Technological Change and the Finance Wage Premium*

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Abstract

We use a massive matched employer-employee database to explain the financial wage premium in the Netherlands. Using this data, we show that the excessive wage in the finance industry steadily increased over the period 2006-2018 despite the Global Financial Crisis (GFC) and the European Debt Crisis. Consistent with the substitution of capital for unskilled labor to exploit technical change, we also observe that the number of high-skilled workers and the capital associated with information and computer technologies (ICT) increased rapidly post-GFC. Guided by these facts, we study if the finance wage premium is explained by ICT capital-skill complementary at industry level when controlling by the observed and unobserved worker and firm characteristics. Contrary to a long literature documenting an excessive and unexplained wage premium in the finance industry, we find a low (even negative) finance wage premium.

Keywords: finance wage premium, wage profile, allocation of workers.

JEL Codes: G20, J24, J31, O33.

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1 Introduction

Two stylized facts characterize the employee profiles of the financial industry. On the one hand, as an extensive literature has recognized, the average employee compensation in the finance industry is high (Célérier and Vallée, 2019; Oyer, 2008; Philippon and Reshef, 2012). Philippon and Reshef (2012) define the finance wage premium as the difference of the average wages paid in finance relative to the rest of the society and show that the finance wage premium (FWP) was 50% in 2006 for the average worker, and 250% for the top decile earners in the industry, which was perceived as to be fuelling excessive risk-taking in the financial industry (Rajan, 2006). On the other hand, as argued by Célérier and Vallée (2019) and Boustanifar et al. (2018), the average human capital (both in terms of education and talent) of the finance industry is also relatively high compared to the rest of the economy, which according to Böhm et al. (2021) explains finance wage premia to a good extent, but the FWP is still large and persistent. Since the Global Financial Crisis, the finance wage premium continued to remain as a controversial topic (Zingales, 2015). Despite the new regulations targeted to curtail worker's pay in the finance industry, there is evidence that after the financial crisis, the finance wage premium has not decreased (Bell and Van Reenen, 2014) and to the contrary, it continued to grow (Böhm et al., 2021; Lindley and McIntosh, 2017). The human capital employment of the industry also remains high in recent years (Böhm et al., 2021; Boustanifar et al., 2018).

In our research, we approach these two stylized facts and the role of human capital in explaining the finance wage premium from a different angle. We utilize administrative data on employee contracts and investigate the role of technical transformation of the financial sector towards a more ICT-intense structure and analyze the consequences of this technical change in explaining the employee compensations in the financial sector.[1] Our motivation to conduct this empirical analysis is twofold. The ICT spending of the finance industry rose substantially over the last decade, an empirical pattern that is not common to a large fraction of the industries in the country. The literature highlighted the role of matching ICT capital with high human capital employees 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 (measured by the share of workers with masters and Ph.D.) compared to any other industry accompanying the developments in ICT capital. We combine this evidence with the theory of skill-biased technical change,

[1] ICT stands for information and computer technologies.

pioneered by Acemoglu and Autor (2011); Autor et al. (1998), which argues that a main engine of growth is the complementarity between high technology capital and high human capital. Based on this evidence and the theory, we argue that finance wage premia are to be largely explained by capital-skill complementarities.

Since our primary goal is to explain the finance wage premium and quantify the importance of ICT capital's complementarity with human capital, we use a massive employer-employee data set covering workers and firms for the entire Dutch labor market from 2006 to 2018. Our data set has several advantages for studying the finance wage premium. First, the data covers 100% of workers and firms, and 19 industries (1-digit NACE). Second, it covers an interesting 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 very low and even negative levels over the period (Buch and Dages, 2018).[2] Our first main result is that the finance wage premium, when calculated under the traditional approach (i.e., indicator variable for working in the finance industry and a rich set of both demographic and time-varying controls), is much smaller than the very well-known (and highly cited) 50% FWP reported by Philippon and Reshef (2012) for the U.S. or the 31.4% FWP identified by Lindley and McIntosh (2017) for the U.K. In particular, we show that the FWP is 11.3% and 16.4% for the fixed hourly wage (fixed wage over basic hours) and the full hourly wage (yearly gross wage over total paid hours), respectively. If we do include worker fixed effects, which allow us to compare to two recent papers (Böhm et al., 2021; Célérier and Vallée, 2019), we show that the FWP is 5.6% and 8.7% for the fixed hourly wage and the full hourly wage. As a result, we consider our FWP values as a lower bound when compared to Célérier and Vallée (2019) (France, 1983-2011, 22.4%) and Böhm et al. (2021) (Sweden, around 20% in 2017). Since we are able to very well replicate all FWP estimates reported by the previous paper, we conclude that the rich set of controls (and the large dataset) that we use in this paper may explain the difference among the FWP estimates.

Two factors can account for the remaining FWP. First, the rise of firms pay premiums in finance, that is, firms in finance paying more, adjusting for worker composition. Second, the covariance between high-wage workers and high-wage firms in finance (called

[2]The finance industry is relatively large in the Netherlands. While the number of workers in the finance industry represented 2% of the working population in 2018 the share of its gross added value (GAV) was 10%. Furthermore, the finance industry in the Netherlands is higher in relative terms than the financial industry in the U.S as the total asset ratio of the finance industry relative to the GDP was 11 (a traditional measure of the size of the finance industry) while this ratio was 5 for the U.S. in 2018. See https://fred.stlouisfed.org/graph/?g=smH.

sorting by Song et al. (2019)). If high-wage workers are moving to high-wage firms in finance, this may explain by itself the finance wage premium (or part of it). To account for these factors, we extend the standard approach by incorporating firm fixed effects into the traditional specification. This specification is usually referred as the AKM model (Abowd et al., 1999b). Under this approach, we calculate the finance wage premium as the simple average of firm fixed effects within the finance industry minus the average firm fixed effects in the rest of the economy. Our second main finding is that FWP is not further explained by the widening in the average workplace premia or sorting between high-wage workers and high-wage firms in finance. We show that under the AKM approach, the FWP is 6.9% and 11% for the fixed hourly wage and the full hourly wage-slightly higher than before. Over the years, we find that the FWP has moved from the variable part of the salary to the fixed part as the fixed hourly wage has grown from 5.2% in 2006 to 9.7% in 2018 (a 87% increase) while the full hourly wage has moved from 10.6% in 2006 to 13.3% in 2018. We also find that this FWP is 2% lower for women and not driven by the highest earners. Interestingly, the FWP for the fixed hourly wages is lower for these top earners confirming the importance of bonus payments in finance. Finally, we show that FWP is driven by banks, which have the highest premium (22.8%), followed by pension fund services (19,1%), insurance services (14.5%), fund management services (13.2%), and auxiliary services (6.9%).

The existence of a large excess wage in finance has motivated a long list of alternative explanations for the finance wage premium, for instance, the riskier wage profiles (Philippon and Reshef, 2012) or the higher complementarity between talent and scale in finance (Böhm et al., 2021; Célérier and Vallée, 2019), industry rents (Böhm et al., 2021), regulation (Boustanifar et al., 2018; Philippon and Reshef, 2012), and other factors that go with working in the finance industry, such as as working hours, risk and travel (Oyer, 2008). While we discard most of these explanations, each of these papers have discussed the importance of information technologies as a potential driver of the FWP. For instance, Célérier and Vallée (2019) argues that their results are consistent with the evolution of wages reflecting a disproportionate increase in returns to talent for certain occupations, as their scale expand due to technological change. Along similar lines, Kaplan and Rauh (2010) argue that new technology has enabled the most productive finance workers to apply their talents to a larger capital base, giving rise to superstar effects. Our third main finding is that the FWP can be further explained by the complementarity of technology advances (by the advent of digital banking services post-GFC) and high human capital. When we allow for ICT capital and skill intensity interaction to capture possible industry-level complementarities in the AKM setting, the FWP becomes -3.6% (and 7.1% for the banking sector). On the basis of these results, we conclude that worker's pay in finance is high because of the intensive use of two complementary inputs: technology and human capital. The observations that (i) finance industry uses three times more ICT capital per worker and (ii) two times more skilled worker per unskilled worker than the average industry in the economy, are two facts that are in line with our argument. Our findings with respect to ICT-Human capital interactions are robust to alternative measures of ICT capital, different levels of disaggregation for capital and skill intensity measures (i.e., industry, sector, and sub-sector), and alternative set of controls as firm-level variables (i.e., profits per worker, log assets, and log leverage).

All in all, we document the finance wage premium persisting and even becoming more prevalent during the Global Financial Crisis and its aftermath despite the reregulation of the financial sector and policies targeting excessive compensation (such as capping bonuses after 2015). Our analysis indicates that the transformation of the finance industry in this period to a more skilled and informational capital-intensive industry was critical to explain the persistence of the FWP. Our results are important for the policymaking as it suggests that financial industry has become much more sophisticated compared to the pre-GFC period, when the industry was enjoying a wage premium despite lower education and less use of ICT capital. Thus, apparent high compensation in the finance industry can be explained by the finance industry becoming a high-tech industry where skill-technology complementaries are driving competition and compensation at the industry level.

The remainder of the paper is organized as follows. Section 2 reviews the related literature, whereas section 3 presents the employer-employee dataset. Section 4 explains the estimation methods to identify the finance wage premium. Section 5 presents the results. Finally, section 6 concludes.

2 Literature Review

The paper is related to several strands of research in labor and finance. The first is the literature that discusses the compensation in the finance industry (Boustanifar et al., 2018; Célérier and Vallée, 2019; Lindley and McIntosh, 2017; Philippon and Reshef, 2012). This literature has documented a large finance wage premium and much of the recent literature has focused on explaining the sources of it. The literature identifies worker composition (and talent), financial regulation, and to a less extent, information and computer technologies as the three most important factors behind the large worker's pay in finance. A shortcoming of this literature is that most studies lack rich datasets to account for basic controls, for instance, worker fixed effects, the most important control in any wage regression.[3] These studies also lack information to identify firms (instead of industries) and thus, they cannot study the role of individual firms in determining wages (Card et al., 2018) and their interaction with worker fixed effects, namely, the sorting between high-wage workers and high-wage firms (Card et al., 2013; Song et al., 2019). We also try to identify and explain the finance wage premium over time, but we do it in a much richer framework. We use a massive matched employer-employee dataset (that covers 100% of the Dutch labor market) along with an extended set of controls such as the type of the contract, educational attainment, degree subject (Diploma), and detailed information about firms.[4] As a result, our paper offers much richer data, which allow us to replicate most of the paper discussing the finance wage premium, and methods, which allow us to better explain the finance wage premium.

A paper that is closely related to ours is Böhm et al. (2021). They study the hypothesis that the increase in finance wages observed in Sweden over the period 1990-2014 is due to an increase in the relative demand for talented workers. Using an employer-employee dataset for the entire population of workers, they conclude that changing composition of workers or return to talent cannot account for the surging wage premium. Importantly for us, they find that the increase in relative finance wage has been an industry rather than an occupational phenomenon. This is because the relative compensation in finance has risen over time for all occupations in finance, regardless of skill requirements and income level. Complementary to this paper, we find that changing composition of workers does not explain the finance wage premium but the matching between ICT capital and high human capital at the industry level does it. As a result, this paper shows that finance wage premium is an industry phenomenon (as suggested by Böhm et al. (2021)) driven by capital-skill complementarities.

[3] As we shown in Table A2, worker fixed effects explain 55% of the log hourly wage. For that reason, it is important to incorporate worker fixed effects to get a precise value of the FWP out of time-invariant unobserved individual characteristics.

[4] These massive employer-employee databases have been long used to explore important topics in labor economic like the wage gender gap (Card et al., 2016), wage inequality over time (Song et al., 2019), imperfect competition (Lamadon et al., 2019), and sources of wage variation (Torres et al., 2018), among others topics and this kind of database are critical to identify and explain the finance wage premium going beyond an industry dummy and considering the firm-level dynamics.

We are not the first one to propose the ICT capital as a potential driver of the finance wage premium. Lindley and McIntosh (2017) study whether the finance wage premium may be a consequence of the finance sector becoming more intensive in non-routine task inputs (i.e., numeracy, literacy, problem-solving, and influencing people) and computer use. By using cross-sectional data for 1997, 2001, 2006, and 2012, they find no evidence that the higher levels of non-routine task inputs and computer use complexity observed in the finance sector in the U.K. can fully explain the finance pay premium, nor its increase. In the same line, Boustanifar et al. (2018) study the allocation and compensation of human capital in the finance industry in a set of developed economies in 1970-2011. They document that finance increased its relative intensity of ICT, and they estimate that ICT is relatively more complementary to skill in finance than in other sectors. Although they find a positive relationship between ICT and skilled wages in finance, they conclude this relationship is not causal (and cannot explain the dynamics of the finance wage premium). We also try to explain the finance wage premium by controlling for ICT capital intensity. However, we are the first one to control for ICT capital intensity (as a proxy of technical change). This is the reason why, perhaps, we find that capital-skill complementarities help to explain the finance wage premium in the Netherlands.

Second, we also contribute 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). We add to this literature by showing that finance industry bonuses are important to explain the finance wage premium, although far less important than previously suggested -possibly due to the regulatory changes in the post-GFC period. We also show that the finance wage premium related to the variable part of the worker's pay has decreased over time, while the finance wage premium related to the fixed part of the worker's pays has increased, consistent with the new regulation targeted to curtail worker's pay (bonuses) in the finance industry. Importantly, we also show that the FWP is not driven by the highest earners (the top decile).

The third strand of literature that this paper relates to is the line of research that studies employee compensations with the additive worker and firm effects model proposed by Abowd et al. (1999a), usually referred as the AKM model (Card et al., 2018, 2016;

Song et al., 2019), the literature that discusses compensation using structural models (Bonhomme et al., 2019; Lamadon et al., 2019), and the literature that relates the profitability of firms and worker's pay (Barney et al., 2019; Barth et al., 2016, 2018; Card et al., 2018, 2014; Gürtzgen, 2009). Although we exploit the employer-employee relationship in our analysis and aforementioned approaches to support our results, we are mostly interested in the inter-industry wage differences as in Krueger and Summers (1988) and Dickens and Katz (1987). We also focus on the role of industry affiliation in explaining relative wages without limiting our analysis to the finance industry.

3 Institutional Context and Data

3.a The Dutch Labor Market

The Netherlands is a small open economy and part of the eurozone with a population of 17 million inhabitants and a working population of 9 million in 2018. During the period 2006-2018, the Dutch labor market faced two aggregate shocks: the Global Financial Crisis and the European Debt Crisis. Accordingly, the economy contracted in 2009 and then again in 2012 and 2013, when the unemployment rate peaked at 7.6%. From then on, the economy has recovered rapidly to achieve an unemployment rate of 3.6% in 2018. In addition, the employment-to-population ratio has remained stable, around 66%.

Like other European countries, the Dutch labor market is characterized by centralized collective bargaining (CAO). CAOs are a collective agreement between employers (or employer's associations) and trade unions about wages[5] and other conditions of employment like leave, pension, and social security. Although a CAO can apply to a single firm, it is mostly negotiated at the industry level. CAOs are mandatory, but firms may deviate from this if it benefits employees. Around three-quarters of the Dutch labor force is covered by collective agreement (Hartog and Salverda, 2018). Therefore, the evolution of hourly wages reflects, in general, the pay increases established between unions and employers in their CAOs.

In the Dutch labor market, all employees between 21 and state pension age (i.e., default retirement age which was 65 in 2018) are entitled to the statutory minimum wage. However, the law does not lay down a minimum wage because the number of hours in

[5] Regular wage bargaining cover the general adjustment of nominal wage levels to account for the evolution of prices and productivity.

a working week can differ from firm to firm. Then, the law sets a minimum monthly wage for everyone in full employment. For instance, the hourly minimum wage was 9.11 euros in 2018 for a full-time worker (40 hours per week). The minimum wage can differ per industry and it can also be laid down by the CAO, yet this must not be lower than the statutory minimum wage.

