“Since you’re so rich, you must be really smart”:

Talent and the Finance Wage Premium

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Abstract

Relative pay in the financial sector has experienced an extraordinary increase over the last few decades. A proposed explanation for this trend has been that the demand for skilled workers in finance has risen more than in other sectors. We use Swedish administrative data, which include detailed cognitive and non-cognitive test scores as well as performance in high-school and university, to examine the implications of this hypothesis for talent allocation and relative wages in the financial sector. We find no evidence that the selection of talent into finance increased or improved, neither on average nor at the top of the talent and wage distributions. A changing composition of talent or their returns cannot account for the surge in the finance wage premium. These findings alleviate concerns about a “brain drain” into finance at the expense of other sectors, but they also suggest that rents in finance are high, increasing, and largely unexplained.

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1 Introduction

Since the 1980's, relative wages in the finance industry have risen dramatically in many countries around the world (e.g., Philippon and Reshef, 2012, Bell and Van Reenen, 2013, and Boustanifar et al., 2014). As a partial explanation of these patterns, Philippon and Reshef (2012) propose that financial deregulation in the 1980's led to an increase in skill intensity and job complexity in finance relative to other industries, and that finance wages, especially for skilled workers, increased as a consequence.

These findings raise important issues about the competition for talent across sectors and its implications for the allocation of talent in the economy, which we aim to address in this paper. First, the results of Philippon and Reshef (2012) and Célérier and Vallée (2015) suggest that a significant part of the increase in finance wages is due to the increase in the marginal productivity of talented workers in finance (i.e., finance has become more skill-biased). Consistent with this hypothesis, Goldin and Katz (2008), Oyer (2008), or Shu (2013) document that a large fraction of students from top universities have joined the finance sector in recent decades. Moreover, to the extent that higher wages may draw talent into the financial sector, this could also have negative effects on the productivity of other sectors in the economy (Baumol, 1990; Murphy et al., 1991). Exploiting variation in financial liberalization across countries and time Kneer (2013a,b) argues that financial deregulation led to a flow of talent into finance, which resulted in a reduction in productivity in non-finance skill intensive industries.

In this paper we use administrative records for the whole population of Sweden in the period of 1990 to 2013 to examine whether finance has become more skill-biased during the last two and a half decades and whether it has increasingly absorbed talent from other sectors. Our earnings data from tax records is uncensored, includes bonuses and other variable pay, and contains separate information on capital income as well as disposable income after taxes and benefits. We focus on talent related to innate ability, rather than education and other investments in human capital (e.g., acquisition of specific skills on the job). Talent has the benefit of being largely exogenous to career choice, and it is less sensitive to composition changes over time compared to education. Our primary measures of talent are fine-grained ability assessments from military enlistment at age 18-19, including cognitive and non-cognitive test scores, which are available for most of the male Swedish population. In addition, we use detailed information from secondary education, such as grade, program, and school characteristics, which are also available for the female part of the population. The level of detail in the data also allows us to analyze the right tails of the talent and earnings distributions.[1] Recent research has found that test scores, and cognitive performance in particular, are among the most important predictors of innovation (Bell et al., 2016), so the compensation and allocation of talent with respect to these variables may have first-order consequences.[2]

We obtain no evidence at all in support of the idea that a rising productivity of skill in finance has caused its surging earnings or drawn more talented workers into the sector. In none of our measures, and neither on average nor at the top of the distribution, do we find an increased talentedness of finance. Observed and unobserved talent, or rising returns to talent, also cannot explain the finance earnings premium. We further find that finance pay rises across very detailed occupations, many of which are lower-skilled and not finance-specific, that hours worked have not increased, and that demand for (skilled) finance workers from abroad also remained unchanged. Our results indicate that substantial wage premia for working in finance built up over time and that they did not get competed away even in the mid-run by more (talented) workers entering the sector. On the flipside, concerns about a large absorption of talent into finance (and for that matter, law, consulting, and accounting) appear unsubstantiated.

We start by showing that the finance wage premium in Sweden increased strongly over the last 24 years, similar in level and in fluctuations to the US and the UK.[3] Relative finance earnings rise (and fluctuate) more when we add capital income to our main labor earnings, and they increase to a similar extent when we use disposable income after taxes and benefits. The dispersion within the sector also rises substantially, with top 1 percent earners in finance receiving almost three times the pay of top 1 percent earners outside it, but in fact every relative quantile improves (i.e., the shift in relative finance earnings is first-order stochastically dominating). Additional data we collected

[1] Unless otherwise noted, all our information from the Swedish registers are linked to each other on the individual worker or firm level, which allows us to have one single large micro-database with a rich amount of information about each individual unit.
[2] Previous research employing similar Swedish data has also shown that our talent measures are strong predictors of future income, as well as other socio-economic outcomes such as unemployment, health, divorces, illicit activities, and becoming a manager or CEO (see e.g., Lindqvist and Vestman, 2011; Håkanson et al, 2012; and Adams et al, 2014).
[3] Throughout the paper, we benchmark our facts to the US when data for the latter is available.

reveal that finance earnings were rising at least since the beginning of the 1980s and therefore were not just catching up after the 1991-92 Swedish banking crisis.

We then directly analyze whether more talent has selected into finance, together with or as a consequence of the sector's strongly rising wages.[4] We show that, while in levels more talented than the rest of the economy, finance's average or relative talent has not increased over time according to any of our measures. If we compare finance to other high-talent sectors like law, consulting, and accounting (LCA) or information technology (IT), we also find strongly rising wages but no increase the relative talent of finance (on average LCA has higher and IT much higher cognitive ability than finance, so measurable talent in finance has not reached a ceiling). The same findings hold true if we only focus on the share of top talented individuals according to our ability measures or the ability of top 95 (99) percent earners, and if we focus on 30 year olds whom we use as a proxy for recent entrants into the labor market. When we run choice regressions controlling for other skill determinants such as education and experience as well as for other sector determinants such as parents' jobs, municipality, and high-school, we do not find any increased role of talent for entering finance over time. The sector's share of overall employment also remains constant, implying that there is no inflow of low-talent individuals that offsets an increased talent-intensity of finance labor demand.

Our second main test of the skill-bias hypothesis examines the relationship between talent and earnings.[5] Running wage regressions controlling for standard Mincer variables as well as our cognitive and non-cognitive measures, or using fixed effects on the individual and the individual-firm level, do not explain the increase in the finance premium. It is unlikely that demand for other (initial) skills is the driving force, because these would have to be uncorrelated with our multiple observable talent proxies and not be part of the individual fixed effects. Allowing for a time-varying overall return to talent only marginally affects the rise in the finance premium. Together with the rising finance wages relative to other high-talent sectors (i.e., ALC and IT), this suggests that

[4] In the appendix we show in a standard two-sector Roy model that rising skill-bias of finance generally leads to more workers or increasingly talented workers entering this sector. A superstars or polarization-of-talent-demand version of the model predicts that more top-talented workers should enter finance and that the relative talent of finance top earners should rise.

[5] The standard Roy model with increasing finance skill-bias predicts that controlling for talent or fixed effects should substantially reduce the measured finance wage premium. The wage premium should also rise more for more talented workers and for top talented workers in particular. The task or occupation composition in finance should change strongly and the wage premium should not rise in occupations that are not finance-specific.

economy-wide increases in skill demand are not the explanation. Importantly, the finance premium also does not rise more for high- than for mid-ability individuals (though it fluctuates more). When we analyze different subsectors and in particular detailed four-digit occupations, finance pay rises across the board. That is, not only business professionals and accountants, but also secretaries, tellers, and even doorkeepers earn increasingly more inside finance than outside it over time.

Finally, we present some further important tests. Using additional survey data, we find that hours of work in finance are high, especially in markets-related activities, but that they have not increased over time. This also reassures us that average trends in our annual earnings measure reflect increases in average wage rates. Talented workers and finance workers are more internationally mobile than average, but the (relative) migration rates of (talented) finance workers have not increased over time. The task composition of finance does not shift from routine towards abstract or service tasks more than other high-talent sectors or the economy overall. We draw 95 percent confidence in all figures in order to illustrate the statistical significance of our analyses.

While it is not clear that all of our results are generalizable beyond the Swedish context, the Swedish financial sector is in many respects comparable to that of countries such as the US and the UK. As in the UK and the US, the Swedish financial market was deregulated in the mid-1980's, and growth of the industry has been comparable in these countries over our sample period. We show that the time-series of both relative wages, xxx relative growth in value added (?) xxx, and relative education in the finance sector look remarkably similar in Sweden and the US.[6] While the finance wage premium in Sweden increased from more than 20% in 1991 to almost 70% in 2013, the finance wage premium in the US increased from about 20% to almost 50% over the same period.[7]

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[6] Boustanifar et al. (2015) analyze the development of relative finance wages for 22 different countries (using data from KLEMS), and find that not all countries display similar patterns. In particular, deregulation is an important predictor of increasing finance wages and relative skill in their data. Although Sweden has a smaller finance sector than the US and UK, it is still sizable compared to many other countries.

[7] Moreover, previous research has documented that the post-secondary and college education shares of workers in finance compared to the real economy have risen substantially (e.g., Philippon and Reshef, 2012, and Boustanifar et al., 2015). We show that this is also true for Sweden., but we also show that overall post-secondary and college education attainment rates in the population have increased substantially over our sample period, and, as a consequence, the average talent highly educated workers has declined. This suggests that the increase in relative education is not a sign that more talented individuals are going into finance over time, but rather that conditional on talent, an individual entering the sector in recent years is more highly educated than before. Consistent with this, Boustanifar et al. (2015) do not find that higher skill-intensity as proxied by relative university shares explains the dynamics of the finance wage premium in a panel of countries from 1970 to 2005. In contrast, our talent measures, which are immune to such

The paper is structured as follows. The next section documents the striking relative wage facts in finance. Section 3 summarizes the related literature and lays out the main hypotheses brought forward to explain these facts. Then we test the talent selection into finance (Section 4) and whether talent or skill can explain the wage premium (Section 5). Section 6 conducts the main robustness checks. In addition to concluding the last section provides a macro-perspective on the allocation of talent across the overall economy. In the text we refer to several additional tests and a formal model that are in the appendix. We also introduce the respective registers as we go along, while a detailed description of all data sources is relegated to Appendix Section XXX.

2 The Finance Wage Premium in Sweden and the United States

We present the main stylized facts about finance earnings and its distribution as well as employment, sector profits, and performance for Sweden and the United States.

2.1 Income Data and Definition of Finance Sector

We draw on the longitudinal integration database for health insurance and labor market studies (LISA) provided by Statistics Sweden (SCB), which is our main dataset to which the other information is linked. The database presently holds annual registers since 1990 and includes all individuals 16 years of age and older that were registered in Sweden as of November for each year. The dataset contains employment information (such as employment status, the identity of the employer, and wages) as well as demographic information (such as age, basic education information, family composition).

Our main measure of earnings is the annual labor income from the largest source of income, in case somebody has multiple employers. One advantage of having annual earnings compared to hourly wages is that they include bonus payments that are likely an important part of compensation in finance. We use the terms earnings and wages largely interchangeably in the following, because we focus on trends rather than levels and show in Section 6 that hours worked in finance have neither changed in Sweden nor the US. We also analyzed fulltime workers only and found qualitatively the same results. In the paper we further compare finance to other sectors with high earnings and high working hours, professional services (law, consulting, and accounting) and

composition effects (the high school grades are scaled to achieve this), do not indicate any increase for finance workers over time.

information technology. In robustness checks we also include capital gains (annual labor income plus annual capital gains) and other benefits and deductions (disposable income). None of these income measures are top-coded or censored. To compare wages over time, we deflate all earnings using the official consumer price index.

We define individuals' sectors according to the Swedish Standard Industrial Classification (SNI) code reported for the establishment at which they are employed. The SNI classification is based on the European Union's NACE standard. Our sample years are covered by the SNI1992 (1990-2001), SNI2002 (2002-2010), and SNI2007 (2011-2013) classification. We construct a balanced SNI industry code for the years 1990-2013 based on the SNI2002 by aggregating non-unique mappings between SNI1992, SNI2002, and SNI2007.[8]

To arrive at our analysis sample, we first drop all observations with incomplete data (e.g., missing gender information or age). Following Edin and Frederikson (2000), we only keep workers whose declared labor income exceeds the minimum amount of earnings that qualifies to the earnings related part of the public pension system. In 1998, this amount was 36,400 SEK per year, approximately 4,500 US$ in contemporary exchange rates. Finally, in line with Philippon and Reshef (2012) we only keep workers who are dependently employed in the private and non-farming sector, although including self-employed workers does not change the results. This selection process results in a sample of about 79.2 million individual-year observations. Table 1 provides summary statistics for our sample.

2.2 Drastically Rising Pay in the Finance Sector

The first row of Figure 1 depicts relative average pay in finance compared to the rest of the economy during our main sample period. Relative average pay is defined as the ratio of the average pay in finance and average pay in the non-financial, nonfarm private sector. In the top left panel of Figure 1, we see that in Sweden annual labor earnings in finance were about 20 percent higher than the rest of the economy in 1990 and that they rose to about 60 percent higher in 2013.[9]

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[8] In the financial sector, there is no loss of information for subsectors and aggregation works perfectly for SNI1992 and SNI2002 (1990-2010). For the mapping with SNI2007, finance subsectors have to be aggregated substantially and other sectors' definitions change even on the one-digit level. Therefore, there can be small continuities in the time series between 2010 and 2011.

[9] Our preferred Swedish earnings measure, declared annual labor income (deklon), is not available in 1990. Instead a related measure with only the labor income for which employers have notified the tax authorities (loneink) is available.

The top right panel of Figure 1 depicts the comparison to the US. Similar to Philippon and Reshef (2012), we use hourly wages from the Current Population Survey (CPS; for details see Flood et al., 2015). US finance wages rise from almost 20 percent to around 45 percent above the wages of the rest of the economy. In the Sweden as well as the US, relative finance pay is higher for males than for females, but it rises for both genders. Moreover, there appears to be some co-movement between the series in both countries. In particular, after the crisis of 2001 relative finance pay, specifically for males, dropped substantially, but it quickly recovered.

In the figure, the level of relative finance pay is slightly lower in the US than in Sweden because the CPS data are top coded and hourly wages do not include end-of-year bonuses and other payments. Philippon and Reshef (2012) therefore approximate (top) wages using US Industry Accounts. Comparing our Figure 1 to Figure 1 in Philippon and Reshef (2012), we observe that also the level of relative pay in finance is about the same in Sweden and the US. We further show in Section 6 that working hours in finance have not changed during our main sample period, and thus trends in hourly wages reflect trends in earnings and vice versa. We corroborate this finding by directly computing trends in hourly wages from the Swedish Labour Force Survey. The 95 percent confidence intervals drawn around the estimates illustrate the high precision afforded by the Swedish population data, while there remains some variability for the US evidence.

The second row of Figure 1 shows that the rapidly rising earnings in finance are not simply a catching up after the economic crisis of the early 1990s, which in Sweden was a severe banking crisis. Using an administrative 3-4% sample data for the period 1978-1992 (LINDA; refer to Edin and Fredriksson, 2000, for a detailed description), we see that rising finance earnings constituted a long-running trend in the U.S. as well as Sweden from the early 1980s onward.

The third row of Figure A1 (left panel) includes capital income in the relative finance earnings series and uses only disposable income after taxes and benefits. Moreover, relative wages in finance only in Stockholm, where many finance employees work and reside, and where living costs are

Both of these measures are highly correlated and we use the relationship between them for the years 1991-1993 to predict each individual's deklon in 1990. The second row of Figure 1, using LINDA data from 1978 up to and beyond 1990 verifies that this is not a problem.

very high and rising, are plotted (right panel).[10] Relative disposable income rises about as much as (gross) labor income, labor plus capital income and relative earnings in Stockholm rise even slightly more.

Finally, the top left panels of Appendix Figures A1 and A2 compare finance earnings to earnings in two other high-talent, high working hours, and high-earnings sectors: Law, Consulting, and Accounting (LCA), which are among the main professional services industries, and information technology (IT), respectively. We see that even compared to these sectors, average finance earnings are growing strongly. In fact, they start out below average earnings in both sectors but end up substantially above them.

2.3 Constant Employment Size of the Financial Sector

The fourth row of Figure 1 depicts the employment share of finance over time, measured as number of workers in the financial sector divided by the total number of workers in the nonfarm private sector. As discussed below, one reason why talent in finance may not rise is that employment of the sector is growing and thereby drawing in marginal workers who are less talented.

The left panel shows the employment share of finance in Sweden. The share of employment in finance among females is somewhat higher than among males, but narrowing over time. However, the overall employment share is constant. In the U.S. (right panel), again using CPS data, these facts are similar. In particular the finance employment share is not rising, although the levels are different (the finance employment share is about 5-5.5% in the US).[11]

2.4 Finance Sector Performance

This Section summarizes the finance sector's overall profits and per employee (relative to GDP), stock market index, etc.

2.5 The Distribution of Finance Earnings Becomes Even More Extreme

An important advantage of our administrative population data for Sweden, including end-of-year bonuses, is that we can estimate all parts of the wage distribution with precision. Figure 3 depicts

[10] About 45 percent of overall and 80 percent of top 5% earning finance workers in Sweden are working in Stockholm. These (top) employment shares in finance are comparable to London's share in the UK (Bell and Van Reenen, 2013a).

[11] In the UK, the finance employment share declined slightly from around 5.7 percent to 5.3 percent between 1997 and 2009 (Lindley and MacIntosh 2014).

the relative percentiles of finance pay in Sweden compared to the respective percentiles in the rest of the economy (including 95 percent confidence intervals). Relative finance wages are strongly upward trending for all percentiles of the wage distribution over our sample period. Year-to-year fluctuations are larger for the top of the distribution, especially for the 95th and 99th percentiles, underscoring that bonus payments and other performance-based compensation are particularly important for this group. Bell and Van Reenen (2013) document similar findings for the UK.

