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WAGE GROWTH AND HUMAN CAPITAL IN THE UK FINANCE SECTOR

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Abstract

Despite the recent financial crisis the UK financial pay premium has continued to rise. To some extent this is a consequence of increased skill intensity in the finance sector, but this paper shows that finance workers have higher cognitive skills, on average, and this partly explains their higher wages. These are significant across all post-secondary education groups and not just those at the top. However, after controlling for unobserved heterogeneity we still find unexplainable rents to finance sector workers which are largely a consequence of bonuses. Though we also show that finance workers are more likely to be insecure about their job especially those that receive higher bonuses. In keeping with the existing literature on inequality we estimate demand and supply models to explain increasing inequality between finance workers vis-à-vis other workers. We find that finance workers are not perfect substitutes for non-finance workers in production, which is consistent with them having higher cognitive skills. Finally, we find relative demand shifts in favour of finance sector workers which are partially correlated with increased financial innovation and technical change, but most importantly we find that these demand shifts are slowing down.

Keywords: wage inequality, financial services, cognitive skills, bonuses

JEL Codes: J20, J31, I24

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1. Introduction

Explaining wage growth in the UK financial sector has remained a relatively under researched area in economics, despite receiving a lot of attention in the European media and the recent implementation of the Capital Requirements Directive capping bankers 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 growth in the 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. But 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.

To get some idea to the extent of the labour market differences in finance vis-à-vis the rest of the economy, Figure 1 uses national taxation data collected by HMRC taken from the Survey of Personal Incomes (SPI) to plot employment shares and average annual earned income ratios for the financial sector relative to that for all the private sector between 1997 and 2009.[1] The finance employment share is relatively small and has remained fairly constant (and even fallen slightly) over time, from 0.057 in 1997 to 0.053 in 2009. But at the same time the financial sector earned income ratio is very large and has increased (from 1.81 in 1997 to 2.75 in 2009). This suggests that the average wage in the financial sector was almost three times as large as the average wage across the whole private sector in 2009. Consequently, the main aim of this paper is to try to explain this much larger, and increasing, wage premium in the financial sector. We do this by drawing upon existing theories and potential explanations from the existing literature on more general labour market inequality.

It has been well documented that some countries, most notably the US and UK, experienced substantial growth in labour market inequality over the last two to three decades.[2] This has led to an area of research investigating whether growing wage inequality can be explained through technical change. The basic idea is that the falling price of information technology has led to the substitution of routine labour for technology capital. As routine tasks tend to be performed in jobs situated in the middle of the job quality distribution, economies with access

[1] Following Philippon and Reshef (2012) most of our analyses excludes the public sector so that we focus specifically on explaining the private sector wage premium.
[2] See Acemoglu and Autor (2010) for a review of this literature.

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.[3] This process has become known as task-biased technological change (TBTC).[4] Here routine tasks are thought to be substitutes, whilst non-routine tasks are thought to be complements with new technology.

Whilst 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 try to explain long run wage growth in the US financial sector by looking for changes in relative skill intensity. They find that the US financial sector became more skill-intensive during the 1980s. However they also find that it was equally as skill-intensive in the 1930s and that the long–run skill-intensity in the US financial sector therefore displayed a U shape. Moreover, after controlling for skills they still find significant financial sector wage differentials which they attribute to rent sharing amongst financial sector workers. These rents are increasing in education levels. So again following the existing literature they investigate the role of technical change in explaining the more recent trends.

Philippon and Reshef (2012) find some evidence that TBTC played a role in explaining increasing financial wage differentials, since they find that financial occupations have become relatively less routine in terms of the tasks that workers perform and more complex in terms of their mathematical aptitude. However, given the long-run U shaped trend for skill intensity in the financial sector, coupled with the fact that technical change can only explain recent trends, they investigate whether financial deregulation had also been an important factor. They find that information technology played an indirect role facilitating recent innovation in financial products and services but also that financial deregulation in the 1980s stimulated innovation (and therefore also prior financial regulation in the 1940s stunted innovation) explaining increasing rents alongside increased financial risk.

In terms of UK evidence, Bell and Van Reenen (2010) document increasing `extreme' wage inequality by focussing on the income growth of the top 5 percent of British workers between

[3] See Katz and Murphy (1992), Autor, Katz and Kearney (2008) for the US and also Machin (2011) and Lindley and Machin (2011) for Britain.
[4] This concept was first introduced by Autor, Levy, and Murnane (2003) in their more refined treatment of skill bias technical change (SBTC). For a survey of the literature on SBTC see Katz and Autor (1999).

1998 and 2008. They find that 60 percent of the increase in this extreme wage inequality can be attributed to the growth in bonuses paid to workers in the financial sector. They suggest the existence of superstar effects since the dispersion of wages is higher in finance than in other sectors.[5] So in keeping with this idea, we investigate to what extent finance workers are paid more because they have better cognitive skills. This is related to, but not exactly the same as, superstar effects since we do not focus solely on chief executive pay. We also look for evidence of rent sharing which might be associated with increased financial risk. Financial workers could have an incentive to take more short term risks if they are paid handsomely for their results and beyond their marginal productivity. In the long run the worst that can happen to workers is that they lose their job (and keep their bonuses) but the banks have guarantors to protect them. Indeed Bell and Van Reenen (2013) find that the probability that finance workers remained in employment is the same as for non-finance workers, but that finance workers are less likely to be working for the same firm. So we might expect greater job insecurity amongst finance sector workers. Finally we estimate demand and supply models and look for potential drivers of demand shifts that have worked in favour of finance sector workers.

To preview our results, we find that the UK financial sector has become more skill intensive but we also find evidence of rents over and above those that can be explained through having better educated workers. Moreover, despite the financial crisis in 2007-2010, we show that the financial wage premium has continued to rise. So we investigate whether finance workers have higher cognitive skills. We find that finance sector workers have higher adult numeracy scores as well as higher childhood mathematics and reading test scores, on average, compared to non-finance sector workers. We also find that 19 percent of the observed financial monthly wage premium to graduates can be attributed to higher cognitive skills, with 58 percent being attributed to other unobserved heterogeneity and 23 percent to rent sharing, although this largely excludes bonuses. In the second half of our paper we look for potential explanations for increasing finance rents from bonuses. Job insecurity is higher in the finance sector and finance workers who receive higher bonuses also report significantly higher job insecurity, compared to non-finance bonuses receivers, even after controlling for unobserved heterogeneity. This is in line with the idea that bonus rents to finance sector workers are in part a consequence of greater unemployment risk. Finally we find that the

[5] See Rosen (1981) for a discussion of superstar effects.

relative demand for finance sector workers has increased but we also find that this is slowing down. Drivers of these financial relative demand shifts include financial product/service innovation and technical change, but only when technology is measured using computer software (not computer equipment) capital compensation intensity.

The paper is structured as follows. The next section provides a discussion on measuring the UK financial pay. Section three investigates to what extent the UK financial sector has become more skill intensive, whilst section four provides estimates of the conditional financial pay premium and section five investigates whether finance workers have higher cognitive skills on average, relative to non-finance workers. Section six explores job insecurity in the financial sector, paying particular attention to the role of bonuses. Section seven focusses on technical change as a potential driver of the growth in the financial pay differential, whilst section eight estimates demand and supply models. Section nine concludes.