The flexibility of the Dutch labor market is the most notable feature of it. The Dutch labor market is highly flexible, being characterized by a large share of part-time contracts (49% in 2018) and flexible work arrangements (26% in 2016) like on-call contracts, temporary agency workers, and fixed-term contracts without fixed hours. As a reference, the share of part-time contracts and flexible work arrangements was 26% and 15% for the United States in 2015 (Katz and Krueger, 2016). This flexibility of the Dutch labor market may have important implications for wage determination. For instance, Grajales-Olarte et al. (2021) shows that employees with flexible-hour contracts (such as on-call workers) exhibit also more flexible hourly wage rates compared to the workers with fixed-hour employment contracts. These results are very important because according to the analysis this growing segment of the labor force not only appears to be absorbing shocks in terms of "hours-worked" but also through "unit-wage compensations." As a whole, even though the Dutch institutional arrangements seem to differ from on the ones in the U.S., we will see later that the log earnings decomposition, after controlling for a rich set of controls, is similar between these two countries. We expect then that our results are general enough to inform about the dynamics of the finance wage premium.

3.b The Finance Industry

The finance industry is large in the Netherlands. From a local perspective, while the number of workers in the finance industry represented 2% of the working population in 2018, the ratio of gross added value (GAV) to the rest of the Dutch economy was 10%. The Dutch finance industry is also large from an international perspective. The ratio of assets to GDP for the finance industry in the United States was 5 in 2018, while it was 11 in the Netherlands. [6]. On top of that, the Netherlands is regarded to have a systemically important financial sector by the International Monetary Fund (IMF Country Report No. 17/79, 2017).

The finance industry is large in the Netherlands because of the banking sector. The

[6] See https://fred.stlouisfed.org/graph/?g=smH.

banking sector held 47% of the finance industry's assets in 2018, while the pension system, insurance companies, and investment funds held 28%, 9%, and 16%, respectively (DeNederlandscheBank). The banking sector is very concentrated. The largest five banks in the Netherlands held 84% of the total assets in 2018 and one of those banks, ING, is a globally systemically important bank (G-SIB). The Dutch banking sector has gone through important transformations over the period 2006-2018, especially after the Global Financial Crisis, when the government bailed out several banks. The number of banks has rapidly decreased over time, from 103 in 2007 to 43 in 2018.[7] Furthermore, after having held around 550% of the GDP in 2007, the banking sector's assets have since fallen to 330% of the GDP in 2018. This has come with major reorganization at all banks. While the sector employed more than 100,000 workers in 2008, this number has fallen to less than 70,000 in 2018. The key element of this transformation has been the increasing demand for highly educated talent with specific competencies including ICT (see Figure 3).[8] The sector has also faced major regulatory reforms, which has enhanced the supervision of banks, along with strengthened capital, liquidity regulations, and compensation regulation.

Regarding other sectors in the finance industry, the Dutch pension system has rapidly grown in importance. As the banking sector, the pension system has also suffered important transformations over the period 2006-2018. While there were 767 active pension funds in 2006, there were 220 pensions funds in 2018 (company pension funds, compulsory industry-wide pension funds, company savings funds, optional industry-wide pension funds, and occupation pensions funds)[9] due to a pension consolidation process. However, the pension system has become larger. The pension system share in the finance industry's assets went from 17% in 2008 to 30% in 2018 (more than two times the GDP). On the contrary, the insurance companies[10] have kept their share of the finance industry's assets (9%). As with other sectors in the economy, the number of company insurers has also decreased over the period 2006-2018. While the number of insurance companies was 368 in 2006, it was 160 in 2018. Finally, the size of the investment funds has also rapidly increased over the period 2006-2018. The investment funds share in the finance industry's assets went from 5% in 2008 to 17% in 2018 (more than one time the GDP), going from 1,356 funds in 2008 to 1,714 funds in 2018. This increase in the number of invested assets is explained by the investments of the pension funds,

[7]See for more details at DNB website.

[8]"Agenda for the Dutch Banking Sector for 2019 and beyond" by the Dutch Banking Association.

[9]See https://www.pensioenfederatie.nl for more information.

[10]Insurance companies provide life-insurance, non-life insurance, and funeral in-kind insurance.

as they can externalize the management of their assets through investment funds.

Capital intensity (i.e., the value of capital per worker) is a defining characteristic of the finance industry. After the mining and quarrying industry, finance is the industry with the largest level of capital per worker in the Dutch economy. For instance, over the period 2006-2018, the labor-income ratio decreased in the finance industry from 56.9 in 2006 to 43.2 in 2018 (the average was 73.13 across industries).[11] This capital deepening is largely explained by the rise of ICT capital per worker. The ICT capital per worker has increased from around €6,000 in 2008 (the lowest value) to around €11,000 in 2018 (a 87% increase). Innovation in information technologies has been key to the transformation of the finance industry after the Global Financial Crisis. The finance industry is the second largest employer of IT workers in the Dutch economy, just behind the information and communication industry.[12]

3.c Description of the Employer-Employee Dataset

The main administrative data we use is an integral worker-firm dataset containing monthly wages and contract information. While the wage information includes the total decomposition of the salary (fixed wage, overtime wage, wage discounts, bonuses, etc.), the contract information includes information about the type of contract (tenured, untenured or does not apply), if the contract is full-time or part-time, fixed or flexible, weekly working time and type of job (director, intern, regular worker, temporary agency worker, on-call employee, and other). Information is also collected on the Standard Industrial Classification (SBI), the number of workers, and the municipality of the firm. The data is collected by firms and used to calculate the length and level of unemployment benefits by the government agency that pays out unemployment benefits. Since all workers (including workers in the public sector) are covered by unemployment insurance, the data is comprehensive for all (legal) employment. All workers and firms are anonymized, and Statistics Netherlands (CBS) provides identifiers to track workers and firms over time.

To be able to work with this massive database, we calculate the total salary and worked

[11] The labor-income ratio is equal to the total pay for labor over total pay for labor and capital. Over the period 2006-2018, the total pay to labor has remained roughly the same. The pay for labor is the economic output that accrues to workers in the form of compensation.

[12] Figure A1 shows how financial firms hired more (and spend more for) informatics graduates with respect to financial management and tax law workers (one of the largest groups of employees in finance and a comparison group) after the Global Financial Crisis.

hours over the year. As in Card et al. (2016) and Philippon and Reshef (2012), we calculate the hourly wage. Since we are interested in the fixed part of the salary and in the variable part, we create two measures for the hourly wage: the fixed hourly wage and the full hourly wage. We calculate the fixed hourly wage as follows:

$$\text{Fixed hourly wage}_{iy} = \frac{\sum\limits_{c\in C}\sum\limits_{m=jan}^{dec} \text{Fixed salary}_{cm}}{\sum\limits_{c\in C}\sum\limits_{m=jan}^{dec} \text{Fixed worked hours}_{cm}}. \tag{1}$$

Thus, the fixed hourly wage$_{iy}$ for a worker i in the year y corresponds to the sum of the fixed wage over months and contracts divided by the sum of the fixed worked hours over months and contracts. To incorporate the variable part to the fixed part, we calculate the full hourly wage as follows

$$\text{full hourly wage}_{iy} = \frac{\sum\limits_{c\in C}\sum\limits_{m=jan}^{dec} (\text{Fixed salary}_{cm} + \text{extra salary}_{cm})}{\sum\limits_{c\in C}\sum\limits_{m=jan}^{dec} (\text{Fixed worked hours}_{cm} + \text{Overtime worked hours}_{cm})}, \tag{2}$$

where extra salary$_{cm}$ considers bonuses, overtime salary, and any other item. Since a worker may have different contracts over time, we consider the firm information corresponding to the largest contract at the end of the year. We classify contracts as full/part-time, tenure/untenured, fixed/flex, weekly work time, and type of job (i.e. director, intern, regular worker, temporary agency worker, on-call employee, rest).

We complement this dataset to four extent. First, we incorporate demographic information: age, gender, and Dutch background (native, first-generation, and other). Second, we incorporate information about the highest education degree achieved by the worker by 2018, which we classified into five levels: basic education, Middle-level education, Bachelor's degree, Master's degree, and Ph.D. degree.[13] Given that we are interested in

[13]The five categories correspond to the following level in the Dutch education system. "Basic education" corresponds to primary education, practical education, or VMBO (preparatory secondary vocational education) as the highest degree of education completed. "Middle-level education" corresponds to MBO (middle-level applied education) or any of these two streams of secondary education, VWO (senior general secondary education), and HAVO (university preparatory education), as the highest degree of education completed. "Bachelor's degree"' corresponds to any of the two types of bachelor's degrees, HBO (university of applied sciences) and WO (academic university education), as the highest degree of education completed. "Master's degree"' corresponds to any of the two types of master's degree, HBO and WO, as the highest degree of education completed. Finally, "Ph.D." corresponds to Doctor of Philosophy.

understanding the skill intensity at the industry level, we construct the ratio of workers with a master's degree or a Ph.D. degree over the number of workers with basic education (i.e., primary or practical education as the highest degree of education completed). We call this ratio as the ratio high to low skilled workers in Figure 3. As a robustness check, we also consider alternative ratios (see Table 2 and A5). Third, we include information about capital stock for two categories ICT capital and non-ICT capital. ICT capital is the gross fixed capital in the categories IT equipment, communication equipment, and software. Non-ICT capital refers to all other capital excluding ICT-capital.

Unfortunately, Statistics Netherlands reports this information at the industry level. As we will show later, the ICT capital variables may be very well approximated by the IT wage bill (see Figure A2). This is because the finance industry invested mostly in *in-house* software development over the sample period considered here (see Figure A1).[14] As a result, the IT wage bill is a very good approximation for the ICT capital spending. Finally, we complement this dataset with the balance sheet and income statement of all companies with legal personality that are active in the Netherlands in the non-financial industry. As we are interested in the financial industry, we include the balance sheet and income statement of the banking sector from Orbis Banks Focus. This extended dataset comprises $39,320,449$ worker-year observations.

3.d Summary Statistics and Stylized Facts

Table 1 characterizes the finance industry when compared to the rest of the industries. We see that the average finance worker is 41 years old and they are much more educated than workers in other industries. For instance, 17% of workers in the finance industry holds a master's degree when compared to the 11% of workers in the rest of the industries. Finance workers work under more traditional long-term types of contracts (full-time and permanent contracts with more than 35 working hours per week) and also work in larger firms with a much larger ICT capital per worker. We can also see that the full hourly wage of a worker in the finance industry is 27€, which is 6€ higher than the average full hourly wage in the rest of the industries. While we observe this difference in almost every developed finance industry nowadays, it is surprising that this hourly wage difference grew after the Global Financial Crises. We can see this in Figure 1. Figure 1 (a) shows the average of both the fixed hourly wage and the full hourly wage in the finance industry and the rest of the economy and panel (b) shows their difference. As in Table 1, we observe that there is a large difference in the hourly

[14]See "Agenda for the Dutch banking sector for 2019 and beyond" from the Dutch Banking Association.

wage between the finance industry and the rest of the economy, and importantly, we can see that this difference in the hourly wage has grown over time despite all the new regulations aimed to curtail the worker's pay in finance (e.g., Bonus cap for the finance industry in 2015[15]).

Table 2 reports descriptive statistics for the finance industry, the rest of the economy, and all industries. We highlight two features. First, the ICT-K per worker is high in the finance industry. For instance, ICT-K per worker is around $9,000$€ in the finance industry while it is around $3,160$€ in the rest of the industries. Second, the skill intensity is also high in the finance industry. On average, we observe five workers with a master's degree or Ph.D. degree for each worker with basic education in the finance industry. On the contrary, we observe only three workers with a master's degree or Ph.D. degree for each worker with basic education in the rest of the industries. We also observe that this difference in skill intensity and ICT-K (between finance and the rest of the economy) has grown over time. We start with the skill intensity in the finance industry. Figure 2 reports the share of workers, for whom we have information, with given educational attainment in the finance industry. Education corresponds to the highest educational attainment observed in 2018. We define five categories: Basic education, Middle-level education, Bachelor's degree, Master's degree and, Ph.D. We see a dramatic change in finance workers' education. The skill intensity in the finance industry increased rapidly since the Global Financial Crisis by replacing workers of low education levels with workers with master's degrees (mostly young ones). The finance industry also enjoyed a relative increase in terms of the share of workers with graduate education with respect to other industries during this period. We finally study the evolution of the ICT-K per worker over time. Figure 3 shows the evolution of the ICT capital per worker and the ratio of high to low skilled workers for both the finance industry and the rest of the economy. Along with the rising of the skill intensity in the finance industry, we observe that the share of ICT-K increased rapidly over the period, an empirical pattern that is not common to a large fraction of the industries in the country. We are going to show later how these dynamics in the finance industry largely explain the finance wage premium.

[15] See for example "A bonus cap for all Dutch Financial Undertakings" at https://www.leidenlawblog.nl/articles/a-bonus-cap-for-all-dutch-financial-undertakings

4 Estimation methods

4.a Estimation of the Finance Wage Premium

We start with the traditional specification used to identify the finance wage premium as a baseline (Célérier and Vallée, 2019; Lindley and McIntosh, 2017; Philippon and Reshef, 2012). The regression is

$$\ln w_{i,t} = \phi \mathbf{1}^F_{i,t} + \boldsymbol{X\beta} + \alpha_i + \epsilon_{i,t}, \tag{3}$$

where $w_{i,t}$ may be the log fixed hourly wage or the log full hourly wage for worker i in year t; $\mathbf{1}^F_{i,t}$ is a dummy for employment in finance; $\boldsymbol{X}$ corresponds to covariates, where we include a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract,[16] municipality and firm size[17]; α_i are worker fixed effects; ϵ_{it} is the idiosyncratic error clustered at firm level. The finance wage premium is given by ϕ.

We then estimate the additive worker and firm effects wage model introduced by Abowd et al. (1999a), the AKM model. Thus, we run

$$\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}, \tag{4}$$

where $\psi_{J(i,t)}$ are firm fixed effects. Firm fixed effects contain a matching function J that assigns worker i in year t at firm j. Under this specification the finance wage premium is calculated as follows

$$\text{Finance wage premium} = \left(\frac{1}{N^f} \sum_{j=1}^{N^f} \bar{\psi}_j^{finance} - \frac{1}{N^r} \sum_{j=1}^{N^r} \bar{\psi}_j^{rest} \right), \tag{5}$$

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. We

[16] Type of contract classifies contracts on: full/part-time, tenure/untenured, fixed/flex, weekly work time (four categories) and type of job (i.e. director, intern, regular worker, temporary agency worker, on-call employee, rest).

[17] Firm size is a categorical variable based on the number of employees at business unit. The lowest level corresponds to firms with one employee and the highest level corresponds to firms with more than 2,000 employees. The variable has 15 categories.

get $\bar{\psi}_j$ by weighting the number of employees in firm j and their employment-duration

$$\bar{\psi}_j = \frac{1}{N_j} \sum_{i=1}^{N_j} \left(\sum_{t=1}^{N_{T(i,j)}} \frac{\psi_{j=J(i,t)}}{N_{T(i,j)}} \right), \tag{6}$$

where N_j is the total number of workers employed in the firm j over the period 2006-2018; $N_{T(i,j)}$ is the total number of years that the worker i was employed in the firm j; finally, $\psi_{j=J(i,t)}$ corresponds to the firm fixed effect for firm j.