Despite the large fluctuations at the top, the differences between percentiles are increasing over time. Therefore, finance's relative wage distribution is "fanning out", with the top percentiles experiencing the largest gains. While median finance earners obtain a 20 percentage point increase in their relative earnings from 1990 to 2013, the top percentile increase is over 100 percentage points. This implies that in the end of the 2000s, the very top earners in finance take home around 2.5 to 3 times as much pay as the very top earners in the rest of the economy. Nonetheless, the relative downside risk of pay in finance is not increasing, as all relative earnings quantiles are rising (i.e., the shift in relative finance earnings is first-order stochastically dominating). We further show below that earnings in finance are rising across detailed occupations, including very high-skilled as well as middle- and low-skilled jobs, that earnings risk did not rise during the financial crisis either, and that the firing risk has also not increased.

Finally, the large level and increase of finance wages at the top of the distribution is also reflected by finance workers' representation among the highest percentile earners. The share in our data of top 1 (0.1) percent earners who hail from the financial sector increased from 9 (16) to 16 (29) percent respectively during 1991-2010 (not tabulated but available upon request). These shares are of a similar magnitude to the ones that have been documented for the US and the UK.[12]

[12] Using UK administrative records, Bell and Van Reenen (2013b) show that almost the entire increase in the earnings share of top earners during 1999-2008 is due to the finance sector. For the US, Philippon and Reshef (2012) estimate that the fraction of finance workers in the top decile of earners in the nonfarm private sector increased from 1.3% in 1979 to around 10% in 2009. Kaplan and Rauh (2010) calculate that a subset of the highest paid finance workers (financial firm executives, investment bankers, hedge fund managers, and VC and private equity managers) account for 5-10% of the top 0.5% of earners in 2004, and roughly twice this fraction of the top 0.01%. They also argue that the fraction of this group of finance workers in the top earnings distribution has increased substantially over time. Guvenen et al (2014) use administrative records for the US and estimate that workers in Finance, Insurance, and Real Estate (FIRE) accounted for 18.2% of the top percentile of earners over the period of 1983-2006

3 Economic Hypotheses

3.1 Hypotheses in Previous Literature

First of all, our paper is related to the emerging research documenting the allocation and compensation of human capital in the finance industry, such as Kaplan and Rauh (2010), Philippon and Reshef (2012), Bell and Van Reenen (2013), Lindely and Macintosh (2014), and Boustanifar et al (2014).

Combining data from the U.S. Census and the Current Population Survey, Philippon and Reshef (2012) document that relative wages are higher in finance overall, and increased significantly over the period 1985-2005. They propose an explanation for this based on the mid-1980s financial deregulation together with technological developments in IT, which increased the demand for skilled labor in the financial sector, resulting in higher salaries for skilled workers. Consistent with this explanation they also find that relative education in finance followed a similar pattern to relative wages over this period (higher and increasing); while the size of the financial sector, measured by the employment share, remained relatively flat. They estimate that finance sector can explain 8% of the increase in the college premium over this period. 13

Using data on occupational titles and task skill intensities, Philippon and Reshef (2012) also present evidence that finance jobs became more complex and non-routine following deregulation in the mid-1980s. Their analysis further shows that the increase in relative finance wages is particularly pronounced at the top of the income distribution, with finance contributing to 6.2% of the increase in 90/10 inequality and 15% of the increase in 97/10 inequality in the U.S. Consistent with this, Kaplan and Rauh (2010) and Bell and Van Reenen (2013) find that the increase in the finance wage premium is concentrated at the top percentiles of the wage distribution.

Boustanifar et al (2014) extend Phillipon and Reshef's analysis to international data, examining relative finance wages for 22 industrialized and transition economies over the period 1970-2005. They use the EU KLEMS database, which has aggregate wage data by industry and education level (college vs not) for each sector over time. Boustanifar et al (2014) report significant heterogeneity in the evolution of wages across countries, with about half the countries experiencing an increase

[13] Related to this, Juhn et al (1993) and Lemieux (2006) show that wage inequality has increased substantially within the group of college-educated workers in recent decades.

in relative wages over their sample period. Consistent with Phillipon and Reshef, they find that finance was a main contributor to the increases in the wedge between skilled and unskilled labor for many countries, and that the finance wage premium is driven more by changes in skilled vs unskilled wages rather than a changes in the educational composition in finance. They also suggest deregulation as a main factor causing increases in relative wages in finance, while IT played a relatively minor role.

A limitation of these papers in testing the skill-intensity hypothesis is the reliance of college education as the sole measure of human capital. As pointed out by Philippon and Reshef (2014), "although education is a good indicator of human capital, it is far from perfect. There is significant variation in human capital within educational groups and the meaning of any particular level of education may not be stable over time. For example, high school graduation indicated relatively more human capital before the expansion of college education than after."

The unique feature of data set we use in our analysis is that we observe direct measures of different dimensions of human capital (e.g., cognitive and non-cognitive skills) whose distributions are stable over time and are not based on outcomes (e.g., share of top-earners (Philippon and Reshef, 2012)). In addition, there is considerably more dispersion in our talent measures compared to simple education measures, which enables us to test the correlation between talent and wages at the top of the distribution. This is important given that increases in finance wages have been found to be particularly pronounced in the right tail. Moreover, our data set includes matched worker-firm data, which enables us to test new predictions regarding several other potential determinants of the finance wage premium. We can also use the rich panel structure of our data to examine hypotheses related to earnings risk.

While we believe that we probably have the best available measures of skills for a large and representative sample, there is also other research that does not rely purely on education. Celerier and Vallee (2014) use the ranking of French engineering schools, the admission to which depends on the results of a nationwide test, to rank graduates from these schools into ten "talent groups". They argue that increases in relative finance wages can be explained completely by increases in the sector-specific payoff to talent, i.e., it is the top talent groups that drive the relative increase in finance wages.

Shu (2013) looks at bachelor students from MIT and employs “the index score” which is a weighted average of objective measures such as standardized test scores, high school grades, and the difficulty of high-school courses. Shu does not have access to wage data, but focuses on occupational choice and does not find any increase in the proportion of talented MIT graduates starting a career in finance between 2006 and 2012.[14] Though the samples in Shu (2013) and Celerier and Vallee (2014) are interesting, they are very specific and not likely to be representative neither of the population nor of the financial sector workers, which limits the ability to draw general conclusions based on their findings.

The research that is closest to ours in that spirit is Lindley and Macinthosh (2014), who examine data on numeracy skills from the British Cohort Study (BCS) and the National Child Development Study (NCDS) in the UK. Lindley and Macinthosh find that finance college workers have not become relatively more numerate over time, but that instead their numeracy slightly declined.[15] These results rely on a very small sample, however, as there are only 378 finance workers in the BCS, and covers only two cohorts, which prevents them from accounting for composition effects in the financial sector.

We also contribute to the literature that studies negative externalities of high wages in the financial sectors for the allocation of skills (“brain drain”), either within a country and between different sectors (see Shu (2013) and Kneer (2013b)) or between different countries (see Kneer (2013a) and Boustanifar, Grant, and Reshef (2014)). Using an indirect approach, Kneer (2013b) finds that labor productivity in non-finance sectors falls after the relaxation of US interstate banking restrictions. She attributes this to more talented people moving into finance and concludes that the financial sector absorbs talent at the expense of the real economy. On the contrary, Shu (2013) does not find any increase in talented workers going into finance for her sample of MIT graduates between 2006 and 2012. Exploiting the recent financial crisis as an exogenous shock to the number of vacancies in the financial sector, Shu presents further evidence suggesting “that finance does not attract the most productive scientists and engineers from MIT”.

[14] The proportion is actually declining from about 12% in 2006 to about 4% in 2012 which she attributes to the financial crisis.
[15] We also find a slight decrease of some dimensions cognitive over time. This trend is, however, neither economically nor statistically significant.

3.2 Focus on Skill-Based Explanations

- Philippon and Reshef (2012), other Reshef papers
- Cellerier and Vallee (2016)
- Kaplan&Rauh, Lindley&MacIntosh, Goldin&Katz, Shu, Kneer,

3.3 Testable Predictions from a Roy Model

A Simple Roy Model of Finance Sector Choice and Wages is spelled out in Appendix A. This model provides the following empirically testable predictions from a general version of the skill-based explanation of rising finance wages (in Section 4.2):

- Average talent in the financial sector relative to the average talent in the real economy increases over time.
- Top talent in the financial sector relative to top talent in the real economy increases over time.
- Talents become more important for choosing a career in the financial sector increases over time.
- The changing composition of skills in the financial sector and the changing economy-wide return to talent explain (at least a significant part of) the trend in the financial wage premium.
- The rising implies that the finance wage premium rises more strongly for high(er)-talent workers. Moreover, the premium for the lowest talent workers stays flat.

4 Has the Financial Sector Become More Talented?

4.1 Rising Relative Education in Finance May Be Misleading

In addition to the rising pay in finance, several studies have documented high and rising relative skill levels in the finance sector (e.g., Philippon and Reshef, 2012, for the US; Boustanifar et al., 2015, for a panel of developed countries), using relative education as a proxy for skill. Following Philippon and Reshef (2012) we use education groups as a first proxy for skill. We assign individuals *education groups* based on their highest level of education. Our main groups of interest are "post-secondary education" and "university degree", which are classified in the same way as in Philippon and Reshef (2012).

In the top left panel of Figure 4 we use our Swedish data to plot the relative share of individuals who attained more than a high-school degree (*postsecondary education*) and of those who attained a university degree (*university education*) in finance compared to the rest of the economy. We see that the increase in relative education is present also in the Swedish data, with relative postsecondary (university) education increasing from about 2% (2%) in 1990 to 15% (12%) in 2013. Compared to the US, which is again computed using CPS data in the right panel, the level differences in relative education are somewhat smaller but the trend is similar. US post-secondary relative education increases from 14% to 18%, relative university education increases from about 11% in 1991 to about 19% in 2013.

Education, however, may not be a good measure for comparing the skill intensity of the financial sector over time. First, education is a relatively crude proxy of skill and will not allow us to identify the most talented individuals as a large fraction of the population increasingly completes some sort of post-secondary training.[16] Accordingly, among the top 95 (99X) percent Swedish earners, which are analyzed below, X percent hold a college degree and the relative share of college degree holders in finance is falling (mechanically) from X% to X%. Education may further be endogenous to an individual's sectoral choice. In particular, individuals who wish to work in the financial sector today are likely to need a university degree.

Finally, overall post-secondary and university attainment has risen strongly over the last decades, resulting in substantial decline of average talent in the group of post-secondary education or university graduates. The bottom panel of Figure 4 illustrates this in our Swedish data, plotting the post-secondary share in Sweden against average cognitive ability among those who attained post-secondary education. During 1990-2013, post-secondary attainment rose from 21 to 37 percent among males (left panel), while average cognitive ability in the post-secondary group declined by about a quarter of a standard deviation. The results are similar for both genders (right panel). Related evidence has been documented for the U.S. by Carneiro and Lee (2011), who show that higher college attainment leads to a decline in the average quality of college graduates. In fact, in Appendix B we show that when we condition on male cohorts for whom attainment has not

[16] In 2013, x% (x%) of our sample of Swedish workers hold a post-secondary (university) degree, up from 48% (27%) in 1990. In the CPS data for the US, the corresponding numbers are 66% (38%) and 48% (27%). Besides the comparability problem, such high shares put into question that university degree can be considered an appropriate measure of talent toward the end of our sample period.

increased (identified by Card and Lemieux, 2000, among others), relative education of the financial sector is largely constant in the United States.

4.2 Our Detailed Talent Data

Given the caveats for using education as a proxy for talent, we henceforth analyze skill selection into finance in Sweden using our detailed talent measures over time.[17] These measures contain a substantial innate component and they are predetermined (elicited before most individuals choose their careers); they are comparable (their distribution is stable over time); [18] and they are fine-grained (we can analyze the top percentiles of the talent distribution). As the finance wage premium rises most strongly at the top of the wage distribution, the latter feature is of special interest.

Our main proxies of talent measure different aspects of cognitive and non-cognitive ability for 18-19-year-old males. They originate from the Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for cohorts enlisted between 1983 and 2010 and from the Military Archives (Krigsarkivet) for cohorts enlisted between 1969 and 1983. Lindqvist and Vestman (2011) provide a detailed description of the data and its collection.

The test of cognitive ability consists of four different parts (logic, verbal, spatial, and technical comprehension) of which each is constructed from 40 questions. The test is arguably a good measure of general intelligence and it thus has a stronger fluid IQ component than the American AFQT, which focuses more on crystallized IQ (Lindqvist and Vestman, 2011). We obtain both the raw results of the subtests as well as a transformed discrete variable, aggregating the individual results into one score of cognitive ability. This standardized variable ranges from 1 (lowest) to 9 (highest) and follows a Stanine scale that approximates a normal distribution. While our main analysis is based on the aggregated variable, we also examine the raw scores in parts of the analysis.

[17] Wage regressions controlling for education in Section XX show that rising finance wages are not simply a compensation for having to attain more education. In addition, note that relative education of top X percent earners in finance does not rise (available upon request), while their relative wages soar.

[18] Flynn (1984) reports substantial improvements in average intelligence during the mid-20th century. However, these gains seem to have petered out in the Nordic countries for a large part of our study population. For example, Sundet et al. (2004) find that 18 year old Norwegian male conscripts born after the mid-1950s had rapidly decreasing gain rates with a complete cessation of the Flynn effect for birth cohorts after the mid-1970s (similar findings exist for Danish conscripts and for Swedish 13 year olds born 1947-1977 including girls). For our purposes, even if the population distribution of cognitive ability changes across birth cohorts, it is still informative to study fixed percentiles of the ability distribution over time.

We obtain a standardized score for non-cognitive ability ranging from 1 to 9, following a Stanine scale as well.[19] The score is based on a 25-minute semi-structured interview by a certified psychologist. It is designed to elicit, among others, willingness to assume responsibility, independence, outgoing character, persistence, emotional stability, and power of initiative (Swedish National Service Administration referenced by Lindqvist and Vestman, 2011). At the end of the interview, the psychologist assigns one final score out of 1-9, weighing the different components of the tests. Lindqvist and Vestman (2011, p109) argue that the non-cognitive score is different from other measures often used in the literature on personality and labor market outcomes. Instead of assessing a specific trait, the non-cognitive score assesses the ability to function in a very demanding environment (military combat) and is likely to be rewarded in the labor market.

As an additional component of the military enlistment test, we obtain a measure of leadership. This is the result from a test that assesses the suitability for a career as an officer and is conducted only for those who scored above the mean in the cognitive test (score of 5 or higher). The leadership score arguably captures additional characteristics beyond the cognitive and non-cognitive that may be valuable in the labor market, especially for management jobs. The leadership measure again spans over a range of 1 to 9, follows a Stanine scale, and it is relatively strongly correlated with the non-cognitive score.

The military test scores have been identified as strong predictors of labor market outcomes. Lindqvist and Vestman (2011) show that controlling for the respective other score, cognitive ability is a somewhat stronger determinant of wages while non-cognitive ability is more important for not being unemployed. The positive effect of non-cognitives on wages is about linear over their distribution, the effect of cognitives is stronger at higher levels, and there seems to be no saturation point for either measure.[20] The positive effect of better cognitives and non-cognitives holds up within specific labor market groups such as managers, and cognitives, non-cognitives, and leadership also predict a higher likelihood of becoming a manager (e.g., Grönqvist and Lindqvist 2015).

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[19] Referring to this construct as non-cognitive ability is somewhat inaccurate as it is also influenced by individuals' cognitive processes and therefore it might be better to refer to it as character ability. Nonetheless, we stick with the literature on the Swedish enlistment scores and use the term non-cognitives in the paper.

[20] In contrast, for alternative measures of non-cognitives, such as the Big Five personality traits, higher or lower scores may not always be better.

The availability of the military test scores is not constant over time. For individuals born before 1950 we do not have the conscription information and the share of males for whom we observe the score starts dropping for birth cohorts after 1980, due to the gradual abolition of compulsory military service. For men aged 30, the coverage is roughly constant at around 70-80 percent during our whole sample period We therefore redo all our talent analyses for this group born 1960-1980 separately.[21] Appendix Figure A4 shows that, as required, the distribution of cognitive and non-cognitive talent measures is highly stable in the population over time.

An obvious limitation of the talent measures provided by the recruitment agency is its gender selection. While almost all men are required to do the enlistment tests when they turn 18 or 19, only a small fraction of women are tested. For this reason, we employ the type of program ("track") chosen in high school together with the grade point average as an alternative measure of talent.

We collect information from the high school register on the final grade, graduation year, and the track the person was enrolled in from 1973 onward. We then construct a predicted cognitive talent measure for males and females by regressing cognitive ability on a third order polynomial of high-school grades interacted with track and the age at graduation for each graduation year in the male subsample. The resulting parameters are then used to predict individual cognitive ability for both genders. This predicted talent measure alone explains more than 35 percent of the variation in the actual cognitives for males. Finally, we normalize this measure to percentiles (1 to 100) within graduation year and gender to account for possible grade inflation and for the fact that females on average have better grades in high school. As a result we obtain a fine-grained relative and early talent measure for both genders that is stable across years.

We also construct an alternative talent measure for females purely based on their grades in order to potentially capture their non-cognitive ability as well. Pooling grades across all the high school programs of varying length and difficulty that Swedish students may be enrolled in would be problematic in terms of comparability. We therefore only consider the students attending programs that lead to university admission and compute students' percentile rank (graderank).[22] We further

[21] In unreported robustness checks we use 35 year olds born 1955-1975 and find the same results.

[22] While there are about 20 different programs in the late 1990s and 2000s, four programs (science, social science, "special programs", and art) account for 85% of all university admissions.

restrict our grades sample to the science track in high-school, which traditionally enrolls the most able students.

As in the case of military enlistment scores, the share of individuals for whom we have grade and track information is not to the same across cohorts. For 30-year olds of both genders coverage is largely constant at around 60 percent. We therefore redo all our talent analyses based on grades for this group born between 1960 and 1980.

