OXFORD BULLETIN OF ECONOMICS AND STATISTICS, 0305–9049
doi: 10.1111/obes.12155

Finance Sector Wage Growth and the Role of Human Capital

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Abstract

We reveal the pervasiveness of the finance sector pay premium, across all OECD countries, as well as all sub-sectors and occupations within the UK financial sector. Moreover, the UK premium has continued to rise despite the financial crisis. We show that earnings increase faster with value added in certain sub-sectors of finance, compared to the general economy, providing evidence of profit-sharing in these sub-sectors. Other possible explanations, such as workers with higher qualifications or better cognitive skills, or technological change and differing job characteristics, can explain some of the finance sector pay premium, but are not sufficient on their own.

I. Introduction

Explaining wage growth in the UK financial sector has remained a relatively under-researched area in economics, despite the issue receiving a lot of attention in the European media and the implementation of policies designed to affect it, such as the Capital Requirements Directive capping banker's bonuses at a maximum of one year of salary from 2014. Reed and Himmelweit (2012) loosely link the recent stagnation of UK wage growth to the increased importance of financial services in the aggregate profit share. Also Bell and Van Reenen (2010, 2013) document how high UK financial sector salaries are an important feature of growing wage inequality at the top end of the wage distribution. However, there are few studies that seek to explain why the financial sector wage premium has risen so quickly and why it is now so high.

Consequently, the main aim of this paper is to explain the large, and increasing, wage premium in the financial sector. We do this by drawing upon existing theories and potential explanations from the available literature on more general labour market inequality. For any theory to be accepted as a possible explanation, it must be able to explain both the high finance sector premium, and its further increase over time.

JEL Classification numbers: J20, J31, I24

The first potential explanation that we consider is that of rent-sharing, whereby rents created in the finance sector are shared with employees. In order to explain both the high and the rising finance sector wage premium, such an explanation would need to offer a reason why such rent-sharing is particularly and increasingly prevalent in the finance sector. Such issues have been discussed in previous literature. For example, Bivens and Mishel (2013), with reference to the US but also relevant to the UK, suggest that the removal or reduction of regulations on the finance sector, the implicit insurance provided by government bail-outs of struggling financial institutions, and the increasing complexity of financial instruments that allow financial workers to hide risk from their investors, have all helped in the creation and increasing extraction of rents in the finance sector. As well as this opportunity to engage in rent-sharing, Bivens and Mishel (2013) also discuss a rising incentive to do so, due to falling marginal tax rates on high incomes raising the benefits from pursuing a larger share of rents. As evidence for such a claim, the authors cite Piketty, Saez and Stantcheva (2012) who show that higher pre-tax income in the top 1% of the distribution is associated with lower marginal tax rates at the top, both over time in the US and across countries.

There are, however, other potential explanations of the high and rising finance sector pay premium that we must also consider. It has been well documented that some countries, most notably the US and UK, experienced substantial growth in general labour market inequality over the last two or three decades.[1] The forces that have increased inequality generally may therefore be the same that have increased the finance-non-finance wage differential specifically. One such general explanation that has received a lot of attention in the literature is technological change. The basic idea is that the falling price of information technology has led to the substitution of routine labour by technology capital. As routine tasks tend to be performed in jobs situated in the middle of the job quality distribution, economies with access to information technology have witnessed decreasing employment shares in the middle of the earnings distribution. Consequently, employment has polarized into high paid and low paid jobs and inequality has risen.[2] This process has become known as task-biased technological change (TBTC).[3] Here routine tasks are thought to be substitutes with new technology, whilst high-skill, analytical non-routine tasks are thought to be complements. An analysis of skill intensity and task use in the finance sector would therefore determine the relevance of this theory to explaining the high and rising finance sector pay premium.

While the literature on inequality and TBTC spans a number of dimensions and now also a number of countries, there have been relatively few studies that focus specifically on the financial sector. One notable exception is the study by Philippon and Reshef (2012) who consider long-run variation in relative finance wages over the previous century. They find a U-shaped pattern, with finance sector wages being higher relative to average private sector wages in the periods 1909–33 and again from 1980 onwards, while losing their relatively high status in the interim period. They go on to consider relative education levels and relative task complexity levels, and find a similar U-shaped pattern for both time

[1] See Acemoglu and Autor (2010) for a review of this literature.

[2] See Katz and Murphy (1992), Autor, Katz and Kearney (2008) for the US and also Machin (2011) and Lindley and Machin (2011) for Britain.

[3] This concept was first introduced by Autor, Levy and Murnane (2003) in their more refined treatment of skill biased technical change (SBTC). For a survey of the literature on SBTC see Katz and Autor (1999).

series; skill-intensity and task complexity were relatively higher in the early and recent periods, but not in the intervening period. The fact that relative wages, skill-intensity and task complexity were just as high pre-1933 as post-1980 casts doubt on technology being the underlying cause. Furthermore, after controlling for education they still find significant financial sector wage differentials, in the pre-1930s and post-1990s periods. Instead, they focus on, and find a key role for, the role of financial regulation, and conclude that financial deregulation in the 1980s stimulated innovation (and therefore also prior financial regulation in the 1940s stunted innovation) explaining the rising wages and skill intensity in the finance sector.

In terms of UK evidence, Bell and Van Reenen (2010) document increasing 'extreme' wage inequality by focussing on the income growth of the top 1% of British workers between 1998 and 2008. They find that 60% of the increase in this extreme wage inequality can be attributed to the growth in bonuses paid to workers in the financial sector. They consider rent-sharing as a potential explanation, and in support show evidence that during the 1995–2007 period, rents (measured by GVA per head) rose much more in finance than in the economy as a whole. However, they go on to show that, although the finance premium is observed at all points of the wage distribution, the *increase* in this premium has occurred exclusively at the top end of the distribution, an argument against the widespread distribution of rents across all finance workers. As an alternative, Bell and Van Reenen suggest the existence of superstar effects,[4] since they find that even within the top 1%, the largest gains have gone to those at the absolute top, the highest 0.02%, a phenomenon which they find to be more extreme in finance than in other sectors.

While such superstar effects may well be a main cause of the very high and rising wages at the top end of the finance sector wage distribution, the focus in this paper is on the slightly lower but still prevalent finance sector pay premium that we observe throughout the wage distribution, and for which superstar effects cannot be the explanation. This idea is therefore not explored any further in this paper. Instead, we investigate to what extent finance workers are paid more because they are better qualified or have better cognitive skills. We also look for evidence of TBTC in terms of any differences in the non-routine task inputs of finance sector workers. In both cases, we will also investigate trends, to determine whether the theory can explain the rising finance sector pay premium, as well as its initial size.