Since the former procedure does not allow us to calculate the standard errors, we estimate the finance wage premium by using the following auxiliary regression

$$\hat{\psi}_{J(i,t)} = \phi \mathbf{1}^F_{i,t} + \xi_{i,t}. \tag{7}$$

where $\hat{\psi}_{J(i,t)}$ is the estimated fixed firm effects from regression (4). The parameter $\hat{\phi}$ is finance wage premium, namely, the simple average of firm fixed effects within the finance industry minus the average firm fixed effects in the rest of the economy.[18] To calculate the standard errors, we bootstrap at firm level[19]

$$\hat{se} = \left\{ \frac{1}{k-1} \sum_{r}^{k} (\hat{\phi}_r - \bar{\phi})^2 \right\}^{1/2}, \tag{8}$$

where $r = 1, 2, ..., k$ denote the bootstrap samples and $\bar{\phi} = \frac{1}{k} \sum_r^k \hat{\phi}_r$. According to Hall and Wilson (1991), formula (8) gives an estimate of the standard error of the statistic. Regarding the estimations of equation (3) and (4), we exclude firms changing industries and firms with less than 10 employees. We also consider workers from 18 to 65 years old, and we drop extreme values. We follow Abowd et al. (2012); Card et al. (2013) by including only observations in the largest connected set of workers and firms through worker mobility.[20] This is because we can only identify worker and firm effects in connected sets, and thus, we choose the largest connected set.[21] We refer to the Appendix B for a detailed discussion about the assumptions in the AKM framework. To demon-

[18] We use the original observed value of the statistic, $\hat{\phi}$, as the finance wage premium (instead of $\bar{\phi}$).

[19] Bootstrapping provides a way to get standard errors when no formula is otherwise available.

[20] This concept is explained by Abowd et al. (2002) as follows: "When a group of person 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 person 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."

[21] We lost around 1% of the original sample.

strate the strength of our database, in Table A2, we show the decomposition of log earnings by various fixed effects (worker and firm fixed effects) and control variables. We do this because the variance wage decomposition is a standard exercise in the AKM regressions (Lachowska et al., 2020; Lamadon et al., 2019), which allows us to compare against different datasets for different countries. In this respect, we relate to Song et al. (2019). They run a variance wage decomposition by using an employer-employee dataset that covers 100% of the workers in U.S. Table A2 shows components of variance both for the full period and 2007-2013 subsample, which matches the studied period in Song et al. (2019). We find that the components of the variance are rather similar to Song et al. (2019). For instance, while we find that firm fixed effects explain 7% of the wage variability in our sample, Song et al. (2019) show that firm fixed effects explain 9% of the wage variability for the U.S. Yet the residual in our analysis is smaller (8% for the full sample and 7% for the 2007-2013 period compared to 15% in Song et al. (2019)) mainly thanks to the covariates explaining a relatively larger share of the variance in wage composition.

4.b Capital-skill Complementarity in the AKM Setting

We are interested in the value of the finance wage premium when controlling for industry-level capital-skill complementarities. To study this, we run the following regression

$$\ln w_{i,t} = \theta_1 K_{I,t} + \theta_2 HL_{I,t} + \theta_3 (K_{I,t} \times HL_{I,t}) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}, \tag{9}$$

where $K_{I,t}$ is one of three measures of capital: ICT capital per worker at the industry level (gross fixed capital stock in the categories IT equipment, communication equipment, and software), Non-ICT capital at industry level, and IT wage bill per employee at the industry level (total gross wage spending on IT workers over the total number of workers); $HL_{I,t}$ is the ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education at industry level. We then calculate the finance wage premium as equation (5), namely, $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. As a robustness check, we include a $Industry \times Year$ fixed effect into equation (9), which drops variables $K_{I,t}$, $HL_{I,t}$, and $(K_{I,t} \times HL_{I,t})$, to explore if the FWP may be explained by industry trends over time instead of the particular capital-skill trend we are considering in equation (9). We will see later that these industry trends over time cannot explain the FWP as capital-skill complementarity does it. We also consider the following regression

$$\ln w_{i,t} = \theta_1 K_{I,t} + \theta_2 (K_{I,t} \times S_i) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}, \tag{10}$$

where S_i is the level of schooling at the individual level: Basic, Middle, and High (i.e., any level equal or higher to Bachelor's degree). This specification allows us to incorporate a measure of capital-skill complementarities alongside with *Industry* $\times$ *Year* fixed effects. If we do include *Industry* $\times$ *Year* fixed effects, we omit the term $\theta_1 K_{I,t}$ from equation (10).

5 Results

5.a Benchmark Estimate of the Finance Wage Premium

The traditional approach to estimate the finance wage premium, which is given by equation (3), may be characterized by three main features. First, the use of an indicator variable for working in the finance industry to calculate the average wage premium in finance over a given sample period. Second, the use of worker fixed effects to control for any time-invariant unobserved individual characteristics. Third, the use of datasets with limited information about worker's contracts and firm information. To build on the literature, we replicate the traditional approach to estimate the finance wage premium but in a much richer framework. First, we consider an employee-employer dataset that covers 100% of the Dutch labor market. As a result, we can calculate the average wage premium comparing against the rest of the economy, as in the traditional approach, but also against each other industry (i.e., inter-industry wage premiums).[22] Second, our dataset is rich enough to allow us to use wage rates instead of gross wages, which is arguably, a more precise measure of worker's pay. We can also differentiate between the fixed hourly wage and the full hourly wage. This allows us to identify whether the source of the wage premium is the fixed or the variable part of the worker's pay. This distinction is very important as this bonus culture is a very well-known characteristic of the finance industry (Bell and Van Reenen, 2014; Efing et al., 2019). Finally, our dataset allows us to control for the type of contract of workers. It is common to calculate the finance wage premium over workers with full-time type of contracts. While this is a good assumption for the finance industry (see Table 1), it is not for the rest of the economy, in which we observe a higher prevalence of part-time

[22] Furthermore, this dataset allows us to get a very precise estimate of the finance wage premium as we cover all movements in and out of the finance industry for a period of 12 years.

and/or flex contracts, and thus we may over-estimate the finance wage premium if we do not control for the type of contract. The nature of our data allows to control for such contractual differences.

Table 3 shows results for the traditional approach to estimating the finance wage premium. In regression 1 in Panel A and B, we start with a basic specification without control variables or fixed effects and show that finance workers are getting 19% or 24.6% higher wages for their fixed wage or full wage including variable pay such as bonuses, respectively. Unsurprisingly, the finance wage premium is more pronounced for the compensation including variable pay. In regression 2, we include individual control variables as well as year fixed effects and macro factors, such as financial crises. The FWP gets smaller yet still sizable at 11.3% and 16.4% for the fixed hourly wage and the full hourly wage, respectively. Then in regression 3, we include worker fixed effects. We find that the FWP is down to 5.6% and 8.8% much smaller compared to the earlier regressions for the fixed hourly wage and full hourly wage, respectively. These results show that worker fixed effects are critical for the FWP as they account for unobserved time-invariant factors such as talent.

Table 4 compare and replicate the estimates in Table 3 (regression 3) with those obtained by Böhm et al. (2021); Boustanifar et al. (2018); Célérier and Vallée (2019); Lindley and McIntosh (2017); Philippon and Reshef (2012), the studies more similar to ours. Where possible, we report estimates of the finance wage premium when controlling for worker-firm effects.[23] Using data for Sweden, Böhm et al. (2021) estimate a finance wage premium ranging from -18% in 1990 to 23% in 2017. They read this increase in the finance wage premium over time as showing that time-invariant unobservable individual characteristics cannot account for the rise in relative finance wages. Similar to these authors, we also conclude that worker firm effects cannot account for the rising finance wage premium in the Netherlands, yet, our point estimates are very much smaller (e.g., the FWP is 8.8% over the period 2006-2018). Contrary to their work, we use wage rates (instead of the gross wage) and we control for a much rich set of controls, for instance, type of contract, firm size, and municipality of the firm. All these controls are important and may explain the difference between our estimates. We confirm this by replicating,

[23] We consider worker fixed effects as a feature because they are by far the most important control in wage regressions (also recognized by the finance wage premium literature). As we shown in Table A2, worker fixed effects explain 55% of the log hourly wage. For that reason, it is important to incorporate worker fixed effects to get a precise value of the FWP out of time-invariant unobserved individual characteristics.

as much as possible, their approach on the last column of Table 4. We find an FWP equal to 11.4% over the period 2006-2017, very similar to the FWP reported by them, $\approx$ 10%. Using data from the U.S., Philippon and Reshef (2012) show that the finance wage premium reached, on average, 50% in 2016. However, the estimated FWP when controlling for worker fixed effects is around 6.2%. While this result is in line with ours, this FWP comes from a very complicated sample as reported by the authors.[24] Importantly for us, this result shows, if something, how sensible is the FWP to control for worker fixed effects. As in the case with Böhm et al. (2021), we are able to get very close FWP estimates using our sample and their sample/method restrictions. Using data from France, Célérier and Vallée (2019) show that the finance wage premium is 22.4%. As with Böhm et al. (2021), we have a much richer set of controls, but perhaps more importantly for this paper, we are considering the full Dutch economy and including all industries. Contrary to us, Célérier and Vallée (2019) use only a very limited sample with 22 thousand observations (versus our 39 million sample). Boustanifar et al. (2018), by using data from a sample of developed countries and industry-level data for ICT capital in finance, show that the finance wage premium is higher than 30% (without controlling for worker firm effects), and in general, the FWP has increased over time for a large number of countries (including the Netherlands). Finally, Lindley and McIntosh (2017), using data from the U.K., show that the finance wage premium is 31.4%, however, they do not control for worker fixed effects. If we do that, by using again their sample/methods restrictions, we get an FWP very close, 32%.

We can conclude then that the rich set of controls (and the large dataset) that we use in this paper explains the differences among the FWP estimates among studies. This is because we are able to replicate the FWP estimates of Böhm et al. (2021); Célérier and Vallée (2019); Lindley and McIntosh (2017); Philippon and Reshef (2012) (or get close results) but by using our data and their sample/method restrictions.

5.b Extending the Finance Wage Premium Estimation

We extend the traditional approach to estimating the FWP by incorporating firm fixed effects along with worker fixed effects into the regressions. We do this because an extensive literature has recognized that firm pay premium contribute substantially to the

[24]They argue the following regarding their FWP estimates "A shortcoming of using the Matched CPS is that individuals who change their residential address are dropped from the sample. This affects mostly young people, but also job switchers, who may decide to move on account of changing jobs. This sample selection biases our fixed effects estimator toward zero. We find economically significant finance premia in the latter part of the sample, while job switching is no less prevalent in that period."

distribution of earnings even when controlling for differences in the composition of observed and unobserved worker characteristics between firms (Abowd et al., 2002, 1999b; Goux and Maurin, 1999; Song et al., 2019). For instance, Card et al. (2013) show that a rise in the dispersion of firm pay premia has contributed substantially to recent increases in wage inequality in Germany. Importantly for our paper, they show that inequality rose because of large changes in worker compositions - high-wage workers became increasingly likely to work in high-wage firms, and high-wage workers became increasingly likely to work with each other. Similar phenomena of changes in firm pay premiums and worker composition may explain the rising worker's pay in finance relative to the rest of the economy. To account for these factors when estimating the FWP, we estimate the additive worker and firm effects model introduced by Abowd et al. (1999b), the AKM model.

In Table 3, regression 5, we use the AKM model, where we employ both worker and firm fixed effects and estimate the FWP from the estimated firm fixed effects (as described by equation (4)). The FWP from the AKM regressions is 6.9% and 11% fixed hourly wage and full hourly wage, respectively -slightly higher than the worker fixed effect specification.[25] Figure 4 shows the FWP over time for these estimates. We can see that fixed hourly wage has grown enormously over this period, from 5.2% in 2006 to 9.7% in 2018 (a 87% increase in 12 years). Contrary to the fixed hourly wage, the full hourly wage has grown slowly over this period and just after the GFC, from 10.6% in 2006 to 13.3% in 2018. Likely because the new regulation post-GFC targeted the bonuses in finance,[26] we see that FWP has moved from the variable part of the salary to the fixed part over the years. This change in the worker's pay (and its consequences) has been recently documented by several papers (Cerasi et al., 2020; Colonnello et al., 2020; Kokkinis, 2019), especially for managers' compensation. However, we will show that this change is not limited to manageal compensation, but for all industry.

[25] This is also observed by Böhm et al. (2021), which document a higher FWP when including person-firm fixed effects. However, the authors do not further discuss this specification and the traditional checks we need to run this type of regressions. See Appendix B.

[26] On 5 March 2013 the EU finance ministers decided that European banker's bonuses should be capped at a maximum of 100% their base salary, rising to 200% if shareholders explicitly agree. On 7 February 2015 was introduced the Dutch Act on the Remuneration Policies Financial Undertakings. The central point of the Act is the 20% bonus cap: a financial undertaking cannot pay any person "working under its responsibility" variable remuneration that exceeds 20% of the fixed remuneration on an annual basis. Employees may be awarded a bonus exceeding 20% of the fixed pay in 2015 if such award stems from an obligation existing prior to 1 January 2015. The Minister of Finance has made it clear that this exception only applies to 2014 performance bonuses that are awarded in 2015. As from 1 January 2016, any bonus award is subject to the rules of the Act.

In Table 5, we show the robustness of the FWP estimated with the AKM regressions. Regression 1 shows that the FWP is lower for women but still large around 10% for the full hourly wage and statistically significant. In regression 2, we show that the FWP is not driven by the highest earners (the top decile) even though the FWP is slightly higher when the full hourly wage is considered. Interestingly, the FWP for the fixed hourly wages is lower for these top earners confirming the importance of bonus payments in finance (Bell and Van Reenen, 2014). We also find evidence that FWP spreads equally through all workers in the finance industry. This is likely because the FWP is an industry phenomenon, as argued by Böhm et al. (2021).[27] For instance, the top quartile in the finance industry enjoys an FWP of only 5.9% higher than the bottom quartile (i.e., administrative staff) and no difference when we consider the fixed hourly wage (see Table A3).[28] This result is also confirmed for the analysis with the type of jobs (whether the worker is a temporary agency, on-call, or a director). The results from Table 6 indicate that the FWP is smaller for on-call workers but not for temporary agency workers (or even directors). This means that temporary agency workers, who are usually recently graduated workers, enjoy the same FWP as regular workers with longer tenure.

In Table 5, regressions 3 and 4 demonstrate that the FWP exist both against the related industries (top-4 industries where finance workers usually move in or come from) and unrelated industries (top-4 industries where finance workers rarely move in or come from), but it is higher for related industries (around 11%) compared to unrelated industries (6.7%). Regression 5 shows that the FWP is independent of the inclusion of firms that are changing industries (mostly small firms).[29] Thanks to the granularity of our dataset, we can also explore the finance wage premium within sub-industries. In Table 7 (regressions 1 and 3), we show how the FWP varies for sub-industries using the AKM regressions. The results suggest that the FWP is driven by banks, which have the highest premium (22.8%), followed by pension fund services (19,1%), insurance services (14.5%), fund management services (13.2%), and auxiliary services (6.9%).

Our findings in Table 3, 5, 6, and 7 allow us conclude three important points. First, the FWP is an industry phenomenon, as argued by Böhm et al. (2021). Second, the sorting

[27] This is particularly true within sub-industries.

[28] These results are not reported.

[29] This sample allow us to calculate "pure industry effects", as called by Abowd et al. (2002, 2012), in the presence of person and firm effects. The pure industry effect is defined as the one that corresponds to putting industry indicator variable in equation (4) and then defining what is left of the pure firm effect as a deviation from industry effects. When we calculate the pure FWP, out of firm movements among industries, we find that this is close to 0 and non-significant.

between high-wage workers and high-wage firms, while important in finance, is not important enough to explain the FWP. Third, the FWP is lower than reported in the literature but still large for some sectors in finance, e.g., banking (22.8%).

