"Since you're so rich, you must be really smart":

Talent and the Finance Wage Premium

Michael Böhm, Daniel Metzger, and Per Strömberg*

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IN PARTS PRELIMINARY AND INCOMPLETE

Abstract

Relative pay in the financial sector has experienced an extraordinary increase over the last few decades. A proposed explanation for this pattern 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 distribution. 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 are also consistent with high, increasing, and largely unexplained rents in finance.

* Böhm is with University of Bonn; Metzger is with Stockholm School of Economics (SSE), Swedish House of Finance (SHoF), and Financial Markets Group (FMG), and Strömberg is with SSE, SHoF, SIFR, ECGI, and CEPR. E-mail: mboehm1@uni-bonn.de, daniel.metzger@hhs.se; per.stromberg@sifr.org. We would like to thank seminar participants at Oxford University, the University of British Columbia, University of Bonn, University of Munich, Sveriges Riksbank, Swedish Ministry of Finance, Stockholm School of Economics, Carnegie Mellon, and HKUST for helpful comments and suggestions. All remaining errors are our own. We are grateful to the Ragnar Söderberg Foundation for financial support. Strömberg also acknowledges the generous support from the Söderberg Professorship in Economics.

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, 2013a,b; 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. 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 skilled workers in finance, that is, 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 Swedish population data from administrative records for the period of 1991 to 2010 to examine whether finance has become more skill-biased during the last two decades and whether it has been increasingly absorbing talent from other sectors. Our wage 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 primarily on talent that is constant in the population, rather than education and other time-varying skill proxies. Our talent measures have the benefit of containing a substantial innate component and of being largely exogenous to career choice, and they are not sensitive to composition changes over time contrary to education. Accordingly, 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.[1] In addition, we use detailed information from secondary education, such as grades, program, or school characteristics, which are available for the female part of the population, too. The detail of the information allows us to also reliably analyze the right tails of the talent and wage distributions.[2]

We first address the question whether finance has become more skill-biased. A simple Roy (1951) model of workers' sectoral choice predicts that in this case average relative talent in finance should increase compared to the rest of the economy. If finance skill-bias only rises at the top of the skill distribution or if skill demand polarizes, the relative share of top talented workers entering the finance sector should increase. In addition, the dispersion of talent in finance should decline, talent should become a more important determinant of an individual choosing finance, and changing returns to talent and fixed effects should explain the rising wages in finance.

While consistent with the Roy model in the cross-section, our empirical findings do not support these predictions of a rising skill-bias over time. While finance wages have increased dramatically in Sweden during the period 1991-2010, particularly at the top of the wage distribution, we do not find any contemporaneous increase of talent in the financial sector.[3] Both, average talent in finance and the fraction of top talented workers going into finance, remain roughly constant over this period. Finance's share of the overall labor force is constant, so it is not an inflow of low-talent individuals at the bottom that masks an increase in its talent-intensity. Talent also does not become a more important determinant of entering finance in choice regressions on the individual level. In our wage regressions, we include individual and individual-firm fixed effects in order to control for additional unobservable components of skill. We find that rising skill or rising returns to talent can at best explain a small part of the increase in finance wages, and that the finance pay premium rises across the whole talent distribution.

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[1] Cognitive and non-cognitive test scores also partly depend on schooling and other investments during youth. We nonetheless call them talents, because they do contain a substantial innate component and because their population distribution is constant across cohorts, which is the comparison we make in this paper. We refer to education, potential experience, and other characteristics that may be endogenous to sector choice and not constant in the population as skill proxies. In the theoretical model of Section 3, talents and skill proxies combine into skill, which ultimately generates earnings in the two sectors.
[2] Previous research employing similar Swedish data has shown that our talent measures are indeed strong predictors of future income, as well as other labor market outcomes such as unemployment or the likelihood of becoming a CEO (see e.g., Lindqvist and Vestman, 2011; Håkanson et al, 2012; and Adams et al, 2014).
[3] Even when we restrict the comparison to other high-skilled sectors, such as IT, law, consulting, and accounting, we see a significant and steady increase in relative finance wages during 1991-2010 .

These empirical results hold no matter if we define talent as (a combination of) cognitive or non-cognitive test scores for males, separate scores for the various enlistment sub-tests, or predicted cognitive test scores and high school grades for females. They also hold for the group of 30 year olds, for which the share of individuals with enlistment scores and high school grades has been high and constant over our sample period.

In the second part of the analysis, we take a step back from the specific skill-bias hypothesis and ask the more general question whether the financial sector has been absorbing a larger fraction of the most talented people in the Swedish population. We focus on 30-year olds, whom we use as a proxy for recent entrants into the sector. We find that the share of (top) talent that works in the financial sector has stayed roughly constant over the entire period. We also replicate our analysis for subgroups where the concern about externalities of an absorption of talent may be strong, such as science, technology, engineering, and mathematics (STEM) graduates or graduates from competitive university programs. We do not find a substantial increase in the fraction of finance sector workers for these subgroups either. Another concern is that talented people may move abroad to work in large financial centers such as London or New York, which would not be picked up in our data. In order to address this possibility, we also analyze whether the likelihood of finance workers moving abroad or business school graduates starting their career abroad has increased over time, and find that this has not happened.

Taken together our findings do not support the hypothesis that finance has become more skill-biased over time. More broadly, they alleviate concerns about a "brain drain" into finance at the expense of other sectors, e.g., along the lines of Baumol (1991) and Murphy et al. (1991), but they are also consistent with rents in finance being high, increasing, and largely unexplained. The findings further suggest that a bonus tax currently discussed among Swedish policy makers would not have a large effect on the allocation of talent between the financial sector and the real economy.

While we cannot be sure that our results are generalizable beyond the Swedish context, there are several features of the Swedish financial sector that are similar to countries such as the US and the UK.[4] As in these countries, the Swedish financial market was deregulated in the mid-1980's and

[4] Boustanifar et al. (2014) 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.

we show that the growth of the industry has been comparable over the period we study.[5] Moreover, we show that the time-series of both relative wages and relative education in the finance sector look remarkably similar in Sweden and the US. 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., 2014), and we show that the same is true for Sweden.[6] In addition, we show that overall post-secondary and college education attainment rates in the population have increased and, as a consequence, the average talent in these groups has declined. This suggests that the increase in relative education is not a sign that more talented individuals are going into finance, but rather that conditional on talent, an individual entering the sector attained more education over time. In contrast, the distribution of our talent measures is constant over time (the high school grades are scaled to achieve this), thus avoiding such composition effects.

The remainder of our paper is organized as follows: Section 2 explains the data and the talent measures, and it establishes the main stylized facts in the finance sector in Sweden, where possible comparing it to the evidence in the US and the UK. Section 3 presents our model and derives the empirical predictions. Section 4 tests the predictions, analyzing average and top talent selection, workers' sector choices, and wages in finance relative to the rest of the economy. In Section 5, we investigate whether the financial sector is absorbing more talent over time, by examining the career choices of high-talent workers. The last section concludes.

2 Data and Stylized Facts

2.1 Sample Construction from Different Registers of Statistics Sweden

Our basic sample is the longitudinal integration database for health insurance and labor market studies (LISA) provided by Statistics Sweden (SCB). The database presently holds annual registers since 1991 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

[5] Although Sweden has a smaller finance sector than the US and UK, it is still sizable compared to many other countries.
[6] The relative importance of Stockholm as the financial center of Sweden is comparable to what Bell and Van Reenen (2013a) report for London in the UK.

status, the identity of the employer, and wages) as well as demographic information (such as age or family composition).

Our main measure of wages is the annual labor income from the largest source of income, in case somebody has multiple employers. One advantage of having annual wages compared to hourly wages is that they include bonus payments that are likely an important part of compensation in finance. In robustness checks we also include capital gains (annual labor income plus annual capital gains) and other benefits and deductions (disposable income).[7] To compare wages over time, we deflate all wages using the consumer price index.

We supplement the initial sample with various items that are also provided by SCB: We obtain information on education (grades, track, school, and university) from the "Gymnasieskolan" and "Universitet/högskolan" registers and further details on the job from the "Jobb" register.

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

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. Finally, in line with Philippon and Reshef (2012) we only keep workers who are dependently employed in the private, non-farming sector. This selection process results in a sample of about 65 million individual-year observations. Table 1 provides summary statistics for our sample.

[7] One argument for including capital income in our wage measure is that it would capture equity-based compensation. The drawback is that our data cannot distinguish equity-based compensation from other capital income, such as return on personal savings and investments. Importantly, there was no particular tax advantage in Sweden from paying employees in options or restricted stock as opposed to regular bonuses over the time period we study. Therefore, equity-based compensation was uncommon in Sweden, even for public company CEOs.

2.2 Talent and Skill Measures

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).

Similar to the US, the fraction of people with post-secondary and college education has increased in most Western European countries including Sweden. Given that the composition of college graduates has shifted significantly, it is unclear whether the relative increase of education in finance, documented in Philippon and Reshef (2012) and other studies, coincides with a commensurate rise in relative human capital in that sector. In particular, it is not clear whether the relative innate skill component of human capital in finance actually increased.

Using our data we are able to address this question as 1) we have direct ability measures with a substantial innate component (e.g., cognitive and non-cognitive test scores), 2) the distributions of these measures in the overall population are largely stable over time,[8] and 3) they are elicited before most individuals choose their careers. Moreover, these proxies for talent are fine-grained, which allows us to examine the tails of the talent distribution. Given that the finance wage premium rises strongly at the top, this 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

[8] 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.

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. Because the raw scores are more refined they allow us to study the right tail of the talent distribution in more detail.

We obtain a standardized score for *non-cognitive ability* ranging from 1 to 9, following a Stanine scale as well.[9] 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 test according to their discretion. Lindqvist and Vestman argue that the *non-cognitive score* is different from other measures often used in the literature on personality and labor market outcomes. They write that, instead of assessing a specific trait, the *non-cognitive score* assesses the ability to function in a very demanding environment (military combat) and that this is likely to be rewarded in the labor market (Lindqvist and Vestman 2011, p109).

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 only for those individuals who scored above the mean in the cognitive test (score of 5 or higher). It therefore may be one way to identify high-potential individuals, that is, those who are not only intelligent but also can take on leadership roles. 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

[9] 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.

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.[10] The positive effect of better cognitives and non-cognitives holds up within specific labor market groups such as managers, and cognitives and non-cognitives also predict a higher likelihood of becoming a CEO (e.g., Adams et al, 2014).

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.[11]

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 on the final high school grade, graduation year, and the track the person was enrolled in. 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 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.

[10] In contrast, for alternative measures of non-cognitives, such as the Big Five personality traits, more (or less) may not always be better.
[11] In unreported robustness checks we use 35 year olds born 1955-1975 and find the same results.

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*).[12] In robustness tests we further 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 again redo all our talent analyses based on grades for this group born 1960-1980.

2.3 Relative Earnings and Education in the Swedish Financial Sector

As a start of our analysis we compute stylized facts about the evolution of earnings and education in the Swedish financial sector compared to the rest of the economy. Where possible, we relate these facts to the evidence available for the US and the UK. We also use US Current Population Survey (CPS) data to (re-)construct part of the evidence ourselves.

The top row of Figure 1 depicts the relative average wages in finance in Sweden (left panel) and the US (right panel). Relative wages are defined as the ratio of the average wage in finance to the average wage in the non-financial, nonfarm private sector. We see that the finance wages in Sweden start out at about 30-35 percent higher than in the rest of the economy in 1991 and that they rise to almost 70 percent higher in 2010. In the US over the same period, finance wages rise from about 20 percent to almost 50 percent above the rest of the economy. There appears to be some co-movement between the series in the two countries. In particular, after the crises of 2001 and 2008 relative finance wages, both in Sweden and in the US, dropped substantially, but they recovered swiftly afterward.

While the trend and the fluctuations are similar, the level of relative finance pay in the US is lower than in Sweden in the top row of Figure 1. Part of the reason for this is that we use CPS data for

[12] 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.

the US, which are top coded and report hourly or weekly wages that 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 their paper, also the levels of relative wages in finance are about the same in Sweden and the US.

An important strength of our administrative population data, which include end of year bonuses, is that we can compute precise wage facts in all parts of the distribution. The bottom row of Figure 1 depicts the relative quantiles of finance pay in Sweden compared to the respective quantiles in the rest of the economy. It is clear in the figure that 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 higher quantiles. This is strikingly so 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 quantiles are increasing in the bottom row of Figure 1 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 15% increase in their relative earnings from 1991 to 2010, the top percentile increase is over 70%. 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. 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 for saving space). These high shares are of a similar magnitude as the ones that have been documented for the US and the UK.[13]

[13] 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.

In Appendix A we report additional facts about wages in Swedish finance. First, we 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 pay not just reflect the rising cost of living in Stockholm. We also compare finance relative wages to other high-skill, high-earning sectors such as IT, consulting, law, and accounting. Finance wages are rising as strongly compared to these high-skill peers as compared to the whole rest of the economy. Finally, we 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 with these measures.

In addition to 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. for a panel of developed countries), using relative education as a proxy for skill. In the top left panel of Figure 2 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 1991 to 15% (12%) in 2010. Compared to the US, which is 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 education increases from 14% to 18%, relative university education increases from about 11% in 1991 to about 16% in 2010.

However, education 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 it will not single out very high talented individuals nowadays that a large fraction of the population goes through some sort of post-secondary training. It may further be endogenous to an individual's sectoral choice, in particular, individuals today may often need to get at least something like an accounting degree to be able to work in the financial sector. Moreover, overall post-secondary and university attainment has risen strongly over the last decades, so that the talent shares that they approximate are likely to have declined over time.

The bottom panel of Figure 2 illustrates these points in our Swedish data, plotting the post-secondary share of Swedish 30 year olds against average cognitive ability among those who attained post-secondary education. During 1991-2010, post-secondary attainment rose from 20 to 35 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). We therefore analyze the skill selection into finance using our fine-grained, predetermined, and comparable-over-time talent measures in the following.

3 Empirical Model of the Effects of Finance Skill-Bias

To fix ideas we propose a simple but general 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.[14]

3.1 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}:[15]

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

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. Appendix C.2 shows that s_{it} should be interpreted as deviations from a population average skill, that is, $s_{it} > 0$ are relatively high-skilled and $s_{it} < 0$ are relatively low-skilled workers. Moreover, $E(s_{it}) = 0$, $Var(s_{it}) = \sigma_s^2$, and s_{it} can be negative for many workers. The wages in (1) may, but do not need to, be determined competitively according to workers' marginal product in

[14] 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.

[15] The model can be extended to more than two sectors. The binary choice regressions proposed below would then become multinomial choice regressions.

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.

