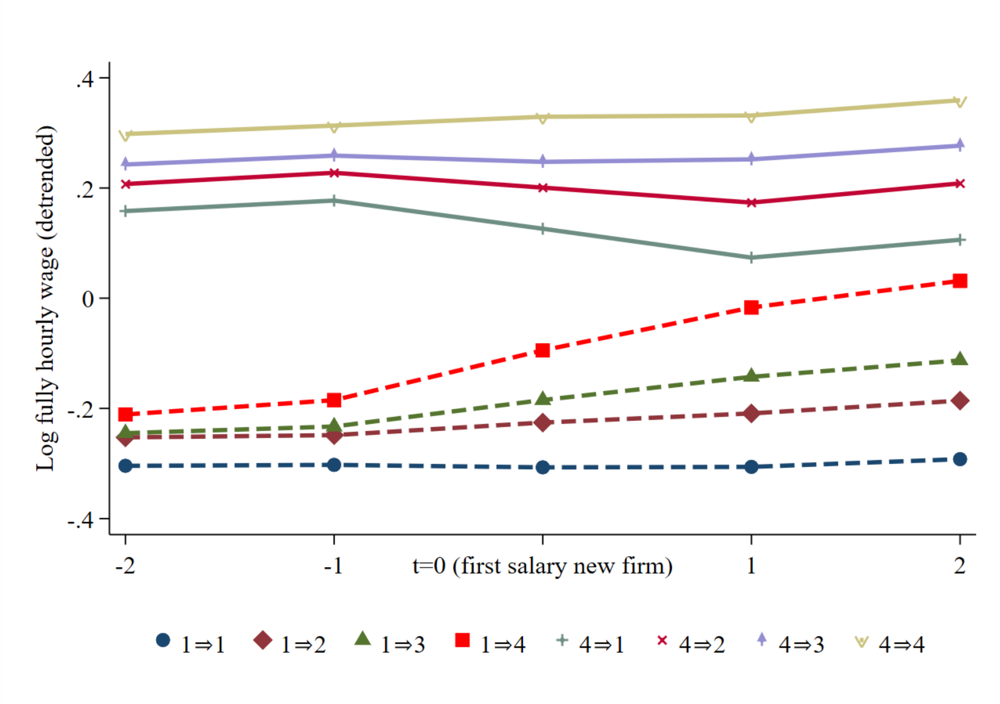
From subsection 3.a, the AKM specification we use is given by:

$$\ln w_{it} = \boldsymbol{X_{i,t}}\boldsymbol{\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{it}, \tag{A7}$$

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 asses 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. Similar to their study, we define groups of firms based on co-worker pay quartiles (using data on male and female co-workers). Figures A2 and A3 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 coworkers experience a wage raise, while

Figure A2: Event study of changes in earnings when male workers move between firms.