2. Measuring Wages in the UK Financial Sector

This section discusses some important measurement issues relevant for estimating the financial 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 a large proportion of bonus payments, since these tend to paid at the end of the financial year. So for example, in the much utilised Labour Force Survey (LFS) where individuals are surveyed over five quarters and wages are surveyed twice a year but reported as weekly wages, only the wages of individuals surveyed in March/April will contain bonus receipts paid at the end of the financial year. The extent of the problem can be seen in Figure 2 where the finance employment share is only a little lower than in Figure 1 and demonstrates a similar pattern, but the financial sector average weekly wage ratio grew by only 0.05 (1.47 in 1997 and 1.52 in 2008) which is much lower than that for earned income in the SPI which grew by 0.4 (1.81 in 1997 and 2.21 in 2007). This renders wages in the LFS as unsuitable for capturing relative wage growth in the financial sector. So we turn to the British Household Panel Survey (BHPS) an alternative dataset.

The BHPS is a national longitudinal dataset which contains questions on annual earned income and bonuses since 1997.[6] 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. Figure 3 contains finance employment shares and annual earned income ratios between 1997 and 2008 using the BHPS. The employment share again displays a similar pattern to that observed in Figure 1 although the proportions are slightly higher at around 0.07 in 2008 (compared to 0.05 in 2007). However, the growth in the financial sector average annual earned income ratio is more similar to that found in the SPI at 0.28 (from 1.32 in 1997 to 1.60 in 2008) although the levels are still lower. One can see that total annual earned income from the BHPS provides a higher financial premium than using monthly wages, but if anything our analysis using the BHPS will underestimate the true extent of the financial wage premium compared to that suggested by the SPI. However, the other main advantage of using the BHPS as opposed to the LFS for the purpose of explaining the financial wage premium is that it is a longitudinal dataset which therefore allows the estimation of panel data models to control for unobserved heterogeneity.

3. Is the Finance Sector More Skill Intensive?

Clearly higher average wages in the finance sector could be explained by better qualified workers on average, in the finance sector relative to all other industries. So we begin by investigating whether the finance sector has become relatively more skill intensive. It has been well documented that the total employment shares of graduates has increased, for example Lindley and Machin (2012) use the LFS to show that the employment share of graduates increased from 0.14 in 1996 to 0.23 in 2006 and to 0.31 in 2011. But what has happened in finance? The first panel in Figure 4 uses the LFS to show that the finance employment share of graduates has increased from 0.05 in 1997 to 0.06 in 2008. Hence the proportion of graduates employed in finance in 2008 is larger and has increased, compared to the employment share of finance workers in the private sector which has fallen slightly (0.04 in 2008, from Figure 2). Rather interestingly, the second panel in Figure 4 shows that this

[6] 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. Unlike Bell and Van Reenen (2010) we do not use the Annual Survey of Hours and Earnings (ASHE) data here because this does not provide information on qualifications or schooling.

increase in graduate intensity has mainly come from postgraduate workers. The finance employment share amongst graduates has remained relatively constant at 0.06, whilst the finance employment share for postgraduates has increased by 0.02. In 2008 over 5 percent of all postgraduates (including those in the public sector) were employed in the financial sector compared to 6 percent for graduates. So clearly the finance sector is getting relatively more skill intensive.

So what can we say about changes in the subject majors of finance graduates? The two lower panels in Figure 4 show that the finance employment share is much larger for maths/computing graduates, management/business graduates and economics graduates, with the latter demonstrating the largest increases.[7] In 2008 over a quarter of all economics graduates were employed in the financial sector. Figures for maths/computing and management/business were 10 percent and almost 15 percent respectively in 2008. Given these subjects are by nature more numerical, this also suggests numerical skill upgrading (mainly from economics graduates) in the financial sector, even within the graduate group. So the financial sector is becoming more skill intensive by increasing its share of postgraduate workers and more numerically skill intensive by increasing its employment share of economists. Consequently we now turn to estimating conditional financial pay differentials.

4. Estimates of the Conditional Financial Pay Premium

In this section we estimate the conditional financial pay premium using the data described earlier from the BHPS by estimating standard Mincer style wage equations. We use two measures of wages. Firstly we use monthly wages (excluding bonuses) and annual labour income (including bonuses). Both are inflated into constant 2011 prices using the RPI. This provides 52,185 observations over the 1997-2008 period excluding missing values and workers from the non-finance public sector. We keep financial public sector workers in our sample because of the nationalisation of some banks (like for example the Royal Bank of Scotland in 2008). Including non-finance public sector workers strengthens our results in that

[7] The subject of degree question in the LFS refers only to the undergraduate degree and therefore we do not know the subject of postgraduate qualifications. For detailed definitions of the subjects listed in Figure 4 see Lindley and McIntosh (2012).

they are qualitatively the same but the financial premiums are everywhere larger. Of our 52,185 observations 3,588 (6.87 percent) are finance sector workers. The average monthly wage over the period is £1,958 and the average annual labour income is £22,636. In finance this is £2,536 and £32,191 respectively.

Table 1 compares the educational distribution of the BHPS sample for finance and non-finance workers, as well as providing average monthly wage and annual income. The finance sector is relatively better qualified on average since graduates, some college and 2 plus A level workers are over-represented compared to the distribution in the non-finance sector. In order to provide sensible sample sizes our wage equations combine postgraduates and graduates into one composite group, as well as other and no qualifications. Table 1 also shows that monthly wages and annual incomes are higher in the finance sector relative to the non-finance sector across all education groups.

Table 2 provides the OLS estimates for the financial wage premium. We condition on marital status, region of residence, age, age squared and year dummies. The conditional log monthly wage differential over the period is 0.225 which suggests that wages in the financial sector were around 26 percent higher than in the rest of the private sector. The second column shows significant variations over education groups, with graduates receiving the largest financial monthly wage differential (0.566 log percentage points) with no significant differential to workers with 2 A levels or lower/no qualifications. The third column provides the conditional log annual labour income differential which, not surprisingly, is higher at 0.29l log points. The final column shows that this is only statistically significant for graduate and some college workers. Notice also the including bonuses seems to make more difference to the finance premium of some college workers, more so than for graduates.

Since the BHPS is a panel data set we are able to control for individual unobservable heterogeneity by estimating a fixed effects model. This sweeps out any of the fixed biases between the covariates and the error term in the OLS wage/income equations. This is especially important given that finance has a relatively large proportion of economics and maths graduates, as well as having increased its postgraduate share.

Table 3 provides the fixed effects estimates. Both the finance monthly wage and annual income premiums fall (compared to the OLS estimates) which suggests positive biases between finance workers and the un-observables (like gender, cognitive skill, postgraduate qualifications, subject of degree etc). The first column shows evidence of higher monthly wages in finance using the fixed effects estimator, but adding in bonuses doubles the premium (from 7 to 13 log points). The second and final columns show that there is no significant monthly wage financial premium for graduates. It is only when we add bonuses in that we get a significant graduate financial premium. Also the difference between the monthly wage premium and the annual income premium is increasing in education levels. For example, the graduate monthly finance wage premium is zero but once bonuses are included the differential is 17 log points. For other/no qualification workers, adding in bonuses increases the differential by only 3 percent (from 7 percent for monthly wages to 10 percent for annual labour income).

Overall Table 3 suggests that bonuses do explain a large part of the higher wage premium in the financial sector more so for graduates and some college workers. Comparing Tables 2 and 3 shows that conditioning on unobserved heterogeneity suggests higher ability graduates and some college finance workers. This is not the case for workers with lower education levels where controlling for the fixed effects suggests OLS biases in the opposite direction. But our fixed effects estimates provide a similar sized financial labour income differential across all education groups.