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

The existence of a "large" excess wage in finance has motivated a long list of alternative (but rather unsuccessful) explanations for the finance wage premium.[30] For instance, Philippon and Reshef (2012) argue that the FWP may be further explained for the wage profile in finance, which has become steeper and riskier than in the rest of the economy (which is not observed in our sample[31]). Célérier and Vallée (2019) argue that the FWP may be explained by high complementarity between talent and scale, although Böhm et al. (2021) arrive at the opposite conclusion. They find that the changing composition or return to talent cannot account for the surging wage premium. Rather, Böhm et al. (2021) argue that the rising FWP is more consistent (though, the analysis is only suggested without identifying the dynamics) with imperfect competition leading to industry rents, which are being shared with workers (which we discard by using rent-sharing regressions as Card et al. (2018))[32]. Boustanifar et al. (2018), and also Philippon and Reshef (2012), argue that financial deregulation is the most important factor driving up wages in finance, yet, it has largely documented that after the Global Financial Crisis, a period of radical reforms in the finance sector, the FWP has continued to grow (Bell and Van Reenen, 2014; Böhm et al., 2021; Lindley and McIntosh, 2017).

One potential explanation that has been suggested in each of these papers is the role of information technologies in finance on different sample periods and countries (see Table 4). The post-GFC period is largely marked by the advent of digital banking. Digital banking services have created large gains in productivity and efficiency in the finance industry by allowing it to offer new products and services, reduce costs, expand geographically, and compete globally (Chowdhury, 2003; Gupta et al., 2018). As result, the worker's pay may have increased in finance post-GFC thanks to the heavy investment on ICT capital, to develop digital banking services (among others) that boosted productivity, and the ensuing reorganization of finance from low- to high-skill employees

[30] It has also generated a discussion about the consequences of the brain-drain towards finance (Célérier and Vallée, 2019; Philippon, 2010; Philippon and Reshef, 2012).

[31] We arrive at this conclusion after replicating Table V (career wage profile) from Philippon and Reshef (2012).

[32] We do not report these results.

to cope with new technological advance.[33] We propose the ICT capital demand as a complement for demand for high human capital and the matching between the two as a determinant of the finance wage premium (on top of the other controls). In particular, if ICT, from which the finance industry has greatly benefited (Figure 3), have substituted middle-skill workers while having complemented the high-skill workers, then high demand for high-skill workers coupled with capital-skill complementary can explain both, the allocation of high-skill workers (Figure 2) and wage premium observed in the finance industry (Figure 1) (Autor et al., 1998, 2003).[34] However, we do not limit our argument to finance. We believe (and we will show) that industry-level trends in human capital and technological transformation (and possibly their interaction) are critical for inter-industry wage differentials, not just finance.

To study technological change associated with digital banking services, we rely on two proxies. We use ICT capital per worker (i.e., gross fixed capital stock in the categories IT equipment, communication equipment, and software) and IT wage bill per employee (i.e., gross wage spending on IT workers divided by the number of workers at the industry level).[35] These two measures are input-based measures and all have been shown in previous work to be good proxies for technological change (i.e., the development of digital banking services).[36] Although our measures are not perfectly correlated (which allow us to capture a different aspect of technological change), we can see in Figure A2 that more ICT capital is highly correlated with more IT wage bill per employee. To study capital-skill complementarities, we need a measure of skill intensity. We proxy the level of skill intensity by the ratio of workers with graduate degrees (i.e., skilled labor) over workers with basic education (i.e., unskilled labor), as in Acemoglu (2002); Acemoglu and Autor (2011), by following the tradition of the macro growth literature of differentiating labor according to educational attainment (Duffy et al., 2004). As a robustness check, we also consider alternative proxies for the level of skill intensity; (i) the ratio of workers with graduate degrees over workers with middle and basic edu-

[33]Innovations in information technology can have an important influence on the structure of information-intensive industries, like the finance industry - as argued by Buch and Dages (2018). We document this in the Data section for the Netherlands. Morrison and Wilhelm Jr (2004); Mortensen (2003) also document that investment in ICT affected the optimal organization of investment banks in the U.S.

[34]Boustanifar et al. (2018) formulate a similar argument at footnote 11.

[35]As a robustness check, we also consider the gross wage spending on IT workers at industry-level but excluding the firm spending. We also consider the share of IT worker over the total number of workers at industry level. For both variables, the results are similar.

[36]For instance, Berman et al. (1994) use the computer investment variable as their proxy for the rate of technological change and Allen (2001) show that the scientists and engineers variables are highly correlated with the R&D to sale ratio in the industry.

cation (as in Katz and Murphy (1992)); (ii) the ratio of workers with graduate degrees over the total number of workers.

We are not the first one to study the relationship between ICT and the finance wage premium. There are two papers very close to us. Lindley and McIntosh (2017) study whether the finance wage premium may be a consequence of the finance sector becoming more intensive in non-routine task inputs (i.e., numeracy, literacy, problem-solving, and influencing people) and computer use. By using cross-sectional data for 1997, 2001, 2006, and 2012, they find no evidence that the higher levels of non-routine task inputs and computer use complexity observed in the finance sector in the U.K. can fully explain the finance pay premium, nor its increase. Contrary to their work, we do not have information about tasks inputs and computer use, but we believe that ICT capital per worker at the industry is a good proxy of technology advance. In the same line of research, Boustanifar et al. (2018) study the allocation and compensation of human capital in the finance industry at the country-level for a set of developed economies for 1970-2011. They document that finance increased its relative intensity of ICT, and they estimate that ICT is relatively more complementary to skill in finance than in other sectors. Although they find a positive relationship between ICT and skilled wages in finance, they conclude that this relationship is not causal. Similar to their study, we also try to explain the finance wage premium by using a measure of technological change, ICT capital per worker at industry level (without individual level data), however, we exploit within-industry variation with individual data (while Boustanifar et al. (2018) exploit cross-country variation with industry-level data for finance). Regarding the empirical approach, we follow Bartel and Sicherman (1999). They study how the technological change affected the 1973-93 inter-industry wage structure in the U.S by using five proxies for technological change, two of them very similar to ours, investment in computers and the share of scientists and engineers in industry employment. Based on a cross-section approach, they conclude that sorting is the dominant explanation for higher wages in industries with higher technological change. We follow their econometric approach, by incorporating capital-skill complementarities through an interaction between technological change and a measure of schooling. Yet, we conduct a within-industry analysis.

In Table 8, we introduce industry level skill intensity and capital per worker into the AKM regression. This specification corresponds to equation (9). In these regressions, we focus on full hourly wages, as they capture a more thorough picture of worker compensation. As we do not have capital per worker information for all the industries number of observations is around 30 million (down from 39 million). With this sample, the estimated FWP with the AKM model is around 12.9%. In regression 2, the addition of log ICT capital per worker reduces it to around 10.4% and in regression 3, the industry-level skill intensity proves to be even more important as its inclusion brings the estimated FWP to around 5.3%. When both ICT capital intensity and skill intensity are included (regression 4) the FWP becomes even smaller at around 4.9%. Most importantly, when we allowed for ICT capital and skill intensity interaction to capture possible industry-level complementarities the FWP becomes negative and statistically significant suggesting the finance wage premium is -3.6%. Our interpretation of these results is that industry-level trends in human capital and technological transformation (and their interaction) are critical for inter-industry wage differentials, especially for finance. In regression 5, we find that returns to schooling are higher in industries with higher rates of ICT capital per worker (not necessarily finance) even after controlling for unobserved individual and firm characteristics. At a higher rate of both ICT capital per worker and skill intensity, the worker's pay grows more than proportionally due to capital-skill complementarities. On the basis of the results, we can conclude that worker's pay in finance is high because of the intensive use of two complementary inputs: ICT capital per worker and skilled workers. The descriptive statistics reported in Table 2, that shows that the finance industry use 3 times more ICT capital per worker and 2 times more skilled workers per unskilled worker than the average industry, support this assessment.[37]

To see the robustness of these results, we replace the ICT capital per worker with non-ICT capital per worker (i.e., a placebo test). The results from regressions 6 to 8 suggest that the FWP is positive and significant despite the inclusion of non-ICT capital and its interaction with skill intensity. Moreover, when we use IT wage bill per employee as an alternative measure to ICT capital per worker in regressions 9 and 11, the FWP is negative confirming industry-level ICT transformation is a critical factor for the FWP. The results are similar when we control for the firm-level variables in Table A4 (i.e., profits per worker, log assets, and log leverage). Even though the number of observations is much lower due to lack of firm balance sheet data (number of observations are around

[37]To discard ICT as a potential explanation of the FWP, Boustanifar et al. (2018) state the following (footnote 12) "*ICT make skilled workers in investment banking more productive than skilled workers at Google? The results suggest that the answer is no.*" We do indeed observe that capital-skill complementarity is not stronger in the finance industry, so our explanation for the FWP is more related to how intense the finance industry started to exploit capital-skill complementarities than whether this relationship is stronger or not in finance.

14.4 million observations) the results are very similar to Table 8 confirming when the industry-level technology and skill intensity transformation and complementarities are controlled the FWP becomes much smaller and even negative. Our results also hold when alternative capital and skill-intensity measures are used and even when we consider IT wage bill measures and skill intensity measures at a more disaggregated level (Table A5).[38] Finally, in Table 7 regression 4, we show how the FWP varies for sub-industries when we control for capital-skill complementarities. As discussed before, the FWP is driven by banks, which have the highest premium for the benchmark specification, but gets much smaller (actually disappears for the fixed hourly wage and is around 7.1% for the full hourly wage) when we include ICT capital and skill intensity in the analysis.

Finally, we have not incorporated $Industry \times Year$ fixed effects into equation (9), as it would absorb our measures of capital-skill complementarities. To incorporate $Industry \times Year$ along with some measure of capital-skill complementarity measure, we extend equation (9) by replacing the measure of skill intensity by the level of schooling at the individual level (i.e., basic, middle, and high), S_i, and incorporating $Industry \times Year$ into the specification as shown by equation (10). We interact then S_i with the industry ICT capital per worker, thus allowing the effect of schooling on wage to vary with the industry level of ICT capital (i.e., a measure of capital-skill complementarity). As we do not have educational attainment for all workers, the number of observations is around 19 million (down from 30 million). With this sample, in Table 9 (regression 3), the estimated FWP with the AKM model is 13.1% (very close to the 12.9% identified in Table 8). In Table 9 regression 5, we show that the addition of the level of schooling interacted with log ICT capital per worker along with the inclusion of $Industry \times Year$ fixed effects reduces the FWP to 6.2% (a 52% reduction from 13.1%). These results reaffirm the conclusion that the FWP can be considerably explained by capital-skill complementarities.[39]

[38] We can calculate the IT wage bill per employee at industry level (19 levels), sectors (88 levels), and sub-sectors (261 levels). We can do the same with the measures of skill intensity and thus, we can calculate the FWP along with these more disaggregated measures. The results are robust to this exercise.

[39] Although we observe a difference between the -3.6% FWP identified in regression 5 of Table 8 and the 6.2% FWP identified under this approach, this is because the current approach, which includes S_i and $Industry \times Year$ fixed effects, does not incorporate the intensity of both ICT capital per worker and skills (only the interaction) as S_i and log ICT capital per worker are both absorbed by worker fixed effects and $Industry \times Year$ fixed effects, respectively. To further prove this point, if we do incorporate $Industry \times Year$ fixed effects but not any measure of capital-skill complementarity in the regular sample (30 million samples), the FWP moves from 12.9% to 11.7% (see regressions 1 and 2 from Table 9 or regressions 3 and 4 for the 19 million sample). Thus, we can conclude that $Industry \times Year$ fixed effects do not capture the dynamics of capital-skill complementarity measures (at industry level). It is the inclusion of a measure of

6 Concluding Remarks

We used a massive matched employer-employee database and studied the finance wage premium in the Netherlands. We obtained several key results. First, we show that the excessive wage in the finance industry steadily increased over the period 2006-2018 despite the Global Financial Crisis (GFC) and the European Debt Crisis. Second for the same time period, we also document that the number of high-skilled workers and the capital associated with information and computer technologies (ICT) increased rapidly. Third, we uncover that the finance wage premium is explained by ICT capital-skill complementary at industry level when controlling by the observed and unobserved worker and firm characteristics. Our results thus indicate a structural transformation within the finance industry, which benefits the employees in the industry.

capital-skill intensity at the individual or industry level that explains a large portion of the FWP.

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Table 1: Characterization of the finance industry.

	Finance industry	Rest of the industries		
	Mean	Mean	Min.	Max.
Age:				
Mean age	41	42	37	45
Fraction < 30 years old	0.15	0.19	0.10	0.38
Fraction 50> years old	0.23	0.29	0.15	0.40
Gender:				
Fraction male workers	0.52	0.61	0.15	0.90
Education (fraction):				
Unknown	0.35	0.38	0.24	0.51
Basic education	0.04	0.09	0.02	0.21
Middle-level education	0.21	0.24	0.09	0.36
Bachelor	0.23	0.18	0.07	0.36
Master	0.17	0.11	0.01	0.27
Ph.D.	0.01	0.00	0.00	0.01
Contracts (fraction):				
Full time	0.64	0.60	0.25	0.84
Tenured	0.15	0.21	0.08	0.58
>35 hours per week	0.62	0.61	0.20	0.87
Regular worker	0.98	0.94	0.59	0.99
Size firm-business unit (fraction):				
<100 workers	0.34	0.44	0.03	0.81
Between 100 and 1,000 workers	0.32	0.34	0.17	0.61
>1,000 workers	0.34	0.22	0.00	0.73
Hourly-wage (Euros):				
Fixed hourly wage	22	19	12	27
Full hourly wage	27	21	13	34
Capital at industry level:				
Capital per worker (thousands)	31	169	6	1,945
Fraction ICT capital	0.30	0.20	0.01	0.54
Spending on IT workers per worker:				
at industry level	1,663	713	93	7,643
at firm level	2,107	1,070	173	7,643
Ratio high to low skilled workers:				
at industry level	5.82	2.65	0.23	13.67
at firm level	11.36	6.99	0.46	26.78
Observations:				
Fraction workers	0.02	0.05	0.00	0.27
Number different workers	139,442	363,040	7,210	1,405,528
Number different firms	2,158	4,496	56	16,932
Total observations	39,320,449			

Notes: This table shows descriptive statistics at the industry level. We define industries by using the sections of the Standard Industrial Classification (SBI). Finance corresponds to the finance industry (section K) and the rest of the economy corresponds to all industries except the finance industry. See Table A1 for more details about the rest of industries. Education corresponds to the highest educational attainment observed in 2018. We define six categories. "Unknown" corresponds to workers without information about educational attainment. "Basic education" corresponds to primary education, practical education or VMBO (preparatory secondary vocational education) as the highest degree of education completed. "Middle-level education" corresponds to MBO (middle-level applied education) or any of these two streams of secondary education, VWO (senior general secondary education), and HAVO (university preparatory education), as the highest degree of education completed. "Bachelor's degree"' corresponds to any of the two types of Bachelor's degrees, HBO (university of applied sciences) and WO (academic university education), as the highest degree of education completed. "Master's degree"' corresponds to any of the two types of Master's degree, HBO and WO, as the highest degree of education completed. Finally, "Ph.D." corresponds to Doctor of Philosophy. Regular worker is defined by Statistics Netherlands. A non-regular worker is a director, intern, temporary agency worker, and on-call worker. The fixed hourly wage corresponds to the basic wage over basic hours. The full hourly wage corresponds to the gross wage over paid hours (basic hours plus overtime hours). The ICT capital corresponds to the gross fixed capital stock in the category's IT equipment, communication equipment, and software. ICT data is not available for industries L (Real estate activities), O (Public administration), and P (Education). Fraction ICT capital corresponds to ICT capital over total capital. Spending on IT workers per worker at industry (firm) level is the total gross wage spending on IT workers over the total number of workers at industry(firm) level. The ratio of high to low skilled workers is calculated as the ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education. Regarding the number of firms, we exclude firms changing industries and firms with less than 10 employees. Furthermore, the number of firms at the sub-industry level is 86 monetary intermediation services (banks); 150 insurances services; 31 pension funding services; 23 fund management services; and 1,921 other auxiliary financial services.