Our paper shows that, despite the recent financial crisis, the UK financial wage premium has continued to rise. This premium is received by finance workers across all sub-sectors, occupations and across the whole pay distribution. We show that the premium rises more quickly with larger sectoral rents in certain sub-sectors of finance than in most other areas of the economy, with a consequent suggestion of rent-sharing in these sub-sectors. Considering alternative explanations, we find that the UK financial sector has become more skill intensive and that finance sector workers had higher childhood mathematics and reading test scores, on average, compared to non-finance sector workers. However, these differences cannot explain all of the high level, or the increase in, finance sector wages. We then go on to show that finance workers display higher levels of non-routine task

[4] A 'superstar effect' is where small numbers of people dominate their particular field and receive very large sums of money, far above those only slightly below them in the ability distribution within their field. See Rosen (1981) for a discussion of superstar effects.

inputs than those of non-finance workers, but we find no evidence that this differential has widened. Moreover, controlling for tasks performed, as well as for complex computer use, qualifications and subject of degree, cannot fully explain the finance sector pay premium, with significant premiums for finance workers still remaining. The UK demonstrates the second largest of these premiums in 2012, out of 21 OECD countries.

The principal contributions of the paper to the literature are (i) a more extensive documentation of the finance sector pay premium in the UK than previously available, with evidence presented for the existence of the premium within detailed occupation codes for the first time, (ii) a focus on not only the high level of wages in the finance sector, but also the increasing size of this premium, (iii) new evidence to support the rent-sharing theory, showing the elasticity of wages with respect to value added in the finance sector relative to other sectors, and (iv) a more extensive analysis of alternative explanations for the finance pay premium.

The paper is structured as follows. The next section measures the UK financial pay differential. We document the size of the finance sector pay premium, show the importance of including annual bonuses, and reveal how the premium varies across sub-sectors within finance. Section III investigates whether rent-sharing is a plausible explanation of the finance sector pay premium. Section IV investigates to what extent the UK financial sector has become more skill intensive, whilst section V considers whether finance workers have higher cognitive skills on average, relative to non-finance workers and section VI considers technological change and the role of job tasks. The final section concludes.

II. Documenting the UK financial sector pay premium

In order to measure the UK financial pay differential and to see how it has evolved over time, we start by using the New Earnings Survey Panel Dataset (NESPD). The NESPD contains a sample of all working individuals, specifically those whose National Insurance numbers end in a given pair of digits. The survey is distributed to and completed by firms in April each year. It produces close to a 1% sample of all employees in the UK and so the sample is large relative to other UK surveys. One drawback of the NESPD is that it does not collect information on the qualifications or skills of workers. From 1996, however, it did start to collect the annual gross pay of workers, including incentive and bonus payments, which makes it particularly attractive for measuring the finance pay premium. As was first identified by Bell and Van Reenen (2010), using weekly or monthly data to capture salaries in the UK financial sector leaves out bonus payments that tend to be paid just before the end of the financial year, for all but the small proportion who happen to be reporting for the bonus-paying period.[5]

The finance sector is here defined to include any business involved in financial transactions. It therefore includes, for example, the brokers and dealers in the financial area of London ('the City'), central bankers, retail bank staff, and activities connected to insurance and pension funds. A diverse range of activities can thus be found within the finance sector.

[5] Although we can include such income-based annual bonuses, we do not observe capital income, which is likely to be rising more quickly in the finance sector than elsewhere. To this extent, our results may understate the true finance premium.

TABLE 1

OLS and fixed effects comparison of the finance pay differential 1996–2011

	Log gross weekly pay		*Log annual gross pay*	
	OLS	*Fixed effects*	*OLS*	*Fixed effects*
Finance	0.413*	0.268*	0.478*	0.314*
	(0.100)	(0.003)	(0.103)	(0.004)
Including controls	Yes	Yes	Yes	Yes
N	1,628,372	1,628,372	1,628,372	1,628,372
R^2	0.324	0.024	0.282	0.013

Notes: Table reports the coefficients on a finance sector dummy variable, in separate OLS and Fixed Effects equations. NESPD sample of men and women age 16–65. Controls are gender, region, age and age squared. Year dummies are also included, the OLS clusters on industry. Excluding the non-finance public sector. Standard errors are in parentheses. *Significant at the 1% significance level.

Our approach is to estimate Mincer style wage equations of the form

$$Y_{it} = \alpha + \beta F_{it} + \boldsymbol{X}_{it}\Gamma + \gamma_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the real log wage of worker i at time t, and F is a dummy variable that equals one if the worker is employed in the finance sector and zero otherwise at time t. Controls for gender, age and its square, as well as region of residence, are included in the vector $\boldsymbol{X}$. γ_t are year fixed effects which we capture using year dummies, whilst ε_{it} is the error term. We use two measures of wages. The first is gross weekly wages which is likely to largely exclude bonuses. We also use gross annual pay which will capture all labour income, including bonuses. Both measures are inflated into constant 2011 prices using the RPI. This provides 1,628,372 observations from 1996 to 2011, excluding missing values and workers from the non-finance public sector. We keep public sector workers who work in banks in our sample because of the nationalization of some banks during the financial crisis (for example the Royal Bank of Scotland in 2008). Including non-finance public sector workers strengthens our results in that they are qualitatively the same as when excluded, but the financial premiums are everywhere larger. Of our 1,628,372 observations 125,277 (7.7%) are finance sector workers. The real average weekly wage over the period is £492 and the real average annual labour income is £25,296. In finance these are £709 and £42,202 respectively.

Table 1 provides the estimates of β in equation (1), clustering the standard errors on one-digit industry. The first column of results shows that on average, gross weekly wages were around 39%[6] higher in the finance sector relative to the rest of the private sector. Using annual gross pay (which includes bonuses) results in a larger finance pay premium of 48%.

[6] Calculated as $e^{\beta} - 1$.

TABLE 2

Changes over time: OLS estimates of the log annual pay finance differential 1996–2011

	Finance sector coefficient	*N*	R^2
1997–99	0.362* (0.113)	411,472	0.231
2000–02	0.455* (0.101)	304,158	0.313
2003–05	0.483* (0.102)	306,891	0.299
2006–08	0.553* (0.099)	281,496	0.275
2009–11	0.569* (0.095)	324,355	0.278

Notes: NESPD sample of men and women age 16–65. Controls are gender, region, age and age squared. Year dummies are also included. Excluding the non-finance public sector. Standard errors are in parentheses. *Significant at the 1% significance level.

Since the NESPD is a longitudinal data set, we are able to control for individual unobserved heterogeneity by estimating a fixed effects (FE) model, including the individual fixed effects, λ_i:

$$Y_{it} = \alpha + \beta F_{it} + \boldsymbol{X}_{it}\Gamma + \gamma_t + \lambda_i + \varepsilon_{it}. \tag{2}$$

The FE specification sweeps out any of the biases in the OLS weekly/annual wage equations caused by correlations between the covariates, in particular the finance sector dummy, and the time-invariant components of the error term. This is especially important here, given we cannot control for the highest qualifications, which are fixed over time for most adults and so should largely be picked up by the fixed effects.[7] The FE results in the second and fourth columns of results show that the finance sector premium falls relative to the OLS estimates, as one would expect if there are unobservables that are positively correlated with working in the finance sector and also receiving higher wages, though rather surprisingly, it does not fall by much. Annual wages in the finance sector are still 37% higher on average, relative to those for non-finance workers in the private sector, even after conditioning on age, region and unobserved heterogeneity. In analysis not shown, the change in wages is observed both for those who join and those who leave finance.