Table 4 shows how the fixed effects financial annual labour income premium has changed over the time period we cover. It is necessary to pool years of data here into three year intervals to obtain reasonable sample sizes. Table 2 shows that the average over the full period is 0.127 log percentage points, but this has increased over time from being zero in 1997-1999 to being 0.139 log percentage points in 2006-2008. This last time period is the period of the financial crisis and therefore the financial annual income premium shows no signs of slowing down despite the start of the great recession in 2008.

In short, we find evidence of a financial wage premium for all workers which is larger when we include bonus payments (especially for graduates and some college workers) even after controlling for unobserved heterogeneity. This suggests rent sharing through finance bonuses, across all education groups. Our fixed effects finance premium is lower than the OLS estimates which is suggestive of higher cognitive skills for finance graduates and some college workers. But we cannot say how much of the unobserved heterogeneity observed here is a consequence of cognitive skill differences. We return to this issue in the next section of the paper.

5. Do Finance Sector Workers Have Higher Cognitive Skills?

In this section we investigate to what extent the finance premium might be a consequence of higher cognitive skills amongst finance workers, paying particular attention to differences in adult numeracy skills, as well as childhood mathematics and reading skills. We start by looking at whether finance workers have better adult and childhood numeracy skills on average and we then we go on to estimate finance wage premiums conditioning on our measures of cognitive skills.

We draw upon the British Cohort Survey (BCS) which is a sample of men and women born in 1970 and the National Child Development Survey (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 age 38 (50) and questions were asked on various socio-economic and work characteristics of the respondents. The surveys provide information of gross pay, highest educational qualification, industry of employment, marital status, gender and region of residence. Similar follow-ups were undertaken in 2004 but in addition to the standard socio-economic questions, respondents in the BCS were also tested for their numeracy skills.

5.1 Differences in Adult and Childhood Test Scores

The 2004 BCS contains more than one measure of adult numeracy skills. We use the score from all 23 numeracy questions that were asked but we also use the derived numeracy level variable which is coded into five categories. Given that finance workers could be more numerate only because their job involves more numerical tasks, we additionally use childhood test scores for mathematics and reading taken when the respondents were aged 10 and 11. The BCS 1980 and NCDS 1969 follow-ups provide reading and mathematics tests. We think these childhood measures are better measures of cognitive skill since they were undertaken before the respondent was influenced by secondary and higher education, but more importantly before they started work in the finance sector.

Our initial BCS sample consists of 5,968 individuals of which 378 (6.3 percent) are employed in Finance. Table 5 shows that there is a significant financial differential in terms of both adult numeracy measures. This is largest for graduates and workers with A-levels. Of course we would expect this and the causality here is questionable. But Table 6 shows that childhood mathematics and reading scores were also higher in finance relative to workers in other sectors. Although this is only statistically significant for mathematics for post-secondary educated workers, as well as reading skills for all workers. So this provides better evidence that most finance workers have higher cognitive skills, on average, relative to non-finance workers.

Table 7 shows the same as Table 6 but for 6,790 workers from the NCDS who were 46 in 2004. The average finance differential for maths scores is 4.39 which is similar to that for the BCS for 34 year olds (4.59).[8] This shows that maths and reading test scores are again higher in finance, but much more so for maths skills. The finance differential for reading is lower (1.723) relative to that for the BCS (4.51). The financial graduate maths differential (13.07) is slightly larger that found in the BCS (11.99), the same is true for some college workers (7.92 compared with 5.12 from the BCS). This suggests that finance sector college workers might be becoming less numerate over time, whereas finance A-level workers are becoming more numerate since the maths test score in finance is higher in the BCS (8.88) than from the NCDS (6.98). All finance workers appear to have become relatively more competent in reading.

5.2 Wage Equations

Given we can observe the same respondents both in the 2004 and 2008 BCS and NCDS we can estimate panel data wage equations to control for cognitive skills, whilst also controlling for other unobservable heterogeneity.[9] In the BCS and NCDS respondents are asked the question *`the last time you were paid, what was your gross pay before deductions'*. Unfortunately the 2004 BCS (and NCDS) do not include questions for annual labour income

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[8] 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. The 1999 NCDS (age 41) provides a financial differential (standard error) on maths scores of 5.53(0.549) and on reading scores of 2.09 (0.324). This suggests that the older cohort has higher cognitive mathematical skills but lower reading skills.

[9] 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. Annual income is not included any of the datasets. 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.

or bonuses, so we are faced with the familiar problem of potential under-reporting. For example, only 665 (14 percent) of our 4,693 BCS sample with reported earnings listed their gross earnings responses as being annual.[10] Nevertheless we continue to estimate financial earnings premiums using log monthly gross pay, bearing in mind that these are likely to be under-estimates of the total financial income premium.

We start by estimating the pooled OLS financial wage premium without conditioning on cognitive skills, we then also estimate the same using fixed effects to control for unobserved heterogeneity and finally we do the same conditioning on cognitive skills. Our sample consists of 15,642 individuals of which 1,063 (6.3 percent) are employed in finance. We control for marital status, region of residence, age and year.[11] We can only control for childhood test scores here since the NCDS does not provide measures for adult test scores. Table 8 provides the pooled OLS and fixed effects estimates for the finance premium.[12] The first and third columns in show that the average financial wage premium falls (from 0.235 to 0.052 log points) when we control for unobserved heterogeneity, though the fixed effects estimate is not statistically significant for individual education groups. This is slightly lower than that found using monthly wages from the 1997-2008 BHPS from Table 3 (0.067 log points). Of course one cannot tell to what extent the fall from the OLS to the fixed effect estimate is a consequence of cognitive skills or other unobserved heterogeneity. So in the final two columns we condition on childhood test scores to control for cognitive skills. The pooled OLS financial childhood maths premium is 0.009 log points showing that in finance there is a greater return to childhood maths scores relative to not being employed in finance, on average. The estimate of the graduate wage premium falls from 0.852 to 0.693 suggesting cognitive skills explain 0.159 log points of the financial wage premium. For some college workers the cognitive bias is 0.132 log points (based on a fall from 0.526 to 0.394) and for A-Level workers this is 0.115 log points (based on a fall from 0.269 to 0.154). The final

[10] 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 use employment income.

[11] The number of individuals is 9345 and these are observed on average 1.7 times.

[12] We get a slightly smaller OLS estimate for the financial wage premium (0.235 log points) when we pool the 2004 and 2008 datasets compared to that found for just 2004 (0.290 log points) reflecting the fact that the average financial pay premium has fallen over time. Of course we might expect this since the 2004-2008 period covers the start of the financial crisis, although the finance premium for graduates has actually increased (0.852 log points using the pooled data compared to 0.782 in 2004). The same can be said, but to a greater extent for `some college' workers (0.526 compared to 0.456 in 2004) and to a lesser extent for `A-Level' workers (0.269 compared to 0.261 in 2004). It is the finance workers with `Other Qualifications' that completely lost their financial wage premium (zero compared to 0.126 log points in 2004) during the onset of the financial crisis.

column conditions on unobserved heterogeneity and show that the financial wage premium is now only statistically significant for graduates (0.198). This suggests that 0.495 (0.693-0.198) of the graduate financial pay differential is a consequence of unobserved heterogeneity with a remaining unexplainable rent of 0.198 log points.