Table 2: Descriptive statistics.

	Statistics:					
	Observations	Mean	Sd.	*p*1th	*p*50th	*p*99th
Finance:						
Fixed hourly wage	697,898	21.77	9.08	7.77	19.55	47.86
Full hourly wage	697,898	26.64	16.53	8.43	23.28	65.64
Municipality ID	697,898	486.41	310.56	34.00	363.00	1,892
Size firm-business unit	697,898	73.21	22.11	10.00	82.00	93.00
Dummies type of contract	697,898	68.39	20.05	19.00	69.00	99.00
Age	697,898	41.22	9.91	22.00	41.00	62.00
ICT-K per worker	697,898	9.00	1.85	6.44	8.91	12.77
Non-ICT-K per worker	697,898	21.71	3.48	18.45	21.01	32.03
Ratio ICT-K / Total K	697,898	0.29	0.05	0.22	0.29	0.40
IT wage bill per employee	697,898	1,628.83	308.17	1,027.02	1,726.94	1,963.78
Ratio (Master+PhD) / (Basic)	697,898	5.51	2.29	2.49	4.79	9.62
Ratio (Master+PhD) / (Basic + Middle)	697,898	0.82	0.22	0.51	0.76	1.19
Ratio (Master+PhD) / (Total)	697,898	0.18	0.03	0.13	0.18	0.22
Rest of the industries:						
Fixed hourly wage	38,622,551	17.81	7.08	6.33	16.52	41.76
Full hourly wage	38,622,551	20.28	8.85	6.77	18.66	49.43
Municipality ID	38,622,551	586.00	449.14	14.00	505.00	1,916.00
Size firm-business unit	38,622,551	73.83	20.51	22.00	82.00	93.00
Dummies type of contract	38,622,551	66.91	21.58	19.00	69.00	99.00
Age	38,622,551	42.22	11.38	20.00	43.00	63.00
ICT-K per worker	29,734,011	3.16	2.63	0.95	2.52	16.56
Non-ICT-K per worker	29,734,011	15.70	91.35	3.51	8.21	132.73
Ratio ICT-K / Total K	29,734,011	0.26	0.12	0.01	0.24	0.58
IT wage bill per employee	38,622,551	515.82	963.80	85.57	333.32	6,241.25
Ratio (Master+PhD) / (Basic)	38,622,551	3.22	4.30	0.16	1.40	15.86
Ratio (Master+PhD) / (Basic + Middle)	38,622,551	0.57	0.70	0.05	0.29	2.50
Ratio (Master+PhD) / (Total)	38,622,551	0.12	0.07	0.02	0.10	0.29
All industries:						
Fixed hourly wage	39,320,449	17.88	7.14	6.34	16.56	42.07
Full hourly wage	39,320,449	20.39	9.09	6.79	18.72	50.02
Municipality ID	39,320,449	584.23	447.25	14.00	503.00	1,916.00
Size firm-business unit	39,320,449	73.82	20.54	22.00	82.00	93.00
Dummies type of contract	39,320,449	66.94	21.56	19.00	69.00	99.00
Age	39,320,449	42.21	11.35	20.00	43.00	63.00
ICT-K per worker	30,431,909	3.29	2.75	0.95	2.69	16.56
Non-ICT-K per worker	30,431,909	15.84	90.30	3.51	9.16	132.73
Ratio ICT-K / Total K	30,431,909	0.26	0.12	0.01	0.24	0.58
IT wage bill per employee	39,320,449	535.57	967.32	85.57	337.85	6,241.25
Ratio (Master+PhD) / (Basic)	39,320,449	3.26	4.29	0.16	1.42	15.86
Ratio (Master+PhD) / (Basic + Middle)	39,320,449	0.57	0.70	0.05	0.29	2.50
Ratio (Master+PhD) / (Total)	39,320,449	0.12	0.07	0.02	0.10	0.29
Total observations	39,320,449					

Notes: This table shows descriptive statistics. Finance corresponds to the finance industry (section K) and the rest of the economy corresponds to all industries except the finance industry. See Table A1 for more details about the rest of industries. The fixed hourly wage corresponds to the basic wage over basic hours. The full hourly wage corresponds to the gross wage over paid hours (basic hours plus overtime hours). Type of contract creates groups based on the full combination of contracts: full/part-time, tenure/untenured, fixed/flex, weekly work time and type of job (i.e., director, intern, regular worker, temporary agency worker, on-call employee, rest). The ICT capital corresponds to the gross fixed capital stock in the category's IT equipment, communication equipment, and software. ICT data is not available for industries L (Real estate activities), O (Public administration), and P (Education). Fraction ICT capital corresponds to ICT capital over total capital. Spending on IT workers per worker at industry level is the total gross wage spending on IT workers over the total number of workers at industry level. Basic stands for basic education, which corresponds to primary education, practical education or VMBO (preparatory secondary vocational education) as the highest degree of education completed. Middle stand for middle-level education, which corresponds to MBO (middle-level applied education) or any of these two streams of secondary education, VWO (senior general secondary education), and HAVO (university preparatory education), as the highest degree of education completed. Master stands for master's degree, which corresponds to any of the two types of Master's degree, HBO and WO, as the highest degree of education completed. Finally, PhD stands for Ph.D. Total corresponds to all educational categories discussed before plus bachelor's degree.

Table 3: The finance wage premium under different specifications.

	OLS I	OLS II	Panel:		AKM
			Worker	Firm	
	(1)	(2)	(3)	(4)	(5)
Panel A: fixed hourly wage					
Finance wage premium	0.190***	0.113***	0.0564***	0.145***	0.0692***
	(10.26)	(7.92)	(16.52)	(7.47)	(7.04)
adj. R2	0.004	0.381	0.903	0.563	0.911
Panel B: full hourly wage					
Finance wage premium	0.246***	0.164***	0.0879***	0.198***	0.1104***
	(11.48)	(10.24)	(19.71)	(8.72)	(8.68)
adj. R2	0.006	0.390	0.894	0.579	0.902
Observations	39,320,449				
N^o workers	5,180,514				
N^o 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 the estimates for the finance wage premium (FWP). Column (1) reports $FWP = \phi$, which we get from the regression $\ln w_{i,t} = \phi \mathbf{1}^F_{it} + \epsilon_{i,t}$, where $w_{i,t}$ may be the fixed hourly wage (basic wage over basic hours) or the full hourly wage (gross wage over paid hours); $\mathbf{1}^F_{it}$ is a dummy for employment in finance; and $\epsilon_{i,t}$ is the error term. Column (2) reports $FWP = \phi$, which we get from the regression $\ln w_{i,t} = \phi \mathbf{1}^F_{it} + \boldsymbol{X\beta} + \epsilon_{i,t}$, where $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm sizes. Column (3) reports $FWP = \phi$, which we get from the regression $\ln w_{i,t} = \phi \mathbf{1}^F_{it} + \boldsymbol{X\beta} + \alpha_i + \epsilon_{i,t}$, where α_i are worker fixed effects. Column (4) reports $FWP = \bar{\psi}^{finance}_j - \bar{\psi}^{rest}_j$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. We get the FWP from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \psi_{J(i,t)} + \epsilon_{i,t}$, where $\psi_{J(i,t)}$ are firm fixed effects. Column (5) reports $FWP = \bar{\psi}^{finance}_j - \bar{\psi}^{rest}_j$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. We get the FWP from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$. See sub-section 4.a for more details. For all regressions, 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. We drop singletons. Clustered standard errors at the firm level. Column (1)-(3) report t-statistics in parentheses. Column (4)-(5) report the z-statistics from bootstrapped standard errors at the firm level (200 repetitions). *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$

Table 4: Estimated finance wage premium, selected studies.

Study	Country	Period	Worker FE	Firm FE	FWP	FWP (own estimation)
Célérier and Vallée (28)	France	1983-2011	No	No	24.2%	31.4%
Böhm et al. (18)	Sweden	2006-2017	Yes	Yes	$\approx$ 10%	11.4%
Philippon and Reshef (57)	U.S.	2001-2005	Yes	No	6.2%	3.7%
Lindley and McIntosh (52)	U.K.	1996-2011	No	No	31.4%	32%
Boustanifar et al. (22)	Several countries	1970-2011	No	No	$>$ 30%	-
This paper	Netherlands	2006-2018	Yes	Yes	11.04%	-

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 (28) 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. (18) estimate of the FWP corresponds to Figure 5 (b). By looking at this figure we can conclude that the FWP moves around 10% over the years 2006-2017. The FWP is calculated by comparing finance (the log of earnings) against the private sector (i.e., they exclude the farming sector, public sector, and self-employed workers). 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 (57) 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 (52) 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. (22) 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 nonfarm, non-finance private sector. This paper reports the results corresponding to Table 3 (Panel B, regression 3).

Table 5: Finance wage premium for different sub-samples.

	AKM regressions				
	Gender	Top-earners	Related Ind	Unrelated Ind	All firms
	(1)	(2)	(3)	(4)	(5)
Panel A: fixed hourly wage					
Finance wage premium (FWP)	0.0797***	0.0849***	0.111***	0.0672***	0.0879***
	(8.14)	(8.65)	(13.84)	(6.57)	(7.67)
FWP × Female-worker	-0.0198***				
	(-8.01)				
Top decile		0.196***			
		(64.48)			
FWP × Top decile		-0.253***			
		(-3.53)			
Observations	39,320,449	39,320,449	10,746,813	28,742,973	68,234,469
Nº workers	5,180,214	5,180,214	1,903,969	3,632,133	7,586,444
Nº firms	83,077	83,077	39,181	45,506	104,508
adj. R2	0.911	0.915	0.927	0.92	0.905
Panel B: full hourly wage					
Finance wage premium (FWP)	0.122***	0.125***	0.157***	0.109***	0.127***
	(9.67)	(9.95)	(15.98)	(7.74)	(8.21)
FWP × Female-worker	-0.0228***				
	(-7.99)				
Top decile		0.248***			
		(74.56)			
FWP × Top decile		0.0625*			
		(2.45)			
Observations	39,320,449	39,320,449	10,746,813	28,742,973	68,234,469
Nº workers	5,180,214	5,180,214	1,903,969	3,632,133	7,586,444
Nº firms	83,077	83,077	39,181	45,506	104,508
adj. R2	0.902	0.910	0.918	0.918	0.896

Notes: This table shows the finance wage premium (FWP) for different sub-samples. The FWP is calculated as follows $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy (as defined by the sample used) weighted by the number of workers and employment-duration. We estimate the FWP from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage (gross wage over paid hours); $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; $\epsilon_{i,t}$ is the error term. However, each column used a different sample of workers-firms. Column (1) makes the distinction between male and female workers to calculate the finance wage premium. Column (2) makes the distinction between top-earners to calculate the finance wage premium. Column (3) considers just industries related to the finance industry in terms of the flow of workers: G (Wholesale and retail trade; repair of motor vehicles and motorcycles), J (Information and communication), M (Professional, scientific and technical activities), and N (Administrative and support service activities). The term "Rel. Ind" stands for related industries. Column (4) includes all industries except G, J, M, and N. The term "Unrel. Ind" stands for unrelated industries. Column (5) includes all firms, independent if those firms changed or not industry over the sample period. See sub-section 4.a for more details. For all regressions, we cover the period 2006-2018. We exclude 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. We drop singletons. The finance wage premium reports the z-statistics in parentheses from bootstrapped standard errors at the firm level (200 repetitions). The interactions between the finance wage premium and the dummy for female-worker and Top decile report t-statistics in parentheses (clustered standard errors at the firm level). $^*p < 0.05$, $^{**}p < 0.01$, *** $p < 0.001$

Table 6: Finance wage premium by type of job.

	Dependent variable:	
	fixed hourly wage (1)	**full hourly wage** (2)
Finance wage premium (FWP)	0.0700***	0.112***
	(7.33)	(8.99)
Temporary agency	-0.0243***	-0.0253***
	(-6.12)	(-5.79)
On-call	-0.0327***	-0.0355***
	(-21.65)	(-22.04)
FWP × Temporary agency	0.0903	0.0794
	(1.54)	(1.36)
FWP × On-call	-0.0307***	-0.0533***
	(-3.57)	(-7.11)
FWP × Director	-0.0315	0.0303
	(-1.80)	(-1.55)
Observations	39,320,449	
N^o workers	5,180,214	
N^o firms	83,077	
adj. R2	0.909	0.901

Notes: This table shows the finance wage premium (FWP) when interacted with the type of contract: temporary agency, on-call, or director. The finance wage premium reports $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy (as defined by the sample used) weighted by the number of workers and employment-duration. We estimate the FWP from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is either the fixed hourly wage (basic wage over basic hours), column (1), or the full hourly wage (gross wage over paid hours), column (2); $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; $\epsilon_{i,t}$ is the error term. For all regressions, 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. Clustered standard errors for all coefficients except the FWP. t-statistics in parentheses. Regarding the FWP, we report bootstrapped standard errors at the firm level (200 repetitions). Z-statistics in parentheses. *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$.

Table 7: Finance wage premium within finance.

AKM regressions	Fixed hourly wage: Benchmark	Fixed hourly wage: With ICT capital	Full hourly wage: Benchmark	Full hourly wage: With ICT capital
	(1)	(2)	(3)	(4)
Wage premium:				
-Banks	0.161***	0.0230	0.228***	0.0709***
	(10.96)	(1.31)	(13.04)	(2.93)
-Insurances services	0.0888***	-0.0566***	0.145***	-0.0202
	(10.13)	(-5.64)	(16.03)	(-1.80)
-Pension funds services	0.154***	-0.00326	0.191***	0.0137
	(7.14)	(-0.27)	(10.82)	(1.21)
-Fund manag. services	0.107*	-0.0793	0.132	-0.0752
	(2.09)	(-1.58)	(1.55)	(-0.89)
-Auxiliary services	0.0388***	-0.110***	0.0695***	-0.0993***
	(4.93)	(-14.45)	(6.38)	(-9.24)
Observations	30,348,728			
Nº workers	4,300,691			
Nº firms	78,673			

Notes: This table shows the wage premium for sectors within the finance industry. Each sector corresponds to one-digit SBI 2008 classification except by auxiliary services, which includes Services of holding companies, Services of trusts, funds and similar financial entities, Other financial services, except insurance, and pension funding, Reinsurance services, and Services auxiliary to financial services. All columns report the sector wage premium, $\theta^{SectorFinance} = \bar{\psi}_j^{SectorFinance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effects on a sector of finance minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. Column (1) calculates the firm fixed effects, ψ_j, from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the fixed hourly wage (basic wage over basic hours); $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old), year, type of contract, municipality, and firm size fixed effects; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; and $\epsilon_{i,t}$ is the error term. Column (3) calculates the firm fixed effects, ψ_j, in the same way than column (1) but using instead the log full hourly wage (gross wage over paid hours). Column (2) calculates the firm fixed effects, ψ_j, from the regression $\ln w_{i,t} = \theta_1 K_{I,t} + \theta_2 HL_{I,t} + \theta_3 (K_{I,t} \times HL_{I,t}) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the fixed hourly wage; $K_{I,t}$ is ICT capital (gross fixed capital stock in the categories IT equipment, communication equipment, and software); and $HL_{I,t}$ is the supply of high-skilled workers (ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education) at industry level. Column (4) calculates the firm fixed effects, ψ_j, in the same way than column (2) but using instead the log full hourly wage (gross wage over paid hours). For all regressions, 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. All columns report the z-statistics in parenthesis from bootstrapped standard errors at the firm level (200 repetitions). *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$

Table 8: Explaining the finance wage premium with ICT capital per worker.