Table 2 shows changes over time in the OLS estimates of the finance sector annual pay premium. The financial pay premium has increased over time from 44% during 1997–99 to 77% during 2009–11. The differential shows no signs of declining, despite the start of the recession in 2008.[8]

One factor not considered so far is that the occupations being performed in the finance sector differ to those in the non-finance sectors. Conditioning on three-digit occupations failed to fully explain these finance sector premiums, and demonstrated

[7] Subsequent sections do introduce qualifications and skills, using alternative data sets.

[8] Supplementary Table S1 shows a similar pattern over time using the FE specification. The changes over time are less pronounced, suggesting an increase over time in the upward bias caused by unobserved (to us) heterogeneity in the OLS results, possibly due to the shake-up caused by the financial crisis and the removal of observed (by the employer) lower-ability employees.

TABLE 3

OLS and fixed effects estimate of the finance annual pay differential, among individuals working in occupations most commonly found in both finance and non-finance sectors

	OLS	*Fixed effects*
111 Corporate managers	0.384* (0.060)	0.263* (0.026)
113 Functional managers	0.323* (0.030)	0.196* (0.008)
114 Customer care manager	0.068† (0.027)	0.206* (0.026)
115 Financial and office managers	0.204* (0.024)	0.173* (0.010)
213 ICT professionals	0.154* (0.010)	0.159* (0.014)
242 Business/statistical professionals	0.109* (0.009)	0.127* (0.014)
313 IT service delivery	0.198* (0.029)	0.188* (0.022)
352 Legal associate professionals	0.259* (0.012)	0.177* (0.046)
353 Business/finance ass. professionals	0.225* (0.026)	0.131* (0.011)
354 Sales associate professionals	0.103† (0.038)	0.163* (0.020)
412 Admin occupations: finance	0.054 (0.040)	0.124* (0.008)
413 Admin occupations: records	0.192† (0.071)	0.147* (0.013)
414 Admin occupations: comms	0.153† (0.060)	0.171* (0.046)
415 General admin	0.260* (0.076)	0.163* (0.010)
421 Secretarial	0.346* (0.081)	0.185* (0.014)
712 Sales related	0.278* (0.047)	0.194* (0.020)
721 Customer service	0.354† (0.131)	0.147* (0.015)
N	548,858	361,761
R^2	0.416	0.250

Notes: NES sample of men and women age 16–65. Reported coefficients are those on an interaction term between working in the finance sector and the named occupation. Other variables included are the same occupations (non-interacted), gender, region, age and age squared. Year dummies are also included, the OLS clusters on industry. Excluding the non-finance public sector. Standard errors are in parentheses. *Significant at the 1% significance level. †Significant at the 5% significance level.

within-occupational premiums for most finance workers.[9] However, for a stronger test, not undertaken in previous literature, we restrict the sample to workers in those occupations that are most commonly found in *both* the finance and non-finance sectors, such as Corporate Managers, Financial and Office Managers, ICT professionals, Secretaries etc.[10] We then interact occupation dummies for each occupation in turn, with the finance sector indicator. The coefficients on these interactions terms are reported in Table 3,[11] and show the finance sector annual pay premium within each occupation, i.e. the difference in wages between workers in the same job but working in the finance or non-finance sectors. The OLS results reveal a positive finance sector premium in every occupation, most of which are statistically significant. Of more interest are the fixed effects results, where a further restriction was imposed, that individuals had to be working in the *same* occupation in

[9] These results are available from the authors on request.

[10] Specifically, we include the 17 three-digit occupations for which at least 5% of workers doing that job are found in the finance sector. The full list of these 17 occupations can be found in Table 3.

[11] The non-interacted occupation dummies are also included in the estimated equation, but not reported in Table 3 for the sake of brevity.

TABLE 4

Quantile regressions for the conditional financial pay differential 1996–2011

Percentile:	*10th*	*25th*	*50th*	*75th*	*90th*	*99th*
Finance	0.582*	0.492*	0.412*	0.348*	0.360*	0.601*
	(0.006)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
N	1,628,372	1,628,372	1,628,372	1,628,372	1,628,372	1,628,372

Notes: NESPD sample of men and women age 16–65. Other variables included are gender, region, age and age squared. Year dummies are also included. Excluding the non-finance public sector. Standard errors are in parentheses, clustered on industry. *Significant at the 1% significance level.

successive periods.[12] The coefficients on the interactions therefore reflect the change in wages earned by the same individual, working in the same occupation, but moving between the finance and non-finance sector. The results reveal a positive and statistically significant finance sector premium in every occupation. These premiums are remarkably consistent across occupations, mostly being clustered around a 20% premium, with the highest being 30% for Corporate Managers, and the lowest being 13% for financial administrative occupations. The occupations considered in Table 3 span the occupation hierarchy, and suggest a pervasive finance sector pay premium. This is consistent with the idea of rent-sharing, with economic rent generated within the finance sector shared between all workers.

So far we have only looked at the average pay differential in the finance sector *vis-à-vis* the rest of the private sector, which ignores potential distributional differences. In quantile regression models the full (conditional) distribution of wages is expressed as a function of the explanatory variables, including the finance sector indicator, rather than just evaluating differences at the mean wage. The difference between finance and non-finance sector wages can then be observed at each quantile of the wage distribution. Practically, obtaining quantile regression coefficients involves minimizing the weighted sum of the absolute residuals, where the weights are determined by the quantile being considered. Specifically, quantile regression chooses the β coefficients to minimize the expression in equation (3) below for any quantile, τ, we choose:

$$\widehat{\beta}_\tau = \min \sum_{i=1}^{n} \rho_\tau (Y_i - \boldsymbol{X_i \beta_i}) \tag{3}$$

where ρ_τ is a check function for the τth quantile, taking the value of τ for positive residuals and $(\tau - 1)$ for negative residuals, hence ensuring positive values in all cases.[13]

Table 4 reports the results for quantile regressions estimated on a sample of all workers. The positive finance pay premium is observed at all points of the wage distribution. The premiums are observed to be large at the 10th percentile (79%), slightly lower in the middle and then even higher at the 99th percentile (82%). These results differ at the lower end from those presented by Bell and Van Reenen (2010). There are some differences in specification and sample between our analysis and theirs, and when we replicate their

[12] The data set contains 2,276 observations involving a move into the finance sector but remaining in the same occupation, and 2,140 observations involving a move out into the same occupation.

[13] Hence the ρ_τ terms provide the weights for the residuals, which will be asymmetric across positive and negative residuals with the exception of where $\tau = 0.5$, i.e. the median quantile.

analysis, we obtain *exactly* the same coefficients in the quantile analysis. The key difference between our analysis and theirs for explaining the difference in results turns out to be our exclusion of the public sector. When attention is focussed on the private sector only, as here, it seems that the finance workers at the lowest decile do better than other private sector low-paid workers.