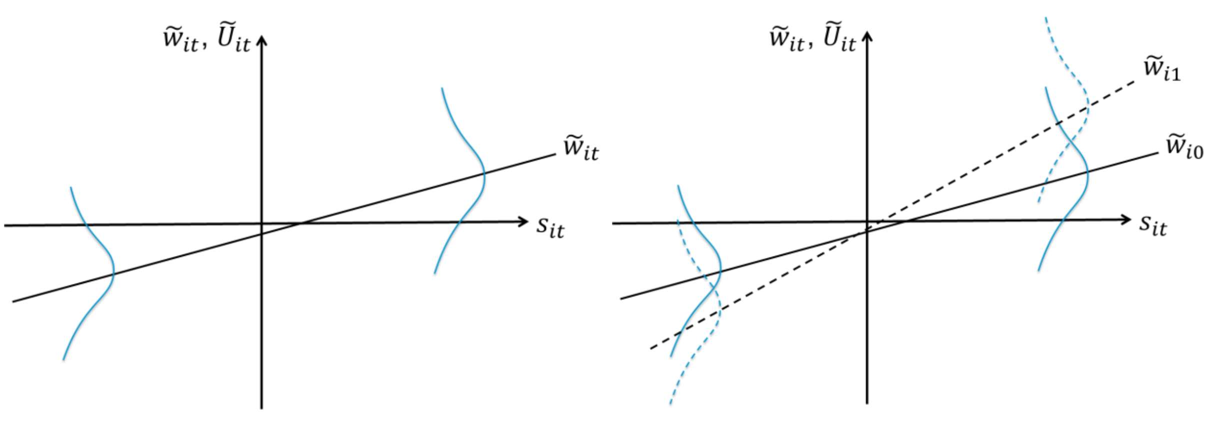
It is convenient to define workers' relative wages and utilities in finance:

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

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

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 utility is above the x-axis. 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 brought forward by Philippon and Reshef (2012), Cellerier and Vallee (2015), and others whereby the relative marginal product of skill increases in finance. An alternative interpretation is 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 $\widetilde{w}_{i1}$ 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.[16]

For each parametrization 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. Empirically, we use components or determinants of skill s_{it} that are arguable 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:

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

[16] 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).

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).

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. $Var\left(s_{it} \middle| \widetilde{U}_{it} > 0\right)$ may actually increase. In that case, however, overall employment in the financial sector will rise (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.,

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

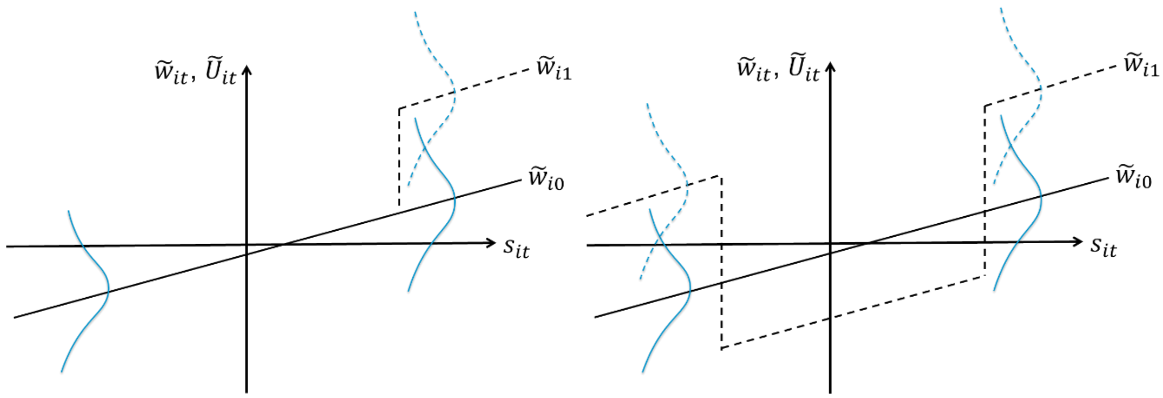
we can use choice regressions to identify the changing slope $\tilde{\beta}_t$ and intercept $\tilde{\alpha}_t + \tilde{\mu}_t$ over time. In addition, we can control in these regressions for variables that one would want to hold constant when examining talent selection, such as age or potential experience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

3.2 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, the extreme increase of finance pay at the very top of the wage distribution that has been documented in the literature (e.g., Kaplan and Rauh, 2010, for the US; Bell and Van Reenen, 2013, for the UK) and that we computed for Sweden in Figure 1, suggests that much of the action of 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 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 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.[17] 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, a non-decreasing dispersion of skill, as well as with the increasing inequality and surging top wages in finance that we observe in the data.[18] Therefore, we **modify our first empirical test** to focus on the top of the skill distribution:

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

[17] Philippon and Reshef (2012, 2013), Boustanifar et al (2014), 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.

[18] 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 $\tilde{\beta}_{Lt}$.

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

3.3 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 in a second step:

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

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. In Section 2 we found that, 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 (partly) account for the rising $\tilde{\alpha}_t$. We therefore run wage regressions adding education, experience, 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 in fact $\tilde{\alpha}_t$ does not rise in equation (12) once we allow for a flexibly 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 support the rising skill-bias hypothesis. The second **part of our third empirical test** examines whether this is the case in the Swedish data as well. 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).[19]

3.4 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,* $E(s_{it}|\tilde{U}_{it} > 0) - E(s_{it}|\tilde{U}_{it} < 0)$*, increases over time.*

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,* $E(H_{it}|\tilde{U}_{it} > 0) - E(H_{it}|\tilde{U}_{it} < 0)$*, increases over time.*

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

> **H-3:** The *talent dispersion within finance, i.e.,* $Var(s_{it}|\tilde{U}_{it} > 0)$*, decreases over time.*

> **H-4:** *Talents become more important for choosing a career in the financial sector and 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 (part of) the trend in the financial wage premium* $\tilde{\alpha}_t$.

> **H-6:** *The changing skill-bias in finance together with the factors in H-5 fully account for the rising* $\tilde{\alpha}_t$*. That is, correctly estimating (12) yields a rising* $\tilde{\beta}_t$ *and constant* $\tilde{\alpha}_t$ *over time.*

[19] Therefore, one may want to in addition run selection-bias adjusted wage regressions.

4 Tests of the Skill-Bias Hypothesis

In this section we test the main hypotheses as outlined in Section 3.4. We show that the average as well as top talent selection into the financial sector has not improved, despite an increase in relative wages. In addition, the dispersion of talent in finance did not decrease, workers do not base their decision of joining finance more on their talent, and skill selection and changing returns to talents do not explain a substantial part of the relative finance wage increase.

4.1 Has Finance Become more Talent-Intensive?

This section tests Hypothesis H-1 under which relative average talent in finance should have increased over time. Figure 3 plots relative talent measures in finance and the rest of the economy as defined in equation (6) between 1991 and 2010. 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 left panel shows the results for men using the different talent measures from the enlistment test. The right panel shows the results for women using different measures based on grades. The corresponding numbers including the average levels for the two sectors can be found in Table 2 (Panels A to C show the results for men, women, and the whole population). To fit results, we display two year averages in Table 2.

The left panel of Figure 3 and Panel A of Table 2 report relative talent for men. Throughout all dimensions of talent we find that men in the finance sector are more talented compared to the rest of the economy, i.e., the relative skills 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 (compare Table 1).

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 2, we do not find that relative talent has improved. The premiums in the left panel of Figure 3 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 women (right panel of Figure 3 and Panel B of Table 2). 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. If at all, there is a slight downward movement in the relative test scores for males.

One potential caveat is that rising demand for skill may have coincided with an overall increase of employment in the finance sector. In this case, average talent may still not increase (and may even decrease), because the inflow of more skilled workers choosing finance is offset by the entry of relatively low-skilled workers at the margin as the sector hires more people. This turns out not to be the case, however. Figure 4 plots the evolution of the employment share, measured as number of workers in the financial sector divided by the total number of workers in the nonfarm private sector. The left panel shows the evidence for Sweden, including and excluding health and education from the public sector. The share of people working in the financial sectors has not changed over time. If anything, the employment share of finance has slightly declined.

The right panel of Figure 4 shows that the finance employment share has been roughly stable in the US as well, although the levels are different (the finance employment share is about 5-5.5% in the US and it is 3.4% in Sweden).[20] These findings contradict the idea that the entry of relatively low-skilled workers on the margin keeps down relative talent in finance, despite an increase in $\tilde{\beta}_t$. Overall, our results therefore do not support the hypothesis that a rising skill-bias in finance has at the same time increased average wages and improved the average selection of talent into this sector.

[20] 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).

4.2 Talent Selection at the Top

As argued in Section 3.2, 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 therefore test Hypothesis H-2 in this section, by examining whether the selection of top talent into finance has changed.

The left panel of Figure 5 plots the relative share of males in finance who score the highest (9 out of 9) in the cognitive and non-cognitive tests, representing a fraction of around 4.5 percent and 2 percent of the population, respectively. It also plots the relative share of males in finance who score at least 8 in both of these tests (4 percent of the population). This selection captures workers who are elite in terms of both test scores and it may to some extent approximate general skills. The right panel of Figure 5 employs corresponding definitions for women using grade information (predicted cognitive ability for women within the top 5% and the top 5% graderank in the university high-school and science track). The graphs show the relative share of these top talented workers over time by plotting the difference between the share in the financial sector and the corresponding share in the real economy.

Similar to the results on average talent, we also find a higher fraction of top-talented men in the financial sector. The relative share of top talent in the left panel of Figure 5 is positive between .01 (cognitive ability) and .025 (non-cognitive ability). However, analyzing their developments over time, we do not find any evidence that these relative fractions increase. While relative top cognitive ability is more or less flat (with some fluctuations), relative top non-cognitive and leadership ability experience a slight down trend. The results for women (left panel of Figure 5) are consistent with the results for men. There is no obvious upward trend detectable. Interestingly, and in contrast to the results for men, the relative fraction of top talented women in the financial sector is negative. The share of top talented women in the real economy is higher than in the financial sector.

Overall, we conclude that the share of top talent has not increased in the financial sector either. We find that finance talent selection at the top neither improved on average nor in relative terms between 1991 and 2010.

4.3 Additional Evidence and Robustness

The results of the previous two subsections do not support our Hypotheses H-1 and H-2 that finance has become more skill-biased over time. In this section we examine the additional Hypotheses H-3 to H-6 by analyzing the dispersion of talent, running choice and wage regressions, and looking at the subsample of 30 year olds.

4.3.1 Dispersion of Talent in Finance

In the following we test Hypothesis H-3 that an increasing skill-bias should lead to a higher concentration, thus to a lower dispersion, of talent in finance.

Panel A of Table 6 displays the components of inequality (7) over time. The dashed horizontal line is the variance of talent $Var(s_{it})$ in the population normalized to one in each year, the solid line is the dispersion of males' (left panel) cognitive ability and both genders' predicted cognitive ability (right panel) in finance $Var\left(s_{it}\middle|\widetilde{U}_{it} > 0\right)$. We find that the dispersion of talent in finance is substantially lower than in the overall economy. This is consistent with the Roy model in the cross-section. However, the dispersion of males' and females' (predicted) cognitive ability in finance seems to moderately increase rather than decline over time.[21] This is not consistent with the rising skill-bias idea in the time series, which predicts that the dispersion of talent in finance should actually decrease with sharper selection according to skill.

4.3.2 Probit Regressions for Choosing Finance

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 such variables as potential experience or years of schooling.

Table 3 reports estimates of equation (8) with the parametrization suggested in (9) using probit choice regressions for working in the financial sector. Controls are a quadratic in potential experience, a sex dummy, and a year trend main effect. Hypothesis H-4 predicts that the coefficients on (predicted) cognitives should rise over time, that is, that talent should become a

[21] The unreported dispersions of logic, verbal, and leadership scores as well as grades in the university and science tracks in high school are also flat or increase. The exception is males' non-cognitive ability, the dispersion of which moderately decreases.

more important determinant of choosing finance. We see in the first column of the table that higher predicted cognitives for both genders are strongly associated with working in finance. This, as before, suggests that finance is a skill-biased sector. However, instead of rising, the estimated $\tilde{\beta}_t$ parameter slightly declines by about one percent over time.[22] This is economically zero, which is precisely estimated because of the large size of our Swedish data.

Column (2) of Table 3 controls for individuals' years of schooling, and columns (3) and (4) use the same specification for the subsample of males where we have actual cognitives as well as non-cognitives. The remaining four columns (5)-(8) then concentrate on the subsample of 30 year olds, whom we consider as recent entrants and for whom the coverage of the talent measures is constant over the sample period. In all of these samples, the changes in the coefficients on our talent proxies are very small and most of them are negative.

In unreported robustness checks, we reran the regressions in Table 3 using our top talent dummies from section 4.2 and from the next subsection. We also estimated linear probability models as a robustness check, and to have an easier interpretation of changing marginal effects than in the probits. We have fully interacted the talent measures with each year. None of these analyses suggested 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. We think this is unlikely. First, we have in our sample measures of several dimensions of talent that are generally unobserved in standard data products. Moreover, in order to not observe any change in the choice regressions (and the plots in sections 4.1 and 4.2), the improving selection or underlying skill-bias would *only* have to affect these additional unobservables and it would have to affect only the part of them that is *uncorrelated* with our quite rich set of talent measures.

[22] Take the year trend coefficient of 0.000046 times 20 years between 1991 and 2010 compared to the level of the coefficient on predicted cognitives of 0.0986.

4.3.3 Wage Regressions

The last two hypotheses (H-5 and H-6) from the theoretical model are related to the wage premium and the wage return to skills in the financial sector. In this section we run wage regressions in order to test these hypotheses. One advantage of the wage regressions is that we can use detailed fixed effects in order to account for (time-invariant) unobservable components of workers' skills. 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 (11). The graph on the left column of Panel B of Figure 6 plots the $\tilde{\alpha}_t$ from three different regressions over the period 1991-2010 for both genders (top) and males (bottom). First, no measures for worker skill s_{it} are included, that is, $\tilde{\alpha}_t$ constitutes the raw finance wage premium in log points. Then, the observable component of $s_{it} = s_{it}^o + s_{it}^u$ contains the standard skill proxies of years of experience and its square as well as talent measures that are usually unobserved:[23] predicted cognitives for both genders in the top panel and cognitives and non-cognitives for males in the bottom panel. Last, we include years of education in the third specification.

The control variables decrease the level of the finance pay premium. Adding predicted cognitives and potential experience alone explains about 10 percentage points (almost 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 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 not very surprising given our above finding that the average talent in finance has remained roughly constant over time.

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. Nonetheless, as an additional check, the middle column of Panel B of Figure 6 accounts the wage premium for time-invariant

[23] 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.

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.[24] 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 column of Panel B of Figures 6 allows for time-varying (economy-wide) returns to observed components of talent, that is, β_t in equation (11) 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 column of Panel B of Figures 6 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.

To summarize, the above results to not lend substantial support to Hypothesis H-5. We find that the changing talent composition of the finance sector and the changing returns to talent in the overall economy can at best only explain a minor part of the rise in the finance wage premium during 1991-2010. Given the results from Section 5, this is maybe not too surprising, since we found there that the talent selection into finance did not change detectably over time. Moreover, the fixed effects results indicate that the importance of a changing selection of unobserved components of skill is unlikely to be very strong, at least as long as the effect is not time-varying. This evidence underscores the argument from the choice regressions that unobservable skill components are unlikely to be driving our findings.