4.3 Average Talent and Relative Task Content in Finance Do Not Increase

Figure 5 plots relative talent measures in finance and the rest of the economy as defined in equation (6) between 1990 and 2013. Each line displays the relative talent, defined as the difference between the average levels of the different dimensions of talent for the financial sector (finance) and the rest of the economy (non-finance, private sector). As argued before, one main advantage of our measures is that their distributions are time-invariant and thus comparable across cohorts. The averages in the rest of the economy (as defined before) can still change over time when the selection into the non-finance, private sector evolves (e.g., because of female labor market participation or the allocation between the public and private sector). These changes are empirically very small. The top and bottom left panels show the results for men of all ages and 30 year olds, as a proxy for recent entrants, using the different talent measures from the enlistment test. The right panels show the results for women using different measures based on grades.

The left panel of Figure 5 and Panel A of Table 2 report relative talent for men. Throughout all dimensions of talent we find that make workers in the finance sector are more talented compared to the rest of the economy, i.e., relative talent of the financial sector are positive. The average aggregated test scores for cognitive, non-cognitive, and leadership ability are between 0.66 (leadership) and 0.85 (cognitive) higher in the financial sector. The raw scores of logic and verbal comprehension are about 3.25 points higher. For each of the measures, this is at least half a standard deviation difference and it is consistent with finance being a skill-biased sector. However, also note that, finance workers are, at least in terms of cognitive skills, substantially less talented than Accounting, Law, and Consulting (ALC) and IT workers (Appendix Figures A2 and A3).

We now turn to our main test. If the financial sector became more relatively skill-biased over time, we would expect to observe that average relative talent is increasing over time (Hypothesis H-1).

Interestingly, and in stark contrast to relative education in Figure 4, we do not find that relative talent has improved. The premiums in the left panel of Figure 5 do not increase over time. The composite talents (cognitive, non-cognitive, and leadership) as well as the raw scores of logic and verbal comprehension are relatively flat (or even slightly decreasing). The picture looks similar for recent entrants (30 year olds). Using different proxies for talent based on grades, we do not find any improvement over time for women working in finance either. In Panel C of Table 2 we also show results for the whole population using the measures based on grades.

We conclude that for all proxies / dimensions of human capital there is no upward trend detectable, neither on average nor for relative average talent in finance, and not for recently entered 30 year olds. If anything, there is a slight downward movement in the relative test scores for males over time. Moreover in the bottom right panels of Appendix Figures A2 and A3 we see that finance sector talent has also not increased compared to Accounting, Law, and Consulting (ALC), despite strongly rising relative wages, and that it has only slightly improved compared to IT, despite a rapid employment expansion, which presumably drew many relatively less talented workers into the IT sector.

Finally, one may detect the finance sector's skill bias from its effect on talent supply, as we have just done, or from measures of talent demand. The task content of occupations can serve as such a measure, and if finance becomes more skill-biased, for example if it adopts computer technology rapidly and thereby sheds a lot of clerical and bank telling jobs, one may expect changes in task content of finance to be particularly stark.

In Appendix Figure A5 we analyze the financial sector from a task perspective.[23] The top two graphs and the bottom left graph show the evolution of the abstract, routine, and service task content of finance; IT, legal, consulting, and accounting ("ILCA"); and the rest of the economy, respectively, over time. The task contents are very different in levels, with finance and ILCA being more abstract and service task intensive and the rest of the economy featuring much more routine

[23] Information about occupations is not available in LISA during 1991-2000. We therefore draw data from the Swedish census of 1990 and LISA from 2001 onward. Information in this data is available on the four-digit level of the Swedish standard for occupation classification (SSYK), which is similar to the International standard for occupation classification (ISCO-88). We match abstract, routine, and service task content information from Goos, Manning, and Salomons (2009) to the occupations on the two-digit SSYK level. Unfortunately, occupational reporting is very incomplete during the years 2001-2004, especially for the financial sector. In order to prevent erratic jumps in our time series we therefore only use the information for 1990 and from 2005 onward.

tasks (see figure caption). We normalized these contents to zero in 1990, so that comparisons of the extent of the changes are easier to draw. In the following we use absolute tasks, but our results are the same when we compute relative tasks such that abstract, routine, and services always sum to 100 percent.

Task changes in the financial sector seem to be modest compared to the rest of the economy as well as to ILCA (which is relatively similar in levels). There is strong task polarization in the rest of the economy, with abstract and service tasks rising continuously and routine tasks falling. And there is a strong increase in abstract tasks in ILCA. In contrast finance seems to be only weakly polarizing, if at all. There is some increase in abstract tasks in finance in the last years of our sample period (when the wage premium is not rising as strongly anymore). Routine and service tasks are essentially flat, which suggests that employment in repetitive clerical and bank telling jobs has not plummeted. Overall, our interpretation is that finance is a rather narrowly-defined sector in which task composition can change by only so much.

4.4 Finance Has Also Not Become More Talented at the Top

As argued above, an unchanged relative average skill in finance, rising finance wages, and rising dispersion of wages in finance, may be consistent with a variant of the skill-bias hypothesis whereby skill demand only rises for the most talented workers or polarizes. We test in this section whether the selection of top talent into finance has changed.

Figure 6 plots the distribution of talent in finance in absolute terms and relative to the rest of the economy from the median Stanine score of 5 upward. In the top row, the absolute and relative share of top 9 score individuals in finance is actually not much higher than in the rest of the economy. Moreover, it is constant over time, while the share of the next best 7 and 8 score individuals slightly decreases. In terms of non-cognitive skills, the (relative) share in finance of top 8 and 9 individuals also slightly decreases (bottom row of the Figure).

These facts are corroborated in the comparison to the other high-skilled sectors of accounting, law, consulting and IT. We see that the share of top 7-9 talent is actually lower in finance than in ALC and in IT, and drastically so for top 9 talent in IT. Further, over time, top cognitive talent (7-9) in finance actually slightly falls compared to ALC (bottom right panel of Appendix Figure A2) and only slightly increases from its very low base compared to IT (bottom right panel of Appendix

Figure A3), although the latter sector grows drastically and presumably draws in many relatively less talented marginal workers.

In addition to analyzing the (relative) selection of top talent into finance, one may also examine the (relative) talentedness of top earners in this sector. If workers have multiple dimensions of skill, even some of the top 1 (or .1%) earners in finance may not be top 9 (non-)cognitively talented because they are extremely talented in another unobserved dimension. When the general demand for talent in finance increases, the average talent among the top 1% earners should increase in all dimensions, including our cognitive and non-cognitive measures.

Appendix Figure A5 plots the average talent of top 5 and top 1 percent earners in finance. We see that finance top earners' talent is neither rising in absolute nor in relative terms. This supports our finding that finance talent is also not rising close to the top of the talent or earnings distribution.

A further robustness analysis for 30 year olds is relegated to the next section, where we estimate linear probability models of choosing finance for this age group.

4.5 Choice Regressions into Finance Controlling for Other Factors

To complement the graphical evidence, we also test the hypothesis of an increased skill demand parametrically by running choice regressions for working in finance on our talent measures. This has the advantage that we can control for and analyze other choice determinants such as formal education or network proxies. We use linear probability models to directly obtain average marginal effects, but probit regressions yield qualitatively similar findings. We also focus on 30 year olds as a measure for recent entrants and in order to use every individual's choice only once.

Table 2 reports choice regressions with an indicator for working in finance for 30 year olds on the left hand side and years of schooling, linear cognitive and non-cognitive talent, and parental sector of work on the right hand side. In the first two columns, we see that, as in Figure 4 above, formal schooling becomes a more important determinant of choosing finance for males and females over time. However, controlling for education, cognitive as well as non-cognitive talent for males and predicted cognitive talent for females' effect for choosing finance declines over time. Conditionally, cognitive talent and education are in fact negative predictors for choosing finance for males and females, respectively.

Column 3 of Table 2 introduces parental finance sector affiliations to the choice regression. These network proxies are arguably substantially more important than talent or education in determining whether an individual chooses finance: even conditional on the other parent's affiliation, a father or mother in finance raises the probability of working in the sector by more than 100% (baseline under 3%, see Figure 2). In the last two columns, father's income (unimportant conditional on parental sector) and the share of individuals in finance in the municipality where the individual grew up (another network proxy) are added. We see that the latter is of substantial additional importance for predicting whether someone enters finance at age 30 (though the effect of parental affiliation declines). These results support the hypothesis that network factors may be at least as important as talent and skills for determining the selection of workers into the financial sector.

Table 4 splits talent in the choice regressions up into an upper middle range (scores 4–8 for males and predicted percentile 40–95 for females) and top talent (score 9 and percentile >95). In column one, while baseline negative, the top cognitive talent becomes a more important predictor of choosing finance for males over time. However, at the same time top non-cognitive talent's effect declines almost twice as strongly. For females, the effects of upper middle- as well as top talentedness on choosing finance both somewhat decline over time (column two). The remaining columns of Table 4 corroborate these findings with different, mainly network-related, control variables, and they underscore the result from above that network variables appear to be very important determinants of finance sector choice. In unreported robustness checks we have included all ages into the choice regressions and we have fully interacted the talent measures with each year. None of our analyses showed that talent became a more important determinant of workers joining the financial sector over time.

Finally, one might argue that although these choice regressions do not yield any stronger relationship between talent and working in finance over time, the selection of unobservable skill components into finance might still have improved. Although this is clearly possible, it does not seem particularly plausible. Our observed measures capture several dimensions of talent that are generally unobserved in standard data sets. To be consistent with the results from the choice regressions (and Figures 5 and 6), the improving selection or underlying skill-bias would *only* have to affect these additional unobservable components of skill and it would have to only affect the part of them that is *uncorrelated* with our rich set of observed talent measures.

5 Do Rising Finance Wages Reflect Talent?

From analyzing the selecting of talent into finance we move to evidence on wages in the sector. We run wage regressions controlling for talent, using individual fixed effects, and time and sector-varying returns to talent. We also compare the wages within detailed occupation groups inside and outside finance, and compared to other high-talented sectors. None of these pieces of evidence suggests that rising productivity of talent in finance explains its soaring wages.

5.1 Accounting for Talent and its Return Does Not Explain the Finance Wage Premium

In this section we run wage regressions to examine whether a changing selection of talent into finance can explain its rising wage premium. One advantage of the wage regressions is that we can use fixed effects in order to account for unobservable components of workers' skills as an alternative to observed talent measures. As in the case of the choice regressions, we can also account for the effects of potential experience, education, and gender in the analysis. We start with the estimation of equation (1):

$$w_{it} = \alpha_t + F_{it}\tilde{\alpha}_t + \beta s_{it} + \varepsilon_{it} \quad (1)$$

where w_{it} is worker i's log wage at time t, s_{it} his skill at time t, and F_{it} is an indicator for working in the financial sector. Therefore, $\tilde{\alpha}_t$ is the time-varying finance wage premium in log points. Second, the observable component of $s_{it} = s_{it}^o + s_{it}^u$ contains the standard skill proxies of years of experience and its square, which are time-varying, as well as our talent measures:[24] predicted cognitives for both genders in the left panel and cognitives and non-cognitives for males in the right panel. These are unobserved in most commonly used datasets. Third, we include years of education in the last specification.

The control variables decrease the level of the finance wage premium. Adding predicted cognitives and potential experience alone explains about 10 percentage points (slightly less than 20% of the premium in 2010) of the premium in the regression including both genders, while cognitive and non-cognitive talents explain around 15 percentage points. Hence, the fact that finance workers are more talented than workers in other sectors explains a substantial part of the pay premium, although

[24] The remaining unobserved component of skill becomes part of the regression error. This could be modeled as $e_{kjit} = s_{it}^u + m_{kjit}$, where m_{kjit} is a remaining error which is not skill-related and which may, for example, be the match quality of worker i with firm j in sector k.

far from all of it. More importantly, even though including talent and education slightly attenuate the rise in the premium (at least in the regressions with both genders included), most of the increase remains unexplained. This result is consistent with our previous finding that the distribution of talent in finance has remained roughly constant over time while relative education increased somewhat.

We have argued in the previous subsection that improved selection into finance according to skill components unobserved in our data is unlikely to have occurred. As an additional check, the middle row of Figure 7 accounts the wage premium for time-invariant component of unobserved skill s_{it}^{u} by including fixed effects. The rich panel dimension of our data allows us not only to compute worker fixed effects, but also worker-firm match-specific fixed effects. The fixed effects bring the level of the finance wage premium down to about zero, which is somewhat mechanical since they constitute worker(-firm)-specific intercepts. Yet, inclusion of fixed effects has no impact on the increasing trend in the finance wage premium. In fact, the rise in the premium is even larger for males when fixed effects are included.

The last row of Figure 7 allows for time-varying (economy-wide) returns to observed components of talent, that is, β_t in equation (1) now obtains a time index (although it is still the same across sectors). It is well known that the returns to education as well as to cognitive and non-cognitive ability have increased in most Western countries, including Sweden, over the last couple of decades. Since finance absorbs relatively talented individuals, the rising returns to their talent should account for some of the trend in the finance premium. Indeed, we see in the last row of Figure 7 that the plot of $\tilde{\alpha}_t$ rotates slightly to the right and becomes flatter. Still, sector-invariant time-varying returns to talent explain only a small fraction of the overall increase in relative finance wages. The last result is corroborated by Appendix Figures A2 and A3. These figures show that finance wages increased strongly compared to IT and Accounting, Law, and Consulting (top left panels), sectors which are at least as talented (bottom panels) and for which wages should have rising strongly if the explanation is just an overall increasing demand for talent.

In Appendix Figure A1 we provide further robustness checks about the rising finance wage premium. We first concentrate our analysis on Stockholm, where about 45 percent of overall and 80 percent of top 5% earning finance workers in Sweden are employed. These (top) employment shares in finance are comparable to London's share in the UK (Bell and Van Reenen, 2013a). We find that finance relative wage increases are somewhat stronger in Stockholm than in the rest of the country, indicating, among other things, that higher finance wages do not just reflect the rising cost of living in Stockholm. We then contrast our preferred measure of yearly labor income to the alternatives of including capital income and to using disposable income after accounting for taxes and benefits. Again, the overall trends are very similar using these measures.

5.2 The Finance Premium Does Not Rise More for More Talented Workers

In Section 4 we found that the (relative) selection of talent into finance is stable. This is not consistent with a core prediction from the rising finance skill-bias hypothesis, which says that more talented workers should enter the sector over time. In the following we provide further evidence against this hypothesis by examining the relative wages in finance across talent groups from the median upward. This modifies equation (2) for the case of cognitive talent groups as follows:

$$w_{cit} = \alpha_{ct} + F_{it}\tilde{\alpha}_{ct} + \beta s_{it} + \varepsilon_{it} \quad (2)$$

where w_{it} is worker i's log wage at time t when he is of cognitive talent $c \in \{5, \ldots, 9\}$, F_{it} is an indicator for working in the financial sector at time t, and s_{it} further skill controls (we do not use any in what is reported below, but the results are similar with standard controls). $\tilde{\alpha}_{ct}$ is the time-varying finance wage premium for cognitive talent c.[25]

Figure 8 reports the results. In the top panels, we see the increase in the finance wage premium for cognitive skill and non-cognitive skill groups of 5, 6, 7, 8, and 9. In levels the finance wage premia largely line up by talent and the differences widen during the market peaks of the early 2000s and of 2007/08. However, the finance wage premium also substantially increases for mid-talent workers and the wedge between talent groups is quite constant over time. This corroborates our evidence that the relative return to (top) talent appears not to have increased in a significant way over time.

[25] We are aware that $\tilde{\alpha}_{ct}$ cannot necessarily be interpreted causally because of self-selection according to other, generally unobserved, skill components. For credible Heckman two-step estimation of equation (2) one would need an exclusion restriction affecting workers' choices but not their wages, which is hard to come by in this setting. We still think the evidence provided in Figure 8 is informative.

5.3 The Finance Premium Rises Within Detailed Occupations and Across Subsectors

In this section we present additional evidence that wages in finance rise across-the-board, and not just in finance-specific or high-talent jobs or subsectors.

In Table 4 we provide information on the 21 largest occupations in finance, at the detailed four-digit level (354 different occupations), for the years 1990 and 2010.[26]

These 21 occupations constitute almost 80 percent of finance employment and around 10 percent of employment in the rest of the economy. "Banking associate professionals" and "Insurance representatives" are by far the largest and second-largest occupation, respectively. In fact, while declining, "Banking associate professionals" constitute a fourth or more of overall finance employment in all years while it has a minuscule share of employment in the rest of the economy.[27] The occupations are ordered in the table by their finance wage premium versus all workers in the rest of the economy, and thus very crudely also by their cognitive and non-cognitive scores. We have also aggregated

The third to last column

We report in Table X1 the finance wage premium for each of these detailed occupations in all three years. The finance premium is increasing from 1990 to 2010 in 25 out of the 26 occupations where we have information for both years. This underscores that the relative finance pay increase is also pervasive fixing occupations.

We have discussed the task composition changes of finance and the rest of the economy in the previous subsection. Here we summarize the occupational changes by grouping the 27 largest four-digit occupations in finance into four groups, detailed in the last column of Table X1. The first group is intended to capture skilled (associate) professional workers, who constitute the bulk of employment in finance. The second group are clerical workers, who have traditionally been a substantial group in finance as well as the overall economy. The third group are particularly high-

[26] As explained in footnote 21, occupation information for the years 1991–2004 is either not available or of low quality. In 2011, the sectoral classification switches from SNI2002 to SNI2007 with some changes affecting finance as well. So it is cleanest to report 2010, but the evidence is the same when we use 2005 or 2013 as endpoints instead.
[27] The share of "Banking associate professionals", "Insurance representatives", and of "Securities dealers and brokers" in the rest of the economy is minuscule, so we do not provide their finance premium versus the same occupation in the rest of the economy in the last columns of the table.

skill (and high-earning) workers that are again more represented in finance than the rest of the economy. Finally, there are workers in computer-related occupations that have become more prevalent across the economy.