Estimating the quantile wage regression for a restricted sample of finance sector workers only,[14] there is a much larger gender pay differential at the 10th and the 99th percentile compared to the rest of the distribution. The gaps between prime-aged relative to young and old, and between London and the other regions, are all also at their largest at the 99th percentile. It therefore seems that the very highest wages in the finance sector are going to 40–49 year old men working in London.

In summary, therefore, our analysis of the NESPD reveals a large and pervasive wage premium to working in the finance sector which is larger when bonuses are included as a measure of pay. While this is in part due to the unobserved characteristics of the individuals who work in the finance sector, and in part due to the jobs being performed in that sector, these factors alone cannot explain the wage premium in full, as a significant premium remains when we control for these factors using the panel element of the NESPD. We suggest that this is consistent with the presence of rent-sharing in the finance sector. To investigate further, in the following section we look for a link between sectoral rents and pay. In subsequent sections we consider other potential explanations for the finance sector wage premium.

III. Does the financial sector share rents?

To look for evidence of rent-sharing in the finance sector, we first investigate whether excess rents exist in the sector. We then look for evidence to suggest that rents are more likely to be shared in finance *vis-à-vis* other sectors. We use two digit sector level data from the EU KLEMS database, for the UK between 1996 and 2007.[15] This provides a panel of 59 industries observed over 12 years.[16] Our main variable is log gross value added per hour worked which is intended to capture rents, where value added is defined as the difference between the value of output in the sector and the value of material inputs, and is consequently the sum of labour and capital compensation.[17]

Table 5 reports the results for the log of real value added per hour worked (in 2011 prices) regressed on a finance sector dummy and year dummies (our base model). This indicates whether rents (proxied using gross value added per hour) exist in the finance sector, over and above the average across all other sectors. In the first column, the coefficient on the finance sector variable is positive, but statistically insignificant. However, the specification in the

[14] See Supplementary Table S2.

[15] Information is provided for consistently-defined sectors in the EU KLEMS database up to 2007, hence the end date for the analysis in this section.

[16] Within finance, there are three two-digit sectors, namely 65 ‘Financial intermediation’, 66 ‘Insurance and pension funding’, and 67 ‘Activities auxiliary to financial intermediation’. Note that there are a small number of missing values for the very small sectors, hence why the sample size is Table 5 is 689 rather than ($59 \times 12 =$) 708.

[17] Output within a sector is defined as the weighted sum of products/services provided, with the weights given by the share of the product in the total nominal value of the sector’s output. A similar method for calculating the value of a sector’s input materials is used. For further information about EU KLEMS, see O’Mahony and Timmer (2009).

TABLE 5

Sectoral variation in log (real value added per hour), 1996–2007

	Base model	*Disaggregating by sub sector*
Finance	0.134 (0.132)	
65. Financial intermediation		2.022* (0.060)
66. Insurance and pension funding		1.408* (0.060)
67. Activities auxiliary to financial intermediation		1.252* (0.060)
Sector dummies	No	Yes
Year dummies	Yes	Yes
N	689	689
R^2	0.008	0.967

Notes: Dependent variable is log (real value added per hour) at the (2-digit) sector level, regressed against a finance dummy and a full set of year dummies in column 1, and against a full set of time and sector dummies in column 2 (the omitted sector in column 2 is sector 93 'other service activities'). Standard errors are in parentheses. *Significant at the 1% significance level.

second column disaggregates the finance sector into its three composite sub sectors, as well as including two-digit sector dummies. For brevity only the coefficients for the three finance sub sectors are presented. The omitted category here is 'other service activities', which has virtually zero value added so that all the coefficients in this specification are positive. All three finance sub sectors enjoy relatively larger rents than those in 'other service activities'. The largest finance sector premium is for 'financial intermediation' (655% higher) and although this is not the largest over all industries, it is the ninth largest in terms of average rents observed over the period. The eight sectors with larger observed value added are all related to petroleum, other energy, tobacco or real estate, which are also likely to be sectors that generate their own excess rents, for various reasons.[18] In addition, further analysis not reported in Table 5 interacted the three finance sub-sector dummies with the time variable. Positive and statistically significant coefficients on these interaction terms were observed for sector 65 'Financial intermediation' (interaction coefficient (standard error) 0.062 (0.012)), and 67 'Activities auxiliary to financial intermediation' (0.021 (0.012)). Thus rents are both high in these three finance sub-sectors, and rising over time in two of the sub-sectors, so that rent-sharing offers a *potential* explanation for both the high finance premium *and* its increase over time.

To investigate whether finance sector rents are more likely to be shared amongst finance sector workers, we revert back to our NESPD worker level wage equations (1) and (2) from the previous section, additionally controlling for industry-level valued added per hour, clustering the standard errors on two-digit industry. The effect of the addition of value added to the fixed effects specification is to reduce the finance pay premium by around

[18] Specifically, the sectors with higher value added are industry SIC codes SIC 11 (Extraction of crude petroleum & natural gas), 16 (Manufacture of tobacco products), 23 (Manufacture of coke, refined petroleum products), 37 (Recycling), 40 (Electricity, gas, steam and hot water supply), 41 (Collection, purification and distribution of water), 61 (Water Transport), 70 (Real Estate activities).

one quarter,[19] thus suggesting that a significant portion of the finance sector pay premium is related to rents. Disaggregating the finance sector by sub sector, all of the finance sub-sector pay premiums fall, to a greater or lesser extent, with the inclusion of the value-added variable.[20]

Additional specifications further included interaction terms between log value added per hour and the finance sub-sector dummies, in order to estimate the elasticities of pay with respect to value added per hour in each finance sub-sector, over and above the average estimated elasticity of 0.15 in the non-finance sector.[21] The fund management and security broking sub-sectors demonstrate the largest positive interaction coefficients, with elasticities 0.81 and 0.48 larger than the non-finance elasticity, respectively.[22] A 1% rise in value added in finance is therefore associated with a significantly larger increase in wages than a 1% rise in value added in most other sectors.

Overall, this section therefore provides evidence consistent with the existence of profit-sharing in the financial sector, at least for the highly paid finance jobs commonly associated with 'the City'. We have shown that value added in finance is higher than in most other sectors, that it has increased more than in most other sectors, and that it is more strongly correlated with wages in finance than in most other sectors. These facts are all consistent with rent-sharing being the cause of the high and rising wage premium in the finance sector. They cannot be claimed as proof of a causal effect of value added on wages, however. It is the case that the correlation is estimated in the presence of sector fixed effects, and so is identified off variation in value added over time within sectors. It is not therefore due to unobserved characteristics of sectors that are correlated with both value added and wages and which are constant over time. It cannot be completely ruled out, however, that other factors may have changed in the finance sector at the same time as the rise in value added, and it is those other factors that have actually increased the wage. In the following sections we therefore consider alternative possible explanations for the high and rising finance sector pay premium, including relatively higher levels of human capital and task biased technological change.