Finally, theoretical Hypothesis H-6 goes one step further than H-5 and states that correctly estimating the finance-specific rising skill-bias $\tilde{\beta}_t$ would lead to a disappearance of the rise in $\tilde{\alpha}_t$ that we plotted in Panel B of Figure 6. Using a sample of French engineers and measuring their

[24] In terms of the previous footnote, the worker fixed effects capture the time-invariant part of unobserved worker skill s_{it}^u in the regression error. The worker-firm fixed effects capture that part plus the time-invariant component of the worker-firm match effect m_{kjit} (or alternatively, the time-invariant component of worker i's firm j-specific skill).

talent by the ranking of the school that they graduated from, Célérier and Vallée (2015) estimate equation (12) using OLS. They indeed find that $\tilde{\beta}_t$ rises strongly while $\tilde{\alpha}_t$ remains largely flat.

We estimate equation (12) with high-, middle-, and low-talent dummies:

$$w_{kit} = \alpha_{Rt} + F_{it}\tilde{\alpha}_t + \left(\beta_{Mt} + \tilde{\beta}_{Mt}\right)M_{it} + \left(\beta_{Ht} + \tilde{\beta}_{Ht}\right)H_{it} + \varepsilon_{it} \quad (12')$$

In Figure 6, Panel C we plot the resulting $\tilde{\alpha}_t$, $\tilde{\alpha}_t + \tilde{\beta}_{Mt}$, $\tilde{\alpha}_t + \tilde{\beta}_{Ht}$ for talent measures of cognitives, non-cognitives for males, and predicted cognitives for both sexes. We split the sample into high-, middle-, and low-talent groups to allow for talent demand possibly only rising at the top or polarizing over time (see definition of the groups in the Figure caption). Panel C of Figures 6 shows that the finance premium for low-talent males $\tilde{\alpha}_t$ increases less than the premium for high- and middle-talent workers ($\tilde{\alpha}_t + \tilde{\beta}_{Mt}$, $\tilde{\alpha}_t + \tilde{\beta}_{Ht}$) when ranking them according to cognitive or non-cognitive talent. Yet, the premium for the high-talent workers does not rise compared to the middle-talented. When including both sexes and using predicted cognitives, the premium of middle-talent over low-talent workers does not rise. Moreover, the premium for the low talent group also rises substantially for all three talent measures.

Interpreting these results within the context of wage equation (12), we neither find that $\tilde{\beta}_t$ increases across the distribution, nor that it polarizes or only increases for high-talent workers. Moreover, the baseline premium $\tilde{\alpha}_t$ for low-talent workers rises considerably over time for all talent groups. In unreported analyses, the results are also qualitatively robust to different definitions of high-, middle-, and low-talent groups and to including a linear coefficient $\tilde{\beta}_t$ instead of the three groups. Therefore, our results do not lend substantial support to Hypothesis H-6.

4.3.4 Relative Talent and Top Talent for 30 Year Olds

We redo our tests of the main Hypotheses H-1 and H-2 for the subsample of 30 year olds. As explained in Section 2.2, this has the advantage that the availability of military test and grade information is high and constant over the whole period of 1991-2010, addressing potential concerns about a changing composition of individuals for whom we have the talent information. 30 year olds also approximate recent entrants into finance, so the effect of an increased skill-bias in finance on the allocation of talent may be most detectable in the group of recently hired workers.

Panel D of Figure 6 redoes the analysis of Figures 3 and 5 for the subsample of 30 year olds. We see in the top row that the relative talent in finance rises neither for men nor for women over time. In the bottom row, there is also no trend in the relative share of top talent in finance detectable. Therefore, our findings from Sections 4.1 and 4.2 are robust to this additional test and we conclude that the main predictions H-1 and H-2 implied by the skill-bias hypothesis are also not supported in the data for 30 year olds.

5 Is the Financial Sector Absorbing the Most Talented Workers?

In the discussion of possible "brain drain" into finance (Baumol, 1990; Murphy et al., 1991; Kneer, 2013a,b), one concern is that the most talented people – including those with the highest cognitive abilities, graduates from elite universities, and graduates from Science, Technology, Engineering, Mathematics (STEM) programs – are drawn into the finance sector because of its extraordinary earnings opportunities. Since these talented individuals have skills that would have been highly valuable in other "more productive" activities, such as science and innovation, the brain drain externality is argued to be particularly damaging for this group.

This section examines whether the finance sector has been absorbing more and more of the most talented workers, in particular focusing on important populations at risk of being absorbed by the financial sector. By doing so, we however do not take a stance about whether such an absorption would constitute a brain drain, a term which is often associated with negative externalities. The analysis in the following is also more general than the skill-bias tests of the previous section, because we simply check whether a large fraction of talented individuals are entering finance, independent of the reasons for the high wages that might draw them in. In terms of the notation from the theory section, we will plot the time series of $E(F_{it}|H_{it} = 1)$, where H_{it} and F_{it} are a high-talent and finance dummy, respectively. We focus on 30 years olds for the reasons discussed above and to capture early-stage career choices.

5.1 Sector Choices of High (Non-)Cognitive Workers

As a first high talent group, we consider all 30 year olds that belong to the top 5% in the talent distribution in Figure 7 and Table 4. High talent in Panel A of the figure is defined as having cognitives of 9, non-cognitives of 9, or exceeding 8 in both cognitive and non-cognitive ability for males. For females we focus on the top 4% in terms of predicted cognitives, the top 5% of the grade rank distribution of university programs or science programs. The graphs in Panel A of Figure 7 depict the fraction of these top talent subgroups working in the financial sector over time. Table 4 Panels A and B show the corresponding numbers. Moreover, the table also shows the top three sectors in terms of average employment for the different top talent groups.

With respect to the financial sector, there are two important facts to note. First of all, there is no clear trend over time for all employed measures of skills. In the case of cognitives, the fraction of high talent males choosing finance fluctuates between 2.0% and 3.6%. The shares are bigger when top talented is solely based on non-cognitive ability (or on a combination of cognitives and non-cognitives). For these two measures, the fraction of individuals who work in the financial sector is between 4.3% and 5.9% (3.75% and 5.1%). However, there is no clear trend and the share of top talented people based on non-cognitives shows quite some variation around a level of about 5%. When analyzing women we observe qualitatively similar results. There is no upward trend. If anything, the fractions slightly decrease over time.

Second, the fraction of high-talent people in the workforce that chooses a career in finance is relatively small. Depending on the employed measure 1.2 to 5.9% of the most talented people choose a career in the financial sector. For men this level is a somewhat higher than the overall employment size of the finance sector of around 2.5 to 3.5% (see Figure 4), consistent with the previous finding that average talent is higher in the financial sector. Top talented women according to predicted cognitives or within the science track, however, are represented less in the financial sector.

Table 4 also shows the top 3 sector choices of the top talented groups. The largest employers of top talented males are Manufacturing, Business Services, and IT, and Trade/Hospitality and Utility/Construction/Transportation to a smaller extent. While Manufacturing is a big employer for top talented men throughout the analyzed period it went down from about 30% for cognitives, for instance, in the beginning of the sample to less than 20% in the most recent years. At the same time business services and in particular the IT sector has grown strongly as a talent absorber.

Talented women, in contrast, choose quite different sectors. While there is also evidence that the most talented women go into Manufacturing and Business Services, the dominant sectors are in fact Health and Education, with a combined share of about 40% on average.

5.2 Sector Choices of STEM and Top Business School Graduates

We replicate our analysis for subgroups where the concern about externalities of a "brain-drain" may even be stronger, such as science, technology, engineering, and mathematics (STEM) graduates or graduates from elite university programs.

First, consider the destinations of university graduates in STEM fields over time. Panel B of Figure 7 shows the industry destination of high talent STEM graduates (males' cognitives of 9, women top 4% predicted cognitives) in the left graph. Only between 0.4 to 2.9% of high talent STEM graduates go to the financial sector. The fraction is relatively flat in the first half of the sample (0.4%-1.3% between 1990 and 2005), while in the last five years of our sample it increases somewhat but with a relatively high volatility (between 1.3% and 2.9%). Still, the average is about 2.1% and thus the financial sector does not seem to be a significant destination for high-talent STEM graduates.

Panel C of Table 4 also reveals that the largest fraction of top STEM graduates goes, as expected, into the Manufacturing sector (about 30% on average). A sector that increases strongly, in particular at the end of the 1990s, is the IT sector. The increase is not only big in relative terms, but also in absolute magnitude. By 2010, Business Services constitutes the largest sector of employment for these graduates, representing about 40-50%. At the same time, the share of STEM graduates working in manufacturing falls from about 40% to less than 30% in 2010. In Appendix B we contrast the development of the IT sector with the one in finance in more detail.

Finally, we look at graduates from the Stockholm School of Economics (SSE), the top business school in Sweden, which only admits students with high-school grades in the top 3%. Panel B of Figure 7 and Panel C of Table 4 reveal that the fraction of students who enter the financial sector is much higher compared to the previous analyzed groups of interest: between 20% and 30% of SSE's graduates work in the financial sector at the age of 30. Thus finance represents the biggest employing sector for SSE graduates in most year. On average about 24% of an SSE cohort work in the financial sector. The variation across years is relatively large and there is no obvious strong upward trend. However, the average fraction in the first part of the sample is 4.7% lower, compared to the second half (26.2% vs 21.5%).

To sum up, our evidence in Sections 5.1 and 5.2 does not suggest that the absorption of highly talented and potentially productive individuals into the financial sector is excessively large or that it increased a lot during these 20 years of surging finance wages. This alleviates potential concerns about an increasing brain drain into finance due to the extraordinary earnings opportunities.

5.3 International Migration

Finally, one last concern may be that highly talented individuals would move abroad to work in the financial sector in London, Frankfurt, or New York for instance. This would effectively understate our previous estimates of the absorption of talent into finance it may affect our assessment of whether finance became more skill-biased. To approximate migration, we consider individuals who disappear from our sample for at least 2 years. This subsample includes cases of individuals permanently disappearing (moving away or passing away, for instance) and of individuals who move away but re-appear in our sample.

If there is "brain drain" into the financial sector outside of Sweden, we would expect to see that more people move to work in the financial sector abroad. Unfortunately, we do not have information on the jobs the leavers obtain abroad. We do however observe the last position of a leaving individual, which we use as a proxy for their next job. In our analysis we focus on individuals between 25 and 40 years of age. The idea is that it is more likely to move abroad earlier in a person's career.

In the left panel of Figure 8 we analyze our proxy for emigration. The red solid line depicts the fraction of the population that works in the financial sector and leaves our sample for at least 2 years. This fraction in the 25-40 age group is on average less than 0.1% of the total population. Given that the finance sector represents about 3.5% of the private sector, this number means that about 2.9% of finance sector workers may emigrate. More importantly, there is no obvious upward trend detectable. The green dashed line shows finance workers as a fraction of all emigrants. About 1.7% of all emigrating workers had a last position in the financial sector, which is about half of the labor share of finance. There is also no obvious uptrend.

In the right panel of Figure 8 we also look at the fraction of graduates from the Stockholm School of Economics who emigrate. The fraction of SSE graduates who leave Sweden is very high (about

10% to 20%). However, there is no visible upward trend. This underscores that skilled emigration into finance seems not to have increased substantially over time.

Overall, our – for now approximate – evidence suggests that migration is unlikely to turn around our conclusions about the absorption of talent into finance and the finance skill-bias. There are also no quantitatively important trends that are consistent with the dynamics of the wage premium.

6 Conclusion

We study the evolution of skill selection and wages in the financial sector for the population of 65 million individual-year observations of Swedish workers between 1991 and 2010. Over this period, average wages in finance relative to the rest of the economy rose from around 130% to 165%, with even stronger increases at the top of the wage distribution. Employing detailed talent measures, which include cognitive and non-cognitive test scores from military enlistment, we find no evidence that these facts may be driven by a rising skill-bias of the financial sector. There was no improved talent selection into finance, neither on average, nor at the top. Moreover, finance is not absorbing a substantially higher fraction of high-talent workers.

We also repeat the analysis on subgroups where the concern of "brain-drain" may be higher, such as science, technology, engineering, and mathematics (STEM) graduates, and we find negligible changes in the fraction of these workers going into finance. Hence, there is no evidence of the increase in finance wages leading to an increased flow of talented workers into the financial sector. These findings are important as they alleviate concerns about a "brain drain" into finance at the expense of other sectors. They also inform policy proposals currently discussed in Sweden (and other countries) for taxing bankers' bonuses in terms of their impact on the allocation of talent into finance.

Our findings finally suggest that – even accounting for talent in a rich way – pay in finance is extremely high, increasing, and largely unexplained. Whether this is driven by compensating differentials or an increase in the rents captured by workers in finance due to moral hazard, asymmetric information and/or governance problems and rent-seeking are important questions that will be an avenue for future research.

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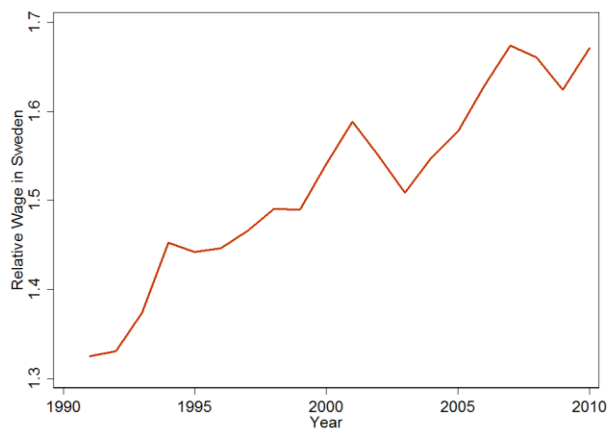
8 Figures

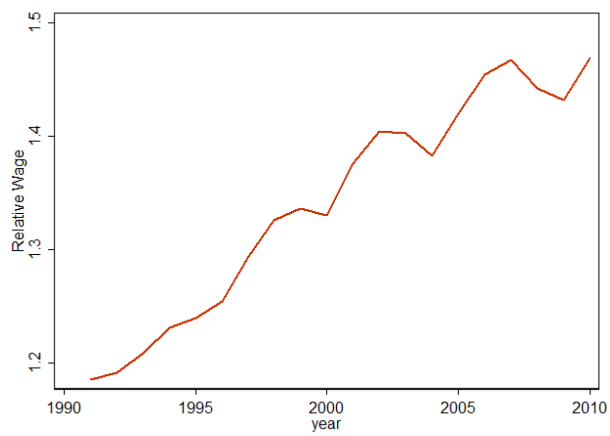
Figure 1: Relative Wages in the Financial Sector

This graph depicts the evolution of the relative wage in the financial sector compared to the rest of the economy during 1991-2010. *Relative wage* is defined as the ratio between the wage in finance and the wage in the non-financial, nonfarm private sector. The top row shows the evolution of the average relative wage in Sweden (left panel) and the US (right panel). The bottom row shows this evolution for different quantiles of the Swedish wage distribution, that is, it compares the respective quantiles in finance with their counterparts in the real economy. Source: Swedish population data LISA from Statistics Sweden; Current Population Survey for the US. Source: Swedish population data LISA from Statistics Sweden.