In summary, of the 0.852 financial wage premium enjoyed by graduates in 2004-2008, 19 percent can be attributed to cognitive skill differences, 58 percent can be attributed to other unobserved heterogeneity and 23 percent remains as unexplainable rents. For some college workers, 25 percent of the 0.526 financial pay differential can be attributed to higher cognitive skills with the remaining 75 percent being attributed to unobservable heterogeneity. For A-level workers 43 percent of the 0.269 finance pay premium can be attributed to higher cognitive skills with the remaining 57 percent a consequence of difference in other unobservables. After conditioning on cognitive skills and unobserved heterogeneity, we find evidence of substantial finance rent sharing using monthly wages, but only for graduates.

6. Job Insecurity in the Financial Sector

In this section we investigate whether job insecurity is higher in the financial sector and therefore whether bonus receipts might compensate workers for greater unemployment risk. That is, do workers in finance experience greater job insecurity and is this larger for workers that receive relatively larger bonuses? Hence we look at whether the higher financial rents from bonuses observed in Tables 2 to 4 might be associated with greater fear of unemployment.

Of our 3,588 finance sector workers from the 1997-2008 BHPS, the percentage that reported themselves as being completely secure in their job was 17.11 percent (compared to 22.24 percent for 48,597 non-finance sector workers). So finance workers are 5.12 percent significantly more likely to be insecure about their job, on average.[13] Table 9 provides conditional Probit estimates for the likelihood of job insecurity in the finance relative to other non-finance sector workers. Equivalent estimates using a linear probability model are provided in Table A1 of the Appendix. After conditioning on marital status, region of

[13] This differential has a standard error of 0.007 and so is statistically significant.

residence, age, age squared and year dummies, finance workers are 4.6 percent more likely to be insecure about their job. The second column in Table 9 includes bonus receipts, as well as an interaction between bonuses and whether the respondent works in the finance sector.[14] Although higher bonuses reduce job insecurity in the non-finance sector, in finance bonuses increase job insecurity by 7.70e-06 percent for each pound received in bonuses, on average.[15] The third and fourth columns provide the fixed effects estimates which although are smaller, still demonstrate higher job insecurity in the finance sector of 5.20e-06 percent for each pound of bonuses received.[16]

7. Technical Change and Task Inputs

In this section we investigate potential drivers of financial wage premiums by looking for descriptive evidence of TBTC in the finance sector. The GB Skills Survey provides information on computer use but also task inputs for two cross sections of workers. These are surveyed in 1997 and 2006 providing a sample of 2467 and 4800 respondents respectively. The first panel in Figure 5 plots the proportion of respondents who reported using a computer in their job by industry in 2006. Not surprisingly the proportion is high for most industries with Finance being the highest at 0.98. The second panel reports the number of workers using a computer for complex procedures. This involves using a computer for advanced statistical analysis and/or programming. The proportions are highest in Finance and Utilities at around 40 percent each.

Panels three to five in Figure 5 provide the proportion of workers reporting tasks that are either `very important' or `essential' in their job. The third panel refers to performing statistical or mathematical tasks. The highest is in Finance (0.37), with Manufacturing being the next highest (0.27) and most other non-service industries also reporting around a quarter of workers. This supports our findings in the previous section where finance sector workers were found to have higher mathematical aptitude relative to non-finance workers. The service sector and farming are generally lower (Distribution/Catering, Transport/Communication, Health/Social Work, Other Services and Agriculture).

[14] Respondents are asked the total value of bonuses received in the last 12 months.
[15] Since 3.56e-06 -2.79e-06 = 7.70e-06.
[16] Since 1.71e-06 -1.19e-06 =5.20e-06.

The fourth and fifth panel refers to `analysing complex problems' and `product knowledge' again we can see that in Finance workers reporting these tasks as important are relatively high. The final panel provides the proportion of workers who report performing repetitive tasks in their job either `often' or `always'. Now Finance is one of the lowest with only 36 percent of workers reporting frequent repetitive tasks in their job, compared to 61 percent in Distribution/Catering.

So we have established that Finance is relatively technical in terms of complex computer use and in mathematical/statistical task performance, but also that more finance workers use computes to undertake complex procedures, are required to have product knowledge and fewer of them perform repetitive tasks. Figure 6 looks at the change over time since 1997. There is little evidence that computer use has increased more in finance but that's not surprising since such a large proportion of workers use computers, though finance workers reporting complex computer use has increased over the period by 0.8 percent although finance isn't really at outlier compared to other sectors. The same can be said for the change in workers reporting maths/statistics and those analysing complex problems. There seems to always have been more workers in finance performing these tasks (or at least from the start of our period in 1997). There was a fall in the proportion of workers reporting product knowledge (-0.005) and repetitive tasks as important (-0.002). The fall in repetitive task performers is only higher in Utilities (-0.009) and has increased in most other industries (with Real Estate/Business, Other Services and Construction being exceptions). This is indicative of TBTC but the changes over the period we cover are not really that large, relative to those also observed in other sectors.

8. Changes in the Demand and Supply of Finance Sector Workers

Given that the financial annual pay premium has increased whilst finance sector employment shares have remained fairly constant (and even fallen slightly), to get some idea of how much demand has shifted in favour of finance sector workers we draw upon the Katz and Murphy (1992) canonical model of relative supply and demand:

$$\log\left(\frac{W_{1t}}{W_{2t}}\right) = \frac{1}{\sigma}\left[D_t - \log\left(\frac{E_{1t}}{E_{2t}}\right)\right] \qquad (1)$$

where, in the original paper, W_{1t}/W_{2t} is the relative wage between college graduates and high school graduates and E_{1t}/E_{2t} is the relative supply of college graduate workers relative to all non-graduates workers at time t. The elasticity of substitution between graduate and non-graduate workers is given by σ. [17]

Our estimating equation is a modified version of the Katz and Murphy (1992) estimating equation:

$$\log\left(\frac{W_{1t}}{W_{2t}}\right) = f(t) + \gamma \log\left(\frac{E_{1t}}{E_{2t}}\right) + \varepsilon_t \qquad (2)$$

where W_{1t} is the mean annual gross pay for finance workers and W_{2t} is the same for all workers at time t. Similarly, E_{1t} is employment for finance sectors workers, whilst is E_{2t} employment for non-finance sector workers. Demand shifts are captured by f(t) which is measured using time trends. Also $\gamma = -1/\sigma$, where σ is now the elasticity of substitution between finance and non-finance sector workers. We take our data from the industry level Annual Survey of Hours and Earnings (ASHE) data available from NOMIS.[18] Pay is measured annually in ASHE and therefore includes bonuses.[19]

Table 10 provides the results for the Katz-Murphy model for 1997-2012. The first specification includes a linear time trend and suggests that the relative demand for finance sector workers has shifted by 0.012 log points per year which is around 19 percent over the full 16 year period. The elasticity of substitution is around 1.27 which suggests that finance sector workers are not perfect substitutes for non-finance workers in production. Of course we would expect this given that childhood test scores are higher amongst finance sector workers across all post-secondary education groups. Also the previous section showed that

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[17] The starting point in this approach is a Constant Elasticity of Substitution production function where output in period t (Y_t) is produced by two groups of workers (E_{1t} and E_{2t}) with associated technical efficiency parameters (θ_{1t} and θ_{2t}) as follows: $Y_t = (\theta_{1t}E_{1t}^{\rho} + \theta_{2t}E_{2t}^{\rho})^{1/\rho}$ where $\rho = 1 - 1/\sigma_E$, and σ_E is the elasticity of substitution between the two groups.