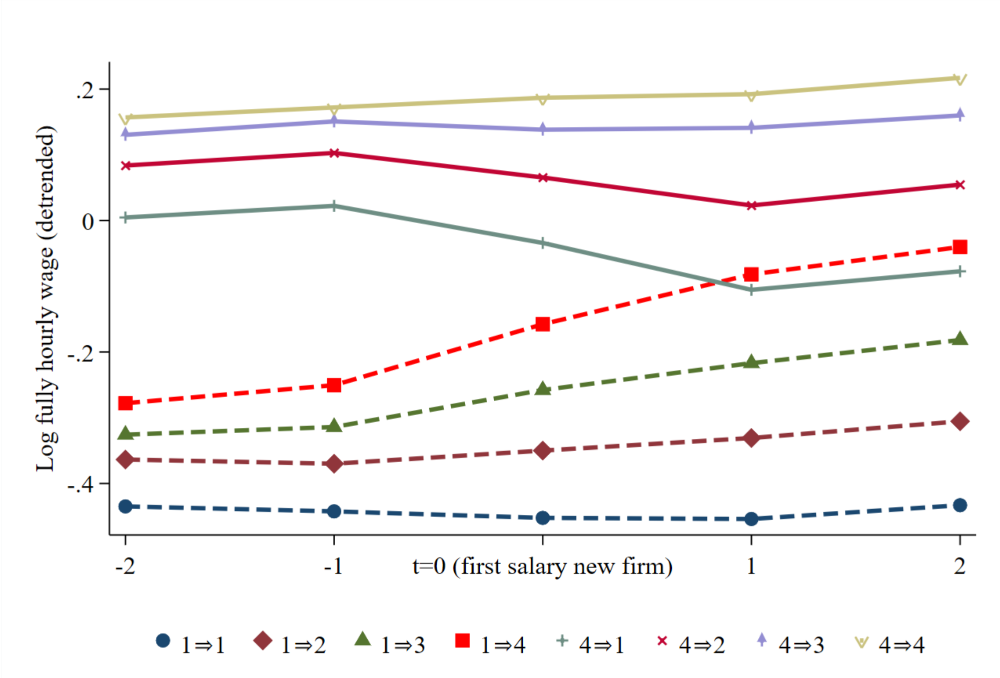


Notes: The figure shows the event study developed by Card et al. (2018, 2016). We consider male workers who switch firms and have worked for at least two years at both the origin and destination firms for the period 2006-2018. We define firms' groups based on co-worker pay quartiles (using data on all coworkers). 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 residual 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 $t = 1$.

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 coworkers. Furthermore, the wage profile for all groups are all relatively stable in the years before and after a job move.

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 gain and losses may look symmetric if workers making upward moves are of the same quality as those mak-

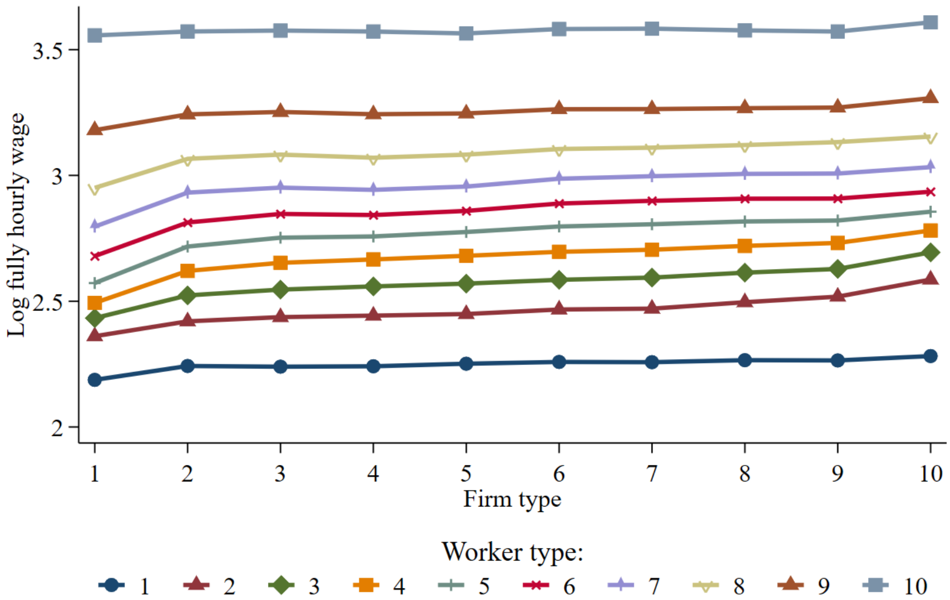
Figure A3: Event study of changes in earnings when female workers move between firms.



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 coworkers). 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 $t = 1$.

ing 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. Figure A4 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

Figure A4: 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 years 2006-2018. We then calculate the average log full-hourly wage for the combinations of worker-firm types (i.e., 100 combinations).

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.