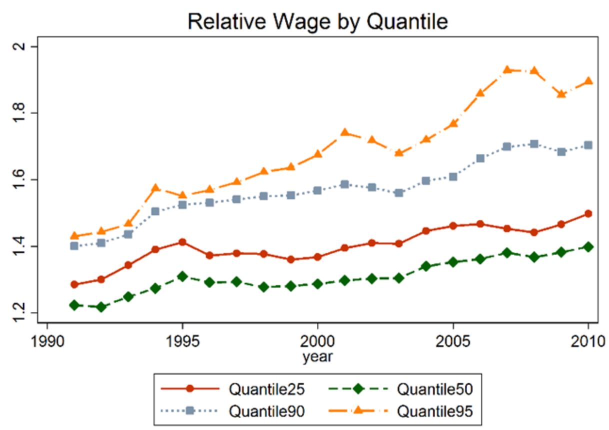
Relative Wage (Sweden)



Relative Wage (USA)



Quantiles (Sweden)



99th Quantile (Sweden)

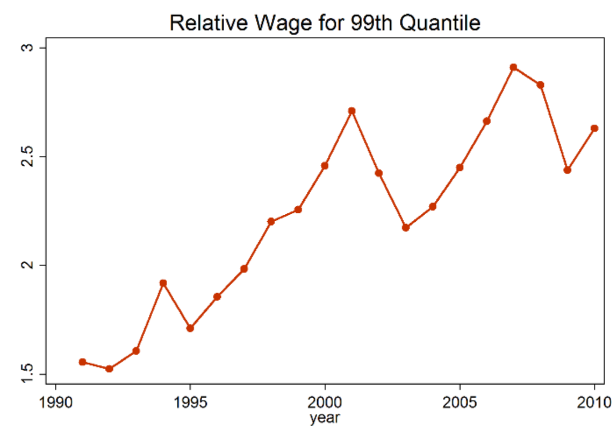
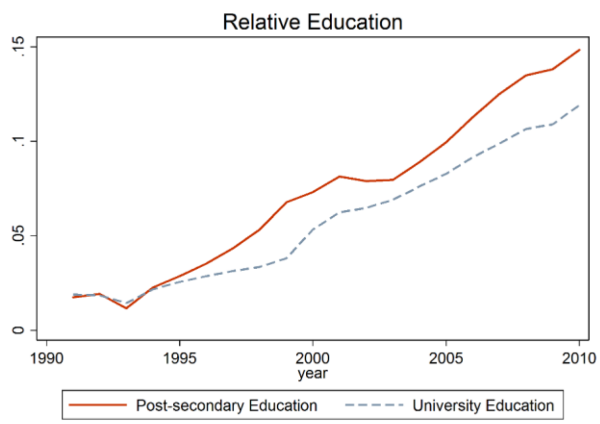


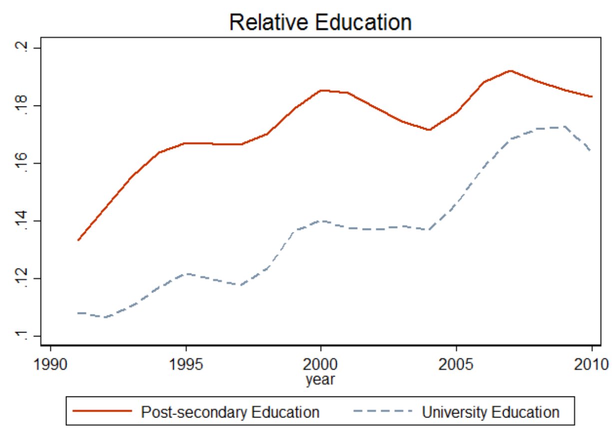
Figure 2: Relative Education in the Financial Sector

The top row graph shows the evolution of the relative education between the financial sector and the rest of the economy during 1991 to 2010. *Relative Skill* is calculated as the 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 minus the corresponding share in the rest of the economy. The graph on the left shows the evidence for Sweden, the right one corresponding evidence for the US. The figures in the bottom row depict post-secondary education attainment for men (both genders) and the average level of cognitive ability (predicted cognitive ability) for 30 year olds with at least a post-secondary education on the left (right). Source: Swedish population data LISA from Statistic Sweden; Current Population Survey for the US.

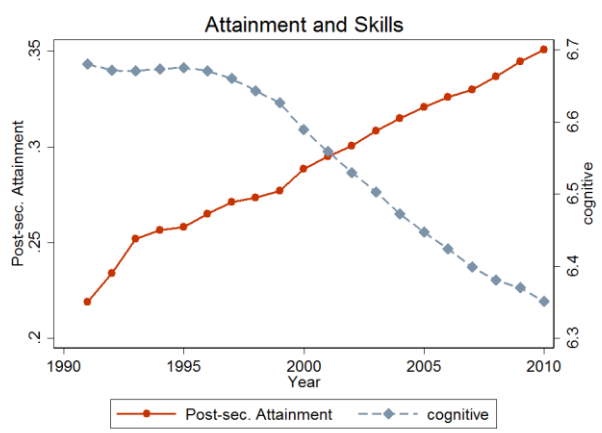
Sweden



US



Post-second. educ. & avg. cognitive ability (men)



Post-second. educ. & avg. predicted cognitive ability (all)

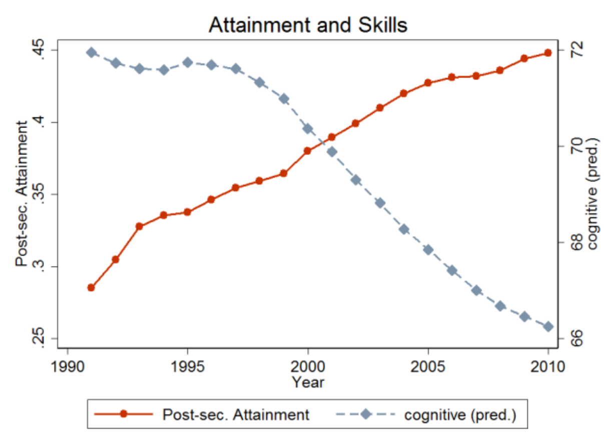


Figure 3:-Relative Talent in the Financial Sector

This graph shows the evolution of relative talent between the financial sector and the real economy during 1991 to 2010. *Relative talent* is defined as the average talent in the financial sector minus the corresponding average of the real economy. The panel on the 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 graph on the right shows corresponding evidence for graderank in the university and science tracks on the left y-axis and evidence for predicted cognitive ability on the right y-axis for women. 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 Statistic Sweden.

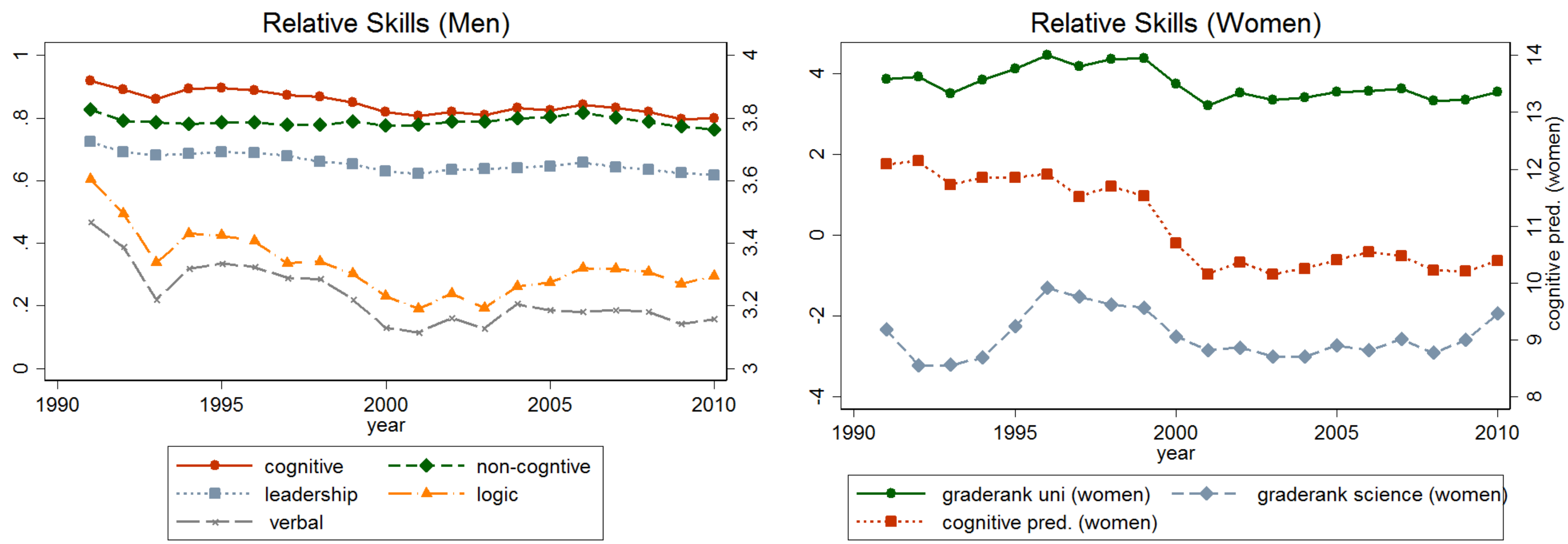
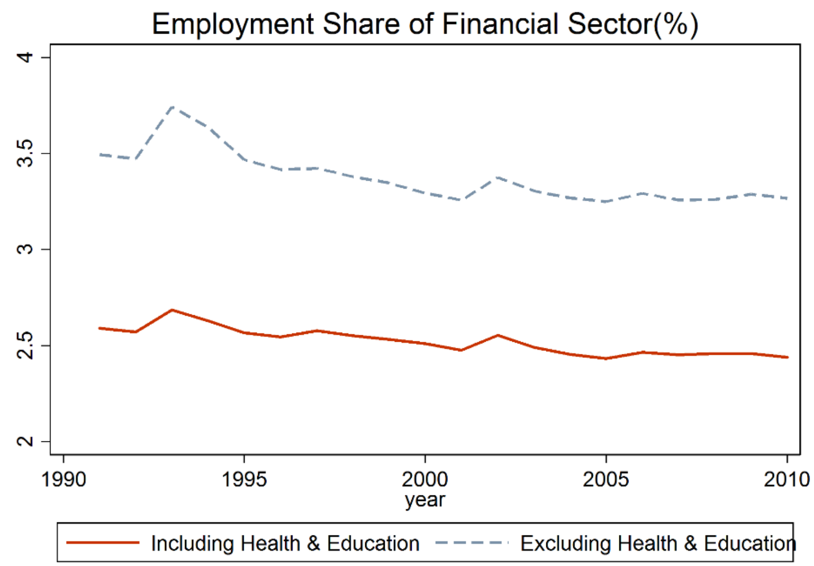


Figure 4: Size of the Financial Sector

This graph shows the evolution of the employment share of the financial sector between 1991 and 2010. *Employment Share of Financial Sector* is measured as number of workers in the financial sector divided by the total number of workers in the nonfarm private sector. The solid line shows the case when we include health and education to the nonfarm private sector. The graph on the left shows the evidence for Sweden, the right one corresponding evidence for the US. Source: Swedish population data LISA from Statistics Sweden; Current Population Survey for the US.

Sweden



US

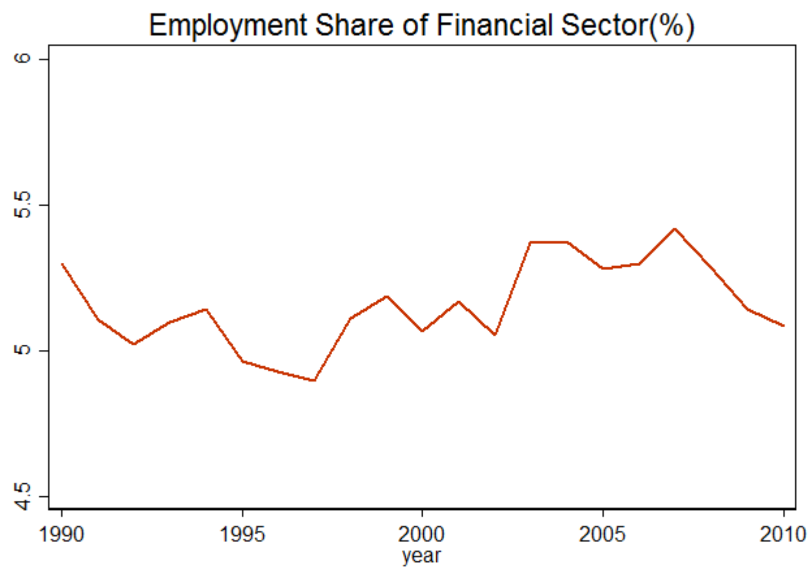


Figure 5: Relative Share of Top Talent in Finance

These graphs show the evolution of relative shares of top talent in the financial sector and the rest of the economy between 1991 and 2010. The graphs plot the difference between the share of top talent workers in the finance sector and in the real economy. Top talent is defined in various ways: cognitive ability equal to 9 (about 4.5% of the male population), non-cognitive ability equal to 9 (about 2% of male population), and cognitive & non-cognitive ability above 8 (about 4% of male population) for males. Top predicted cognitive ability for women (5% of population) and graderank in the science track for women (about 5% of full population). 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.