The first row of Figure X2 plots the employment trends in these occupation groups. In the left panel, employment in the associate professional group declines modestly from 65.5 to 62 percent in the finance sector while it increases modestly in the rest of the economy. Computer-related employment rises substantially in both sectors, though from a higher base and more in absolute (but not relative) terms in finance. The clerical occupation group also strongly declines in finance, but in fact it declines equally strongly in absolute terms and even stronger in relative terms in the rest of the economy. This suggests that rising finance wages do not simply stem from shedding bank tellers and clerks. Finally, the high-skill occupation group employment, though higher in finance, is more or less flat in both sectors.

Overall, just as the task composition, the occupational composition is not changing more fundamentally in finance than in the rest of the economy in our sample period. This is also reflected in our wage comparisons. First, in the left panel of the bottom row of Figure X2 we show the relative finance wages in the four occupation groups. In the associate professionals, high-skill, and computers group this is rising, while it is flat in routine clerical.

We also run wage regressions in the bottom right panel of Figure X2 with the starting point (solid red line) the specification from Figure 6, Panel B that controls for talents, observables, and education. While it of course explains some of the level, accounting for (all 354) detailed four-digit occupations (dashed grey line) does not at all weaken the increase in the finance wage premium. When we control for four-digit occupations interacted with time (dashed green line), we mechanically take away a lot of the finance premium, as many of these detailed occupations are almost unique to one sector or the other. Nonetheless, the relative finance wages still increase even with these controls.

Finally, Tables X2 and X3 show the employment share and the finance and ILCA wage premium for all 26 2-digit occupations (groups) in the economy. The finance premium is increasing for seven out of eight occupation groups from 1990 to 2010 where there is non-negligible (>1%) finance employment. For the ILCA sector this is not the case. The wage premium for that sector is not increasing in most occupations. This underscores that finance wage increases are substantial and pervasive, also relative to comparably high-talent sectors

Table 4 repr

- Table with the Premium by Occupation
- Also premium by subsector

6 Main Robustness Checks

6.1 Hours of Work in Finance Are High but Not Rising

6.2 Further Compensating Differentials Stories

Earnings and firing risk (esp during the crisis), wages rise in 1990s (millennials only later), health, job satisfaction,

6.3 (High-Talent) Finance Workers Are Not Becoming More Likely to Emigrate

7 Conclusion

7.1 Increasing productivity of talent cannot explain (much) of increase in wage premia.

7.2 Brain drain in not a major concern

7.3 Macro perspective: Rise of IT, finance is a side-show

7.4 Outline other stories

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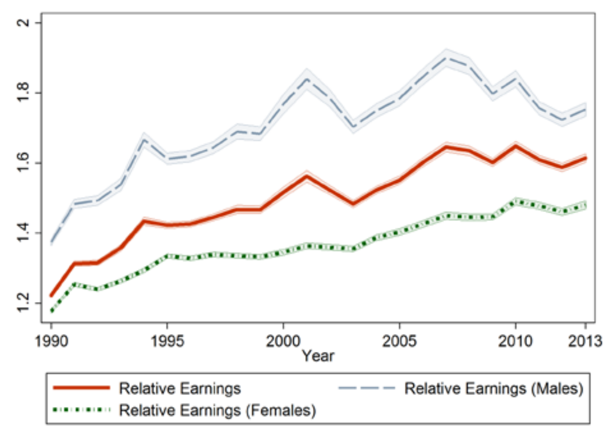
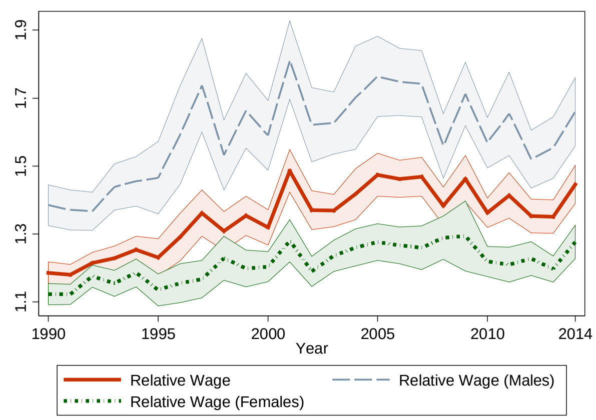
Figure 1: Relative Pay and Employment in the Financial Sector

The top three rows of this figure depict the evolution of relative pay in the financial sector, defined as the ratio of average pay in finance to average pay in the non-financial, nonfarm private sector. Yearly labor earnings are used for Sweden (left panels) and hourly wages for the US (right panels). The first row shows the evolution during our main sample period of 1990-2013 (2014 for the US). The second row shows the longer period from 1978, using a representative administrative sample of 3-4% of the Swedish population (LINDA). The left panel of the third row depicts the evolution of relative earnings in the financial sector according to different income types: labor income, labor plus capital income, and disposable income. The right panel depicts relative finance earnings for individuals working in Stockholm only. The fourth row of the figure shows finance's share of overall nonfarm private sector employment in Sweden (left panel) and the US (right panel). The fifth and last row depicts the relative quantiles of the earnings distribution in the financial sector, i.e., the ratio between the percentile in finance and the respective percentile in the non-financial, nonfarm private sector. Sources: Swedish population data LISA and 3-4% sample LINDA from Statistics Sweden; Current Population Survey for the US. 95 percent confidence intervals are shaded.

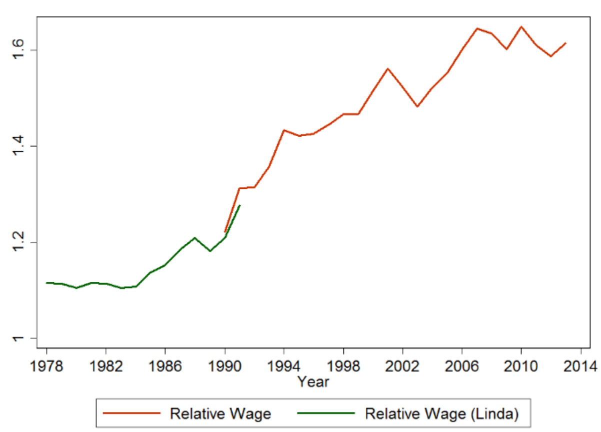
Relative Pay in Sweden



Relative Pay in the US

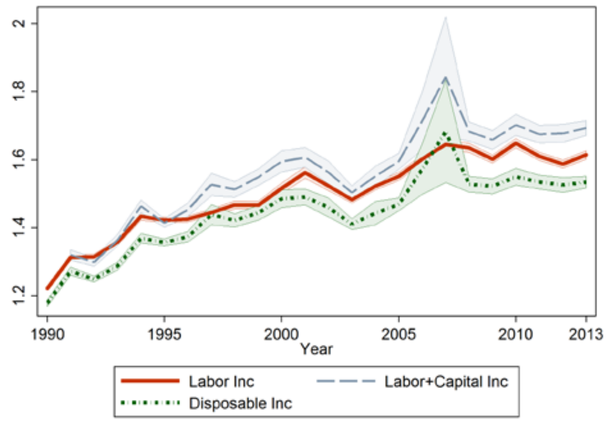


Relative Pay in Sweden 1978+

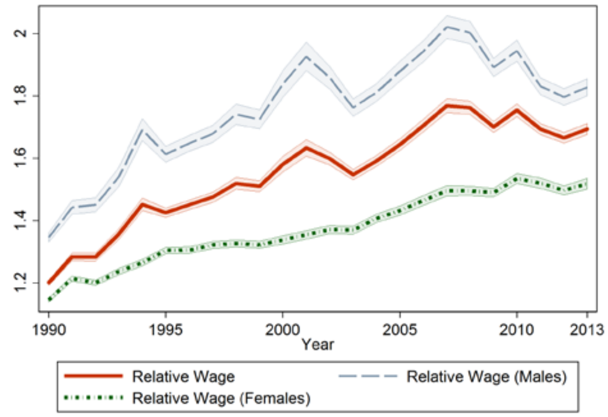


Relative Pay in the US 1978+

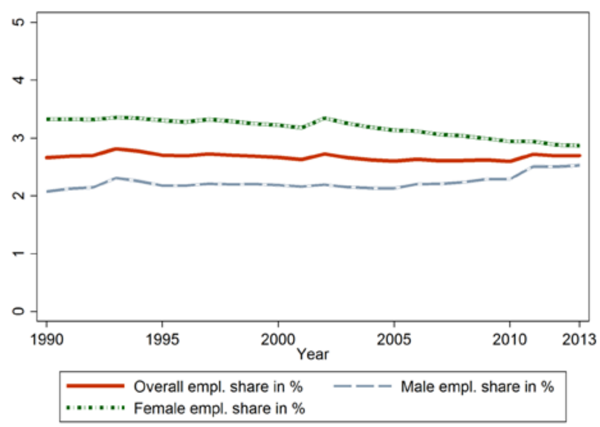
Different Income Types (Both Genders)



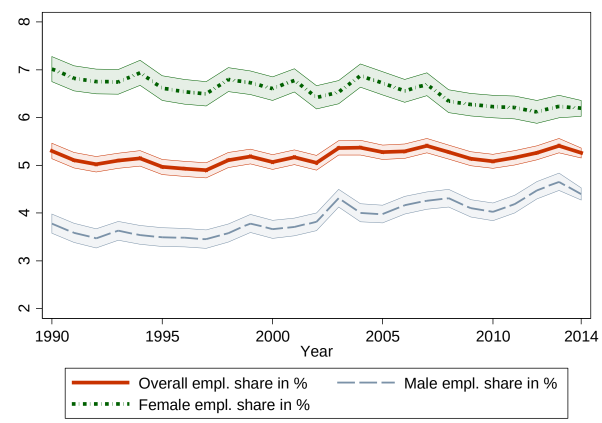
Only Stockholm Area (Both Genders)



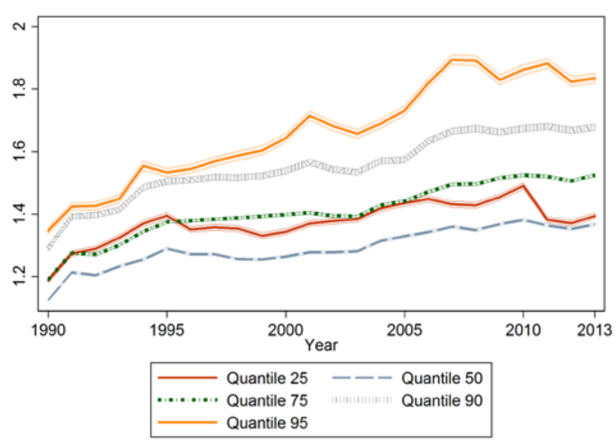
Employment Share in Sweden



Employment Share in the US



Different Relative Percentiles in Sweden



Relative 99th Percentile in Sweden

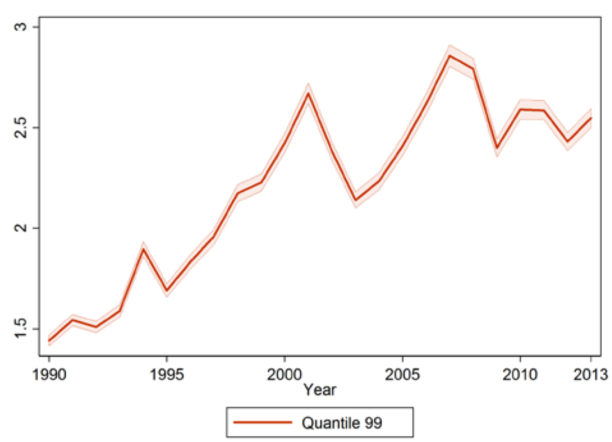


Figure 2: Relative Education in the Financial Sector

The top row shows the evolution of the relative education between the financial sector and the rest of the economy for Sweden (1990–2013, left panel) and the US (1990–2014, right panel). Relative education is calculated as the share of individuals in finance who attained more than a high-school degree (postsecondary education) and of those who attained a university degree (university education) minus the corresponding shares in the rest of the economy. The bottom right panel depicts post-secondary attainment rates and average cognitive ability among workers with at least post-secondary attainment for males. The bottom left panel depicts the corresponding figure for females, using predicted cognitive ability. Sources: Swedish population data LISA from Statistic Sweden; Current Population Survey for the US. 95 percent confidence intervals are shaded.

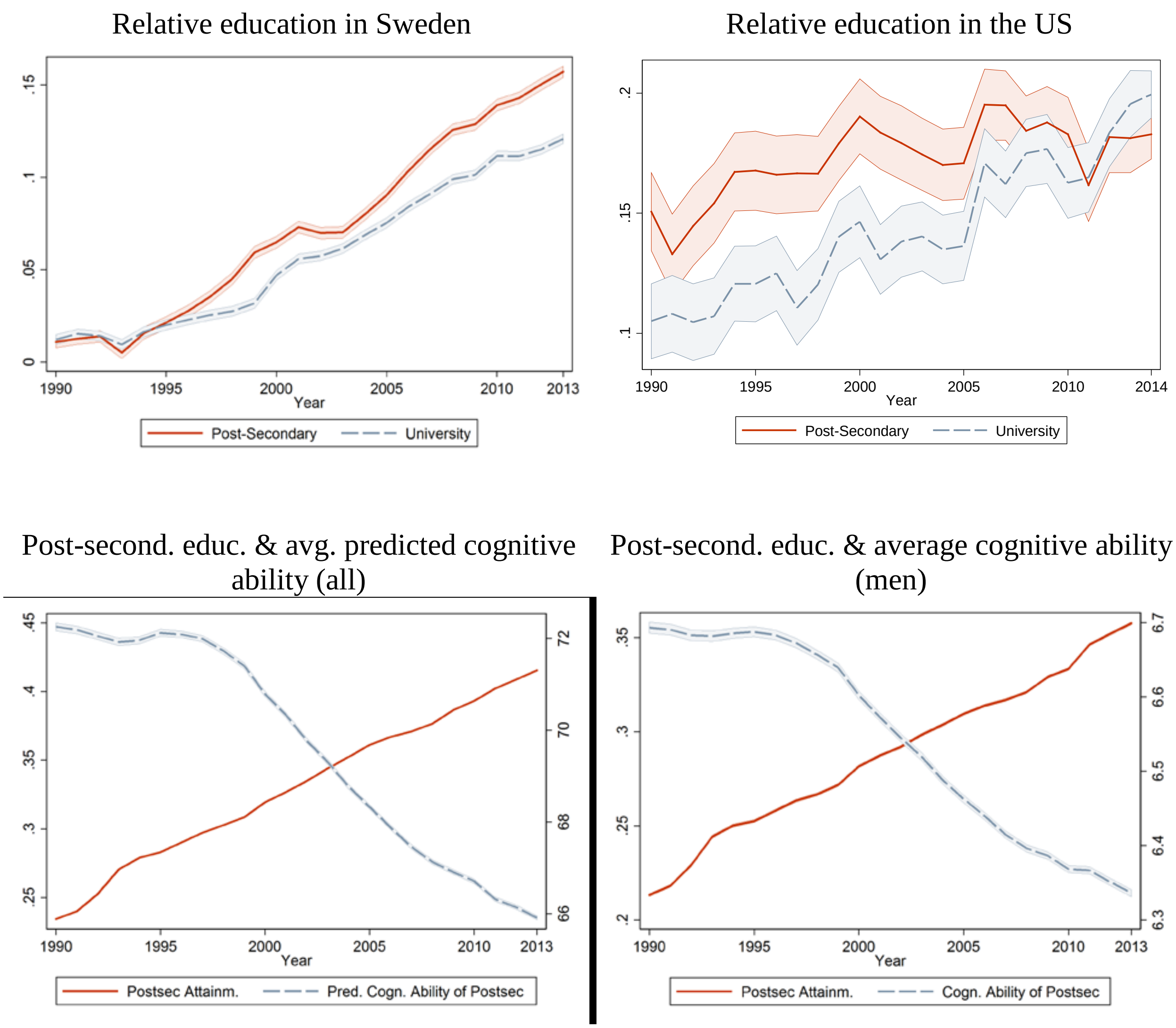


Figure 3: Relative Talent in the Financial Sector

This graph shows the evolution of relative talent in the financial sector during 1990 to 2013. Relative talent is calculated as the average talent in finance minus the corresponding average in the rest of the economy. The panel on the top left shows the results for men. The left y-axis displays the relative levels for cognitive ability, non-cognitive ability, and leadership, while the right y-axis displays the relative levels of logic and verbal comprehension. The panel on the top right shows corresponding evidence for women, using high school graderank in the university and science tracks, and predicted cognitive ability. The bottom row shows the corresponding graphs for 30 year olds only (note we cut off the logic and verbal series after 2007 because their availability drops drastically). Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