	Dependent variable: full hourly wage										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Finance wage premium	0.129***	0.104***	0.0532***	0.0491***	-0.0363**	0.148***	0.0702***	0.0866***	-0.0335**	-0.0492***	-0.129***
	(11.90)	(9.57)	(4.69)	(4.33)	(-2.87)	(13.59)	(6.17)	(7.72)	(-3.13)	(-4.44)	(-10.44)
HL: Log ratio (Master+PhD) / (Basic)			0.0430***	0.0424***	0.242***		0.0425***	-0.000875		0.0342***	-0.129***
			(12.47)	(11.09)	(13.40)		(12.32)	(-0.04)		(9.09)	(-9.39)
ICT-K: Log ICT-K per worker		0.0204***		0.00421	0.0316***						
		(3.65)		(0.73)	(5.25)						
ICT-K × HL					0.0352***						
					(11.99)						
NonICT-K: Log Non ICT-K per worker						-0.0198***	-0.0168***	-0.0165***			
						(-4.39)	(-3.79)	(-3.59)			
NonICT-K × HL								-0.00921*			
								(-2.11)			
IT-spend: Log IT wage bill per employee									0.0942***	0.0683***	0.0830***
									(12.84)	(8.60)	(9.82)
IT-spend × HL											0.0272***
											(11.71)
Observations	30,348,728										
Nº workers	4,300,691										
Nº firms	78,673										
adj. R2	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901

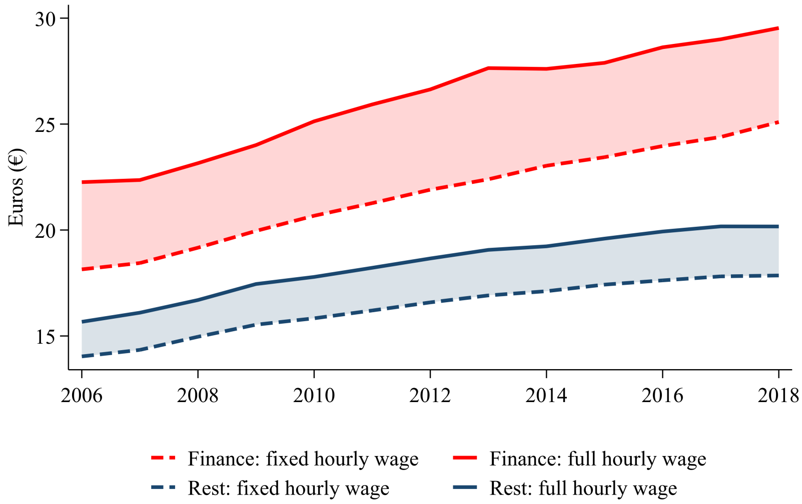
Notes: This table shows the finance wage premium (FWP) when we include a measure of capital-skill intensity. All columns report $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. We estimate the FWP from the regression $\ln w_{i,t} = \theta_1 K_{I,t} + \theta_2 HL_{I,t} + \theta_3(K_{I,t} \times HL_{I,t}) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage (gross wage over paid hours); $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; $K_{I,t}$ is one of three measures of capital: ICT capital per worker at industry level (gross fixed capital stock in the categories IT equipment, communication equipment, and software), Non-ICT capital at industry level, and IT wage bill per employee at industry level (total gross wage spending on IT workers over total number of workers); $HL_{I,t}$ is the ratio ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education at industry level; Finally, $\epsilon_{i,t}$ is the error term clustered at firm level. Column (1) reports the FWP excluding the terms $K_{I,t}$ and $HL_{I,t}$ from the regression (benchmark). Column (2)-(5) includes ICT capital per worker at industry level. Column (6)-(8) includes non-ICT capital per worker at industry level. Column (9)-(11) includes the IT wage bill per employee at industry level. See sub-section 4.b for more details. For all regressions, we cover the period 2006-2018. Since ICT data is not available for industries L (Real estate activities), O (Public administration), and P (Education), we drop those industries. 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. Clustered standard errors at the firm level. t-statistics in parentheses. All columns report, for the finance wage premium, the z-statistics in parenthesis from bootstrapped standard errors at the firm level (200 repetitions). *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$.

Table 9: Finance wage premium when including schooling and $Industry \times Year$ fixed effects.

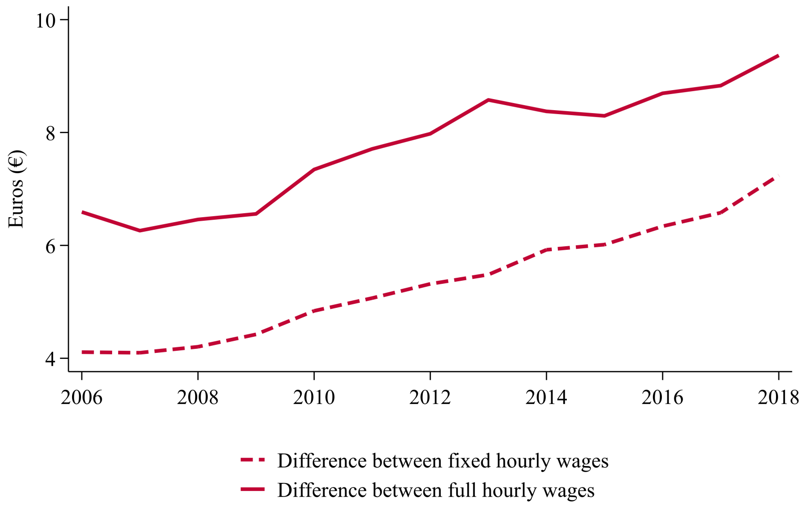
AKM regressions	Sample ICT capital		Sample ICT capital/Schooling			
	(1)	(2)	(3)	(4)	(5)	(6)
FWP	0.129***	0.117***	0.131***	0.126***	0.0913***	0.0623***
	(11.90)	(10.23)	(11.25)	(10.24)	(7.96)	(5.15)
ICT-K					-0.0357***	
					(-5.80)	
ICT-K×MiddleEduc					0.0286***	0.0189***
					(16.76)	(9.08)
ICT-K×HighEduc					0.0943***	0.0745***
					(33.12)	(21.14)
$Industry \times Year$ FE	No	Yes	No	Yes	No	Yes
Observations	30,348,728	30,348,728	19,484,703	19,484,703	19,484,703	19,484,703

Notes: This table shows the finance wage premium (FWP) for different specifications. ICT-K stands for Log ICT-K per worker. All columns report $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. In regression 1, we estimate the FWP from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage; $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; Finally, $\epsilon_{i,t}$ is the error term clustered at firm level. In regression 2, we extend regression 1 by including $Industry \times Year$ fixed effects. In regression 3, we repeat the regression 1 for a sample that only considers workers with education attainment information. In regression 4, we extend regression 3 by including $Industry \times Year$ fixed effects. In regression 5, we estimate the FWP from the regression $\ln w_{i,t} = \theta_2 K_{I,t} + \theta_3 (K_{I,t} \times S_i) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where S_i is a measure of schooling: basic, middle, and high (Bachelor, Master's degree or Ph.D.); $K_{I,t}$ is ICT capital (gross fixed capital stock in the categories IT equipment, communication equipment, and software). In regression 6, we extend regression 4 by considering $Industry \times Year$ fixed effects. For all regressions, we cover the period 2006-2018. Since ICT data is not available for industries L (Real estate activities), O (Public administration), and P (Education), we drop those industries. 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. Bootstrapped standard errors at the firm level (200 repetitions). Z-statistics in parentheses.

Figure 1: Compensation in finance and the rest of the economy.



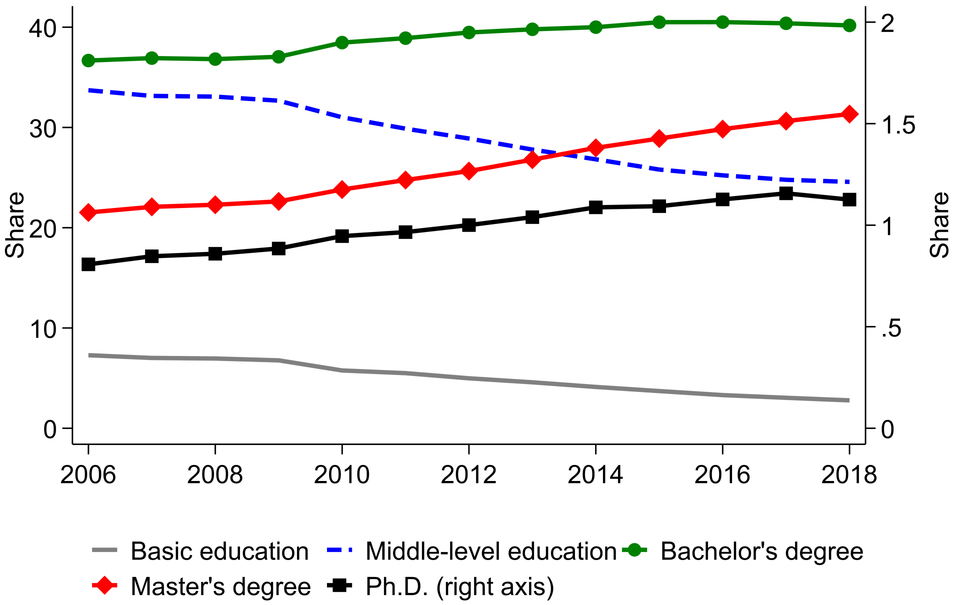
(a)



(b)

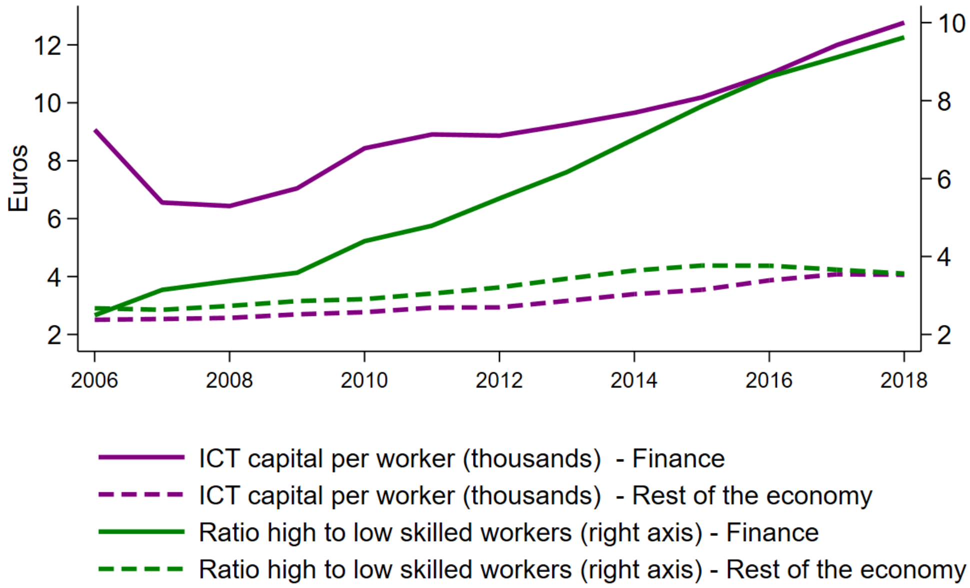
Notes: Figure (a) reports the average for the fixed hourly wage and the full hourly wage in the finance industry and the rest of the economy. Figure (b) reports the difference between finance and the rest of the economy for both the fixed hourly wage and the full hourly wage. The fixed hourly wage corresponds to the basic wage over basic hours. The full hourly wage corresponds to the gross wage over paid hours (basic hours plus overtime hours). We define industries by using the sections of the Standard Industrial Classification (SBI). Finance corresponds to the finance industry (section K) and the rest of the economy corresponds to all industries except the finance industry. See Table A1 for more details about the rest of industries.

Figure 2: Educational attainment within finance.



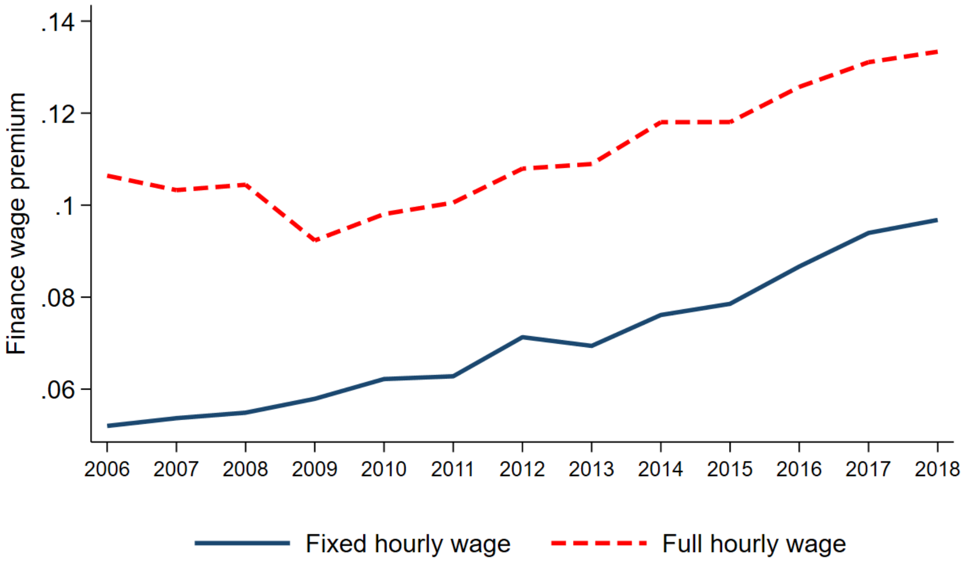
Notes: Figure reports the share of workers, for whom we have information, with a given educational attainment in the finance industry. Education corresponds to the highest educational attainment observed in 2018. We define five categories. "Basic education" corresponds to primary education, practical education or VMBO (preparatory secondary vocational education) as the highest degree of education completed. "Middle-level education" corresponds to MBO (middle-level applied education) or any of these two streams of secondary education, VWO (senior general secondary education), and HAVO (university preparatory education), as the highest degree of education completed. "Bachelor's degree"' corresponds to any of the two types of bachelor's degrees, HBO (university of applied sciences) and WO (academic university education), as the highest degree of education completed. "Master's degree"' corresponds to any of the two types of master's degree, HBO and WO, as the highest degree of education completed. Finally, "Ph.D." corresponds to Doctor of Philosophy.

Figure 3: Capital-skill intensity in the Dutch economy.



Notes: The figure reports the ICT capital per worker and the ratio of high to low skilled workers for the finance industry. The ICT capital corresponds the gross fixed capital stock in the categories IT equipment, communication equipment, and software over the total number of workers in the industry. The ratio of high to low skilled workers is calculated as the ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education.

Figure 4: Finance wage premium over time.



Notes: The figure reports the finance wage premium (FWP) over time. We get the FWP (and its interaction over time) from the regression $\ln w_{i,t} = (\mathbf{1}_{it}^{F} \times \lambda_t)\boldsymbol{\theta} + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ may be the fixed hourly wage (basic wage over basic hours) or the full hourly wage (gross wage over paid hours); $\mathbf{1}_{it}^{F}$ is a dummy for employment in finance; λ_t are year fixed effects; $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: type of contract, municipality, and firm sizes; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects. and $\epsilon_{i,t}$ is the error term. We calculate the FWP as $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. We report then $FWP + \boldsymbol{\theta}$ (except for 2006 where we report only the FWP). 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. We drop singletons.