IV. Is the finance sector more skill intensive?

Higher wages in the finance sector could potentially be explained by better qualified workers in the finance sector relative to all other industries, and rising wage premiums explained

[19] See Supplementary Table S3 for results. Column 1 is the standard OLS equation, and column 2 is the standard fixed effects specification. Adding the industry value-added variable (column 3) reduces the estimated finance coefficient from 0.263 to 0.194.

[20] Compare columns 4 and 5 of Supplementary Table S3.

[21] See column 6 of Supplementary Table S3.

[22] As an alternative test, we collapsed the income, age and region data in NESPD down to the two-digit sector level, so that it was at the same level of aggregation as the value-added data. A similar specification to column 6 in Supplementary Table S3 was then estimated, with the log of value added per hour interacted with all 59 two-digit sector dummies. The coefficients for two of the finance sector interactions with value added (65 'Financial intermediation' and 67 'Activities auxiliary to financial intermediation') were positive and statistically significant, with the latter particularly large at 1.62, the fourth largest of all the interaction coefficients (results available from authors on request). Note that sub-sector 67 is the one that contains fund management and security broking, the two sub-sectors with the largest interactions in the more disaggregated individual level analysis in Supplementary Table S3.

by increasingly well-qualified workers, although these explanations seem unlikely given that we have found a significant premium across the whole distribution. It has been well documented that the total employment shares of graduates have increased in the labour market as a whole. For example Lindley and Machin (2012) using the Labour Force Survey (LFS) show that the employment share of graduates increased from 0.14 in 1996 to 0.23 in 2006 and to 0.31 in 2011. We would like to know how many of these graduates are employed in finance and, conditional on the overall increase in the supply of graduates, whether the number working in finance is rising. In doing so, we must of course acknowledge that the skills of graduates may change over time, and this effect may differ by subject, as Higher Education has expanded to include a wider spectrum of young people.[23] Thus any increase in the number of graduates over time may overstate the increase in skills to a sector.

Data from the LFS show that the finance employment share amongst graduates has increased from 0.046 in 1994 to 0.060 in 2008, but then fell slightly to 0.058 in 2011. So before the start of the recession in 2008, there were relatively more finance workers amongst graduates than amongst the total private sector workforce (the proportion of all private sector workers employed in finance was 0.052 in 2008). Disaggregation by subject area[24] shows that the finance employment share is much larger for economics graduates, maths/computing graduates and management/business graduates, with the economists demonstrating the largest increases.[25] In 2011 over a quarter of all economics graduates were employed in the financial sector. Figures for maths/computing and management/business were 10% and almost 11% respectively. Given these subjects are by nature more numerical, this also suggests that in the long term there has been numerical skill upgrading (mainly from economics graduates) in the financial sector.

Given that we find some evidence of skill upgrading in the finance sector, which may therefore provide the explanation for the high and rising wage premium in that sector, we augment equations (1) and (2) with measures for highest qualifications using the 1997–2008/9 British Household Panel Survey (BHPS). The BHPS is a longitudinal data set that contains questions on highest qualifications as well as a measure of annual labour income, including bonuses, which was first asked in 1997.[26] Consequently we estimate

$$Y_{it} = \alpha + \Sigma \beta^k F_{it}^k + \boldsymbol{X}_{it}\Gamma + \gamma_t + \varepsilon_{it}, \tag{4}$$

$$Y_{it} = \alpha + \Sigma \beta^k F_{it}^k + \boldsymbol{X}_{it}\Gamma + \gamma_t + \lambda_i + \varepsilon_{it}, \tag{5}$$

[23] See Lindley and McIntosh (2015) for a discussion of such issues.

[24] See Supplementary Figure S1.

[25] The subject of degree question for much of this period in the LFS refers only to the undergraduate degree, with subject of postgraduate qualifications only added more recently. We therefore focus only on subject of first degrees here. For detailed definitions of the subjects listed in Figure 2 see Lindley and McIntosh (2015).

[26] The BHPS is a sample of over 5,000 households in the UK, conducted annually since 1991 and contains information on human capital and socio-economic characteristics of each individual in the household. From 1997 onwards the survey also collected information on annual labour income and bonuses. The data on annual earnings in the BHPS is constructed from monthly and weekly earnings rather than being directly asked. From 1997 there was a separate question asked regarding the value of all bonuses received in the last 12 months. Following Bell and Van Reenen (2010), we add this value to the respondent's annual labour income to produce total annual labour income including bonuses.

TABLE 6

Estimate of the log annual labour income finance pay differential, British Household Panel Survey (BHPS) 1997–2008

	OLS		*Fixed effects*	
Finance	0.393* (0.093)		0.127* (0.022)	
Finance × Graduates		0.564* (0.084)		0.172* (0.047)
Finance × SMC		0.575* (0.085)		0.125* (0.049)
Finance × 2 Plus A levels		0.290* (0.094)		0.120* (0.045)
Finance × Other Q		0.242† (0.104)		0.097* (0.038)
N	52,85	52,85	52,85	52,85
R^2	0.287	0.289	0.110	0.111

Notes: BHPS sample of men and women age 16–65. Wage equations for log annual income. conditioning on gender, married, region, age and age squared. Year dummies are also included. Excluding the non-finance public sector. Standard errors are in parentheses, clustered on industry. *Significant at the 1% significance level. †Significant at the 5% significance level.

where F^k is a dummy that is equal to one if worker i is employed in the finance sector, and has highest qualification k at time t, and zero otherwise.[27] There are four highest qualification groups; graduates, some college, 2 plus A-levels[28] and other/no qualifications. Again our controls in vector $\boldsymbol{X}$ are region of residence, gender, age and age squared, but we also now condition on marital status. Equation (5) differs to equation (4) only in that it also includes worker level dummies and thus provides fixed effects estimates.

The estimates of β from equations (1) and (2) are provided in the first and third columns of Table 6, whilst the second column provides the estimates of the β coefficients from equation (4) and the fixed effects estimates of the β coefficients from equation (5) are presented in the final column. The OLS conditional log annual wage differential over the period is 48%, while the second column shows that this is 76% for graduates and 78% for individuals with some college. The final two columns provide the FE estimates. These suggest a similar sized financial labour income differential within each education group. Conditioning on unobserved heterogeneity, the finance premiums are lower than the OLS estimates for all education groups, which is suggestive of unobserved wage-enhancing characteristics, such as greater cognitive ability. However, we cannot say how much of the unobserved heterogeneity observed here is a consequence of cognitive skill differences, to which we now turn.

In summary, the data suggest that the finance sector does employ an above-average proportion of higher-qualified workers, with some evidence that the sector is increasingly attracting the more numerate graduates. Qualification levels, as an indicator of skills, are therefore a potential explanation of the high and rising finance sector wage premium. The

[27] We interact working in finance with the highest qualification in this way, because highest qualification does not vary with time for the vast majority of our subjects, and so would be picked up by the individual fixed effects in equation (5) if entered on their own. Equation (4) is then specified in the same way for comparison purposes. If instead we add the highest qualification variables to an OLS specification as in equation (1), then the estimated finance coefficient falls from the 0.393 reported in Table 6 column 1, to 0.308, revealing that part of the finance sector wage premium is due to differing stocks of qualifications between the finance and non-finance sectors, but that a significant premium remains even after controlling for qualification differences.