[18] We use Table 4.7a which is available to download from http://www.ons.gov.uk/ons/publications/re-reference-tables.html?edition=tcm%3A77-235202.

[19] The ASHE data do not contain qualifications or education levels so we cannot further distinguish between skill groups here.

more finance workers perform mathematical/statistical tasks and analyse complex problems. The second column of Table 10 includes a quadratic time trend in equation (2).[20] The elasticity of substitution is now 1.29. The quadratic time trend is statistically significant which suggests that the relative demand for finance sector workers is increasing over the period but at a decreasing rate, with the turning point at 2011.62. Hence the increasing demand for finance sector workers since 1997 is slowing down.

To look for potential drivers of these demand shifts we use equation (1), and calculate demand from:

$$D_t = \log\left(\frac{E_{1t}}{E_{2t}}\right) + \sigma \log\left(\frac{W_{1t}}{W_{2t}}\right) \qquad (3)$$

We then use D_t as the dependent variable in a series of regressions on various potential drivers for finance sector relative demand shifts. The first is the graduate share in finance. Clearly if the financial sector is becoming more skill intensive this should partially explain the relative demand shifts. We calculate these shares from the LFS. Our next potential driver is the share of workers with job insecurity in finance. These are taken from the BHPS and are based on the job insecurity measure used in the previous section. We also include two measures to capture technological change. These are capital compensation in computer equipment and software as a share of total capital compensation in finance. These are taken from the EU KLEMS database.[21] Capital software intensity is intended to be a more nuanced measure of technical change which would not be subjected to the same upper bound as would computer use and also but to a lesser degree, expenditure on computer equipment.[22] Finally, to capture financial product and service innovation we include the log of published trademarks per worker from the `insurance, financial affairs and monetary affairs, etc' category. These are taken from various Intellectual Property Office (IPO) Facts and Figures publications and are publically available for 2002-2012.[23]

[20] We also included a cubic time trend but this was statistically insignificant.

[21] Taken from the EU KLEMS data October 2012 release.

[22] Beaudry, Doms and Lewis (2010) critically appraise the extent to which the widespread use of personal computers reflects a technological revolution.

[23] According to the IPO `a trade mark is a sign which can distinguish your goods and services from those of other traders. A sign includes, for example, words, logos, pictures or a combination of these.' A trade mark can be used as a marketing tool so that customers can recognise products or services. A published or registered trade mark, gives the owner the legal right to take action against anyone who uses that mark or a similar mark on the same or similar goods and services.

Table 11 provides the results.[24] We use demand shifts calculated from the second column in Table 10 which assumes an elasticity of substitution of 1.29. Not surprisingly there is a positive correlation between finance sector skill intensity and relative demand shifts for finance workers, although there is no statistical relationship between financial demand shifts and job insecurity. The share of finance capital compensation on software is also positively correlated with finance sector demand shifts, though compensation for computer equipment is not. Including graduate intensity and software capital intensity together suggests that technical change is partially driving these demand shifts, even after conditioning on increasing skill intensity, but only through computer software and not through equipment. The final two columns in Table 11 demonstrate that financial trademarks are correlated with financial worker demand shifts, even after conditioning on software capital intensity and skill intensity. So overall, financial innovation is a driver of recent UK finance sector demand shifts, with technical change (via software capital) also being important and skill intensity less so.[25]

9. Conclusion

The UK financial wage premium has increased over time. This is in part because of skill upgrading in the financial sector, although differences in skills and unobservable heterogeneity cannot completely explain the financial pay premium which is largely a consequence of increased bonus remuneration. This pay premium is enjoyed across all education groups and not just those at the top.

We find evidence of higher cognitive skills based on higher adult numeracy scores and childhood test scores for financial sector workers relative to non-finance workers, on average. These are the largest for graduates and workers with A-levels. We also find evidence that cognitive skill explains around 19 percent of the graduate financial monthly wage differential, with 58 percent being attributed to other unobserved heterogeneity and 23

[24] All regressions use the robust Huber-White sandwich estimator of variance-covariance matrix.

[25] The derived demand, computer software and graduate share variables are all integrated of order one I(1), whereas log of financial trademarks per worker is integrated of order 2. The Engle-Granger two step procedure shows that all four of the I(1) variables (hence using the change in log trademarks per worker) are co-integrated suggesting that a long run relationship exists between them.

percent remaining as unexplainable rents. The unexplainable rents provide a 0.198 log percentage point (21.89 percent) graduate financial pay premium, after conditioning on differences in cognitive skills and unobserved heterogeneity. Using the BHPS 1997-2008 data, this amounts to £695.25 more in monthly wages and £8,262.69 in annual income, evaluated at the average graduate monthly wage of £3,176.10 and annual income of £37,746.45.

The paper also quantifies the extent to which the demand for finance sector workers vis-à-vis non-finance workers has increased. We show that finance workers are imperfect substitutes for non-finance sector workers in production. This is likely because of their higher cognitive skills across all post-secondary education groups and because they perform more complex and mathematical tasks. However, we also show that the relative demand shifts are increasing but at a decreasing rate. The main drivers are financial innovation and technical change, but only when technology is measured using computer software capital intensity (not for computer equipment).

Overall the paper finds evidence that finance workers do have higher cognitive skills and this partly explains their higher wages. Over and above this they earn unexplainable rents which are largely a consequence of bonuses. But they are also more likely to be insecure about their job. Finance workers who receive higher bonuses report significantly higher job insecurity, whereas non-finance bonus receivers report significantly lower job insecurity, even after conditioning on unobserved heterogeneity. So the rents they receive might act as compensation for this insecurity. Demand has shifted towards finance workers, but most importantly we find that the demand shifts are slowing down. This could be a consequence of the financial crisis and the eschewing backlash against the sector, placing increasing pressure on the financial sector to regulate bonuses. Or more worryingly this could be a consequence of a slowdown in financial innovation and/or technical change. It will be interesting to see what happens to this demand once the banker's annual salary cap is implemented in 2014.

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Figure 1. Finance Employment Shares and Annual Earned Income 1997-2009 (SPI).

Employment Share | Ratio of Average Annual Earned Income

Notes: For Finance relative to all other private sector workers. Data are weighted.

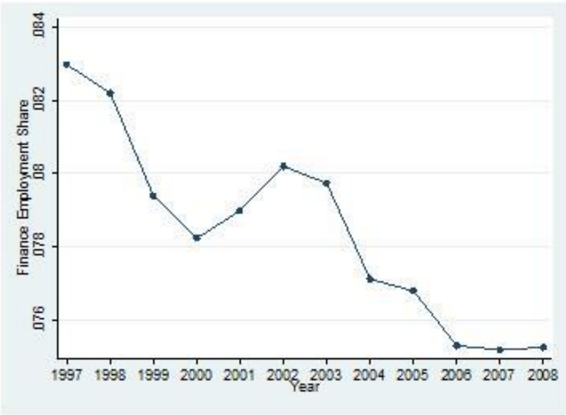
Figure 2. Finance Employment Shares and Weekly Wages 1997-2008 (LFS).