APPENDIX

A Tables and Figures

Table A1: NACE classification.

N	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). "Industry" is the term used by groups of companies with the same main activity, which in this case corresponds to the sections. The SBI 2008 is the version used from 2008 onwards. The SBI 2008 has several levels, which are indicated by a maximum of five numbers. The four-digit level almost corresponds to the European Union (NACE) classification. The first two digits correspond to those of the United Nations Classification (ISIC).

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

	All 2006-2018		**Interval** 2007-2013		Song et al. (59) 2007-2013	
	Comp. (1)	Share (2)	Comp. (3)	Share (4)	Comp. (5)	Share (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	39,320,449		21,905,539			

Notes: This table shows the following wage decomposition $Var(y) = Var(WFE) + Var(FFE) + Var(Xb) + Var(residual) + 2 * Cov(WFE, FFE) + 2 * Cov(WFE, Xb) + 2 * Cov(FFE, Xb)$. We calculate the wage 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 on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; ϵ is the error term. $Var(y)$ is the variance of the log full hourly wage, $Var(WFE)$ is the variance of worker fixed effects, $Var(FFE)$ is the variance of firm fixed effects, $Var(Xb)$ is the variance of covariates. $Var(residual)$ is the variance of the residual, $Cov(WFE, FFE)$ is the covariance between worker and firm fixed effects, $Cov(WFE, Xb)$ is the covariance between worker fixed effects and covariates, and $Cov(FFE, Xb)$ is the covariance of firm fixed effects and covariates. Song et al. (59) do not use hourly-wages as the information is not available in the U.S. Regarding the estimations, 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.

Table A3: Finance wage premium by yearly gross quartile.

	Dependent variable:	
	fixed hourly wage	**full hourly wage**
	(1)	(2)
Finance wage premium (FWP)	0.0163***	0.0309***
	(3.54)	(5.85)
Quartile II	0.204***	0.239***
	(130.00)	(125.11)
Quartile III	0.346***	0.411***
	(134.19)	(135.71)
Quartile IV	0.509***	0.609***
	(144.93)	(150.66)
FWP × Quartile II	0.00511	0.0107
	(0.53)	(1.28)
FWP × Quartile III	0.00691	0.0201
	(0.48)	(1.58)
FWP × Quartile IV	0.0205	0.0586***
	(1.23)	(3.61)
Observations	39,320,449	
Nº workers	5,180,214	
Nº firms	83,077	
adj. R2	0.942	0.941

Notes: This table shows the finance wage premium (FWP) when interacted with by the gross wage quartile. The finance wage premium reports $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy (as defined by the sample used) weighted by the number of workers and employment-duration. We estimate the FWP from the regression $\ln w_{i,t} = (\mathbf{1}_{it}^F \times Q_{it})\boldsymbol{\theta} + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is either the fixed hourly wage (basic wage over basic hours) or the full hourly wage (gross wage over paid hours); $\mathbf{1}_{it}^F$ is a dummy for employment in finance; Q_{it} is the gross wage quartile for worker i in the year t; $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; $\epsilon_{i,t}$ is the error term. For all regressions, 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. Clustered standard errors for all coefficients except the FWP. t-statistics in parentheses. Regarding the FWP, we report bootstrapped standard errors at the firm level (200 repetitions). Z-statistics in parentheses. *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$.

Table A4: Explaining the finance wage premium with ICT capital per worker and controlling for firm characteristics.

	Dependent variable: full hourly wage										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Finance wage premium	0.132***	0.142***	0.0584*	0.0847**	-0.0655***	0.169***	0.0585**	0.147***	0.0877*	0.0586*	-0.0670***
	(3.90)	(4.18)	(2.02)	(2.88)	(-3.44)	(4.83)	(2.03)	(4.33)	(2.64)	(2.03)	(-3.39)
HL: Log ratio (Master+PhD) / (Basic)			0.0342***	0.0372***	0.231***		0.0340***	-0.0422**		0.0352***	-0.142***
			(8.65)	(8.64)	(7.42)		(8.57)	(-2.81)		(8.06)	(-9.35)
ICT-K: Log ICT-K per worker		-0.00615		-0.0198***	0.00481						
		(-1.17)		(-3.35)	(0.64)						
ICT-K × HL					0.0341***						
					(6.66)						
NonICT-K: Log Non ICT-K per worker						-0.0287***	-0.0281***	-0.0254***			
						(-4.75)	(-4.56)	(-4.14)			
NonICT-K × HL								-0.0166***			
								(-5.12)			
IT-spend: Log IT wage bill per employee									0.0272***	-0.00718	0.0254*
									(3.37)	(-0.78)	(2.55)
IT-spend × HL											0.0299***
											(10.89)
Observations	14,438,171										
adj. R2	0.910	0.910	0.910	0.910	0.910	0.910	0.910	0.910	0.910	0.910	0.911

Notes: This table shows the finance wage premium (FWP) when we include a measure of capital-skill intensity. All columns report $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. We estimate the FWP from the regression $\ln w_{i,t} = \theta_1 K_{I,t} + \theta_2 HL_{I,t} + \theta_3 (K_{I,t} \times HL_{I,t}) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage (gross wage over paid hours); $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; $K_{I,t}$ is one of three measures of capital: ICT capital per worker at industry level (gross fixed capital stock in the categories IT equipment, communication equipment, and software), Non-ICT capital at industry level, and IT wage bill per employee at industry level (total gross wage spending on IT workers over total number of workers); $HL_{I,t}$ is the ratio ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education at industry level; Finally, $\epsilon_{i,t}$ is the error term clustered at firm level. Column (1) reports the FWP excluding the term $K_{I,t} \times HL_{I,t}$ from the regression (benchmark). Column (2)-(5) includes ICT capital per worker at industry level. Column (6)-(8) includes non-ICT capital per worker at industry level. Column (9)-(11) includes the IT wage bill per employee at industry level. For all regressions, we cover the period 2006-2018. Since ICT data is not available for industries L (Real estate activities), O (Public administration), and P (Education), we drop those industries. Firm control variable include profits per worker (Euros), log assets, and log leverage (equity over assets). 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. Clustered standard errors at the firm level. t-statistics in parentheses. All columns report, for the finance wage premium, the z-statistics in parenthesis from bootstrapped standard errors at the firm level (200 repetitions). *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$.

Table A5: Explaining the finance wage premium with ICT capital per worker.

	Dependent variable: full hourly wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Finance wage premium	-0.0436***	0.0906***	-0.113***	-0.0156	0.105***	-0.0618***
	(-3.46)	(8.09)	(-9.26)	(-1.30)	(9.64)	(-5.24)
Variables full interaction:						
Capital measure:						
Log ICT-K per worker	Yes			Yes		
Log Non ICT-K per worker		Yes			Yes	
Log IT spend. per worker			Yes			Yes
Skill-intensity measure:						
Log ratio (Master+PhD) / (Basic + Middle)	Yes	Yes	Yes			
Log ratio (Master+PhD) / (Total)				Yes	Yes	Yes
Observations	30,348,728					
Nº workers	4,300,691					
Nº firms	78,673					
adj. R2	0.9013	0.9011	0.9014	0.9013	0.9011	0.9013

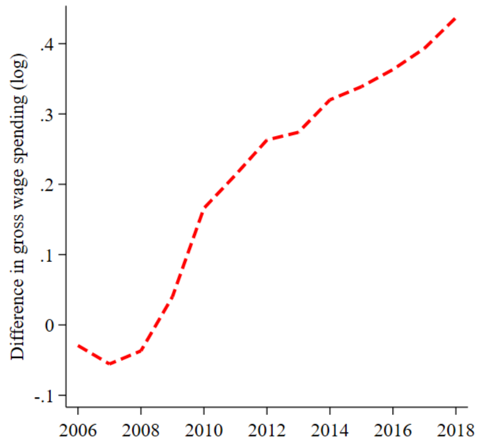
Notes: This table shows the finance wage premium (FWP) when we include a measure of capital-skill intensity. All columns report $FWP = \bar{\psi}_j^{finance} - \bar{\psi}_j^{rest}$, which is the average firm fixed effects on the finance industry minus the average firm fixed effects on the rest of the economy weighted by the number of workers and employment-duration. We estimate the FWP from the regression $\ln w_{i,t} = \theta_1 K_{I,t} + \theta_2 HL_{I,t} + \theta_3 (K_{I,t} \times HL_{I,t}) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage; $K_{I,t}$ is ICT capital (gross fixed capital stock in the categories IT equipment, communication equipment, and software); and $HL_{I,t}$ is the supply of high-skilled workers (ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education) at industry level, $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; $K_{I,t}$ is one of the three measures of capital: ICT capital per worker at industry level (gross fixed capital stock in the categories IT equipment, communication equipment, and software), Non-ICT capital at industry level, and IT wage bill per employee at industry level (total gross wage spending on IT workers over total number of workers); $HL_{I,t}$ is one of the two measures of skill-intensity: the ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic and Middle-level education at industry level, the ratio between the number of workers with a master's degree or Ph.D. and the total number of workers with informed level of education; Finally, $\epsilon_{i,t}$ is the error term clustered at firm level. For all regressions, we cover the period 2006-2018. Since ICT data is not available for industries L (Real estate activities), O (Public administration), and P (Education), we drop those industries. 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. Bootstrapped standard errors at the firm level (200 repetitions). Z-statistics in parentheses. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}\ p < 0.001$.

Table A6: Inter-industry wage differentials when compared to finance.

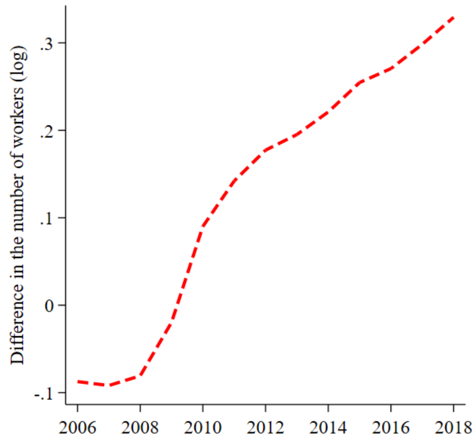
AKM regressions	Full hourly wage	
	Benchmark	With ICT capital
	(1)	(2)
A: Agriculture, forestry and fishing	-0.184***	0.0202
	(-15.37)	(1.49)
B: Mining and quarrying	0.111	0.118
	(1.42)	(1.45)
C: Manufacturing	-0.130***	0.0731***
	(-9.81)	(4.88)
D: Electricity, gas, steam and air conditioning supply	0.0240	-0.0532
	(0.59)	(-1.34)
E: Water supply	-0.0839***	0.101***
	(-4.17)	(4.75)
F: Construction	-0.100***	0.111***
	(-8.95)	(8.51)
G: Wholesale and retail trade	-0.192***	0.00329
	(-17.54)	(0.26)
H: Transportation and storage	-0.144***	-0.0653***
	(-10.85)	(4.52)
I: Accommodation and food service activities	-0.264***	-0.0675***
	(-20.34)	(-4.74)
J: Information and communication	-0.0850***	-0.131***
	(-7.13)	(-9.69)
M: Professional, scientific and technical activities	-0.115***	-0.0751***
	(-10.32)	(-5.82)
N: Administrative and support service activities	-0.197***	0.00608
	(-17.71)	(0.47)
Q: Human health and social work activities	-0.0854***	-0.0827***
	(-7.77)	(6.46)
R: Arts, entertainment and recreatio	-0.147***	-0.00482
	(-8.00)	(-0.26)
S: Other service activities	0.0998***	0.0693***
	(-8.27)	(5.06)
Observations	30,348,728	30,348,728
adj. R2	0.901	0.901

Notes: This table shows the inter-industry wage premium. Each industry corresponds to SBI 2008 classification (see Table A1). All columns report the inter-industry wage premium, $\theta^{Inudstry} = \bar{\psi}_j^{industry} - \bar{\psi}_j^{finance}$, which is the average firm fixed effects on an industry minus the average firm fixed effects on finance weighted by the number of workers and employment-duration. Column (1) calculates the firm fixed effects, ψ_j, from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage; $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old), year, type of contract, municipality, and firm size fixed effects; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm fixed effects; and $\epsilon_{i,t}$ is the error term. Column (2) calculates the firm fixed effects, ψ_j, from the regression $\ln w_{i,t} = \theta_1 K_{I,t} + \theta_2 HL_{I,t} + \theta_3(K_{I,t} \times HL_{I,t}) + \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage; $K_{I,t}$ is ICT capital (gross fixed capital stock in the categories IT equipment, communication equipment, and software); and $HL_{I,t}$ is the supply of high-skilled workers (ratio between the number of workers with a master's degree or Ph.D. and the number of workers with basic education) at industry level. For all regressions, we cover the period 2006-2018. Since ICT data is not available for industries L (Real estate activities), O (Public administration), and P (Education), we drop those industries. 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. All columns report the z-statistics in parenthesis from bootstrapped standard errors at the firm level (200 repetitions). $*p < 0.05$, $**p < 0.01$, $***\ p < 0.001$

Figure A1: Differences between informatics workers and financial management and tax law workers in finance.



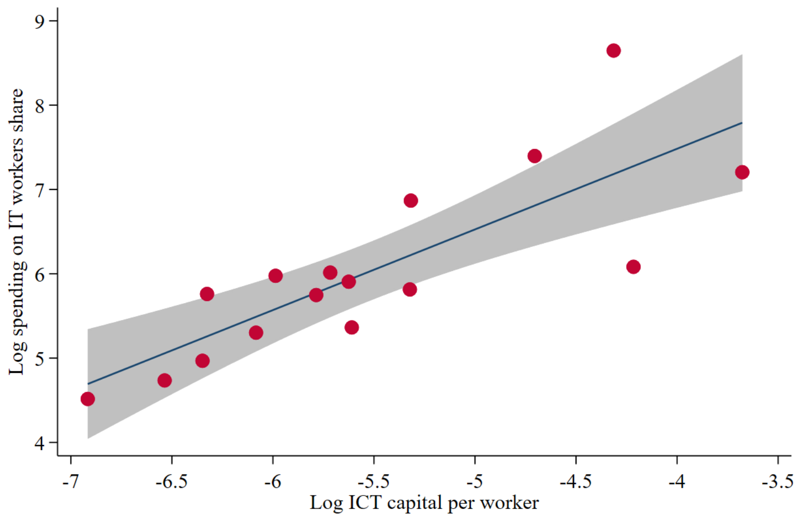
(a) Gross wage spending



(b) Number of workers

Notes: Figure (a) reports the log difference in gross wage spending between informatics workers and financial management and tax law workers. Figure (b) reports the log difference in number of workers between informatics workers and financial management and tax law workers. Informatics workers consider the following degree subjects: computer science, computer use, design and management of database and networks, software development and system analysis and, others. Financial management and tax law workers corresponds to one particular degree subject within the category law, administration, trade and, business services. The full hourly wage corresponds to the gross wage over paid hours (gross wage over paid hours).

Figure A2: Relationship between ICT capital per worker and spending on IT workers share at industry level.



Notes: The figure shows the relationship between ICT capital per worker and the spending on IT workers share at industry level. We calculate the average spending on IT workers for each industry over time as the total gross wage spending on IT workers over the total gross wage. We then average over time. We do the same for ICT capital per worker. ICT-capital is the gross fixed capital stock in the categories IT equipment, communication equipment, and software. We define industries by using the "sections" of the Standard Industrial Classification (SBI). See Table A1 for more details about other industries. We also plot the prediction for the log of spending on IT workers share from a linear regressions between the log of spending on IT workers share and the log of ICT capital per worker. We plot the resulting line and confidence interval.