[28] A levels are national qualifications obtained at the end of upper secondary schooling.

regression results, however, show that although qualifications go some way to explaining the size of the finance sector wage advantage, a significant premium remains, which is similar in size within each education group. This result compares with the analysis of Philippon and Reshef (2012) who similarly find an increasing skill-intensity in the finance sector at the same time as the increase in relative wages, but that the former cannot fully explain the latter, given an increase in the finance sector relative wage post-1990 that is greater than that predicted by the increase in skill-intensity.

V. Do finance sector workers have higher cognitive skills?

In this section we look further into the characteristics considered as unobserved in the previous section, and investigate to what extent the finance premium might be a consequence of high and rising cognitive skills amongst finance workers, paying particular attention to differences in numeracy and reading skills. We start by looking at whether finance workers have better skills on average and whether any such gap is increasing.

We draw upon the British cohort study (BCS) which is a sample of men and women born in 1970 and the national child development study (NCDS) where respondents were born in 1958. The most recent sweeps of the BCS and NCDS were undertaken in 2008, when the BCS (NCDS) respondents were aged 38 (50) and questions were asked about various socio-economic and work characteristics of the respondents. The surveys provide information on gross pay, highest educational qualification, industry of employment, marital status, gender and region of residence.

Differences in childhood test scores

Given that finance workers could be more numerate as adults because their job involves more numerical tasks, we use childhood test scores for mathematics and reading taken when the respondents were aged 10 and 11, rather than adult test scores. The BCS 1980 and NCDS 1969 follow-ups provide reading and mathematics tests when the respondents were aged 10/11, so in addition to being pre-employment, they are also uninfluenced by secondary and higher education. All test scores were standardised to have mean zero and a standard deviation of one, to make them comparable across surveys. We therefore interpret any differences in results between data sets as cohort effects, rather than age or time effects, since both are observed at the same age, and any general increases over time are removed by the standardization to a zero mean in both data sets. Comparison of the finance skill differential between data sets therefore indicates whether the younger cohort of finance workers are relatively more skilled than the older cohort. To the best of our knowledge, this is the first time that the relative cognitive skills of finance workers have been analysed in this way.

To quantify the relationship between childhood cognitive skills and subsequent finance sector employment we estimate the following equations

$$\mathrm{TS}^{R}_{it=\mathrm{age10}} = \alpha_R + \beta_R F_{it=2004} + \varepsilon_{it=\mathrm{age10}} \tag{6}$$

$$\mathrm{TS}^{M}_{it=\mathrm{age10}} = \alpha_M + \beta_M F_{it=2004} + \varepsilon_{it=\mathrm{age10}} \tag{7}$$

TABLE 7

NCDS and BCS: OLS estimates of the finance differential for standardized childhood test scores

	NCDS standardized maths test (age 11)		*NCDS standardized reading test (age 11)*		*BCS standardized maths test (age 10)*		*BCS standardized reading test (age 10)*	
Finance	0.402*		0.235*		0.391*		**0.419***	
	(0.057)		(0.057)		(0.052)		**(0.052)**	
Finance × Graduates		1.195*		0.839*		1.021*		0.909*
		(0.183)		(0.183)		(0.127)		(0.128)
Finance × SMC		0.725*		0.420*		0.436*		0.470*
		(0.141)		(0.141)		(0.115)		(0.116)
Finance × A levels		0.639*		0.442*		0.756*		0.728*
		(0.124)		(0.124)		(0.137)		(0.137)
Finance × Other Q		0.090		0.005		0.089		0.172†
		(0.076)		(0.076)		(0.071)		(0.071)
N	6,790	6,790	6,790	6,790	5,968	5,968	5,968	5,968
R^2	0.008	0.014	0.002	0.006	0.012	0.020	0.016	0.022

Notes: Table shows results from OLS regressions of the indicated childhood test score against, in consecutive columns, a finance sector dummy variable, and the finance dummy interacted with indicators of highest qualification. NCDS sample of men and women born in 1958 and observed in 2004 (age 46). BCS sample of men and women born in 1970 and observed in 2004 (age 34). Conditioning on gender. Standard errors are in parentheses. *Significant at the 1% significance level. †Significant at the 5% significance level. BCS coefficients in bold are statistically significantly different from their NCDS equivalents. BCS, British cohort study; NCDS, national child development study.

$$\mathrm{TS}^{R}_{it=\mathrm{age}10} = \alpha'_R + \sum \beta^k_R F^k_{it=2004} + \varepsilon_{it=\mathrm{age}10} \tag{8}$$

$$\mathrm{TS}^{M}_{it=\mathrm{age}10} = \alpha'_M + \sum \beta^k_M F^k_{it=2004} + \varepsilon_{it=\mathrm{age}10} \tag{9}$$

where the $\mathrm{TS}^j (j = R, M)$ dependent variables are reading and mathematics test scores observed at age 10 (1969 for the NCDS and 1980 for the BCS) and F is a finance dummy observed in 2004 for the NCDS and the BCS (when workers are age 46 and 34 respectively). In equations (8) and (9) the finance dummy is allowed to vary by four highest qualification groups as defined in the previous section. All equations in this section also control for gender.

Table 7 shows that the average childhood maths scores are 0.40 standard deviations higher for those who go on to work in finance in the NCDS than for those who do not, which is very similar, and insignificantly different, to the differential in the BCS for 34 year olds (0.39).[29] For reading test scores, the finance differential in the NCDS is lower (0.24 standard deviations) relative to that for the BCS (0.42). This difference is statistically significant at the 5% level ($t = 2.38$). Looking within education groups, none of the finance-non-finance skill premia are significantly different in the BCS compared to those in the NCDS, though close to significance we observed lower relative maths skills of finance workers amongst those with some college education in the more recent BCS cohort, and

[29] We cannot compare the BCS age 34 in 2004 with the NCDS age 33 in 1991 because current industry of employment is not included in the NCDS 1991 survey.

higher relative reading skills amongst the A level and other lower qualification groups in the BCS. Although finance workers have higher cognitive ability than non-finance workers, on average, there is therefore no evidence that they are becoming relatively more numerate amongst more recent cohorts, and any evidence for improving relative reading skills is restricted to less well educated groups. Therefore even if cognitive skills do have some role to play in explaining the higher wages of finance workers, they cannot explain the rising wage premium.