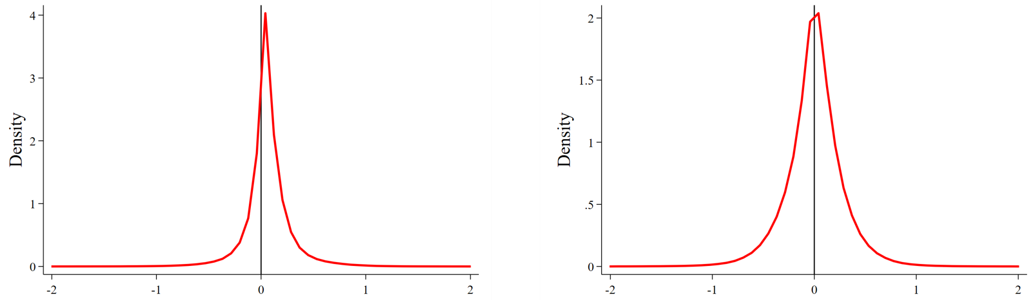
B.b Finance and the Exogeneity Assumption

To estimate equation (A7), the following orthogonality condition must hold:

$$E[(\epsilon_{it} - \bar{\epsilon_i})(D^j_{it} - \bar{D}^j_i)] = 0 \quad \forall j \in [1, ..., J] \tag{A8}$$

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

Figure A5: Distribution of the log full-hourly wage change for job-to-job movements over 2006-2018.



(a) Raw (b) Residuals AKM regression

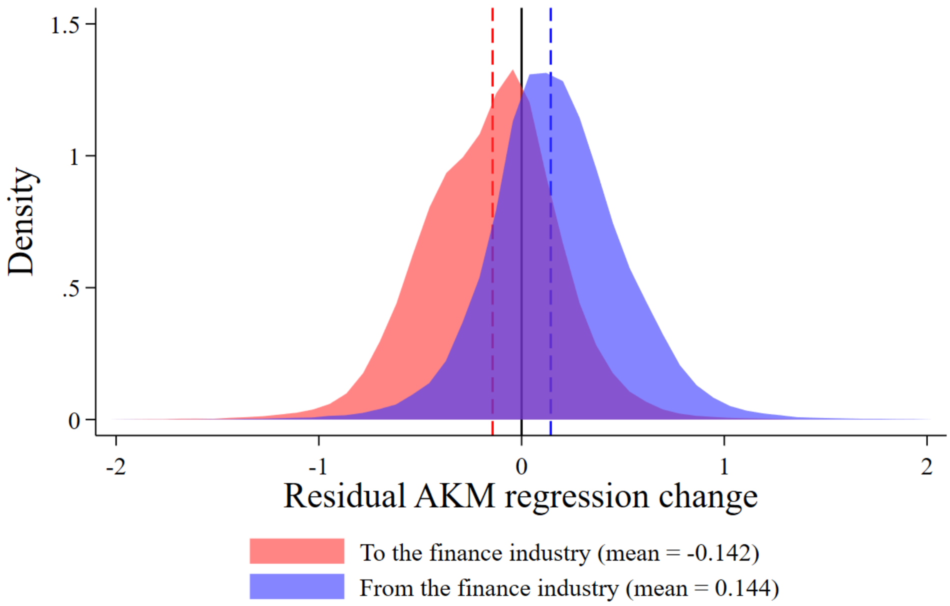
Notes: The figure shows distribution of the change on log full-hourly wage for workers changing jobs over the period 2006-2018. For each job-to-job movement observed in the dataset, we calculate the gains (or losses) on the log full-hourly wage. Panel (a) plots this distribution. On the contrary, panel (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 job, 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 changing industries and firms with less than 10 employees. We also consider workers from 18 to 65 years old. We drop extreme values. Sample includes only observations in the largest connected set.

supported by data,[14] 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.

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. In order to do that we calculate the change in the residual after a job-to-job movement. Figure A6 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 of a rich set of controls).

[14]See figure A5, and the event study discussed before. See Card et al. (2016) for a one-to-one relationship between equation (A8) and the conclusions that we can derive from the event study.

Figure A6: 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 $\ln w_{it} = \boldsymbol{X_{i,t}}\boldsymbol{\beta} + \alpha_i + \psi_{J(i,t)} + \lambda_t + \epsilon_{it}$ 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 job, 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. Sample includes only observations in the largest connected set.

B.c 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 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. (2020), 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 A2 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 go from -1% to 8%, the interquartile range of the bias-corrected estimates of the contribution of sorting lie between 5% and 20%. As reported Table A2 column (2), in the Netherlands the contribution of the variance of sorting is 11%.

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