Employment Share in Finance | Ratio of Average Gross Weekly Wage

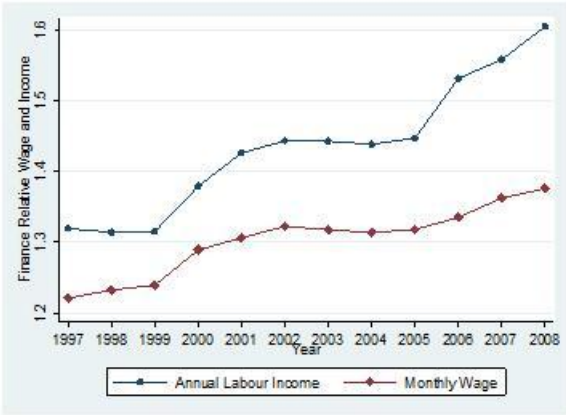
Notes: Weighted using person weights. Employment shares are for employed men and women aged 16-65. The wage sample excludes the self-employed and the non-finance public sector.

Figure 3. Finance Employment Shares, Income and Wages 1997-2008 (BHPS).

Employment Share in Finance



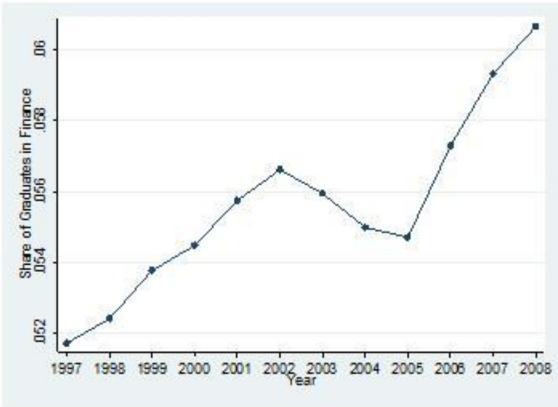
Annual Earned Income and Monthly Wages



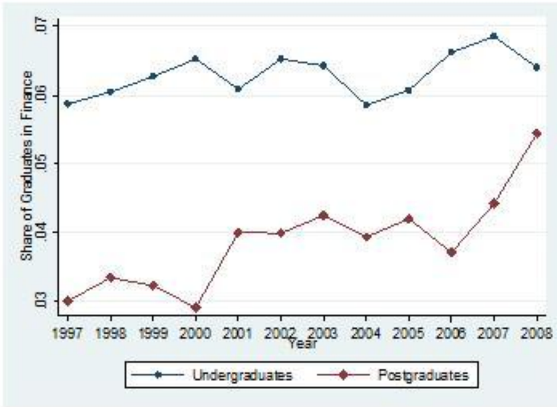
Notes: For employed men and women aged 16-65 (excluding the self-employed and the non-finance public sector).

Figure 4. Finance Employment Shares of Graduates 1997-2008 (LFS)