Wage equations

In this sub-section, we estimate wage equations with NCDS and BCS data, to determine the extent to which inter-sectoral differences in cognitive skills can explain the finance sector wage premium. We pool the two data sets, to increase sample size, and use data from the 2004 and 2008 sweeps, to provide a longitudinal element.[30] Our sample consists of 15,642 individuals of whom 969 (6.1%) are employed in finance.[31]

In the BCS and NCDS respondents are asked '*the last time you were paid, what was your gross pay before deductions?*'. Unfortunately neither survey includes information on annual labour income or bonuses, so we are faced with the familiar problem of potentially under-estimating the true finance premium, by using data on monthly pay.[32] We control for gender, marital status, region of residence, age and year.

The results are shown in Table 8. The first 4 columns replicate the analysis with the BHPS in Table 6, estimating equations (1) and (2) (columns 1 and 3), and equations (4) and (5) (columns 2 and 4), showing the effects of controlling for highest qualification. The results in Table 8 are qualitatively similar to those in Table 6.

The additional analysis in Table 8 comes in the final two columns, where we also condition on childhood test scores. As with the qualification variables, test scores are also entered into the equation via interactions with the finance sector variable, otherwise they would be removed in the fixed effects specification, since the childhood test scores do not change with age as an adult.[33] We interpret the coefficients on the interaction terms as finance-specific returns to maths and reading, though acknowledge that selection effects may mean that these are actually the returns to maths and reading for the factors correlated with the decision to enter finance. Our preferred specification, the fixed effects results controlling for other unobserved heterogeneity, shows that the return to cognitive skills is only marginally significantly different in finance in the case of maths skills, and actually shows a lower return to such skills in the finance sector. Presumably, those with good maths

[30] We do not use the BCS 1996 sweep in our panel analysis since the gross pay variable is measured differently, whereas it is identical in the 2004 and 2008 follow-ups. We also considered using the NCDS for comparable age changes, using sweep 5 (age 33 in 1991) and sweep 6 (age 41 in 1999) but as already mentioned, industry of employment is not included in the 1991 data.

[31] The number of individuals is 9,345 and these are observed on average 1.7 times.

[32] The fieldwork for the 2004 BCS was undertaken between February 2004 and June 2005. There is a question on annual employment income in the 2008 BCS but this is banded and does not appear in the 2004 sweep. Given we estimate panel data models using the 2004 and 2008 BCS/NCDS we do not use this annual employment income data.

[33] If we enter the childhood test scores directly into the OLS equation in column 1, then the finance sector wage premium is reduced, but only from 0.293 to 0.224. Thus, cognitive ability explains at most a small part of the finance sector premium.

TABLE 8

BCS and NCDS: estimates of the finance monthly gross pay differential in 2004 & 2008

	Base model				*Conditioning also on child test scores*	
	Pooled OLS		*Fixed effects*		*Pooled OLS*	*Fixed effects*
Finance	0.293*		0.113†			
	(0.024)		(0.048)			
Finance × Graduates		0.753*		0.270*	0.685*	0.461†
		(0.064)		(0.019)	(0.096)	(0.195)
Finance × SMC		0.487*		0.034	0.432*	0.169
		(0.055)		(0.107)	(0.082)	(0.156)
Finance × A levels		0.254*		0.230‡	0.202†	0.342‡
		(0.055)		(0.133)	(0.081)	(0.177)
Finance × Other Q		0.124*		0.061	0.083	0.158
		(0.032)		(0.069)	(0.061)	(0.125)
Finance × Maths score					0.004	−0.011‡
					(0.003)	(0.006)
Finance × Reading score					−0.003	0.010
					(0.004)	(0.008)
N	15,642	15,642	15,642	15,642	15,642	15,642
R^2	0.231	0.235	0.005	0.005	0.235	0.005

Notes: Dependent variable is monthly wage. BCS (NCDS) sample of men and women born in 1970 (1958) observed in 2004 and 2008. Conditioning on marital status, region of residence and year. Standard errors are in parentheses. *Significant at the 1% significance level. †Significant at the 5% significance level. ‡Significant at the 10% level. BCS, British cohort study; NCDS, national child development study.

skills have a better non-finance option and so a lower return to securing a job in the finance sector. There is therefore no case for higher maths ability being the source of the finance sector wage advantage.

VI. Technological change and task inputs

The final possibility that we consider is that the finance pay premium could be a consequence of workers having different job characteristics, as well as different personal characteristics. In this section we consider whether the finance sector has become more intensive in non-routine task inputs and computer use, as well as looking to see whether these factors can partially explain the financial pay differential. The GB Skills Survey (GBSS) provides usual information on the wages, human capital and socio-economic characteristics of workers, and also includes measures of computer use and job task inputs. The GBSS are cross sectional data available over a number of years, although the task input data are only collected since 1997. Consequently we use data from the 1997, 2001, 2006 and 2012 cross sections providing a sample of 8,294 respondents overall. Of these 8,294 workers, 1,857 (22%) are employed in finance. Again our sample is for workers aged between 16 and 65 and excludes the non-finance public sector. Gross hourly earnings are deflated into constant prices, using the RPI, though note these will exclude annually paid bonuses.

We consider the task input measures that arguably capture non-routine tasks (see Green, 2012). These are numeracy, literacy, problem-solving and influencing people. We also use

TABLE 9

Hourly wages, non-routine task inputs and computer use complexity, 1997 and 2012

	Non-finance			*Finance*			
	1997	*2012*	*2012 − 1997*	*1997*	*2012*	*2012 − 1997*	*Difference in the difference*
Hourly pay	6.561	6.966	0.405†	9.134	11.27	2.138†	1.732*
			(0.173)			(0.872)	(0.568)
Numeracy	1.847	1.897	0.062	2.117	2.170	−0.024	−0.086
			(0.056)			(0.113)	(0.121)
Literacy	2.175	2.323	0.148*	2.746	2.705	−0.041	−0.189‡
			(0.047)			(0.087)	(0.101)
Problem solving	2.697	2.751	0.054	2.892	2.810	−0.082	−0.135
			(0.043)			(0.084)	(0.092)
Influencing	1.954	2.165	0.210*	2.197	2.241	0.044	−0.166‡
			(0.040)			(0.076)	(0.085)
Computer complexity	1.224	1.496	0.271*	2.004	2.179	0.177‡	−0.095
			(0.049)			(0.097)	(0.106)
N	1,102	1,061		264	356		

Notes: GB Skills Survey sample of men and women observed in 1997, 2001, 2006 and 2012. All estimates are weighted using person weights. *Significant at the 1% significance level. †Significant at the 5% significance level. ‡Significant at the 10% level.

'computer use complexity' to measure technological input. The task input measures are derived from a range of questions asking respondents how important a certain skill is in their job, with respondents' options 'not important', 'not very important', 'fairly important', 'very important' and 'essential', ranging between 1 and 5. These various aspects of skill use are collapsed into five groups based on explanatory factor analysis.[34]

Table 9 shows that hourly pay, non-routine task inputs and computer use are generally higher in the finance relative to the non-finance sector. In terms of changes over time, the first row shows that the average hourly pay rate has increased in non-finance to 6.97 pounds per hour in 2012 and in finance to 11.27 pounds in 2012 and the final column shows that this increase in hourly pay is statistically larger in the finance sector relative to non-finance (by 1.73 pounds). However, although workers in the finance sector generally demonstrate higher non-routine task inputs and computer complexity *vis-à-vis* non-finance, if anything this gap is closing rather than widening (certainly in terms of literacy and influencing people). This therefore fails to support the idea that TBTC might be explaining the increase in the financial pay differential through changes in the relative quantities of non-routine tasks being performed.