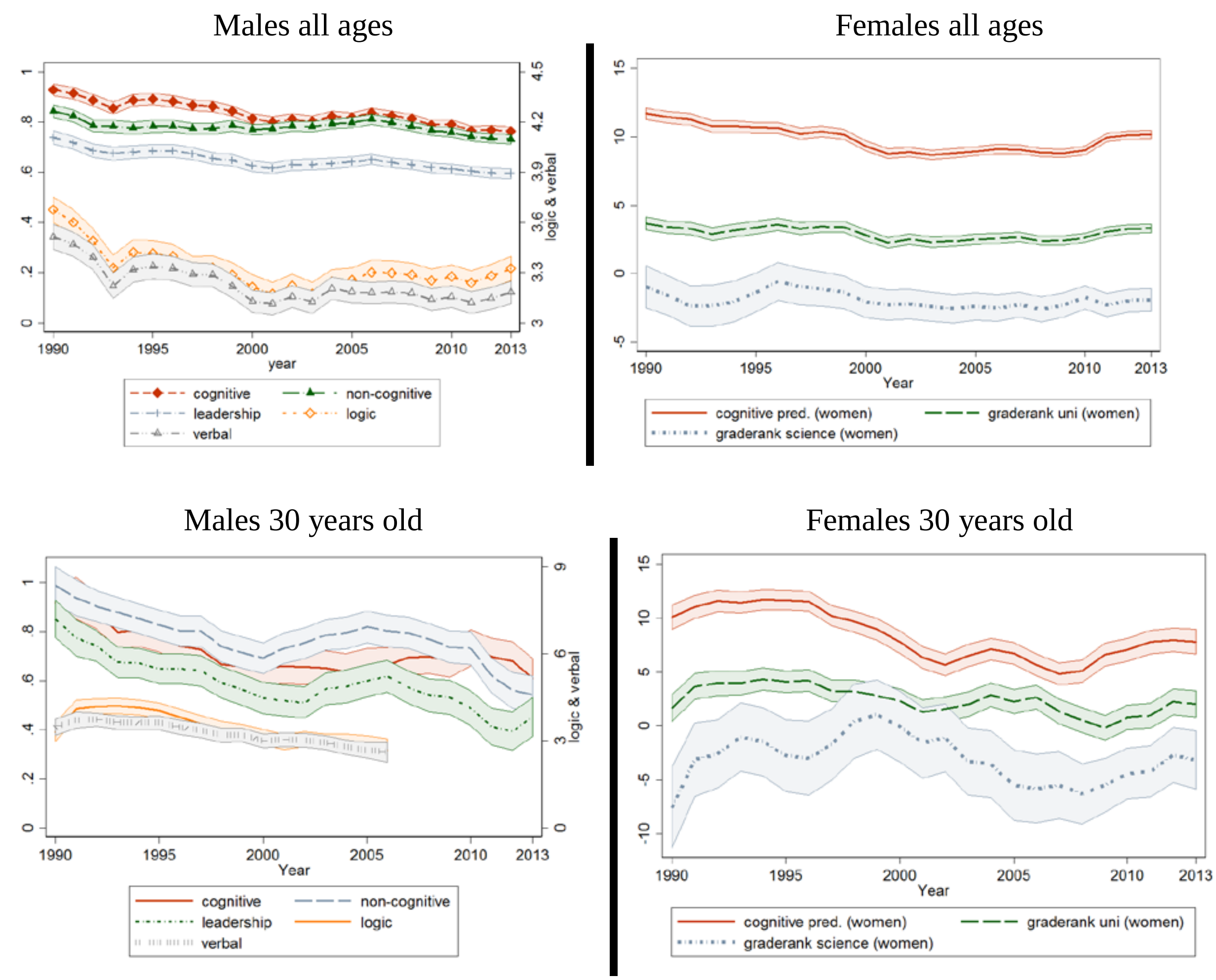


Figure 4: Distribution of Talent in Finance

This graph shows the evolution of relative shares of medium and high talent levels in the financial sector during 1990 to 2013. Relative share is calculated as the share in finance minus (divided by) the share in the rest of the economy in the left (right) panels. The predicted cognitive ability measure is discretized to Stanine scale for this purpose. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

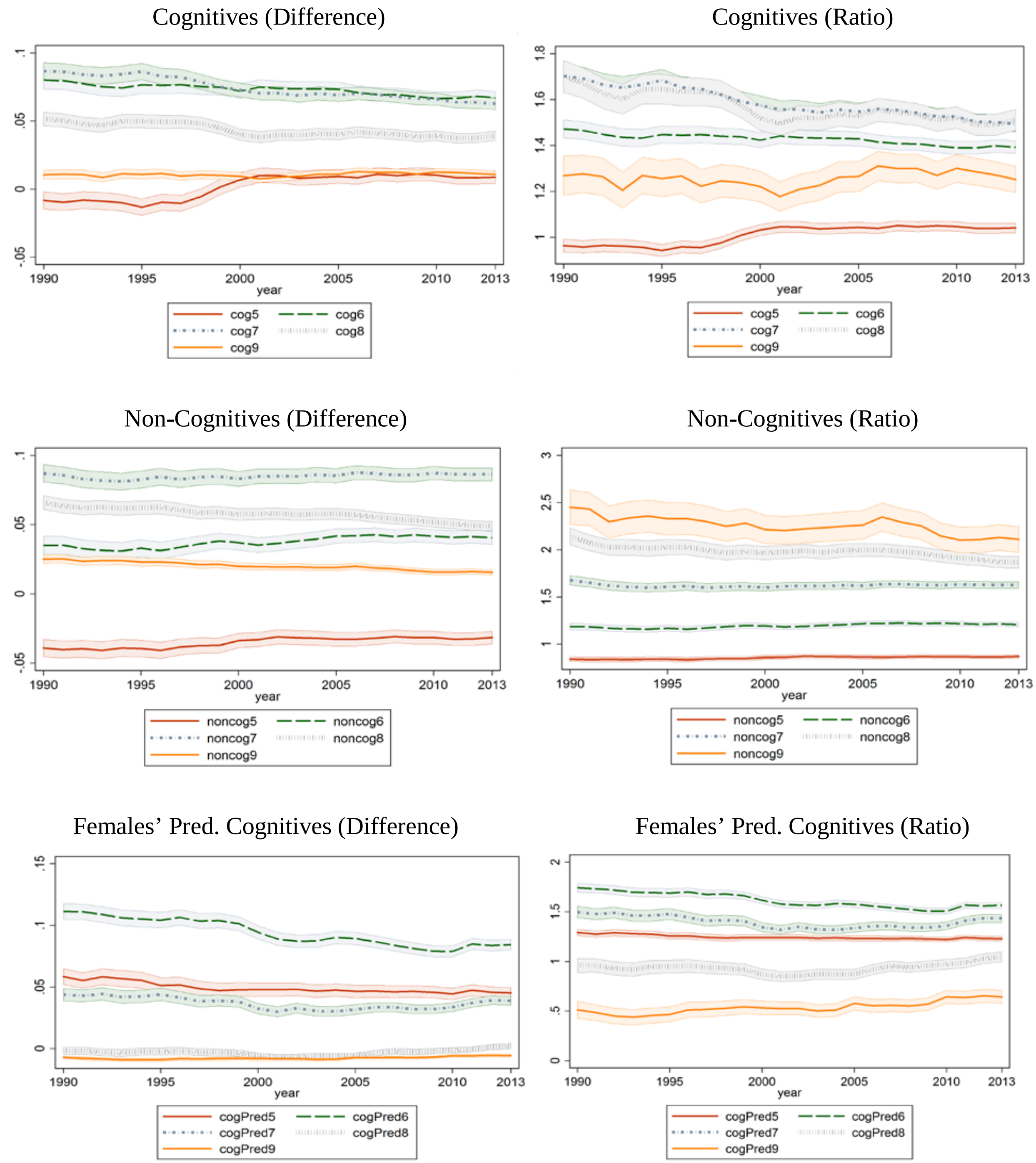


Figure 5: The Finance Premium Controlling for Observed and Unobserved Skills

This shows the finance earnings premium between 1990 and 2013. The earnings premium is obtained from estimating equation (11) $w_{kit} = \alpha_{Rt} + F_{it}\tilde{\alpha}_t + \beta s_{it}$ by OLS. The β is the (economy-wide) return to worker skill, F_{it} is an indicator for the financial sector, and $\exp(\tilde{\alpha}_t) - 1$ the time-varying finance pay premium. The three models are: (i) no controls, (ii) controls for observables (age, gender, potential experience) and talent, and (iii) ads education (years of schooling). The left panels report results for the whole population, the right panels for males only. Predicted cognitive ability is used as a population-wide talent measure and cognitive and non-cognitive ability are used for the male subsample. The middle row adds person fixed effects and person-organization fixed effects to (iii). The bottom row allows for time-varying returns to experience, talent, and education. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

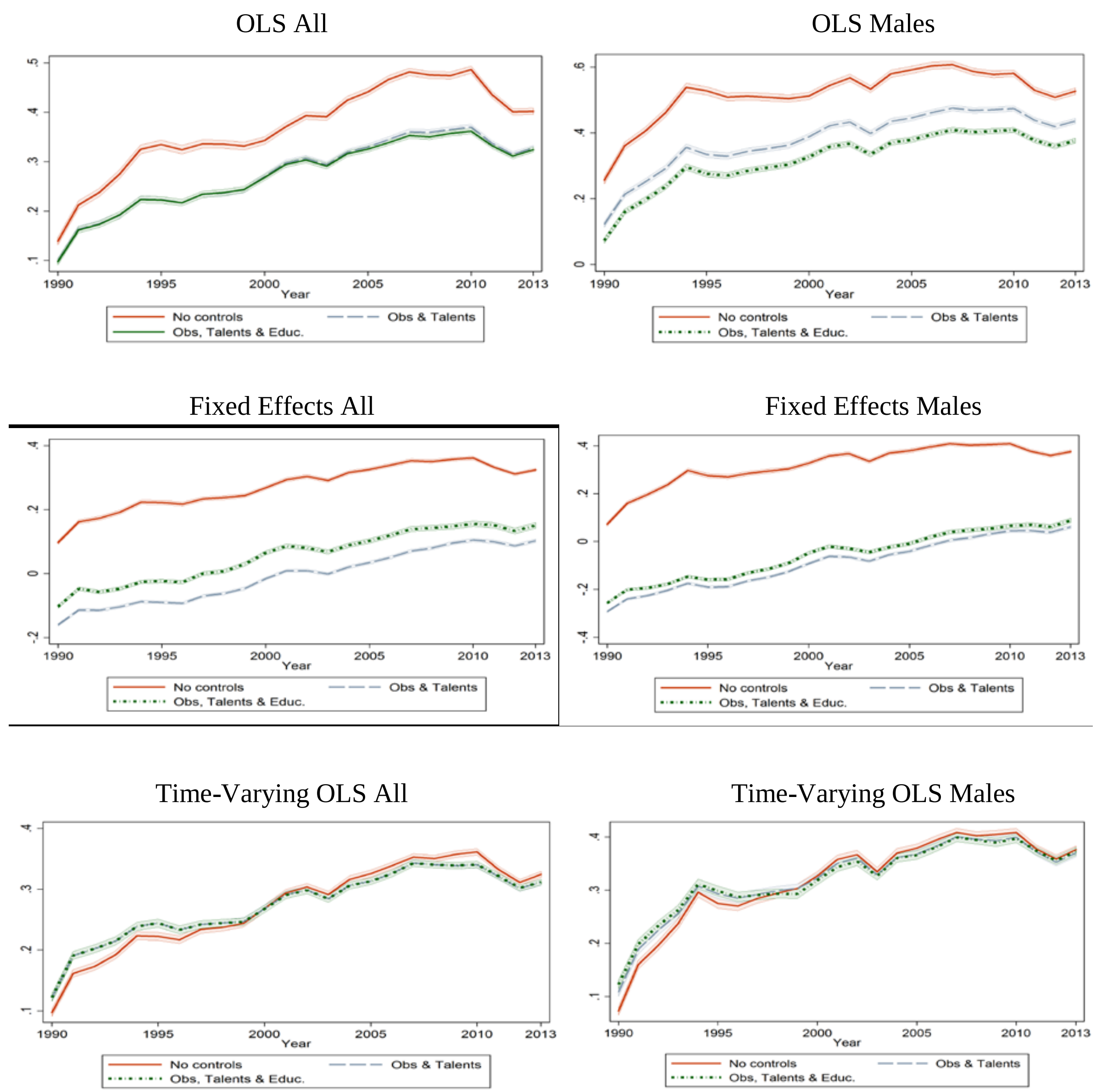


Figure 6: The Finance Premium by Talent Group

This graph shows the finance earnings premium for medium and high talent levels of males and females during 1990 to 2013. The predicted cognitive ability measure is discretized to Stanine scale for this purpose. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

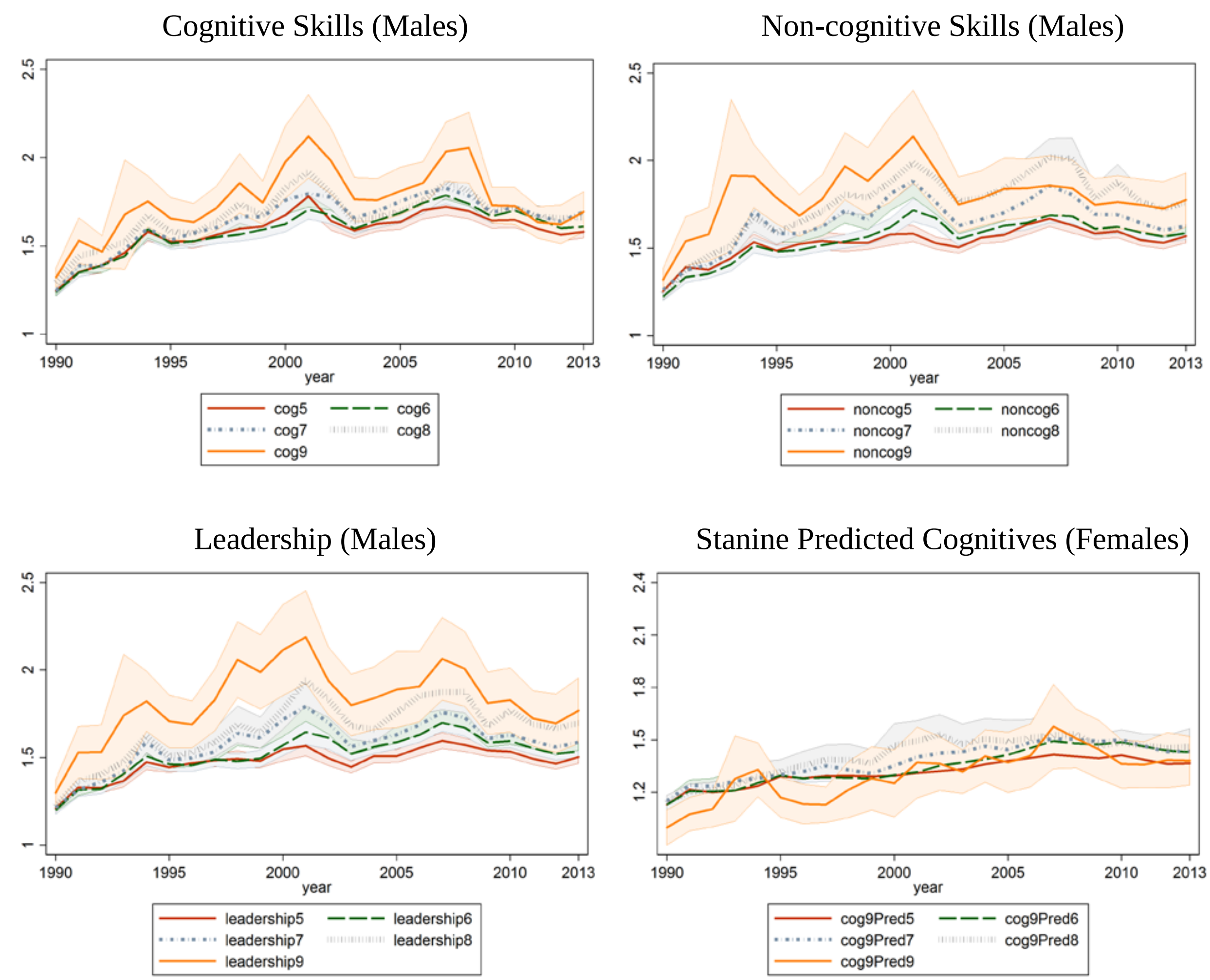


Table 1: *Summary Statistics*

This table shows summary statistics of the main variables. Source: Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for persons enlisted between 1983 and 2010, Military Archives (Krigsarkivet) for persons enlisted between 1969 and 1983. Swedish population data LISA from Statistics Sweden.

Panel A: Population

	count	mean	sd	p10	p25	p50	p75	p90
Age	65,664,203	41.32	12.29	25	31	41	51	58
Gender	65,664,203	1.49	0.50	1	1	1	2	2
Cognitive	20,179,132	5.16	1.89	3	4	5	6	8
Non-cognitive	19,379,711	5.12	1.69	3	4	5	6	7
Leadership	12,711,587	5.31	1.65	3	4	5	6	7
Logic	16,386,163	25.12	6.45	16	21	26	30	33
Verbal	16,280,847	24.15	6.07	16	20	24	28	32
Spatial	16,288,130	19.09	7.76	10	13	17	25	31
Technic	16,169,197	28.13	7.50	19	23	28	33	38
Grade Rank	28,831,521	49.13	28.51	10	24	49	74	89
HS2y	65,382,614	0.83	0.38	0	1	1	1	1
HS3y	65,382,614	0.52	0.50	0	0	1	1	1
Postsec	65,382,614	0.32	0.47	0	0	0	1	1
University degree	65,382,614	0.18	0.38	0	0	0	0	1
PhD	65,382,614	0.01	0.10	0	0	0	0	0
Years of School	65,382,614	11.74	2.73	9	10.5	12	13.5	16
Potential experience	65,664,203	22.39	12.32	6	12	22	32	39
Labor Income	65,664,203	2,331	1,782	885	1,431	2,076	2,829	3,809

Panel B: Men with Non-Missing Cognitive Ability Only

	N	mean	sd	p10	p25	p50	p75	p90
Age	19,245,525	35.90	9.31	24	29	35	43	49
Cognitive	19,245,525	5.21	1.87	3	4	5	7	8
Non-cognitive	19,245,525	5.12	1.69	3	4	5	6	7
Leadership	12,648,892	5.31	1.65	3	4	5	6	7
Logic	16,010,681	25.20	6.42	16	21	26	30	33
Verbal	15,909,970	24.20	6.05	16	20	24	29	32
Spatial	15,916,922	19.11	7.77	10	13	17	25	31
Technic	15,804,221	28.24	7.50	19	23	28	33	39
Grade Rank	12,763,174	45.06	28.31	8	21	43	68	86
At least 2-year high-school	19,225,958	0.87	0.34	0	1	1	1	1
At least 3-year high-school	19,225,958	0.52	0.50	0	0	1	1	1
Any post-secondary education	19,225,958	0.30	0.46	0	0	0	1	1
University degree	19,225,958	0.16	0.36	0	0	0	0	1
PhD degree	19,225,958	0.01	0.10	0	0	0	0	0
Years of School	19,225,958	11.91	2.29	9	10.5	12	13.5	16
Potential experience	19,245,525	17.05	9.29	5	9.5	16.5	24	30
Labor Income (SEK ‘00’s)	19,245,525	2,794	2,222	1,163	1,810	2,471	3,296	4,494