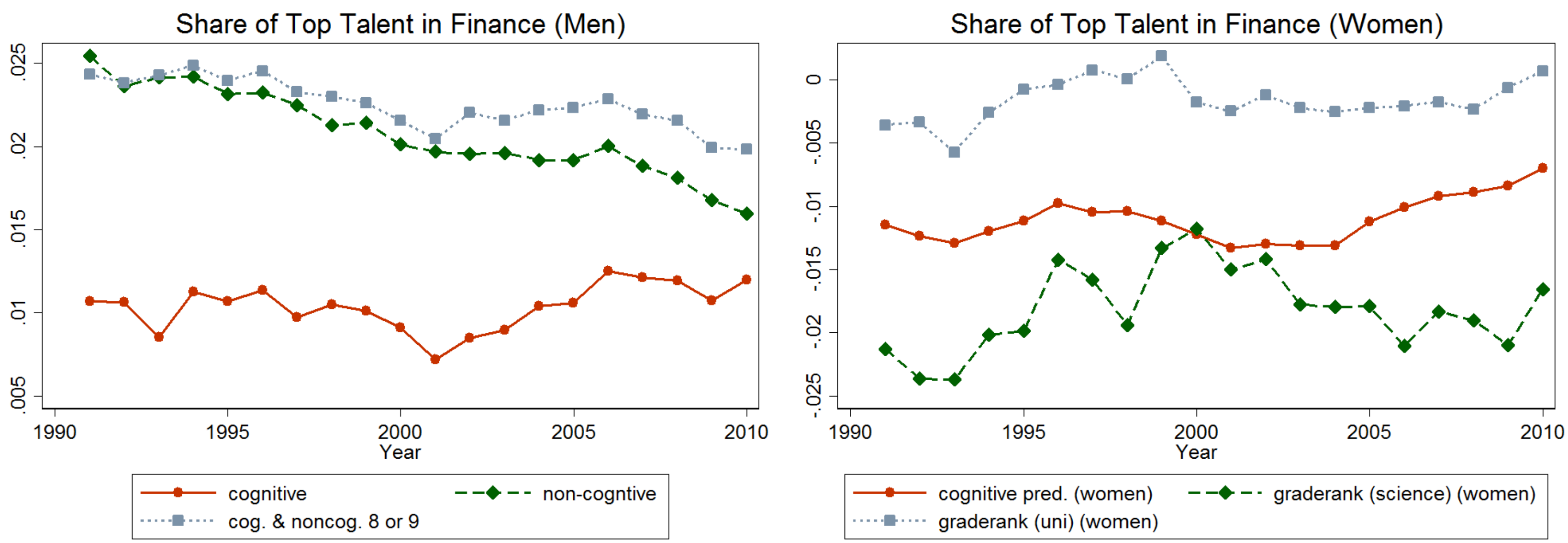
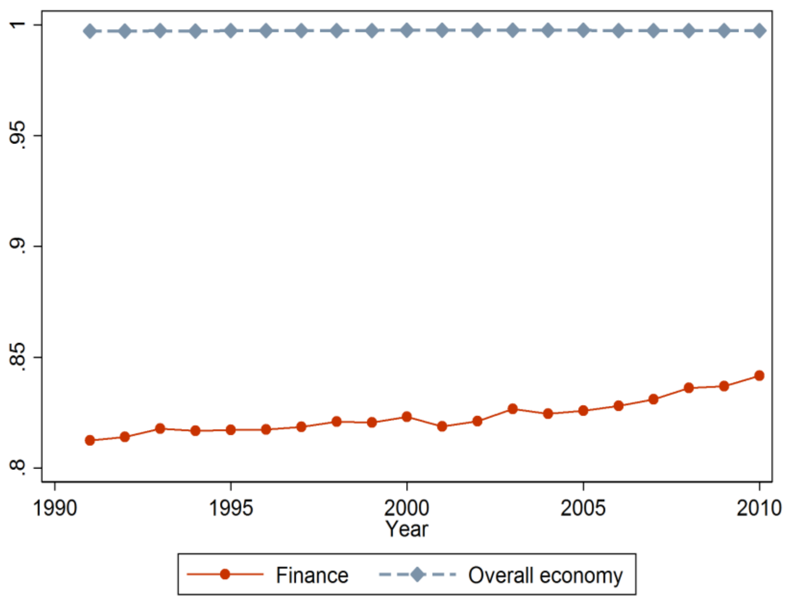


Figure 6: Additional Tests and Robustness

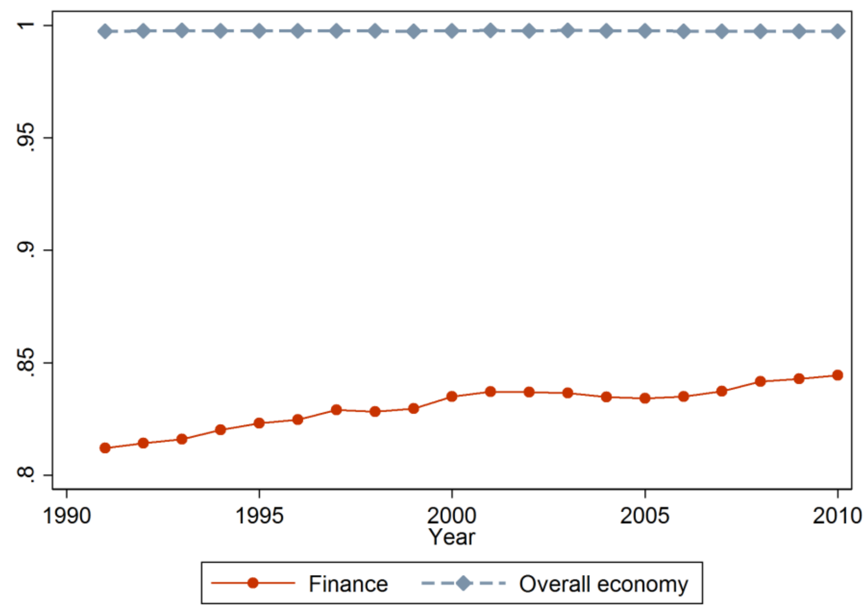
Panel A: Dispersion of Talent

These graphs depict the dispersion of talent in the financial sector over time, normalizing the overall dispersion in the private nonfarm sector to one in each year. The dashed horizontal line is the variance of talent $Var(s_{it})$ in the population normalized to one in each year, the solid line is the dispersion of males' (left panel) cognitive ability and both genders' predicted cognitive ability (right panel) in finance $Var(s_{it}|\widetilde{U}_{it} > 0)$. 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.

Dispersion of cognitive ability (Men)

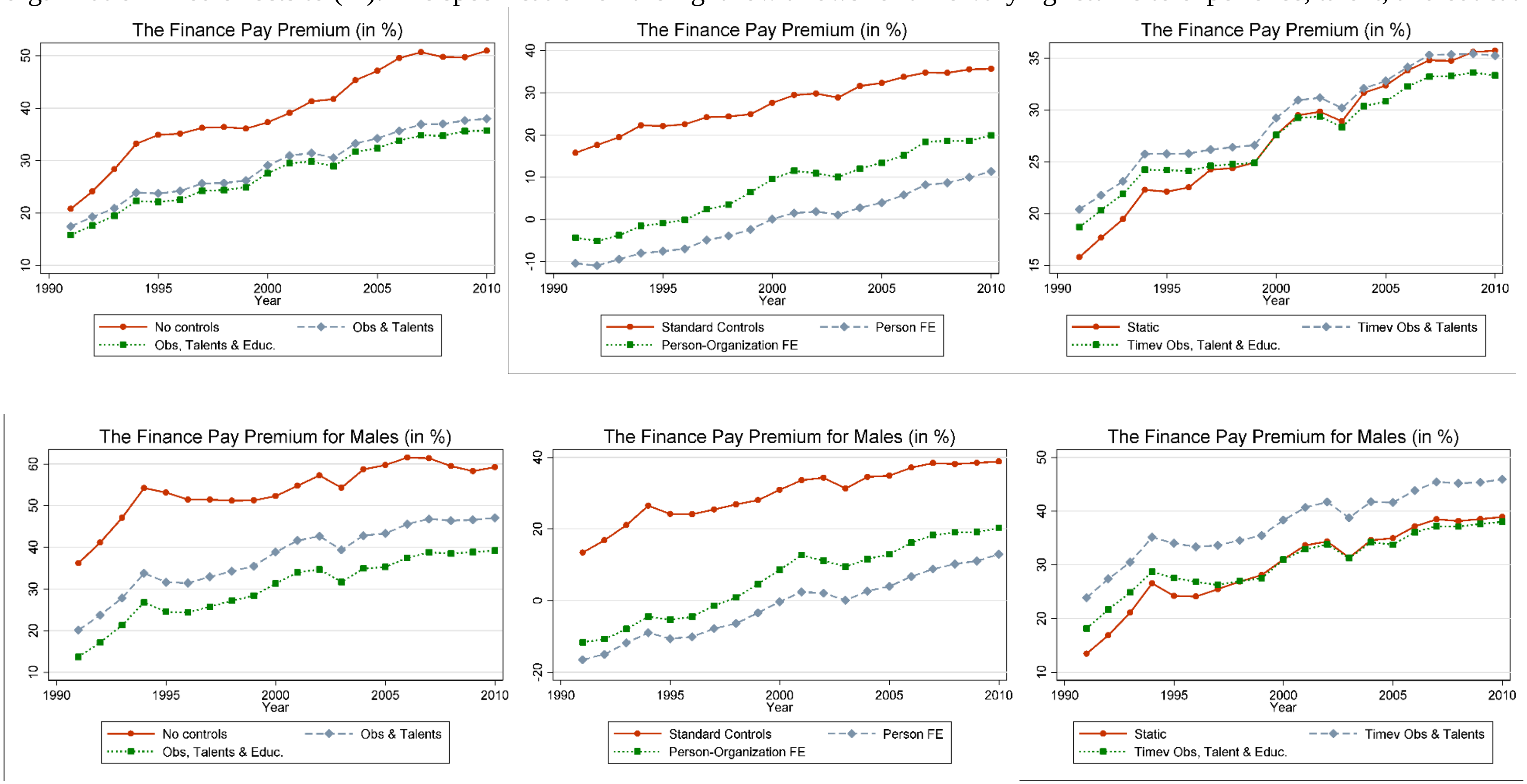


Dispersion of predicted cognitive ability (Population)



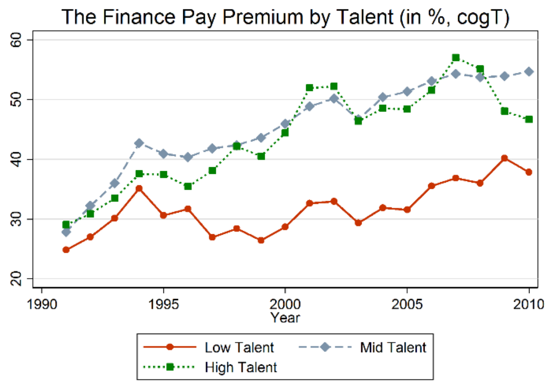
Panel B: The Finance Wage Premium

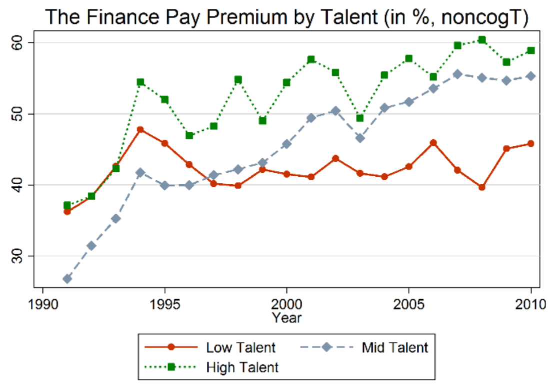
These graphs show the evolution of the finance wage premium between 1991 and 2010. The wage premium is obtained from estimating equation (11) $w_{kit} = \alpha_{Rt} + F_{it}\tilde{\alpha}_t + \beta s_{it}$ by OLS. The β is the (economy-wide) return to worker skill, F_{it} is an indicator for the financial sector, and $\tilde{\alpha}_t$ the time-varying finance pay premium in log points. Three different models are estimated. (i) no controls, (ii) controls for observables (age, gender, potential experience) and talent, and (iii) ads education (years of schooling). The first row reports results for the whole population, the second row 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. Specifications in the middle row add person fixed effects and person-organization fixed effects to (iii). The specification on the right row allows for time-varying returns to experience, talent, and education.

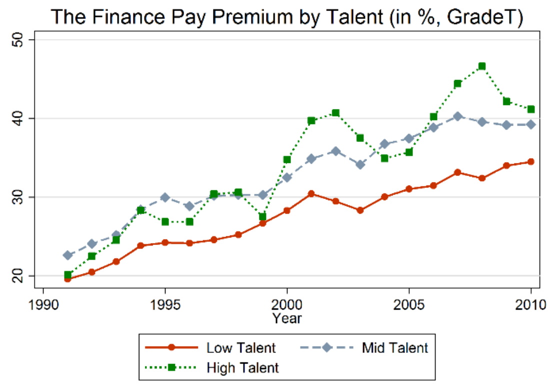


Panel C: The Finance Wage Premium across Talent Groups

These graphs show the evolution of the finance wage premium for different talent groups between 1991 and 2010. Three different talent measures (cognitive, non-cognitive ability, and predicted cognitive ability from grades) are used to form three talent groups: Low Talent (cognitive and non-cognitive ability 1-3 or predicted cognitive percentiles 0-39), Middle Talent (cognitive and non-cognitive ability 4-8 or predicted cognitives percentiles 40-95), and High Talent (cognitive and non-cognitive ability 9 or predicted cognitives percentiles 96-100). 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 D: 30 Year Olds' Relative Talent and Share of Top Talent in Finance

The top row graphs show relative talent between the financial sector and the real economy for 30 year olds during 1991 to 2010 (for definitions, refer to Figure 3). Logic and verbal comprehension are mostly not available for enlistment cohorts after 1978, this is why these series jump in the top left graph. The bottom row graphs show the evolution of relative shares of top talent for 30 year olds (for definitions, refer to Figure 5). 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.