B AKM Assumptions

B.a Log Additive Functional Form in the AKM Regression

The AKM specification is:

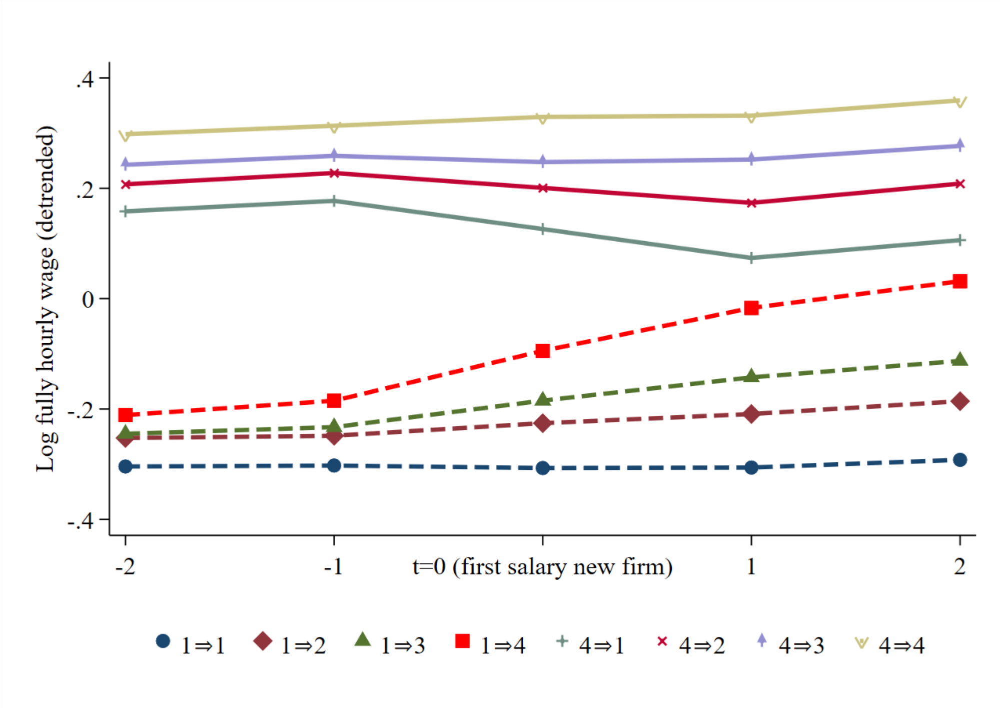
$$\ln w_{it} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{it}, \tag{A11}$$

where w_{it} is the wage of worker i in year t, $\boldsymbol{X}$ are time-varying variables, α_i are worker fixed effects, $\psi_{J(i,t)}$ are firm 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 regression imply 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. (24, 25). The samples are restricted to workers who switch establishments and have worker for at least two year at both the origin and destination firms. Like them, we define firms groups based on co-worker pay quartiles (using data on male and female coworkers). Figures A3 and A4 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 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. Finally, our results are materially identical if we consider just male-workers or female-workers.

Notwithstanding the previous results, it may still be 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 making downward moves (21). Motivated by Lamadon et al. (50), 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 A5 reports the results. Each point represents a worker-firm type ($10 \times 10 = 100$ points). While the figure shows clear evidence of worker heterogeneity (vertical difference), we

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



Notes: The figure shows the event study developed by Card et al. (24, 25). We consider male-workers who switch establishments 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 male and female 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 error 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 bonuses because he decided to change jobs at 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 $t = 1$.

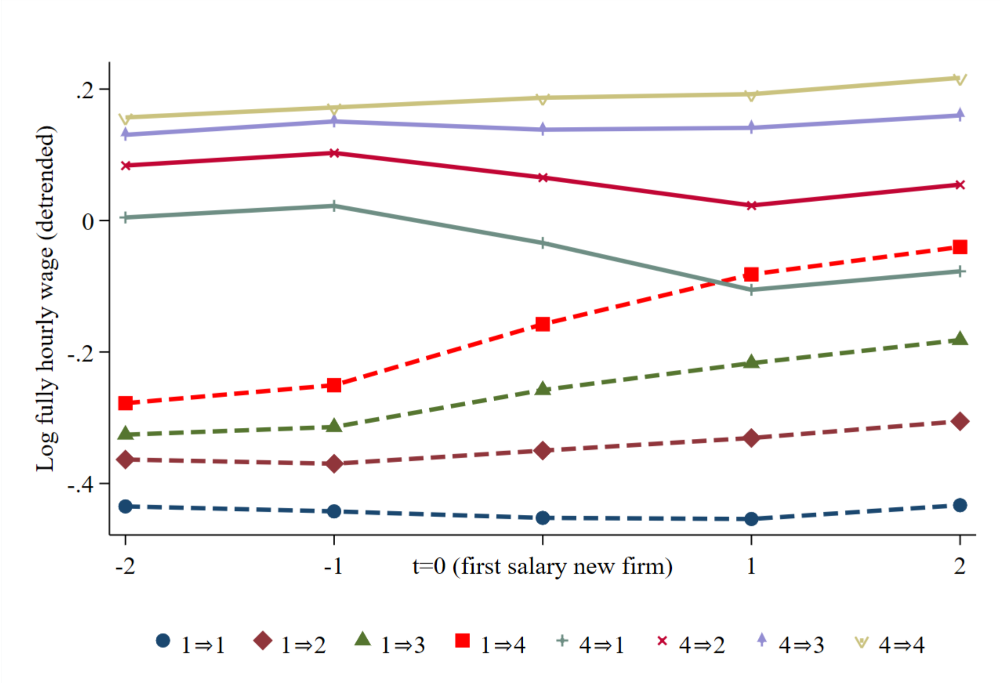
also observe that the gains for high-paid workers moving to high-paying firms (movement from left to right on the first line from top to bottom) are similar to the gains for low-paid workers moving to high-paying firms (movement from left to right on the last line from top to bottom). Thus, the log additive form in the AKM is a fair assumption for our data.

B.b Finance and the Exogenous Assumption

To estimate equation (A11), the following orthogonality condition must hold:

$$E[(\epsilon_{it} - \bar{\epsilon}_i)(D^j_{it} - \bar{D}^j_i)] = 0 \quad \forall j \in [1, ..., J] \tag{A12}$$

Figure A4: Event study of changes in earnings when female-workers move between firms.



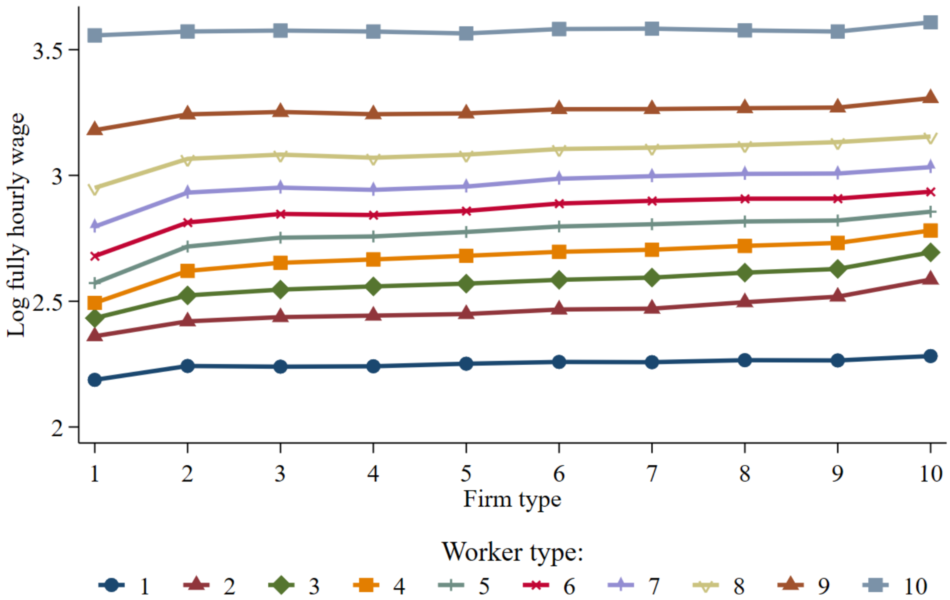
Notes: The figure shows the event study developed by Card et al. (24, 25). We consider female-workers who switch establishments and have worked for at least two years at both the origin and destination firms for the period 2006-2018. We define firms' groups based on co-worker pay quartiles (using data on male and female 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 error 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 bonuses because she decided to change jobs at 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 $t = 1$.

for $D^j_{it} \equiv 1[J(i,t) = j]$ where D^j_{it} is an indicator for employment at firm j in period t and bars over variables represent time averages. While this assumption is generally supported by data,[40] we show that this assumption also applies to the job-to-job movements of workers going into/leaving the finance industry, the main focus of this paper.

Following the decomposition of the residual in terms of the joiners and leavers by Card et al. (25), we decompose the residuals in terms of joiners and leavers of the finance industry for all job-to-job movements involving workers going into/leaving the finance industry during the sample period 2006-2018. To do that this we calculate the change on the error term after a job-to-job movement. Figure A7 reports the results of the exercise.

[40]See figure A6, and the event study discussed before, see Card et al. (25) for a one-to-one relationship between equation (A12) and the conclusions that we can derive from the event study.

Figure A5: 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).

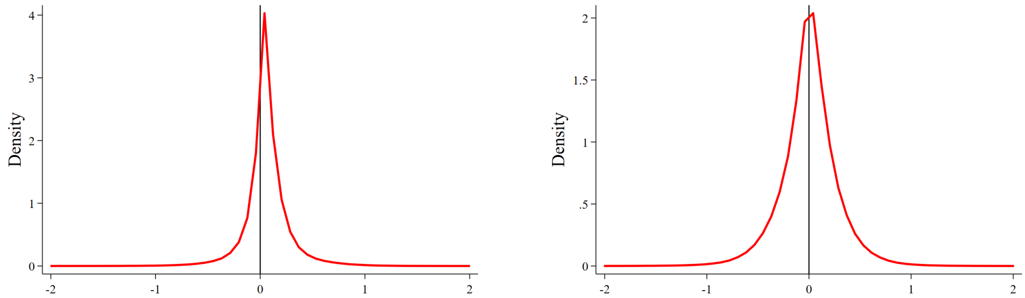
As expected, we do find the average residual of leavers is comparable in magnitude to joiners but opposite sign (after accounting of a rich set of controls). All this evidence support the AKM specification used in this paper to study the finance wage premium.

B.c Limited Mobility Bias

The AKM estimates are sensitive to the limited mobility bias. According to Andrews et al. (8); Bonhomme et al. (20), if firms are weakly connected to one another because of the limited mobility of workers across firms, AKM estimates of the contribution of firm's effects to wage inequality are biased upwards while AKM estimate of the contribution of the sorting to firms are biased downwards. For instance, Lamadon et al. (50) show that the estimated variance of firm effect is several times as large if they only keep ten percent of the mover within each firm as compared to what they obtained if the keep all movers.

Although the limited mobility bias may be more prominent in short panels (49), there

Figure A6: Distribution of the log full hourly wage change on job-to-job movements over 2006-2018.



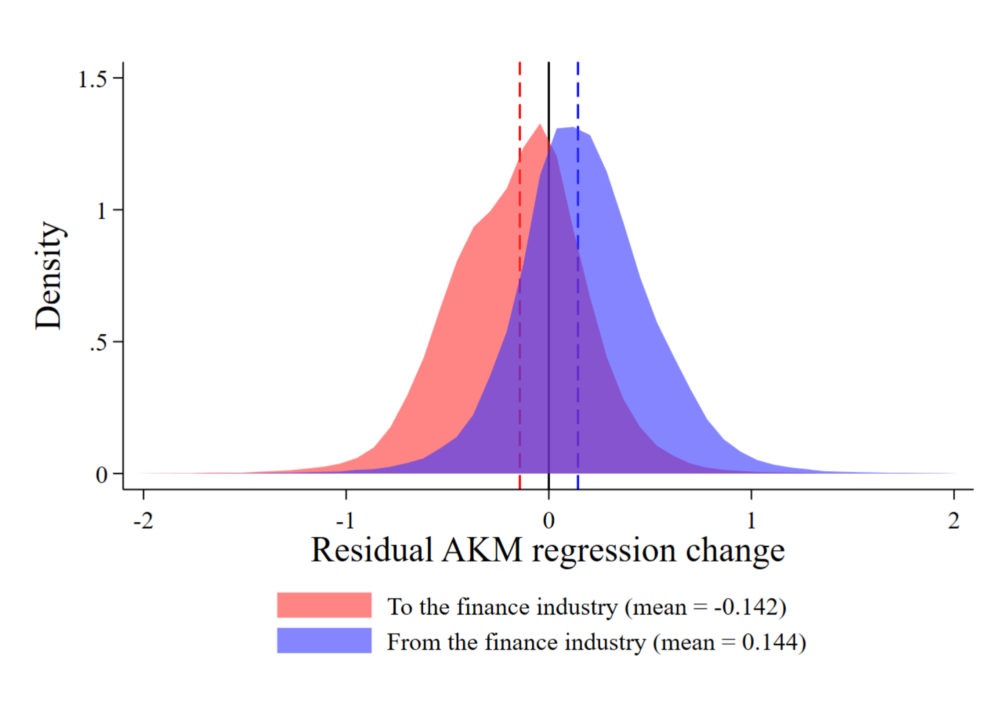
(a) Raw (b) Residuals AKM regression

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 data set, we calculate the gains (or losses) on the log full hourly wage. Panel (a) plots this distribution. On the contrary, panel (b) clean the data first. We run the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$, where $w_{i,t}$ is the full hourly wage (gross wage over paid hours); $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm 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.

is not a formal test to check if the mobility observed in our data set is ok to identify firm pay premiums. However, Bonhomme et al. (20) give us a benchmark to compare with. To show how important the mobility bias may be, they compare the variance of firm's effect from a regular AKM with the bias-corrected estimates of the variance of firm's effects. Importantly for us, the consider U.S. and four European countries: Austria, Italy, Norway, and Sweden. They find that while interquartile range of non-corrected estimates go from 14% to 23%, the interquartile range of bias-corrected estimates of the variance of firm's effects goes from 5% to 16%. As reported in the paper, Table A2 column (2), the variance of firm's effects in the Netherlands is 7%. While the limited mobility bias may be still playing a role, it comes at odds that the variance of firm's effects may explain less than 5%. We arrived to a similar conclusion with the contribution of sorting. While interquartile range of non-corrected estimates go from -1% to 8%, the interquartile range of bias-corrected estimates of the contribution of sorting lie between 5% and 20%. As reported in the paper, the contribution of sorting in the Netherlands is 11%.

As a whole, the limited mobility bias does not seem to be an issue in our estimates. They only way of going further in this topic, it is by implementing one (or both) of the bias-

Figure A7: Distribution of the change on the residual of an AKM regression for job-to-job movements over 2006-2018.



Notes: The figure shows distribution of the change on the residual (or cleaned log full hourly wage) for workers changing jobs from or to the finance industry over the period 2006-2018. For each job-to-job movement observed in the data set, we calculate the gains (or losses) on the residual. We get the residual from the regression $\ln w_{i,t} = \boldsymbol{X\beta} + \alpha_i + \psi_{J(i,t)} + \epsilon_{i,t}$ for the period 2006-2018, where $w_{i,t}$ is the full hourly wage (gross wage over paid hours); $\boldsymbol{X}$ includes a polynomial term on age (normalized to 40 years old) and the following fixed effects: year, type of contract, municipality, and firm size; α_i are worker fixed effects; $\psi_{J(i,t)}$ are firm 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 involving the finance industry. 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.

corrected methods: the correlated random-effects bias-corrected method by Bonhomme et al. (21) or the heteroskedastic fixed-effects bias-corrected method by Kline et al. (46). While it is possible, it may be of limited utility.