Table 2: Linear Probability Occupational Choice Regressions

*This table reports probit regressions of choosing to work in finance as opposed to other sectors. In the first column the finance dummy is regressed on predicted cognitive ability and their interaction with a year trend for both genders. Controls are a quadratic in potential experience, the year trend, and a sex dummy. Column (2) adds years of schooling interacted with a year trend. In the third and fourth column the subsamples of males is used together with actual cognitive ability (different scale than the predicted ones) and non-cognitive ability. Columns (5)-(8) repeat the analysis for 30 year olds. T-statistics below the coefficients. *,**,*** indicate significance at the ten, five, and one percent level. Source: Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for persons enlisted between 1983 and 2010, Military Archives (Krigsarkivet) for persons enlisted between 1969 and 1983. Swedish population data LISA from Statistics Sweden.*

Sample	**Men, 30yo**		**Women, 30yo**		**Men, 30yo**		**Men, 30yo**		**Women, 30yo**	
	Coeff.	*P-val.*	*Coeff.*	*P-val.*	*Coeff.*	*P-val.*	*Coeff.*	*P-val.*	*Coeff.*	*P-val.*
Year	-0.00102	0.000	-0.00147	0.000	-0.00103	0.000	-0.00234	0.000	-0.000689	0.322
Years of school	0.0058	0.000	-0.00528	0.000	0.00571	0.000	0.00434	0.000	-0.00183	0.061
*Year	0.000115	0.000	0.000211	0.000	0.000113	0.001	0.000162	0.000	0.0000569	0.300
Cog talent (lin)	-0.000505	0.032			-0.00128	0.000	-0.000989	0.016		
*Year	-5.17E-05	0.004			-0.0000243	0.250	-0.0000615	0.016		
Non-cog talent (lin)	0.00559	0.000			0.00603	0.000	0.00356	0.000		
*Year	-0.0001	0.000			-0.000135	0.000	-0.0000124	0.654		
Pred. cog talent (lin)			0.000852	0.000					0.0000816	0.207
*Year			-2.73E-05	0.000					7.02E-06	0.048
Father works in finance					0.0409	0.000	0.0101	0.108	0.0233	0.037
*Year					0.000542	0.053	0.00189	0.000	0.000543	0.380
Mother works in finance					0.0308	0.000	0.0153	0.006	0.0317	0.007
*Year					-0.0000305	0.905	0.000587	0.086	0.000738	0.262
Adj. R2	0.014		0.004		0.019		0.027		0.012	
Num obs	787,218		632,847		633,378		398,507		305,989	
Fathers income, *year	No		No		No		Yes (insig)		Yes (insig)	
Finance share in municipality, *year							Yes (pos and sig)		Yes (pos and sig)	

Table 3: Linear Probability Occupational Choice Regressions – Talent Groups

*This table reports probit regressions of choosing to work in finance as opposed to other sectors. In the first column the finance dummy is regressed on predicted cognitive ability and their interaction with a year trend for both genders. Controls are a quadratic in potential experience, the year trend, and a sex dummy. Column (2) adds years of schooling interacted with a year trend. In the third and fourth column the subsamples of males is used together with actual cognitive ability (different scale than the predicted ones) and non-cognitive ability. Columns (5)-(8) repeat the analysis for 30 year olds. T-statistics below the coefficients. *,**,*** indicate significance at the ten, five, and one percent level. Source: Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for persons enlisted between 1983 and 2010, Military Archives (Krigsarkivet) for persons enlisted between 1969 and 1983. Swedish population data LISA from Statistics Sweden.*

Sample	**Men, 30yo**		**Women, 30yo**		**Men, 30yo**		**Men, 30yo**		**Women, 30yo**	
	Coeff.	*P-val.*	*Coeff.*	*P-val.*	*Coeff.*	*P-val.*	*Coeff.*	*P-val.*	*Coeff.*	*P-val.*
Year	-0.000861	0.000	-0.000498	0.054	-0.000887	0.000	-0.00231	0.000	-0.000323	0.641
Years of school	0.00691	0.000	0.00184	0.000	0.00662	0.000	0.00483	0.000	-0.00136	0.145
*Year	0.0000579	0.000	0.0000652	0.002	0.0000604	0.001	0.000124	0.000	0.0000435	0.407
Mid cog talent (4-8)	0.00951	0.000			0.00919	0.000	0.00158	0.135		
*Year	-0.000283	0.000			-0.000279	0.000	0.0000676	0.351		
High cog talent (9)	-0.0196	0.000			-0.0216	0.000	-0.0224	0.000		
*Year	0.000434	0.011			0.000519	0.006	0.000439	0.213		
Mid non-cog talent (4-8)	0.00849	0.000			0.00953	0.000	0.00642	0.000		
*Year	-0.000105	0.072			-0.000194	0.006	-0.0000383	0.629		
High non-cog talent (9)	0.0314	0.000			0.0357	0.000	0.0276	0.026		
*Year	-0.000809	0.038			-0.00121	0.005	-0.000698	0.358		
Mid pred. cog. (40-95pc)			0.042	0.000					0.014	0.000
*Year			-0.00102	0.000					0.000229	0.287
High pred. cog. (>95pc)			0.0171	0.000					-0.0205	0.002
*Year			-0.00097	0.000					0.000656	0.067
Father works in finance					0.0412	0.000	0.01	0.111	0.022	0.048
*Year					0.000537	0.055	0.0019	0.000	0.000614	0.321
Mother works in finance					0.031	0.000	0.0152	0.006	0.0311	0.008
*Year					-0.0000401	0.876	0.000586	0.087	0.000748	0.255
Adj. R2	0.013		0.005		0.018		0.027		0.014	
Num obs	787,218		632,847		633,378		398,507		305,989	
Fathers income, *year	No		No		No		Yes (insig)		Yes (insig)	
Finance share in municipality, *year							Yes (pos and sig)		Yes (pos and sig)	

Table 4: Occupational Employment, Talent, and Finance Premium (27 largest 4-digit occupations in finance)

This table shows employment, talent, and the finance premium of the 21 largest 4-digit occupations in finance, constituting almost 80 percent of finance employment, in 1990 and 2010. The second, fifth, and eights column show the percent employment share in the rest of the economy. The third, sixth, and ninth column show the employment share in finance. The fourth, seventh, and tenth column show the finance wage premium for each occupation and year. The last column shows how the occupations were grouped into (associate) professionals, routine, computer-related, and high-skill professions for Figure X2. Source: Swedish census and population data LISA from Statistic Sweden.

										Finance wage premium			
		Fin. labor share		**Cognitive score**			**Non-cognitive score**			**Vs all workers**		**Vs same profession**	
		Average 2010	*Change 1990-2010*	*Score 2010*	*Change 1990-2010*	*Diff vs ROE 2010*	*Score 2010*	*Change 1990-2010*	*Diff vs ROE 2010*	*Average 2010*	*Change 1990-2010*	*Score 2010*	*Change 1990-2010*
Securities&finance dealers&brokers	HS	3.8%	3.5%	6.2	0.0	NA	6.3	-0.4	NA	3.60	2.15	NA	NA
Finance and admin managers	HS	0.8%	-0.5%	6.5	-0.1	0.1	6.2	0.2	0.1	3.50	1.29	1.38	0.13
Business professionals	AP	6.6%	2.6%	6.5	0.0	0.1	6.2	0.3	0.3	2.79	1.10	1.83	0.61
Corporate legal officers	HS	1.1%	-0.6%	6.6	0.0	-0.1	6.2	-0.3	0.0	2.39	0.72	1.24	0.33
Market res analysts and rel prof	AP	1.4%	0.3%	6.3	0.0	0.1	6.0	-0.2	0.0	2.08	0.35	1.33	0.20
Personnel and careers professionals	AP	0.3%	0.0%	6.2	-0.2	0.5	6.2	0.5	0.5	2.04	0.34	1.70	0.32
Accountants	AP	1.7%	0.7%	6.2	-0.5	0.1	5.8	-0.1	0.1	1.91	0.44	1.25	0.21
Computing professionals	C	4.8%	3.7%	6.5	-0.3	0.0	5.7	-0.2	0.2	1.79	0.10	1.24	0.10
Finance and sales associate prof	AP	0.6%	0.4%	5.9	-0.7	0.6	6.0	0.5	0.6	1.68	0.22	1.38	0.05
Insurance representatives	AP	12.4%	-3.5%	5.5	-0.4	NA	5.8	0.3	NA	1.56	0.08	NA	NA
Comp syst design, analys & programmers	C	4.6%	0.8%	6.5	0.0	-0.3	5.3	-0.2	0.0	1.56	0.07	1.15	0.03
Banking associate professionals	AP	25.8%	-12.8%	5.8	-0.1	NA	5.8	0.1	NA	1.50	0.40	NA	NA
Bookkeepers	R	0.8%	0.7%	6.1	-0.3	0.2	5.6	0.1	0.2	1.48	0.57	1.34	0.39
Admin secret and related assoc prof	R	1.0%	0.1%	5.8	0.2	0.1	5.7	0.1	0.4	1.48	0.19	1.25	0.15
Computer assistants	C	3.0%	2.2%	5.8	-0.2	-0.1	5.1	-0.5	0.1	1.40	0.03	1.28	0.17
Appraisers, valuers and auctioneers	AP	5.2%	0.7%	5.5	-0.4	0.1	5.6	0.1	0.2	1.24	0.03	1.24	0.19
Numerical clerks	R	0.5%	-0.3%	5.7	-0.1	0.2	5.2	-0.1	0.2	1.16	0.11	1.34	0.20
Doorkeepers and related workers	R	0.6%	-0.7%	4.7	-0.1	0.2	5.0	0.5	0.5	1.02	0.23	1.48	0.40
Other office clerks	R	1.4%	-0.1%	5.4	0.0	0.1	5.4	0.2	0.3	0.93	0.00	1.09	0.06
Telephone switchboard operators	R	0.3%	0.2%	5.1	-0.2	0.1	5.6	0.8	0.9	0.82	0.12	1.09	0.19
Tellers and other counter clerks	R	1.1%	0.8%	5.7	-0.4	0.2	5.4	0.5	0.3	0.67	-0.01	1.14	0.41
Associate professionals	AP	53.9%	-11.5%	6.5	-0.1	0.1	6.2	0.2	0.1	1.66	0.40	1.26	0.27
Routine Workers	R	5.8%	0.7%	4.7	-0.1	0.2	5.0	0.5	0.5	1.03	0.02	1.13	0.08
Computer Workers	C	12.4%	6.7%	6.2	-0.2	0.5	6.2	0.5	0.5	1.59	0.15	1.24	0.16
High-Skill Workers	HS	5.7%	2.5%	5.9	-0.7	0.6	6.0	0.5	0.6	3.97	1.69	1.46	0.26

Appendix

A. A Simple Roy Model of Finance Sector Choice and Wages

To fix ideas we propose a simple model of labor supply based on Roy (1951). This model delivers empirical predictions on the selection of skill into finance as well as how workers' sectoral choice and wages should depend on skill, which we can test in the data using our detailed talent and skill measures.[1]

A.1 Average Skill Selection

We consider an economy with two sectors, the financial sector F, and the real sector R. Suppose that log wages in sector $k \in \{F, R\}$ at time t are a function of worker i's skill s_{it}:[2]

$$w_{kit} = \alpha_{kt} + \beta_{kt} s_{it} \qquad (1)$$

Changes in α_{kt} correspond to percentage changes in the wage that are independent of the level of skill, while changes in β_{kt} translate into percentage changes of wages depending on the skill of the workers. We can interpret s_{it} as deviation from population average skill, that is, $s_{it} > 0$ are relatively high-skilled and $s_{it} < 0$ are relatively low-skilled workers (see Appendix C.2). The wages in (1) may, but do not need to, be determined competitively according to workers' marginal product in sector k. Workers have preferences over wages and job characteristics. Hence, utility from working in sector k is given by:

$$U_{kit} = w_{kit} + v_{kit} \qquad (2)$$

where $v_{kit} = \mu_{kt} + \varepsilon_{kit}$ is the worker's preference for the job with μ_{kt} the population mean and $\varepsilon_{kit} | s_{it} \backsim iid(0, \sigma_\varepsilon^2)$ is the individual-specific deviation from that mean. Workers are utility maximizers and choose jobs accordingly.

It is convenient to define workers' relative wages and utilities in finance:

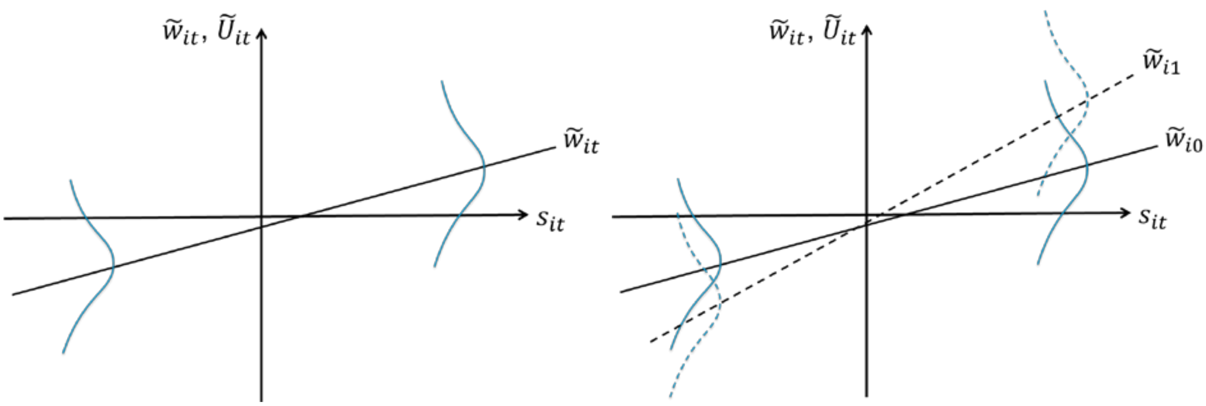
[1] Our results on (relative) talent selection below do not depend on the model and stand on their own. For illustrative purposes we abstract from skills being sector-specific, i.e., possessing an index k.
[2] The model can be extended to more than two sectors. The binary choice regressions proposed below would then become multinomial choice regressions.

$$\tilde{w}_{it} \equiv w_{Fit} - w_{Rit} = \tilde{\alpha}_t + \tilde{\beta}_t s_{it} \qquad (3)$$

$$\tilde{U}_{it} \equiv U_{Fit} - U_{Rit} = \tilde{\alpha}_t + \tilde{\beta}_t s_{it} + \tilde{\mu}_t + \tilde{\varepsilon}_{it} \qquad (4)$$

Illustration 1 plots these relative wages and utilities against workers' skills for the expositionally convenient case of $\tilde{\mu}_t$=0. The distribution of individual-specific relative preferences for finance is indicated by the two curves around the relative wage line. The finance sector is chosen when the worker's relative utility is positive. The left panel of Illustration 1 shows the case in which finance is relatively skill-biased as the relative wage line is upward-sloping (i.e., $\tilde{\beta}_t$>0). High-skilled workers are therefore (relatively) more likely to enter the finance sector than are low-skill workers.

Illustration 1



The idea of an increasing skill-bias in finance is captured by an increase of the relative $\tilde{\beta}_t$ in equation (3) over time. Our main interpretation of the rising skill-bias $\tilde{\beta}_t$ is the one proposed by Philippon and Reshef (2012), Cellerier and Vallee (2015), and others whereby the relative marginal product of skill increases in finance. An alternative interpretation could be that high-skill workers are becoming relatively more effective at extracting rents from their employers in the financial sector. In either case, relative potential wages in finance for high-skill workers rise compared to low skill workers. Illustration 1 (right panel) depicts this by the steeper $\tilde{w}_{i1}$ line. We see that now a larger share of the high-skill and a smaller share of the low-skill workers enter the finance sector.[3]

[3] This immediately leads to the rising relative wages in finance that we observe in the data. In addition, wage inequality in finance will increase when the increase in $\tilde{\beta}_t$ dominates the effect of a potentially more homogenous (high-)skill selection into finance. The relative task price for working in finance $\tilde{\alpha}_t$ may also be affected in general equilibrium (see Appendix C.2).

For each value of $\tilde{\alpha}_t$ and $\tilde{\beta}_t$ we can compute the average skill of workers in the finance sector:

$$E\left(s_{it}\middle|\widetilde{U}_{it} > 0\right) = E\left(s_{it}\middle|\tilde{\varepsilon}_{it} > -(\tilde{\alpha}_t + \tilde{\beta}_t s_{it} + \tilde{\mu}_t)\right) \qquad (5)$$

Under standard assumptions, i.e., a normal distribution of s_{it} and $\tilde{\varepsilon}_{it}$, this conditional expectation increases when the relative skill-bias $\tilde{\beta}_t$ in finance increases. Concurrently, the selection of skill into the rest of the economy $E\left(s_{it}\middle|\widetilde{U}_{it} < 0\right)$ declines. Our **first empirical test** is therefore based on sectoral skill composition by checking whether

$$E\left(s_{it}\middle|\widetilde{U}_{it} > 0\right) - E\left(s_{it}\middle|\widetilde{U}_{it} < 0\right) \qquad (6)$$

rises over time.[4] Empirically, we use components or determinants of skill s_{it} that are arguably comparable over time (i.e., our talent measures).

Philippon and Reshef (2012) also analyze how relative skill proxies (in their case, the relative share of workers who have attained some post-secondary education) between the financial sector and the rest of the economy, that is, $E\left(s_{it}\middle|\widetilde{U}_{it} > 0\right) - E\left(s_{it}\middle|\widetilde{U}_{it} < 0\right)$, evolve over time.