Estimating an OLS financial log hourly pay differential, using the 1997, 2001, 2006 and 2012 cross sectional GBSS data (equation (1)),[35] we find a raw differential of 37%, which falls slightly to 36% once we condition on gender, marital status and region of residence. Allowing the financial pay differential to vary across highest national qualification frame-

[34] See Supplementary Table S4 for details, and Green (2012) for a detailed discussion on the construction of these non-routine task measures.

[35] See Supplementary Table S5.

work (NQF) level (and thus estimating equation (4)) again shows that the financial pay differential is largest for NQF level 4 which contains graduates (72%) and is negative for those with no qualifications (−21%). Conditioning further on non-routine task inputs and computer use complexity reduces these finance pay differentials, but they remain significant for graduates (40%), NQF level three workers (15%) and workers with no qualifications (−9%). So in terms of the increasing prices (wages) attached to non-routine tasks (which are presumably in higher demand through TBTC), there is little evidence that differences in non-routine task endowments can fully explain the existing finance pay premium.

In summary, we find no evidence that the higher levels of non-routine task inputs and computer use complexity observed in the finance sector can fully explain the finance pay premium, nor its increase. Conditioning on non-routine tasks and computer use reduces the differential but a significant premium remains, and exists for graduates and workers with NQF level three qualifications.

We can perform similar analyses, examining the finance sector pay premium controlling for qualifications and job tasks, as well as for adult tests of cognitive ability, across a wide range of 22 OECD countries, using the OECD 2012 Programme for the International Assessment of Adult Competencies (PIAAC) data.[36] Specifically, that data set contains information on monthly wages that contain bonuses, as well as test scores for numeracy, literacy and problem solving, along with information on non-routine task inputs for numeracy, reading, writing, influencing people and computer use complexity. The test scores capture adult cognitive skills rather than childhood skills, but the task input variables are very similar to those used in the GBSS above.

The PIACC data reveal that, in almost all countries, workers in the finance sector have higher adult test scores both for numeracy and literacy, perform more non-routine tasks in their job, and use computers to a greater level of complexity. We therefore estimate the financial sector pay differential, conditioning on these competencies. The PIAAC data are cross sectional observed only in 2012 so our estimating equations are again based on augmented versions of equations (1) and (4), estimated separately by country. Most of these countries have monthly wage data that include bonuses, but for five countries (Austria, Canada, Germany, Sweden and the US) the wage data are banded so that we are only provided with the decile to which each respondent's wage corresponds. For these countries we therefore perform interval regression, which is a generalization of the Tobit model but with variable cut-off points.[37]

The results reveal[38] that the raw finance wage differential is positive and statistically significant for most countries we observe (except for Japan, Russia and the Slovak Republic). The largest raw financial pay differential is 84% for Spain, closely followed by 70% for the UK which is close to that of 77% found earlier, using the NES for 2009–11 (Table 2).

The financial pay differential falls in most countries after conditioning on gender and age, including in the UK, Spain and the US. Further conditioning sequentially on test scores and non-routine task inputs reduces the financial pay differential still further. However, a

[36] See http://www.oecd.org/site/piaac/ for details.

[37] See Amemiya (1973) as well as Stewart (1983).

[38] See Supplementary Table S6.

significant differential remains for 17 of the 22 countries observed. The largest is still in Spain (49%), the second largest is in Germany (44%) and the third largest is in the UK (41%). This provides further evidence of finance pay premiums which cannot be explained by human capital or task variables, which are largest in Spain and the UK but which are prevalent in almost 80% of OECD countries.

VII. Conclusion

The UK finance sector wage premium is large and has increased over time. The largest finance sector returns go to male graduates, living in London, aged between 40 and 49 who are employed as dealers or brokers in the security broking sector. However, the premium is observed for different sub-sectors of finance, for different occupations, for workers with different qualification levels and also across most other OECD countries. Moreover, it can be found at all points of the pay distribution, not just at the mean. It therefore seems to be a pervasive feature of remuneration in the financial sector.

This paper has added to the literature about the finance sector wage premium in a number of ways. First, the descriptive statistics about the premium, as described in the previous paragraph, are more extensive than has previously been the case. In particular, studying the premium *within* occupation (while still controlling for unobserved worker heterogeneity with worker fixed effects) provides new evidence on the pervasiveness of the premium across occupations within finance. Second, we have provided new evidence on a possible rent-sharing explanation of the premium, estimating the elasticities of wages with respect to sector-level value added, and third we have also considered, and ruled out, a wider range of alternative explanations for the finance sector wage premium than is commonly the case.

None of the possible explanations for the finance sector pay premium, involving the characteristics of the workers in the finance sector, or aspects of the jobs that they do, can fully explain why finance sector workers are paid more than non-finance sector workers, or why the same worker moving between the two sectors sees his/her pay rise or fall accordingly (depending on direction of movement) even when doing the same job in both sectors. We therefore propose that the finance sector pay premium is, at least in part, due to the rent-sharing of that sector's profits. This conclusion is supported by the fact that the pay premium is prevalent across jobs at all points of the occupation hierarchy, for workers of all skill types, and at all points of the wage distribution. Furthermore, wages for a number of groups of finance workers are positively related to the value added produced in their sector, suggesting a sharing of rents produced in those sectors. This is the case for workers in the central bank, building societies, security brokers, activities auxiliary to finance, and most strongly for those working in fund management, for whom the elasticity of wages with respect to sectoral value added is approaching unity.

The final question to be answered is whether policy makers should be concerned. These are private sector workers (with the exception of the employees of financial institutions nationalized in the recent crisis), and it could be argued that whatever firms choose to pay these workers, particularly when it is a share of a generated surplus, is of no concern to public policy. However, there is the possibility that the large rewards in the finance sector could lead to an inefficient allocation of labour at the national level. We saw in Section IV that the finance sector is increasingly attracting graduates from the more numerate disciplines. The question for further research therefore becomes whether the finance sector is the optimal place for the most technically proficient workers to add the most social value.

Final Manuscript Received: August 2016

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Supporting Information

Additional supporting information may be found in the online version of this article:

Figure S1. Share of graduates working in the finance sector, by degree subject.
Table S1. Changes over time: Fixed effects estimates of the log annual gross pay finance differential 1996–2011.
Table S2. Quantile pay regressions for finance sector workers 1996–2011.
Table S3. Finance pay differential: NES panel 1996–2007: log real annual earnings.
Table S4. The composition of the specific task measures from the SES.
Table S5. OLS estimates of the finance hourly pay differential 1997–2012.
Table S6. Cross country finance sector log monthly pay differentials (including bonuses) for 2012.