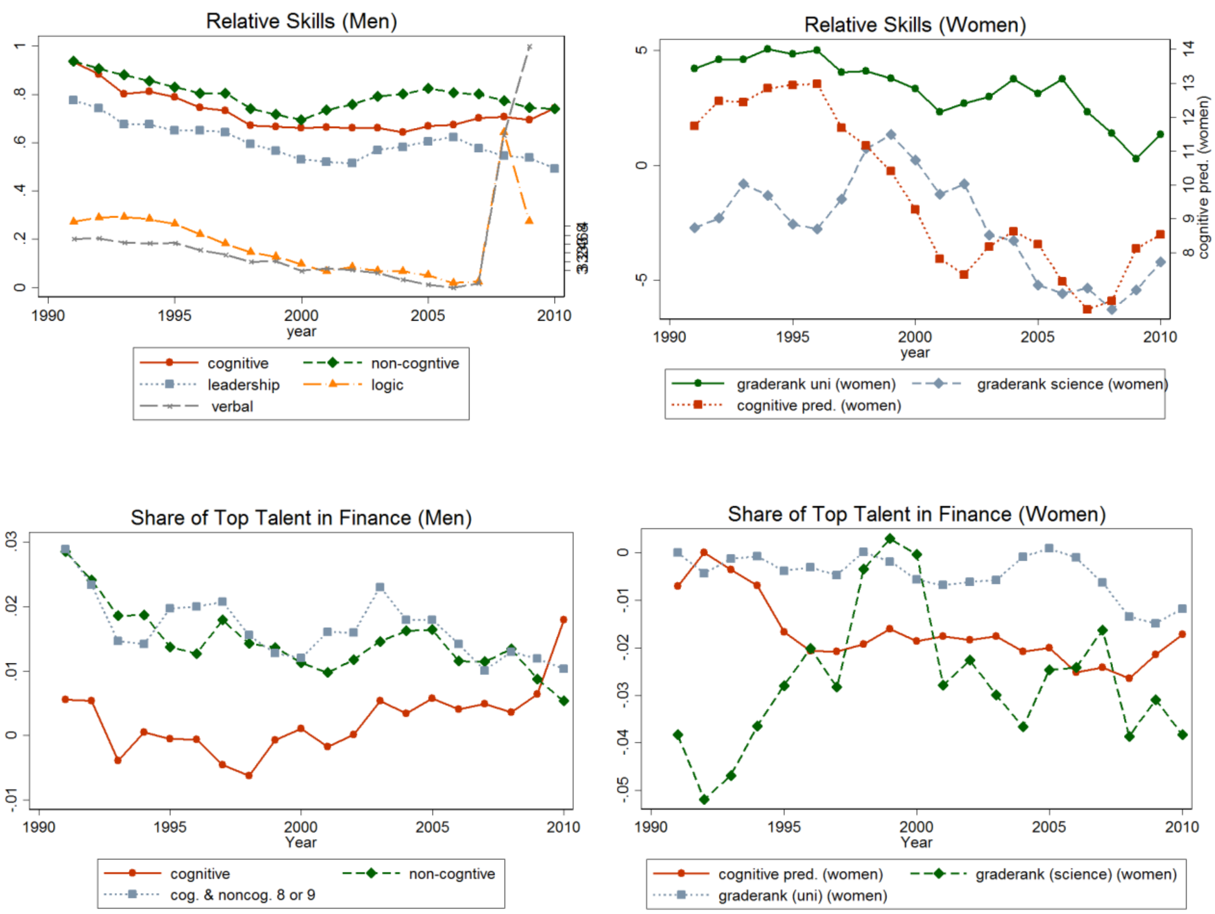
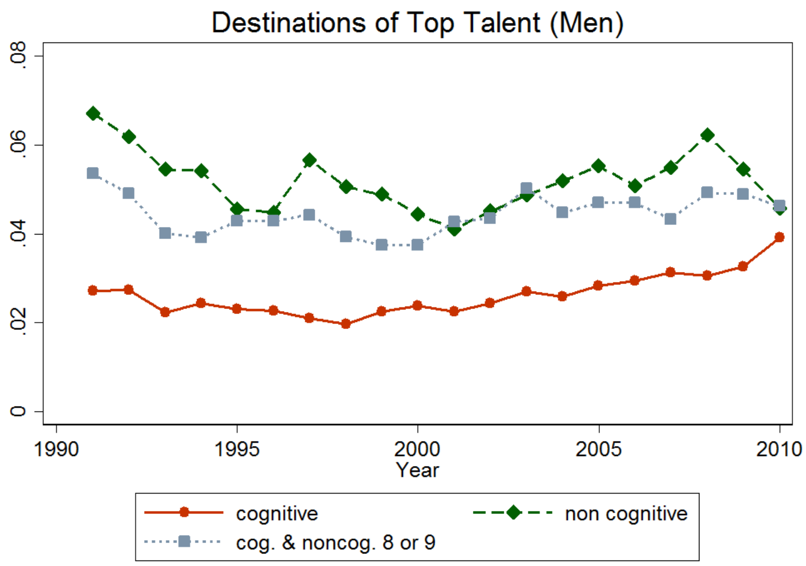
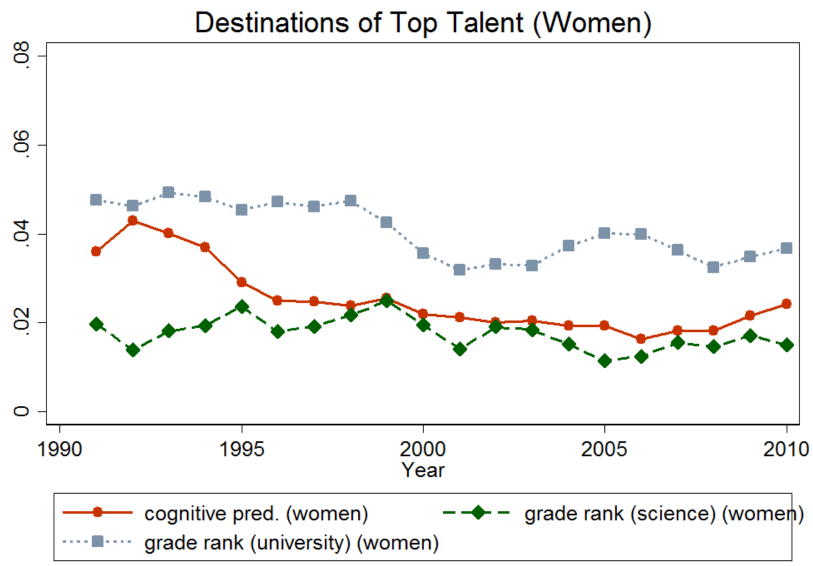


Figure 7: Sector Choices of High Talent Workers

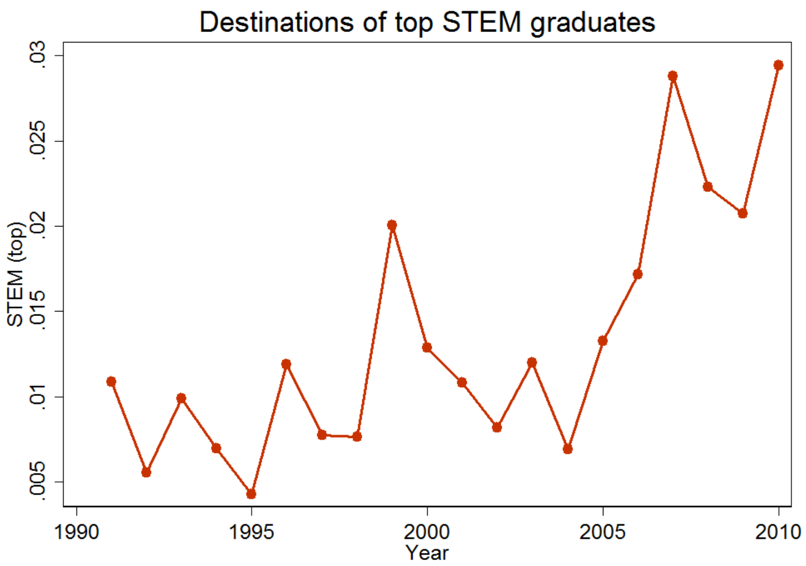
These graphs show the evolution of the fraction of top talented 30 years old individuals that work in the financial sector between 1991 and 2010. Panel A shows results for top talent of men (left) and women (right). Top talent is defined as cognitive ability of 9, non-cognitive ability of 9, or scoring at least 8 in both cognitive and non-cognitive ability for men. Top talent for women is defined as belonging to the top 5% in terms of predicted cognitive ability, grade rank in the university track, and grade rank in the science track. Panel B shows corresponding evidence for top talented STEM graduates (left) and graduates from the Stockholm School of Economics (SSE) (right). Top talent is defined as a STEM graduate that belongs to top cognitive (male) or top predicted cognitive (female) group of the population. 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: Top talent groups





Panel B: Top STEM and SSE graduates



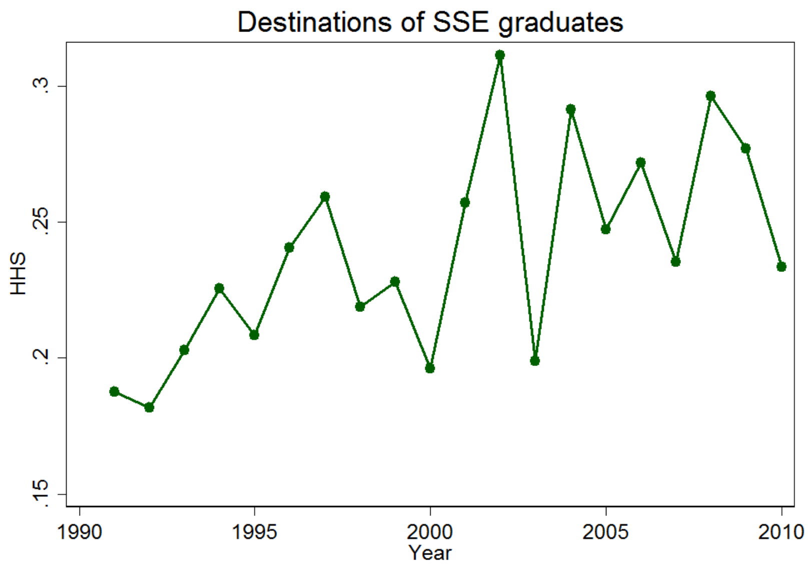
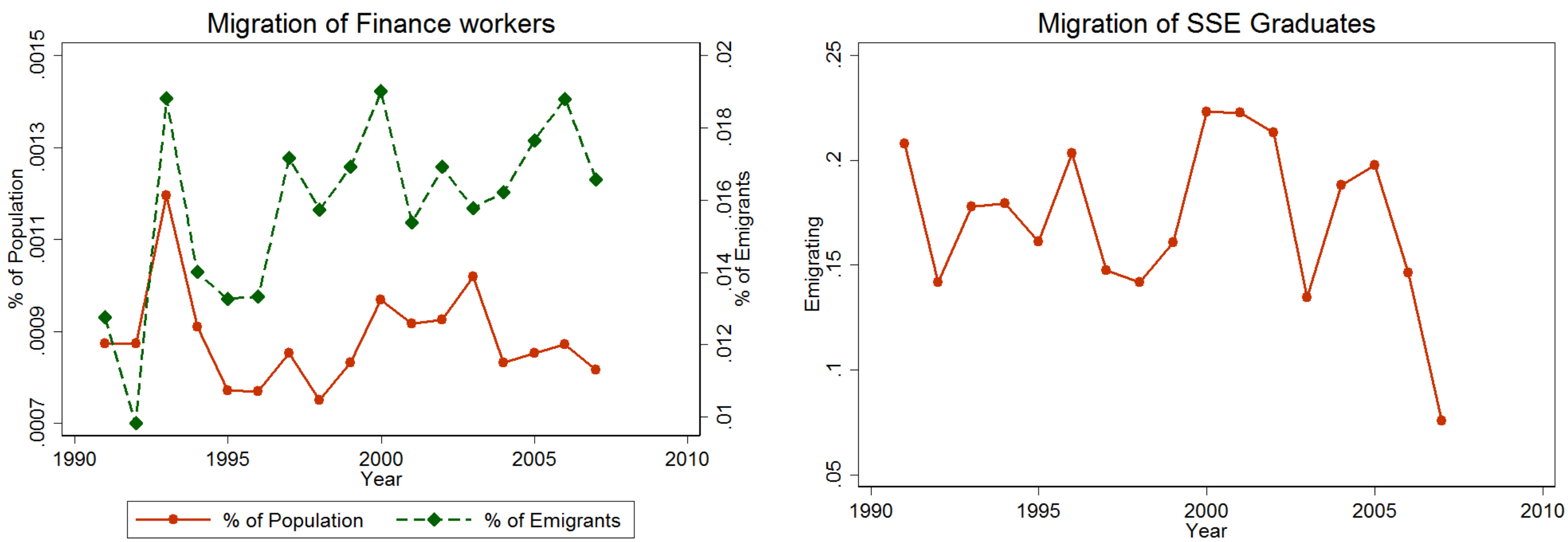


Figure 8: Emigration

The graph on the left shows the fraction of individuals between 25 and 40 years who are emigrating from Sweden with prior work experience in the financial sector (solid line and left y-axis). The right y-axis shows the finance emigrants as a fraction of all emigrants. The graph on the right shows the fraction of students from the Stockholm School of Economics (SSE) who move abroad within 2 years after graduation. Source: Swedish population data LISA from Statistics Sweden.



9 Tables

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: Relative Talent in the Financial Sector

This table shows the evolution of relative talent between the financial sector and the real economy during 1991 to 2010. The first two rows of each panel show the average level of talent for finance and for the real economy. The third row shows the difference (Premium). Panel A shows results for men, Panel B for women, and Panel C for the whole population. Source: Swedish Defence Recruitment Agency, Military Archives, and Swedish population data LISA from Statistic Sweden.

Panel A: Men

Cognitive ability

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	5.13	5.16	5.16	5.17	5.15	5.13	5.13	5.12	5.11	5.12
Finance	6.04	6.04	6.06	6.04	5.98	5.95	5.95	5.96	5.94	5.92
Premium	0.91	0.88	0.89	0.87	0.83	0.81	0.82	0.83	0.83	0.80

Con-cognitive ability

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	5.10	5.13	5.13	5.13	5.10	5.09	5.08	5.06	5.04	5.05
Finance	5.91	5.91	5.92	5.91	5.89	5.87	5.87	5.87	5.83	5.82
Premium	0.81	0.78	0.79	0.78	0.78	0.78	0.79	0.81	0.80	0.77

Leadership

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	5.29	5.31	5.31	5.31	5.30	5.28	5.27	5.26	5.24	5.24
Finance	6.00	6.00	6.00	5.98	5.94	5.91	5.91	5.91	5.88	5.86
Premium	0.71	0.68	0.69	0.67	0.64	0.63	0.64	0.65	0.64	0.62

Logic

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	24.70	24.85	24.93	25.03	25.08	25.10	25.11	25.10	25.08	25.11
Finance	28.24	28.23	28.34	28.37	28.35	28.32	28.33	28.40	28.39	28.40
Premium	3.55	3.38	3.42	3.34	3.27	3.21	3.23	3.30	3.31	3.28

Verbal

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	23.79	23.91	23.96	24.05	24.11	24.13	24.13	24.13	24.12	24.15
Finance	27.22	27.18	27.29	27.34	27.28	27.27	27.30	27.31	27.31	27.30
Premium	3.43	3.27	3.33	3.29	3.17	3.14	3.17	3.18	3.18	3.15

Panel B: Women

Pred. cog. ability (women)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	48.86	49.03	49.01	49.16	48.98	49.03	49.15	49.21	49.10	49.21
Finance	60.98	60.82	60.90	60.77	60.09	59.29	59.35	59.68	59.45	59.50
Premium	12.11	11.79	11.89	11.61	11.12	10.26	10.20	10.47	10.35	10.30

Grade rank university (women, std.)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	48.72	48.89	49.02	49.19	49.21	49.37	49.49	49.56	49.48	49.54
Finance	52.61	52.56	53.30	53.46	53.26	52.73	52.85	53.11	52.94	52.98
Premium	3.89	3.67	4.28	4.27	4.05	3.36	3.36	3.55	3.47	3.44

Grade rank science track (women, std.)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	47.61	48.30	48.77	49.09	49.23	49.41	49.48	49.64	49.55	49.60
Finance	44.83	45.17	46.98	47.47	47.07	46.59	46.47	46.84	46.80	47.32
Premium	-2.78	-3.13	-1.79	-1.62	-2.16	-2.82	-3.01	-2.80	-2.75	-2.28

Panel C: All

Pred. cog. ability (all)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	48.70	49.16	49.00	49.10	48.95	48.96	49.00	49.02	48.96	49.09
Finance	62.16	62.19	62.46	62.53	62.03	61.40	61.45	61.84	61.80	61.87
Premium	13.46	13.03	13.46	13.43	13.08	12.44	12.45	12.81	12.85	12.79

Grade rank university (std.)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	48.40	48.77	48.90	49.09	49.14	49.27	49.36	49.44	49.37	49.46
Finance	52.56	52.77	53.56	53.96	53.81	53.39	53.58	53.97	54.01	54.16
Premium	4.15	4.00	4.66	4.86	4.67	4.12	4.22	4.53	4.64	4.70

Grade rank science track (std.)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Non-fin.	47.86	48.66	48.93	49.23	49.36	49.49	49.58	49.61	49.49	49.59
Finance	48.57	49.20	50.77	51.57	51.28	50.88	50.94	51.28	51.60	52.01
Premium	0.71	0.54	1.84	2.33	1.92	1.39	1.36	1.67	2.10	2.41