When finance's skill-bias changes, the dispersion of skill in the sector should also be affected. A well-known prediction from the Roy model under normality (in the cross-section) is that self-selection produces a lower dispersion of skill within sectors compared to the overall population:

$$Var\left(s_{it}\middle|\widetilde{U}_{it} > 0\right) < Var(s_{it}) \qquad (7)$$

We can get an intuition for this effect in the left panel of Illustration 1, as high-skill workers are more concentrated in finance and low-skill workers are more concentrated in the real economy. A further increase in finance's skill-bias in the right panel of Illustration 1 leads to a further concentration and thus a lower dispersion of skill in the sector. We examine this prediction along with the average skill (empirically, talent) selection as a **part of our first empirical test**. Appendix C.1 provides proofs of these claims and further discussion of why we focus on expressions (6) and (7).

[4] We could equally well check whether $E\left(s_{it}\middle|\widetilde{U}_{it} > 0\right)$ rises over time and the empirical results below would be the same. We decided for $E\left(s_{it}\middle|\widetilde{U}_{it} > 0\right) - E\left(s_{it}\middle|\widetilde{U}_{it} < 0\right)$ because it is consistent with Philippon and Reshef, and because it accounts for a potentially changing selection of skill into the labor market. Empirically, this turns out not to be a major issue.

One case in which skill selection into the financial sector may not improve or the dispersion of skill may not decline even under standard assumptions is if there are many new entrants on the margin. In Illustration 1 (right panel) we can see a small triangle spanned by the $\widetilde{w}_{i1}$, $\widetilde{w}_{i0}$ lines and the x-axis. If there is enough mass of workers within this triangle and their skill is sufficiently low, the expression in (6) may actually not increase and $Var\left(s_{it}\middle|\widetilde{U}_{it} > 0\right)$ may actually increase. In that case, however, relative employment in the financial sector will also need to be rising at the same time (see Appendix C.1).

This last prediction of rising employment of skilled workers in finance could also result from a different interpretation of rising relative skill demand in that sector whereby $\tilde{\alpha}_t$ rises. Appendix C.2 derives such a case where the relative marginal product of working in finance rises within a general equilibrium extension of this model. Alternatively, the increase in $\tilde{\alpha}_t$ may be due to finance workers capturing more rents from their employers. In Illustration 1 (right panel) this would constitute a shift up of the relative wage curve instead of- or in addition to a rotation along the y-axis. We check for rising employment in finance as **part of our first empirical test**.

The **second empirical test** of increasing skill-bias in finance is based on workers' choices. The probability that a worker with skill s_{it} chooses finance is given by

$$Pr(\widetilde{U}_{it} > 0) = Pr\left(\tilde{\varepsilon}_{it} > -\left(\tilde{\alpha}_t + \tilde{\beta}_t s_{it} + \tilde{\mu}_t\right)\right) \qquad (8)$$

If we are willing to approximate the skill composite s_{it} by a linear combination of our talent measures and an unobserved component, e.g.,

$$s_{it} = \gamma_1 cog_{it} + \gamma_2 noncog_{it} + .. + s_{it}^{u} \qquad (9)$$

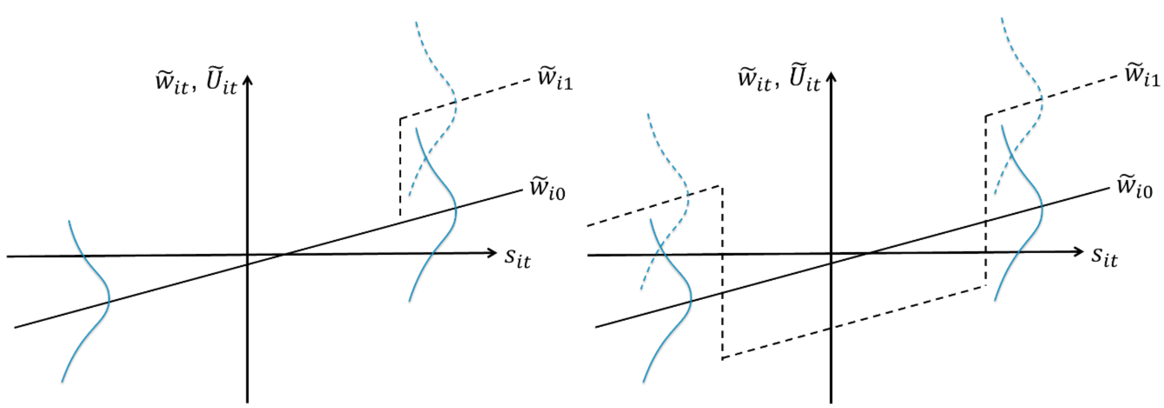
we can use choice regressions to identify the changing slope $\tilde{\beta}_t$ and intercept $\tilde{\alpha}_t + \tilde{\mu}_t$ over time. In addition, we can control in these regressions for variables that one would want to hold constant when examining talent selection, such as age or potential experience and possibly education. For example, we can estimate this relationship in a probit model when $\tilde{\varepsilon}_{it}$ and s_{it}^{u} are jointly normally distributed. Without making particular distributional assumptions, a linear probability model can still estimate the changing marginal effects of the talent measures for occupational choice over time.

A.2 Skill Selection at the Top

An important variant of the skill-bias hypothesis focuses on the top of the skill and wage distribution in finance. In particular, previous literature has documented an extreme increase of finance pay at the very top of the wage distribution (e.g., Kaplan and Rauh, 2010, for the US; Bell and Van Reenen, 2013, for the UK) and we documented a similar trend for Sweden in Figure 1. This suggests that the most interesting changes in skill selection and compensation may have taken place among the highest talented individuals.

Consistent with this idea, Philippon and Reshef (2012) and others have suggested at least two distinct theoretical mechanisms of why increased skill demand in finance may be specifically strong at the top of the skill distribution. First, it seems plausible that there are superstar effects (Rosen, 1981) arising in the financial sector that have become stronger over time. Increased financial globalization, skill-biased technological change, deregulation, and financial innovation may have contributed to a situation where highly productive individuals can manage more and more assets as well as subordinates over time (e.g., Kaplan and Rauh, 2010, 2013, Célérier and Vallée, 2014), similar to the argument for increasing CEO wages made in Terviö (2008) or Gabaix and Landier (2008). This situation where skill demand in finance only rises at the very top is depicted in Illustration 2 (left panel).

Illustration 2



In addition to superstar effects, skill demand in the financial sector may have become increasingly polarized over time. For example, Autor, Levy, and Murnane (2003) propose a model of biased technical change which postulates that, due to new information and communication technology, it is in fact the routine middle-skilled jobs that are threatened by technological change while the high-and even the low-skilled jobs may be more shielded from it. Given that the financial sector has been a quick adopter of ICT, this may have decreased the demand for middle-skilled bank tellers, accountants, or secretaries, who can be replaced by computer/automation technology, compared to both high-skilled professionals (e.g., traders, investment bankers) as well as low-skilled workers in finance (e.g., janitors, receptionists, security guards, etc.), who are non-routine and can thus not easily be automated.[5] Illustration 2 (right) plots the relative polarized skill demand in finance.

The two theoretical mechanisms depicted in Illustration 2 could potentially be consistent with an unchanged (relative) average skill in finance and a non-decreasing dispersion of skill, despite the increasing inequality and surging top wages in finance that we observe in the data.[6] Therefore, we **modify our first empirical test** to focus on the top of the skill distribution:

$$E\left(H_{it}\middle|\widetilde{U}_{it} > 0\right) - E\left(H_{it}\middle|\widetilde{U}_{it} < 0\right) \qquad (10)$$

where, empirically, H_{it} is an indicator for belonging to the top percentiles in terms of our different talent measures. If $E\left(H_{it}\middle|\widetilde{U}_{it} > 0\right) - E\left(H_{it}\middle|\widetilde{U}_{it} < 0\right)$ rose over time, this would be consistent with the rising skill-bias at the top and the polarization of skill demand hypotheses.

A.3 Skills and Wages

Our **third empirical test** of (the different variants of) the increasing skill-bias hypothesis in finance examines the relationship between skills and wages. Since this requires stronger assumptions than the tests based on skill selection, we start with a restricted version of wage equation (1), which we generalize later:

$$w_{kit} = \alpha_{Rt} + F_{it}\tilde{\alpha}_t + \beta s_{it} \quad (11)$$

Here β is the (economy-wide) return to worker skill, F_{it} is an indicator for working in the financial sector, and $\tilde{\alpha}_t$ the time-varying finance wage premium in log points. As we showed in the

[5] Philippon and Reshef (2012, 2013), Boustanifar et al (2015), and Célérier and Vallée (2015) present evidence that is consistent with this polarization of skill demand in finance. Levy and Murnane (2002) document how computer technology replaced routine jobs in two departments of a large bank.

[6] Analytically, one could model these hypotheses by modifying equation (3) to
$$\widetilde{w}_{it} \equiv w_{Fit} - w_{Rit} = \tilde{\alpha}_t + \tilde{\beta}_{Ht}H_{it} + \tilde{\beta}_{Mt}M_{it} + \tilde{\beta}_{Lt}L_{it},$$
where $J_{it} \epsilon \{H, M, L\}$ is an indicator for being a high-, middle-, or a low-talent worker. The superstar hypothesis implies that $\tilde{\beta}_{Ht}$ rises, while the polarization of skill demand implies that $\tilde{\beta}_{Mt}$ falls compared to $\tilde{\beta}_{Ht}$ and $\tilde{\beta}_{Lt}$.

descriptive part (Section 2), without accounting for (changing) s_{it}, the finance wage premium rises strongly over time and especially so at the top of the wage distribution.

However, the skill-bias hypothesis predicts that the composition of skill in finance improves over time (equation 6), which should then (at least partly) account for the rising $\tilde{\alpha}_t$. We therefore run wage regressions adding education, experience, cognitive and non-cognitive test scores, and other variables as proxies of skill and talent. This test based on wage regressions is also useful because fixed effects in the estimation of equation (11) may control for the selection according to additional unobservable components of skill s_{it}^u. The fixed effects can further be made sector- or even employer-specific. In addition, we let the economy-wide return to observable components of skill vary over time.

Of course, the skill-bias hypothesis not only predicts that the selection of skill into finance will improve over time, but also that the relative return to skill rises in the first place. This brings us back to our original wage equation (1), presented slightly differently for the discussion here:

$$w_{kit} = \alpha_{Rt} + F_{it}\tilde{\alpha}_t + (\beta_{Rt} + F_{it}\tilde{\beta}_t)s_{it} \quad (12)$$

The skill-bias hypothesis predicts that $\tilde{\alpha}_t$ should not rise in equation (12) once we allow for a rising $\tilde{\beta}_t$. In a recent paper, Célérier and Vallée (2015) argue that this is the case for graduates from French engineering schools, their findings thus supporting the rising skill-bias hypothesis. The rising $\tilde{\beta}_t$ also implies that the finance wage premium should rise more strongly for higher talented workers and most strongly for the very top talented workers. The second **part of our third empirical test** examines whether this is the case in the Swedish data.[7]

A.4 Summary of Hypotheses

We test the main hypotheses of the model in the next section. We first test hypothesis H1 whether the average relative talent allocation in the financial sector has improved over time.

> **H-1:** *Average talent in the financial sector relative to the average talent in the real economy, i.e.* $E(s_{it}|\tilde{U}_{it} > 0) - E(s_{it}|\tilde{U}_{it} < 0)$, *increases over time.*

[7] However, note that ours as well as Célérier and Vallée (2015)'s test only identify the structural parameters $\tilde{\alpha}_t, \tilde{\beta}_t$ under the assumption that the observable talent measures leave no room for additional skill components (i.e., no selection on unobservables). Therefore, one may want to in addition run selection-bias adjusted wage regressions.

While the mean of the distribution may remain unchanged, there could be still improved skill selection at the top due to superstar effects or polarization. Accordingly, we test hypothesis H2 whether the relative talent allocation at the top in the financial sector has improved over time.

> **H-2:** *Top talent in the financial sector relative to top talent in the real economy, i.e.* $E\left(H_{it}\middle|\widetilde{U}_{it} > 0\right) - E\left(H_{it}\middle|\widetilde{U}_{it} < 0\right)$, *increases over time.*

Moreover, in the last part of the next section we test additional predictions of the model that rely on additional assumptions.

> **H-3:** The *talent dispersion within finance,i.e.* $Var\left(s_{it}\middle|\widetilde{U}_{it} > 0\right)$ *decreases over time. (This prediction need not hold for skill demand only rising at the top or polarizing.)*

> **H-4:** *Talents become more important for choosing a career in the financial sector i.e. the* $\tilde{\beta}_t$ *from a choice regression* $Pr\left(\tilde{\varepsilon}_{it} > -(\tilde{\alpha}_t + \tilde{\beta}_t s_{it} + \tilde{\mu}_t)\right)$ *increases over time.*

> **H-5:** *The changing composition of skills in the financial sector and the changing economy-wide return to talent explain (at least a significant part of) the trend in the financial wage premium* $\tilde{\alpha}_t$.

H-6: *The rising* $\tilde{\beta}_t$ *implies that the finance wage premium rises more strongly for high(er)-talent workers. Moreover, the premium for the lowest talent workers* $\tilde{\alpha}_t$ *stays flat.*

B. Detailed Evidence on Skill Selection in the U.S.

In Section 5.1 we argue that education categories are a potentially problematic measure of workers' skill because they are quite crude and their composition changes with the expansion of higher education. This section nonetheless revisits the U.S. evidence using relative education measures in finance and compares it to our Swedish results. To disentangle effects of educational attainment from fundamental skill or talent, we exploit an episode of a slowdown or reversal of university education.

The top left panel of Figure A6 plots the education series of Figure 4, but with CPS data back to 1968. We see that relative post-secondary as well as university education in finance rise continuously from the 1980s. Next, these relative series are split by gender in the top middle and top right panel of Figure A6. Relative post-secondary education for males is actually flat on a high level, while for females it starts negatively but rises throughout the period. In the top right panel, both male and female relative university education in finance increase continuously (there is a small dip for females in the beginning of the 1970s). For males this series starts out positive and rises strongly, whereas for females it starts negative and rises more modestly. Our analysis in the following concentrates on the university series, since relative post-secondary attainment for males in finance is not rising in the first place.

It is well-known among labor economists that the United States experienced a deceleration of college attainment during the 1970s and 1980s (e.g., Card and Lemieux 2000). This is plotted for thirty year olds by birth year in the bottom left panel of Figure A6. For males born after the end of the 1940s, the slowdown actually consisted of a decline in attainment compared to previous birth cohorts which reversed only after a decade and reached its previous peak almost twenty birth cohorts later. For females, the deceleration was rather a flattening of attainment which lasted about a decade for cohorts born after 1950. Thereafter, the increase in female attainment took off sharply again.

The attainment slowdown documented in the bottom left panel of Figure A6 may help disentangle a faster rate of increase in formal education for finance workers from an improvement in the fundamental skill or talent selected into finance. As argued in the main text, one potential problem with the relative skill measure in finance based on education is that the rise in attainment may have changed (i.e., worsened) the fundamental skill composition of degree holders. In this sense, the deceleration of the 1970s and 1980s is an opportunity to get closer to a comparison of like with like.

The bottom middle panel of Figure A6 plots the relative university attainment in finance for all males as in the top right panel and for males in the birth cohorts between 1950 and 1969. The latter years are approximately at the end points of the slowdown (we also focus on above 25 year olds and the period from 1980 onward to ensure that most individuals have attained their highest level of education). In the plot, the relative education line rises strongly and almost continuously for all males, but it stays largely flat (albeit at a high level) for the birth cohorts with constant attainment.

The graph therefore suggests that a substantial part of the rising relative university attainment in finance may be driven by changing attainment rates of male university graduates rather than an increase in relative fundamental skill or talent in finance. This is also consistent with our results for the more direct talent measures in Sweden. However, it does not necessarily contradict the idea that relative overall skill in finance increased if (formal) educational attainment positively affects productivity conditional on a constant fundamental skill.

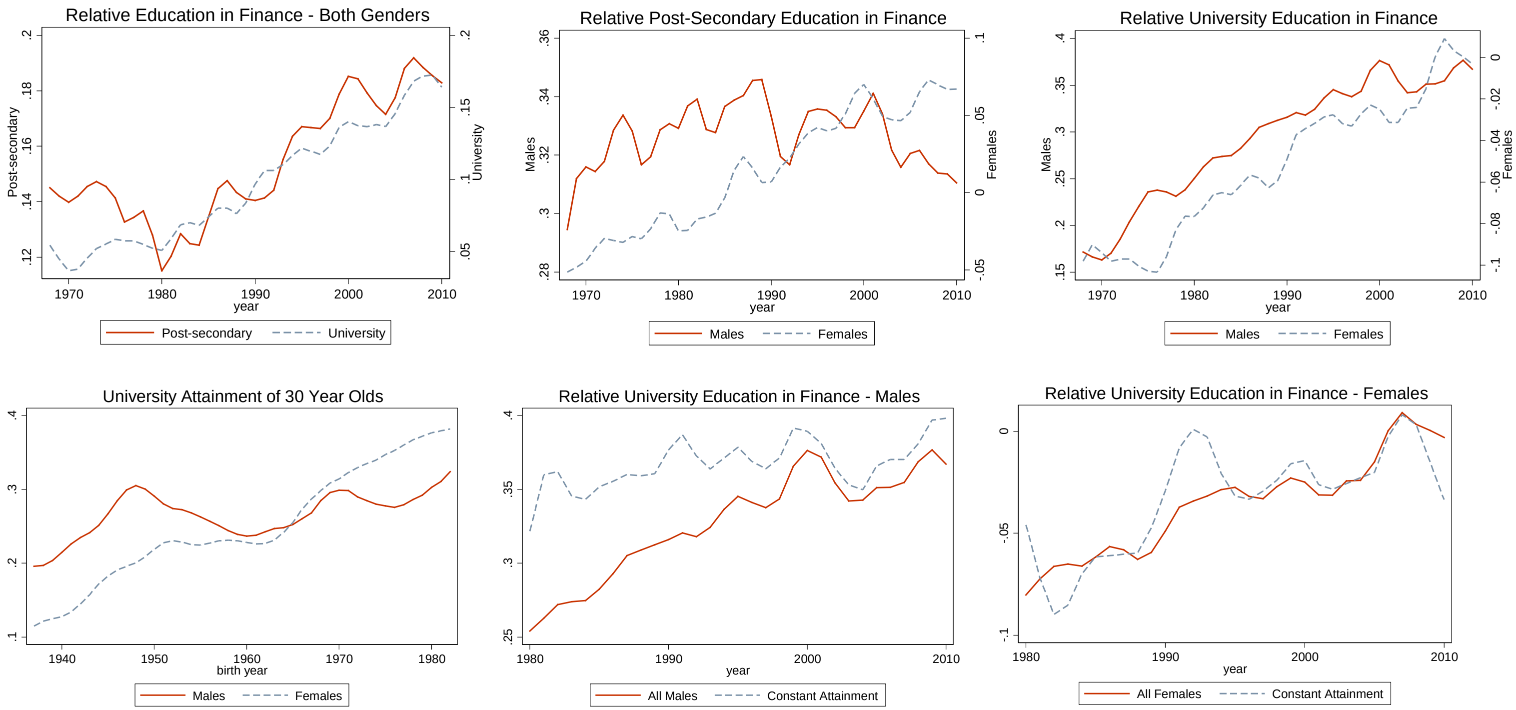
Finally, the bottom right panel of Figure A6 does the same exercise for females using the “almost flat attainment” birth cohorts of 1952-1966. We see that the longterm trend here is similar in these two groups and that composition effects may not confound very much the relative skill measurement for women in finance. Yet, for the period of our focus in this paper 1991-2010, relative female education for the constant attainment groups seems largely flat despite some imprecisions.