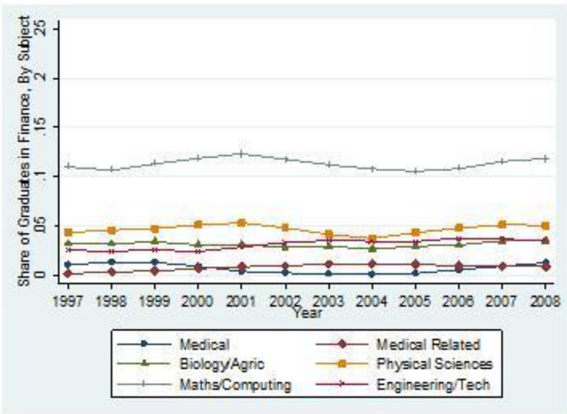
All Graduates



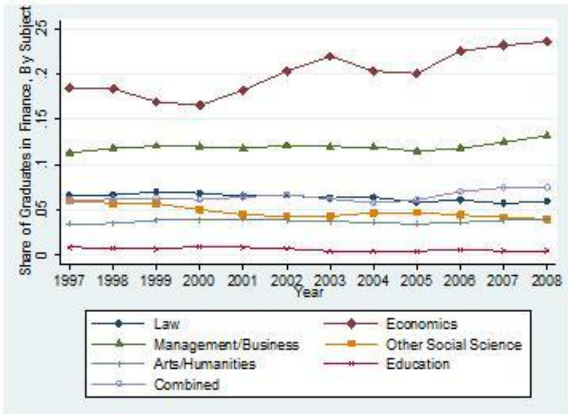
College Only and Postgraduates



STEM Graduates

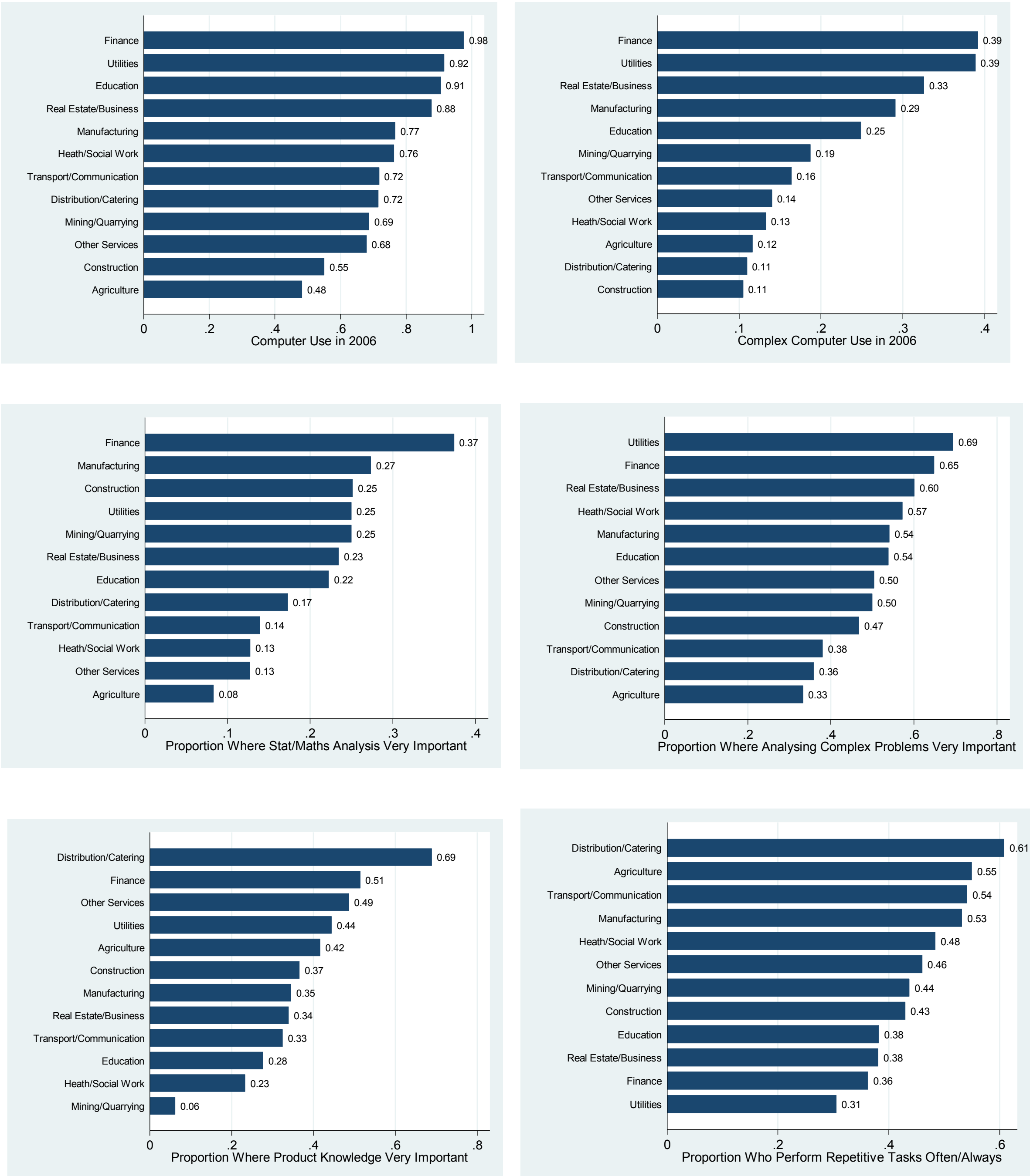


Non-STEM Graduates



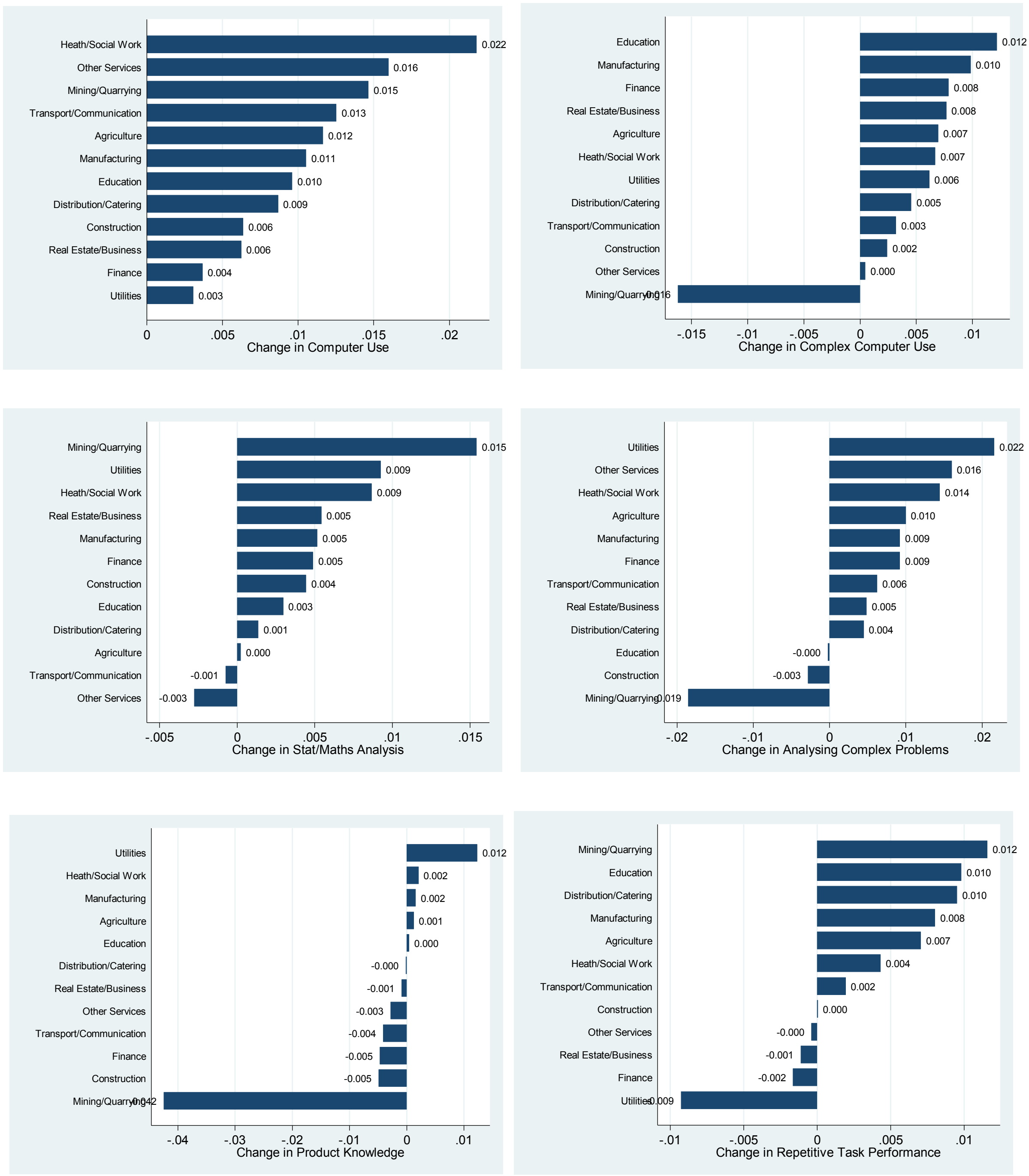
Notes: Weighted using person weights. Employed men and women aged 16-65.

Figure 5. Proportion Using a Computer and Performing Various Task Inputs in 2006 (GB Skills Survey).



Notes: For employed men and women aged 16-65.

Figure 6. Change in the Proportion Using a Computer and Performing Various Task Inputs 1997-2006 (GB Skills Survey).



Notes: For employed men and women aged 16-65.

Table 1. Monthly Wages, Annual Income and Highest Qualifications by Sector, 1997-2008

	Non-Finance			**Finance**		
	Percent of Sample	Mean Monthly Wage	Mean Annual Income	Percent of Sample	Mean Monthly Wage	Mean Annual Income
Postgraduates	2.16	3702.86	43422.54	2.98	4188.04*	52478.74*
Graduates	9.46	3119.47	36343.55	18.92	3582.71*	47820.22*
Some College	17.68	2266.91	26191.96	20.90	3226.08*	43076.60*
2 Plus A Levels	14.60	1935.30	22034.68	24.00	2075.04*	25005.04*
Other Qualifications	44.02	1607.75	18200.33	30.55	1740.61*	20070.38*
No Qualifications	12.10	1341.79	15316.33	2.26	1775.66*	21376.14*
N		48597			3588	

Notes: BHPS sample of men and women age 16-65.* denotes statistically significant from non-finance at the 5 percent level. Excluding the non-finance public sector.

Table 2. OLS Estimate of the Finance Income Differential 1997-2008

	Log Monthly Wage		Log Annual Labour Income	
Finance	0.225* (0.125)		0.296* (0.128)	
Finance*Graduates		0.566* (0.122)		0.582* (0.125)
Finance*SMC		0.482* (0.128)		0.611* (0.132)
Finance*2 Plus A Levels		0.089 (0.122)		0.166 (0.126)
Finance*Other Q		-0.055 (0.124)		0.008 (0.128)
N	52185	52185	52185	52185
R Squared	0.101	0.677	0.144	0.149

Notes: BHPS sample of men and women age 16-65. Conditioning on married, region, age and age squared. Year dummies are also included, clustering on industry. Excluding the non-finance public sector.

Table 3. Fixed Effects Estimate of the Finance Income Differential 1997-2008

	Log Monthly Wage		Log Annual Labour Income	
Finance	0.067* (0.013)		0.127* (0.022)	
Finance*Graduates		0.049 (0.029)		0.172* (0.047)
Finance*SMC		0.058* (0.030)		0.125* (0.049)
Finance*2 Plus A Levels		0.085* (0.028)		0.120* (0.045)
Finance*Other Q		0.067* (0.023)		0.097* (0.038)
N	52185	52185	52185	52185
R Squared	0.070	0.069	0.110	0.111

Notes: BHPS sample of men and women age 16-65. Conditioning on married, region, age and age squared. Year dummies are also included. Excluding the non-finance public sector.