Table 3: Probit Occupational Choice Regressions

This table reports probit regressions on 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(pred) cog	0.0986***	0.138***	1.559***	2.090***	0.378***	0.312***	2.712***	1.779***
	(13.58)	(18.72)	(10.59)	(14.16)	(12.75)	(8.22)	(5.97)	(3.88)
year # (pred) cog	-0.000046***	-0.000065***	-0.00077***	-0.0010***	-0.00019***	-0.00015***	-0.0014***	-0.00090***
	(-12.62)	(-17.77)	(-10.43)	(-14.03)	(-12.51)	(-8.10)	(-5.99)	(-3.92)
noncog			-0.747***	-0.217			4.167***	3.805***
			(-5.13)	(-1.50)			(9.14)	(8.28)
year # noncog			0.000411***	0.000146*			-0.0020***	-0.00186***
			(5.65)	(2.01)			(-8.96)	(-8.09)
yearsofschool		-2.026***		-0.953***		35.10***		11.37***
		(-21.02)		(-8.57)		(15.85)		(16.64)
year # yearsofs		0.00102***		0.00052***		-0.0174***		-0.00560***
		(21.13)		(9.42)		(-15.68)		(-16.39)
Observations	31,378,421	31,378,421	20,004,843	20,004,843	1,239,690	1,239,690	2,134,387	2,134,387
Sample	Both	Both	Men	Men	Both 30 yo	Both 30 yo	Men 30 yo	Men 30 yo
Sex dummy	Yes	Yes	N/A	N/A	Yes	Yes	N/A	N/A
Pot experience	Yes	Yes	Yes	Yes	No	No	No	No
Year trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Sector Choices of High Talent Workers

This table shows the evolution of sector choices of top talented 30 years old individuals between 1991 and 2010. In Panel A Top talent is defined as cognitive ability or non-cognitive ability of 9, or scoring 8 in both cognitive and non-cognitive ability for men. Panel B shows corresponding results for women. Top talent is based on predicted cognitive ability for women within the top 5% and a grade rank in the university track or science track of above 95. Panel C shows results for top STEM graduates and graduates of the Stockholm School of Economics (SEE). Top STEM graduates are STEM graduates who score in the top 5% in terms of cognitive ability (men) or predicted cognitive ability (women). The first three rows show the top 3 largest industry sectors in terms of average employment for the group of interest, while the fourth row shows the fraction that goes into the finance sector. 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: Men

Cognitive ability

	1991-1992	**1993-1994**	**1995-1996**	**1997-1998**	**1999-2000**	**2001-2002**	**2003-2004**	**2005-2006**	**2007-2008**	**2009-2010**
#1 Manuf.	29.86%	29.22%	31.51%	30.43%	25.95%	22.38%	22.33%	21.22%	19.36%	18.81%
#2 Bus. Serv.	13.93%	15.03%	14.55%	14.56%	15.38%	16.37%	16.41%	16.34%	16.89%	16.46%
#3 IT	7.89%	8.55%	10.10%	13.59%	18.73%	20.60%	18.39%	17.60%	20.19%	19.28%
Finance	2.73%	2.33%	2.28%	2.03%	2.32%	2.34%	2.65%	2.89%	3.10%	3.59%

Non-cognitive ability

	1991-1992	**1993-1994**	**1995-1996**	**1997-1998**	**1999-2000**	**2001-2002**	**2003-2004**	**2005-2006**	**2007-2008**	**2009-2010**
#1 Manuf.	23.31%	22.46%	24.63%	25.33%	22.62%	21.58%	23.10%	22.33%	21.37%	19.15%
#2 Trade/Hosp.	18.44%	19.12%	20.77%	18.94%	16.73%	14.68%	13.30%	14.80%	13.71%	15.97%
#3 Utility/Const./Transp.	15.26%	15.02%	13.48%	11.60%	9.34%	8.55%	11.29%	11.31%	12.82%	14.37%
Finance	6.45%	5.44%	4.52%	5.36%	4.67%	4.31%	5.03%	5.30%	5.86%	5.02%

Cognitive & Non-cogntive (above 8)

	1991-1992	**1993-1994**	**1995-1996**	**1997-1998**	**1999-2000**	**2001-2002**	**2003-2004**	**2005-2006**	**2007-2008**	**2009-2010**
#1 Manuf.	25.65%	26.80%	29.04%	28.30%	24.05%	21.12%	20.80%	22.24%	22.39%	19.39%
#2 Bus. Serv.	11.49%	13.34%	12.48%	11.84%	14.38%	15.23%	14.96%	15.12%	15.69%	15.61%
#3 IT	6.55%	7.02%	7.96%	10.73%	15.90%	17.47%	15.35%	13.22%	14.29%	12.82%
Finance	5.13%	3.97%	4.29%	4.18%	3.75%	4.31%	4.75%	4.70%	4.63%	4.76%

Panel B: Women

Pred. cognitive ability (women)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
#1 Manuf.	17.73%	20.65%	23.12%	23.63%	21.30%	17.93%	18.07%	18.57%	16.58%	15.18%
#2 Health	20.69%	17.31%	16.52%	15.66%	15.59%	18.29%	19.13%	20.28%	22.30%	24.23%
#3 Education	19.25%	17.24%	16.00%	15.63%	16.74%	16.54%	17.15%	17.41%	15.54%	14.38%
Finance	3.95%	3.85%	2.70%	2.42%	2.38%	2.06%	1.99%	1.78%	1.81%	2.28%

Graderank uni (women)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
#1 Health	26.27%	24.65%	22.82%	22.09%	22.84%	23.25%	23.31%	23.54%	24.49%	25.21%
#2 Education	24.55%	21.27%	18.21%	17.05%	16.37%	17.11%	18.04%	18.06%	15.96%	16.09%
#3 Manuf.	11.80%	13.21%	15.90%	15.79%	14.28%	12.28%	10.94%	11.46%	11.82%	11.78%
Finance	4.69%	4.88%	4.63%	4.68%	3.91%	3.25%	3.51%	4.00%	3.44%	3.58%

Graderank science (women)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
#1 Health	50.57%	46.69%	40.51%	36.93%	37.91%	42.95%	46.01%	43.74%	39.93%	41.08%
#2 Manuf.	14.09%	16.60%	19.23%	18.00%	17.11%	14.39%	11.58%	12.63%	11.56%	11.67%
#3 Bus. Serv.	9.22%	11.71%	10.26%	12.54%	14.22%	12.66%	12.64%	12.45%	15.54%	13.71%
Finance	1.68%	1.87%	2.08%	2.04%	2.22%	1.65%	1.68%	1.19%	1.50%	1.61%

Panel C: STEM and SSE Graduates

STEM (top)

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
Manufacturing	29.32%	34.72%	37.81%	34.60%	32.29%	28.21%	31.56%	31.62%	30.41%	28.12%
Business Services	29.56%	23.03%	22.41%	21.17%	20.89%	23.04%	22.65%	20.16%	22.00%	24.07%
IT	8.23%	6.46%	11.06%	14.23%	17.21%	19.95%	17.18%	15.14%	17.26%	17.33%
Finance	0.82%	0.84%	0.81%	0.77%	1.65%	0.95%	0.94%	1.52%	2.55%	2.51%

SSE

	1991-1992	1993-1994	1995-1996	1997-1998	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010
#2 Accounting	13.83%	20.07%	22.37%	16.35%	24.51%	21.80%	23.26%	20.66%	18.94%	26.26%
#3 Trade/Hosp.	20.08%	14.27%	9.22%	10.30%	9.56%	5.82%	11.81%	11.07%	15.70%	12.58%
#4 Manuf.	15.34%	9.26%	16.23%	13.66%	4.17%	8.73%	6.72%	11.87%	9.93%	8.00%
#1 Finance	18.47%	21.41%	22.45%	23.90%	21.20%	28.41%	24.52%	25.95%	26.58%	25.51%

Appendix

A. Further Evidence on Finance Wages

TO BE ADDED: RELATIVE WAGES COMPARED TO THE IT SECTOR, WITHIN STOCKHOLM, AND INCLUDING DISPOSABLE AND CAPITAL INCOME

B. Demand for Talent: The case of IT

We have argued that neither the time-series changes in the fraction of talented individuals going into finance, nor the effect of talent on wages, is consistent with increasing demand for talent explaining the increase in finance wages over time. As a contrast, we now repeat this analysis on the IT industry, where patterns seem more consistent with demand for talent driving wages.

In Panel A of Figure A1, we plot the relative wage in IT (right). This industry has seen considerable fluctuations in the relative wages over time, with wages peaking in 1993-94 and at the height of the tech boom in 2000. The increase in relative IT wages around 2000 was particularly pronounced. In Panel B of Figure A1, we plot the corresponding labor share of IT. The labor share in IT rose dramatically around 2000, coinciding with the relative wage increase.

Finally, Panel C of Figure A1 repeats our talent absorption analysis for IT plus finance and accounting/consulting as a comparison. A clear pattern from this picture is that the fraction of top talent going into IT peaked around 2000, coinciding with the peak in relative wages. Moreover, the quantitative impact on talent allocation of IT is substantially higher. While the IT sector overall employs roughly the same fraction of the Swedish workforce as finance, it attracts a substantially higher fraction of top talent. Taking cognitive ability as an example, the fraction of top talent going into IT increased from below 10% in the mid-1990's to over 20% in 2000, and it has remained at a similar level for the remainder of the sample period. This can be compared to the fraction of top cognitive talent going into finance, which was largely flat. Hence, unlike our findings for finance, the pattern for IT is indeed consistent with demand for talent driving relative wages.

Figure A1: IT Sector

These graphs depict the wage premium, sector size, and sector choices of high-talent individuals for the IT sector. Panel A (left) shows the wage premium for these two sectors, Panel A (right) the sector sizes, and Panel B shows the fraction of high-talent 30 years old individuals starting their careers in these sectors of interest. 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: Wage Premium and Sector Size

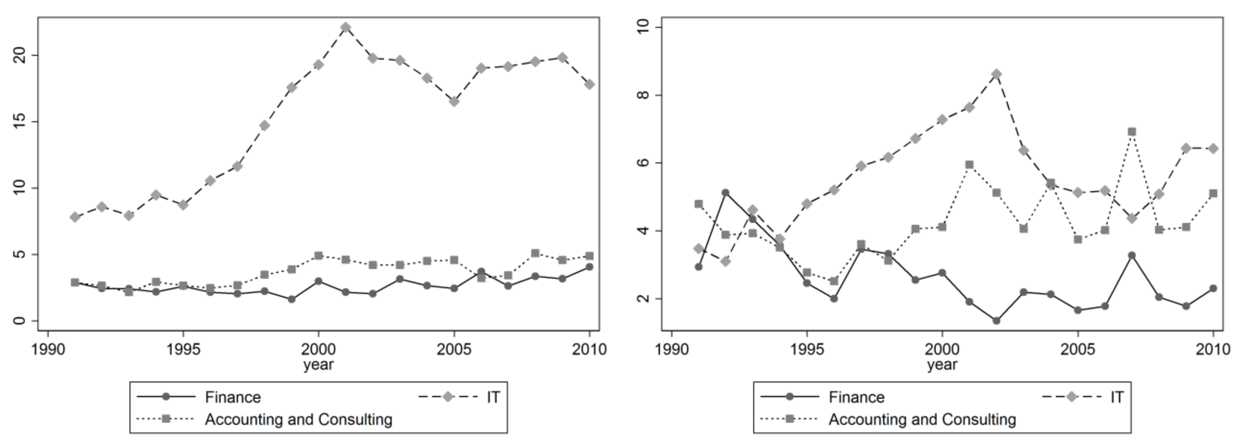
Wage Premium

Sector Size

Panel B: Talent Absorption

Cognitive ability (men)

Predicted cognitive ability (women)



C. Mathematical Appendix - Empirical Framework

C.1 Talent Selection when Skill-Bias in Finance Rises

We use standard selection-bias formulae under normality to proof our claim that the absolute and the relative talent selection (6) into finance rises with $\tilde{\beta}_t$. Among others, Heckman and Sedlacek (1985) provide the following result:

$$E\left(Y_k \middle| Y_k > Y_j\right) = m_k + \frac{\sigma_{kk} - \sigma_{kj}}{\sigma^*} \lambda(c_k) \qquad \text{(A1)}$$

where $Y_k = m_k + u_k, Y_j = m_j + u_j$ are two normally distributed random variables with population means m_k, m_j, and variances/covariance of the individual-specific deviations $Var(u_k) = \sigma_{kk}, Var\left(u_j\right) = \sigma_{jj}, Cov\left(u_k, u_j\right) = \sigma_{kj}$. Further, $\sigma^* = \sqrt{Var\left(u_k - u_j\right)}$, $c_k = (m_k - m_j)/\sigma^*$, and $\lambda(c_k) = \emptyset(c_k)/\Phi(c_k)$ a positive, monotone decreasing, and convex function ($\emptyset(c_k), \Phi(c_k)$ are the normal density and CDF at c_k, respectively, and $\lambda(-c_k)$ is called the inverse Mills ratio for c_k).