To sum up this more detailed analysis of relative skill in the U.S., it seems that especially for males some of the university increase in finance may be due to composition changes of graduates rather than fundamental skill selection.[8] There is also no increase of relative attainment in finance among males when we use post-secondary education as a skill measure. For females, the relative increase of skill in finance appears robust to conditioning on the slowdown cohorts. However, the increase in relative post-secondary and university education starts already during the 1970s and thus before the introduction of computers and the deregulation of finance, which are hypothesized to have driven skill demand in this sector.

[8] The results in the bottom middle panel of Figure A6 are the same when we also include the second slowdown and the male birth cohorts up to 1978 instead of 1969.

Figure B1: U.S. Educational Attainment and Relative Education in the Financial Sector

This graph shows the evolution of educational attainment and the relative education between the financial sector and the rest of the economy in the United States. In the top left panel, the relative post-secondary and university attainment in finance of Figure 4 is plotted for the longer period of 1968-2010. In the top middle and right panel these series are split up by gender. In the bottom left panel, the rate of university attainment at age 30 is plotted against birth year by gender. The bottom middle and bottom right contrast overall relative university attainment in finance with the relative attainment of the birth cohorts for whom attainment slowed down by gender (birth cohorts 1950-1969 and 1952-1966, respectively). This latter series is plotted only for at least 25 year olds and from 1980 onward to ensure that most individuals have attained their highest level of education. Source: Current Population Survey for the US.



C. Further Figures

Figure A1: Law, Consulting, and Accounting (LCA)

This graph shows the main facts pertaining to the LCA sector. The top row depicts the finance earnings premium relative to LCA (left) and LCA's share of overall nonfarm private sector employment. The bottom left panel depicts average talent in finance minus average talent in LCA for males. The relative distribution of medium and high talent in finance relative to LCA, calculated as the share in finance divided by the share in LCA. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency. 95 percent confidence intervals are shaded.

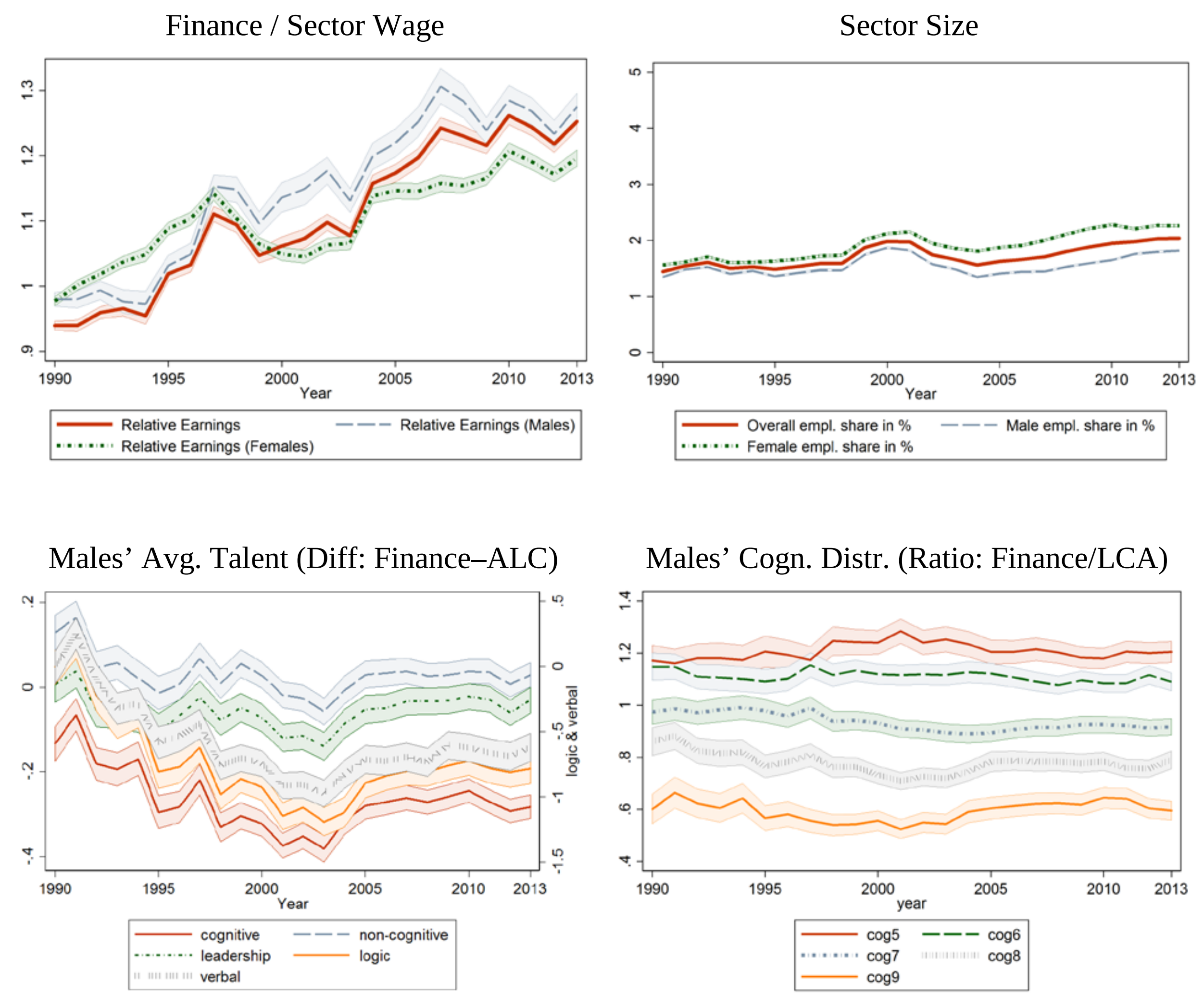


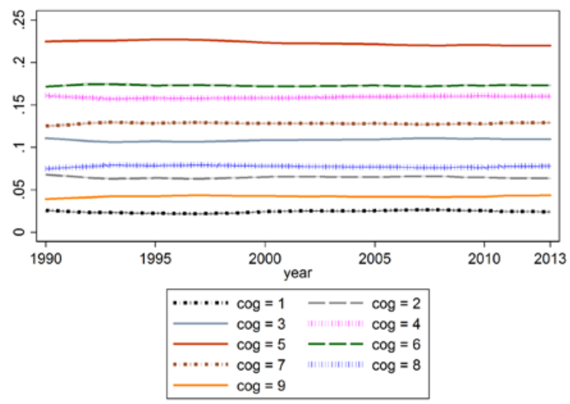
Figure A2: Information Technology (IT)

This graph shows the main facts pertaining to the IT sector. The top row depicts the finance earnings premium relative to IT (left) and IT's share of overall nonfarm private sector employment. The bottom left panel depicts average talent in finance minus average talent in IT for males. The relative distribution of medium and high talent in finance relative to IT, calculated as the share in finance divided by the share in IT. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency. 95 percent confidence intervals are shaded.

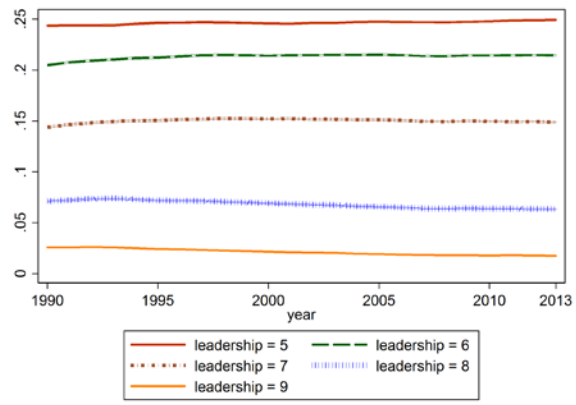
Figure A3: Distribution of Talent Measures By Cohort and Over Time

The top row …. Source: Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for persons enlisted between 1983 and 2010, Military Archives (Krigsarkivet) for persons enlisted between 1969 and 1983. Swedish population data LISA from Statistics Sweden. 95 percent confidence intervals are shaded.

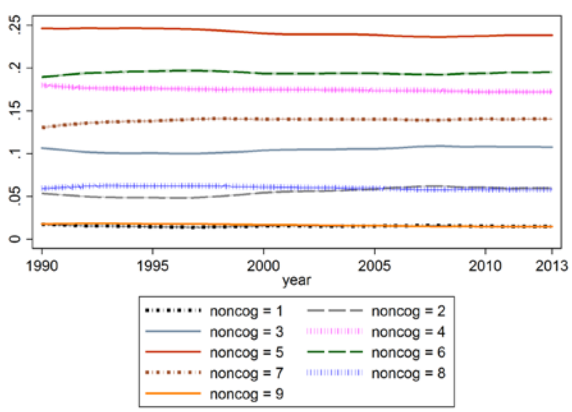
Males' Cognitive Scores



Males' Non-Cognitive Scores



Males' Leadership Scores



Females' Predicted Cognitive. Scores (Stanine Scaled)

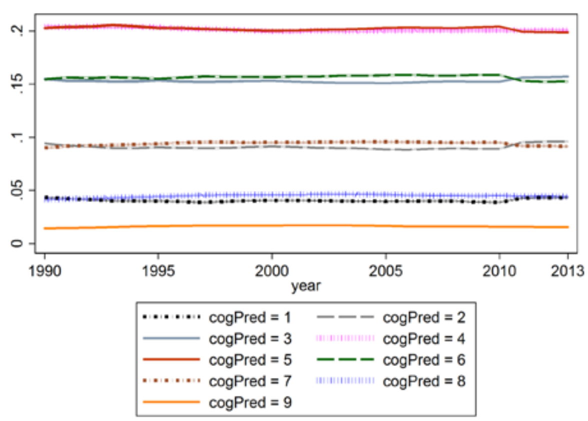


Figure A4: Task Analysis of the Finance, ILCA, and the Rest of the Economy

This shows the abstract, routine, and service task content of the financial sector, the rest of the economy, LCA, and IT during 1990 and 2005 to 2013. The contents are normalized to zero in 1990 as they are very different at the outset: Abstract (Fin 3.070; IT&LCA 3.098; RoE 2.878); Routine (Fin 1.841; IT&LCA 1.957; RoE 2.330); Service (Fin 3.362; IT&LCA 3.141; RoE 3.083). Sources: Swedish population data LISA; O*NET task measures from Goos, M., Manning, A., and Salomons, A. (2009). 95 percent confidence intervals are shaded.

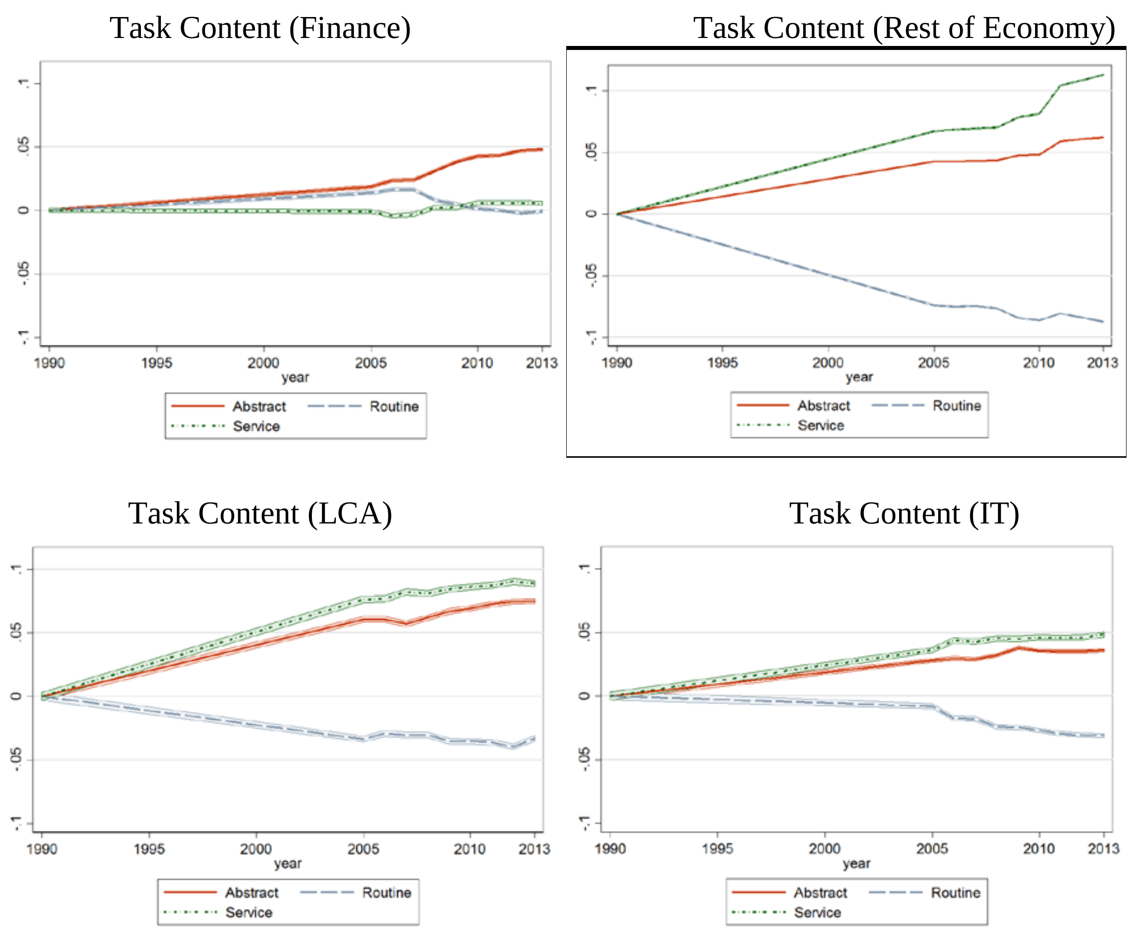
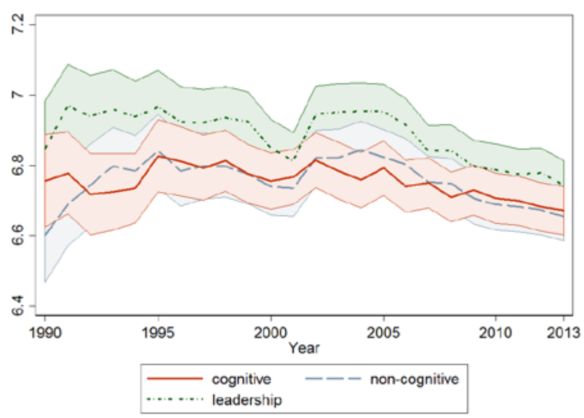


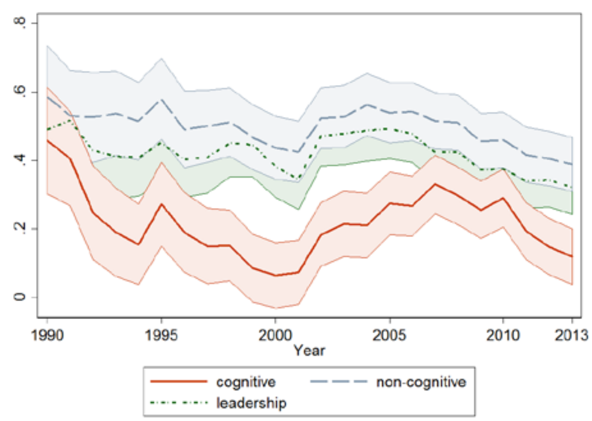
Figure A5: Talent of Top Earners in Finance (Males)

This graph shows average talent of male top 5 and top 1 percent earners in finance relative to top 5 and top 1 percent earners in the rest of the economy. Top earnings are residuals from a wage regression partialling out a quadratic in age. Relative average talent is defined as above. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency. 95 percent confidence intervals are shaded.

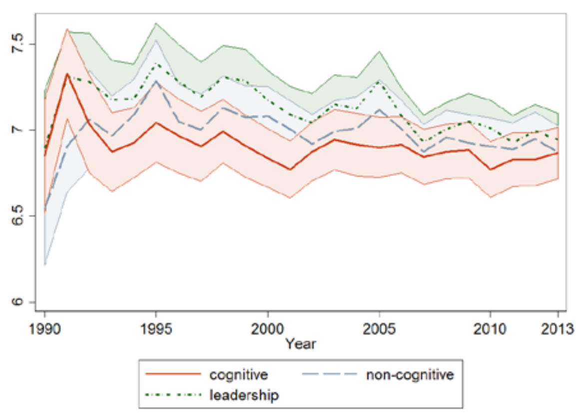
Absolute Talent (Top 5%)



Relative Talent (Top 5%)



Absolute Talent (Top 1%)



Relative Talent (Top 1%)