Table 4. Changes Over Time: Fixed Effects Estimates of the Finance Log Annual Labour Income Differential 1997-2008

	Finance Indicator	N	R Squared
1997-1999	0.022 (0.055)	11428	0.003
2000-2002	0.106* (0.049)	14929	0.084
2003-2005	0.115* (0.042)	13226	0.007
2006-2008	0.139** (0.071)	12617	0.144

Notes: BHPS sample of men and women age 16-65. Conditioning on married, region age and age squared. Year dummies are also included. Excluding the non-finance public sector.

Table 5. BCS: OLS Estimate of the Finance Differential for Adult Test Scores

	Total Numeracy Test Score (from 23 Questions)		Numeracy Level	
Finance	1.644* (0.219)		0.419* (0.057)	
Finance*Graduates		3.170* (0.538)		0.823* (0.140)
Finance*SMC		1.928* (0.487)		0.524* (0.127)
Finance* A Levels		2.549* (0.578)		0.715* (0.151)
Finance*Other Q		0.842* (0.299)		0.181* (0.078)
N	5968	5968	5968	5968
R Squared	0.026	0.029	0.028	0.031

Notes: BCS sample of men and women born in 1970 and observed in 2004. Conditioning on gender.

Table 6. BCS: OLS Estimate of the Finance Differential for Childhood Test Scores

	Maths Test (Age 10) (from 72 Questions)		Reading Test (Age 10) (from 54 Questions)	
Finance	4.590* (0.610)		4.515* (0.560)	
Finance*Graduates		11.993*(1.497)		9.788* (1.376)
Finance*SMC		5.124* (1.356)		5.063* (1.247)
Finance*A Levels		8.878* (1.608)		7.836* (1.479)
Finance*Other Q		1.041 (0.832)		1.855* (0.765)
N	5968	5968	5968	5968
R Squared	0.012	0.020	0.016	0.022

Notes: BCS sample of men and women born in 1970 and observed in 2004 (age 34). Conditioning on gender.

Table 7. NCDS: OLS Estimate of the Finance Differential for Childhood Test Scores

	Maths Test (Age 11) (from 40 Questions)		Reading Test (Age 11) (from 35 Questions)	
Finance	4.392* (0.622)		1.723* (0.416)	
Finance*Graduates		13.069* (2.00)		6.157* (1.340)
Finance*SMC		7.925* (1.540)		3.083* (1.032)
Finance*A Levels		6.985* (1.359)		3.241* (0.910)
Finance*Other Q		0.989 (0.828)		0.039 (0.554)
N	6790	6790	6790	6790
R Squared	0.008	0.014	0.003	0.006

Notes: NCDS sample of men and women born in 1958 and observed in 2004 (age 46). Conditioning on gender.

Table 8. BCS and NCDS: Estimate of the Finance Monthly Gross Pay Differential in 2004 & 2008

	Base Model				Conditioning on Child Test Scores	
	Pooled OLS		Fixed Effects		Pooled OLS	Fixed Effects
Finance	0.235*		0.052**			
	(0.025)		(0.031)			
Finance*Graduates		0.852*		0.129	0.693*	0.198**
		(0.067)		(0.080)	(0.098)	(0.118)
Finance*SMC		0.526*		0.002	0.394*	0.062
		(0.062)		(0.080)	(0.088)	(0.109)
Finance*A Levels		0.269*		0.038	0.154**	0.087
		(0.060)		(0.078)	(0.084)	(0.103)
Finance*Other Q		-0.077		0.048	-0.099	0.088
		(0.034)		(0.048)	(0.061)	(0.072)
Finance*Maths Score					0.009*	-0.002
					(0.003)	(0.004)
Finance*Reading Score					-0.008**	0.002
					(0.004)	(0.005)
N	15642	15642	15642	15642	15642	15642
R Squared	0.041	0.051	0.005	0.005	0.051	0.005

Notes: 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.

Table 9. Estimates for the Likelihood of Job Insecurity 1997-2008 (Marginal Effects)

	Probit		Mundlak Approximation to a Fixed Effects Probit	
Finance	0.046*	0.048*	0.012	0.010
	(0.019)	(0.019)	(0.016)	(0.016)
Bonus Receipts		-2.79e-06*		-1.19e-06*
		(9.84e-07)		(4.84e-07)
Finance* Bonus Receipts		3.56e-06*		1.71e-06*
		(9.70e-07)		(8.44e-07)
N	52185	52185	52185	52185

Notes: BHPS sample of men and women age 16-65. Conditioning on married, region, age and age squared. Year dummies are also included, clustering on industry. Excluding the non-finance public sector.

Table 10. Katz-Murphy Demand and Supply Model, 1997-2012

$$\log\left(\frac{W_{1t}}{W_{2t}}\right) = f(t) + \gamma \log\left(\frac{E_{1t}}{E_{2t}}\right) + \varepsilon_t$$

	Linear Trend	Quadratic Trend
Log Relative Supply	-0.787* (0.319)	-0.776* (0.292)
Trend	0.012* (0.003)	0.029* (0.097)
Trend Squared		-0.010** (0.0005)
Constant	-1.871** (0.935)	-1.891* (0.854)
R Squared	0.826	0.866
N	16	16

Notes: The dependent variable is the log of the average finance wage relative to the total average wage taken from ASHE 1997-2012. Standard errors in parentheses.

Table 11. Demand Shifts, Skill Intensity, Technological Change and Innovation

	Implied Relative Demand Shifts, $\log(E_1/E_2) + \sigma \log(W_1/W_2)$						
Finance Graduate Share	0.846*				0.729*		-0.228
	(0.309)				(0.311)		(0.554)
Finance Job Insecurity Share		0.185					
		(0.149)					
Finance Computer Equipment Share of Capital			-2.590				
			(0.716)				
Finance Computer Software Share of Capital				1.697*	1.006*		4.601*
				(0.919)	(0.404)		(1.058)
Log of Financial Trademarks per Finance Worker						0.233*	0.197*
						(0.081)	(0.082)
Constant	-2.454*	-2.399*	-2.202*	-2.662*	-2.679*	-0.827	-2.145*
	(0.076)	(0.135)	(0.093)	(0.227)	(0.106)	(0.481)	(0.552)
R Squared	0.556	0.126	0.005	0.274	0.642	0.304	0.522
N	16	16	16	16	16	11	11

Notes: The dependant variable is implied demand calculated using the quadratic model in Table 10 so that $\sigma = 1.29$.
Standard errors are in parentheses.

Appendix

Table A1. Estimates for the Likelihood of Job Insecurity 1997-2008

	Linear Probability Model		Fixed Effects LPM	
Finance	0.044* (0.019)	0.041** (0.019)	0.011 (0.015)	0.010 (0.016)
Bonus Receipts		3.13e-06* (1.19e-06)		-1.30e-06* (4.83e-07)
Finance* Bonus Receipts		-3.40e-06* (1.18e-06)		1.41e-06* (5.73e-07)
N	52185	52185	52185	52185

Notes: BHPS sample of men and women age 16-65. Conditioning on married, region, age and age squared. Year dummies are also included, clustering on industry. Excluding the non-finance public sector.