In order to arrive at the corresponding result for the selection of skill into finance $E(s|U_F > U_R)$ in our model, we replace terms in (13) appropriately. For simplicity, individual and time indices i and t are dropped. We set $m_k = \tilde{\alpha} + \tilde{\mu}$, $m_j = 0$, $u_k = \tilde{\beta}s$, $u_j = -\tilde{\varepsilon}$. Further, $Var(u_k) = \tilde{\beta}^2\sigma_s^2$, $Var\left(u_j\right) = \sigma_\varepsilon^2$, and $Cov\left(u_k, u_j\right) = Cov\left(\tilde{\beta}s, -\tilde{\varepsilon}\right) = 0$ (remember that $\tilde{\varepsilon}$ are preference deviations independent of individuals' skills). We also get $\sigma^* = \sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}$ and $c_k = (\tilde{\alpha} + \tilde{\mu})/\sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}$. This, gives us the conditional expectation $E\left(\tilde{\alpha} + \tilde{\mu} + \tilde{\beta}s \middle| \tilde{\alpha} + \tilde{\mu} + \tilde{\beta}s > -\tilde{\varepsilon}\right)$ and exploiting the linearity of the expectations operator we obtain the expression that we are after:

$$E\left(s \middle| \tilde{U} > 0\right) = E\left(s \middle| \tilde{\alpha} + \tilde{\mu} + \tilde{\beta}s > -\tilde{\varepsilon}\right) = \frac{\sigma_s^2}{\sqrt{\sigma_s^2 + \sigma_\varepsilon^2/\tilde{\beta}^2}} \lambda\left(\frac{(\tilde{\alpha} + \tilde{\mu})}{\sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}}\right) \qquad (A2)$$

We perform a similar substitution for the skill selection into the real economy. Setting $m_k = -\tilde{\alpha} - \tilde{\mu}$, $m_j = 0$, $u_k = -\tilde{\beta}s$, $u_j = \tilde{\varepsilon}$ gives $Var(u_k) = \tilde{\beta}^2\sigma_s^2$, $Var\left(u_j\right) = \sigma_\varepsilon^2$, $Cov\left(u_k, u_j\right) = Cov\left(\tilde{\beta}s, -\tilde{\varepsilon}\right) = 0$, $\sigma^* = \sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}$, and $c_k = -(\tilde{\alpha} + \tilde{\mu})/\sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}$ obtains the expectation $E\left(-(\tilde{\alpha} + \tilde{\mu} + \tilde{\beta}s) \middle| -(\tilde{\alpha} + \tilde{\mu} + \tilde{\beta}s) > \tilde{\varepsilon}\right)$. Subtract $-\tilde{\alpha} - \tilde{\mu}$ on both sides and divide by $-\tilde{\beta}$ yields (we assume throughout that in the baseline period $\tilde{\beta} > 0$, since finance is a high-skill sector):

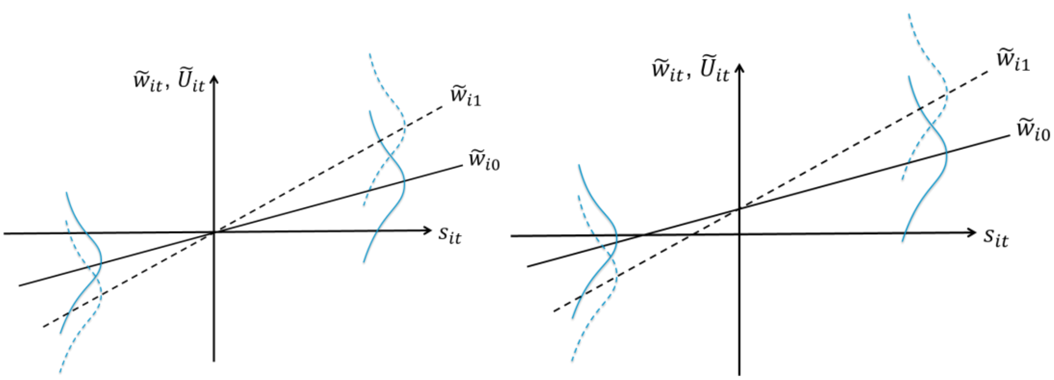
$$E\left(s \middle| \widetilde{U} < 0\right) = E\left(s \middle| -(\tilde{\alpha} + \tilde{\mu} + \tilde{\beta}s) > \tilde{\varepsilon}\right) = \frac{-\sigma_s^2}{\sqrt{\sigma_s^2 + \sigma_\varepsilon^2/\tilde{\beta}^2}} \lambda\left(\frac{-(\tilde{\alpha} + \tilde{\mu})}{\sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}}\right) \qquad (A2)$$

$$E\left(s \middle| \widetilde{U} > 0\right) - E\left(s \middle| \widetilde{U} < 0\right) = \frac{\sigma_s^2}{\sqrt{\sigma_s^2 + \frac{\sigma_\varepsilon^2}{\tilde{\beta}^2}}} [\lambda(c) + \lambda(-c)] \qquad (A4)$$

where we defined $c \equiv (\tilde{\alpha} + \tilde{\mu})/\sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}$ in the last equation. As noted by Mulligan and Rubinstein (2008), equations (14) and (15) depend on two distinct components, the employment share in each sector (second factor) and the selection rule (first factor). Consider first the share of workers choosing finance. Under our normality assumption $\Pr\left(\tilde{\alpha} + \tilde{\mu} + \tilde{\beta}s + \tilde{\varepsilon} > 0\right) = \Phi\left((\tilde{\alpha} + \tilde{\mu})/\sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}\right) = \Phi(c)$. The terms $\lambda(c) = \emptyset(c)/\Phi(c)$ and $\lambda(-c) = \emptyset(c)/[1 - \Phi(c)]$ therefore exclusively depend on the employment share of finance.

In order to analyze the effect of increasing skill-bias on the selection rule, assume for now that the employment share is constant with $\tilde{\alpha} + \tilde{\mu} = 0$. When $\tilde{\beta}$ rises, $\frac{\sigma_s^2}{\sqrt{\sigma_s^2 + \sigma_\varepsilon^2/\tilde{\beta}^2}}$ rises as well. The selection of talent into finance improves and it deteriorates symmetrically in the real economy. Visually, this is a left-rotation of the relative wage curve in the left panel of Illustration A1.

Illustration A1



However, also the size (employment share) of the sectors may change and with it the relative selection of talent. First, suppose that $\tilde{\alpha} + \tilde{\mu} > 0$. An increase in $\tilde{\beta}$ decreases the employment share of the finance sector $\Phi(c)$ and it increases $\lambda(c)$. Finance therefore becomes smaller and more talented, while the real economy becomes larger and also more talented. This is plotted in the right panel of illustration A1. We see that relatively unskilled workers are leaving finance and entering the real economy as relatively skilled workers when the relative wage line rotates to the left.

Now suppose that $\tilde{\alpha} + \tilde{\mu} < 0$. This is the more plausible assumption, as empirically finance is a small sector in terms of its employment share. When $\tilde{\beta}$ rises, the employment share in finance $\Phi(c)$ rises and $\lambda(c)$ falls. Thus, relatively high-skilled workers from the real economy move into finance, where they are however relatively low-skilled. This is plotted in the right panel of Illustration 1 in the main text.

Therefore, as noted in the main text, only if employment in the finance sector rises and if it rises sufficiently to overturn the selection rule, will the skill selection into finance deteriorate with an increase in its skill bias $\tilde{\beta}$. In this case, also the skill selection into the real economy will deteriorate, as both $\frac{\sigma_s^2}{\sqrt{\sigma_s^2+\sigma_\varepsilon^2/\tilde{\beta}^2}}$ and $\lambda(-c)$ multiplied by -1 rise. Therefore, in order to turn the relative skill selection into finance (16) negative, $\lambda(c)$ has to fall even stronger than to turn the absolute skill selection (14) negative. This supports Philippon and Reshef's (2012) focus on the relative skill selection. In all other cases under $\tilde{\alpha} + \tilde{\mu} < 0$, a rising skill bias of finance $\tilde{\beta}$ implies an improvement of the absolute as well as the relative skill selection into that sector.

C.1.1 Dispersion of Skill and Wages in Finance when Skill-Bias Rises

We are interested in how the dispersion of skills and wages in finance reacts to an increase in the sector's relative skill bias. Once again, we use a result from Heckman and Sedlacek (1985):

$$Var(Y_k | Y_k > Y_j) = \sigma_{kk}\{\rho_k^2[1 - c_k\lambda(c_k) - \lambda^2(c_k)] + (1-\rho_k^2)\} \qquad \text{(A5)}$$

where $Y_k = m_k + u_k, Y_j = m_j + u_j$ are two normally distributed random variables with population means m_k, m_j, and variances/covariance of the individual-specific deviations $Var(u_k) = \sigma_{kk}, Var(u_j) = \sigma_{jj}, Cov(u_k, u_j) = \sigma_{kj}$, $\rho_k = correl(u_k, u_k - u_j)$. Further, $\sigma^* = \sqrt{Var(u_k - u_j)}$, $c_k = (m_k - m_j)/\sigma^*$, and $\lambda(c_k) = \emptyset(c_k)/\Phi(c_k)$ a positive, monotone decreasing, and convex function ($\emptyset(c_k), \Phi(c_k)$ are the normal density and CDF at c_k, respectively, and $\lambda(-c_k)$ is called the inverse Mills ratio for c_k).

We replace terms in (X1) appropriately to arrive at the corresponding result for the dispersion of skill in finance $Var(s|U_F > U_R)$ in our model. We set $m_k = \tilde{\alpha} + \tilde{\mu}$, $m_j = 0$, $u_k = \tilde{\beta}s$, $u_j = -\tilde{\varepsilon}$. Further, $Var(u_k) = \tilde{\beta}^2\sigma_s^2$, $Var(u_j) = \sigma_\varepsilon^2$, and $Cov(u_k, u_j) = Cov(\tilde{\beta}s, -\tilde{\varepsilon}) = 0$ (remember that $\tilde{\varepsilon}$ are preference deviations independent of individuals' skills). We also get $\sigma^* = \sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}$ and $c_k = (\tilde{\alpha} + \tilde{\mu})/\sqrt{\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2}$. This, gives us the conditional variance that we are after:

$$Var(s|\tilde{U} > 0) = \sigma_s^2\{1 - \rho_k^2[c_k\lambda(c_k) + \lambda^2(c_k)]\} \qquad \text{(A6)}$$

The first thing we note from equation (X2) is that the dispersion of skill in finance (and in the real sector) is lower than the overall dispersion of skill in the economy ($Var(s|F) < Var(s)$). The reason is that the term in braces is always smaller than one (e.g., see Heckman and Sedlacek 1985). This is the well-known result that self-selection reduces the dispersion of skills and of wages in the different sectors compared to random assignment.

The changing variance of skill in equation (X2) is also very intuitive and it again depends on two components, the "sharpness of talent selection" ρ_k^2 and a function of the size of the finance sector $X(c_k) \equiv c_k\lambda(c_k) + \lambda^2(c_k)$. Start with the former:

$$\rho_k = \frac{cov(\tilde{\beta}s, \tilde{\beta}s + \tilde{\varepsilon})}{\sqrt{Var(\tilde{\beta}s)Var(\tilde{\beta}s + \tilde{\varepsilon})}} = \frac{\tilde{\beta}^2\sigma_s^2}{\sqrt{\tilde{\beta}^2\sigma_s^2(\tilde{\beta}^2\sigma_s^2 + \sigma_\varepsilon^2)}} = \frac{1}{\sqrt{1 + \sigma_\varepsilon^2/\tilde{\beta}^2\sigma_s^2}} \qquad (A7)$$

The sharpness of talent selection rises with finance's skill bias $\tilde{\beta}$, which unambiguously decreases the variance of skill selected into finance in equation (X2). This is intuitive, as sectoral choice now depends relatively more on workers' skills than on their preferences and workers in finance become more homogenous in terms of their skill (compare Illustration A1).[1]

As in the case of talent selection above, the effect of the sector size depends on whether finance is shrinking or growing. First, suppose that $c_k > 0$ depicted in the right panel of Illustration A1. When $\tilde{\beta}$ increases, σ^* rises, c_k falls, and the employment share of the finance sector $\Phi(c)$ decreases. Thus, relatively low-skill workers are leaving finance and the sector becomes more

[1] The sharpness of talent selection rule and the selection rule are closely related. When the selection rule improves, individuals base their choice of entering finance more on their skills and the sharpness of talent selection rises.

homogenously high-skilled (compare right panel of Illustration A1). Conversely, if $c_k < 0$ as depicted in the right panel of Illustration 1 in the main text, an increase in $\tilde{\beta}$ leads to an increase in the finance employment share and the sector becomes more low-skilled and heterogeneous. [2]

We therefore conclude the following about the dispersion of skills and wages into finance under a rising skill-bias $\tilde{\beta}$. If the sector's employment share does not rise, the **selection of skill into finance will become less dispersed**. Wages in finance on the contrary are likely to become more dispersed, since the expression (X2) has to be multiplied by $\tilde{\beta}^2$. However, as in the case about the wage levels, the prediction about wage dispersion does not have much empirical bite for distinguishing the rising skill-bias from other hypotheses such as higher rent extraction. Finally, if the size of the finance sector increases, there is no clear-cut implication about the dispersion of skill in that sector anymore.

C.2 A General Equilibrium Model

This section sketches a general equilibrium model that may underlie the partial equilibrium empirical framework presented in the main text. It is based on the seminal general equilibrium Roy model of Heckman and Sedlacek (1985).

We start with labor demand. Suppose final output in the economy is produced according to a CES production function using input from the financial sector and the real economy:

$$Y = A * [A_R R^\rho + A_F F^\rho]^{\frac{1}{\rho}} \qquad (A8)$$

where F, A_F and R, A_R are the finance and the real economy inputs and their productivities, respectively, A is an overall technology term and $\frac{1}{1-\rho} \geq 0$ the elasticity of substitution between the two inputs.

[2] Unfortunately, I have a hard time deriving these results analytically. Take the case where $c_k < 0$ and $\frac{dc_k}{d\tilde{\beta}} > 0$ and differentiate $X(c_k)$: $\lambda(c_k)\frac{dc_k}{d\tilde{\beta}} + c_k\lambda'(c_k)\frac{dc_k}{d\tilde{\beta}} + 2\lambda(c_k)\lambda'(c_k)\frac{dc_k}{d\tilde{\beta}}$. The first two terms are positive and the last one is negative as $\lambda(c_k) > 0$ and $\lambda'(c_k) < 0$. Although I cannot show it, the overall expression has to be dominated by the last term so that skill dispersion rises. To see this, suppose there is no preference heterogeneity ($\sigma_\varepsilon^2 = 0$) and thus $\rho_k = 1$. Then skill dispersion in finance rises one-to-one with $c_k\lambda(c_k) + \lambda^2(c_k)$ and the size of the sector.

Assume a competitive final producer who takes the input prices Π_F, Π_R as given. Profit maximization then gives the relative first order condition (FOC):

$$\frac{MP_F}{MP_R} = \frac{A_F}{A_R}(\frac{R}{F})^{1-\rho} = \frac{\Pi_F}{\Pi_R} \qquad (A9)$$

We now turn to labor supply in levels (individual and time indices are omitted). A worker of skill S produces ΦS^{β_k} units of the sector $k \in \{F, R\}$ task, where β_k is the sector's skill bias and Φ is a constant. Being paid according to marginal product, potential wages in k become $W_k = \Pi_k \Phi S^{\beta_k}$.

We also assume workers choose the sector where they have the highest utility, that is, $I_F(\mathrm{S}) = 1[\Pi_F S^{\beta_F} \mathrm{M}_F \mathrm{E}_F > \Pi_R S^{\beta_R} \mathrm{M}_R \mathrm{E}_R]$ is an indicator for choosing finance, $\mathrm{M}_k = \exp(\mu_k)$, and $\mathrm{E}_k = \exp(\varepsilon_k)$ the individual idiosyncratic preference for sector k. Labor supply to finance and the real economy become

$$L_F = \int \Phi S^{\beta_F} I_F(\mathrm{S}) \mathrm{dG}(\mathrm{S})$$

$$L_R = \int \Phi S^{\beta_R} [1 - I_F(\mathrm{S})] \mathrm{dG}(\mathrm{S}),$$

where $\mathrm{G}(S)$ is the population distribution of skill (assumed log normal in the previous appendix section and the main text) and in aggregate equilibrium $L_F = F, L_R = R$.

From now write the labor supply side in logs (lower case). That is, the log wage in sector k is $w_k = \pi_k + \theta + \beta_k s$. We see that the intercept $\alpha_k = \pi_k + \theta$ in the wage equation (1) rises one to one with the marginal product of task k input in this competitive labor market. The intercept in the relative wage equation $\widetilde{w} = \tilde{\alpha} + \tilde{\beta} s$ is exactly the relative task price $\tilde{\pi}$.

The skill bias β_k may more realistically be interpreted applying only to excess skill. To see this, suppose θ is the population average log skill and s is the deviation from that average. Therefore, it is not unintuitive to assume a mean zero normal distribution for s in the main paper, with half of the population having negative (less than average) skill.

There are two shocks that we analyze in the main text. Consider first a shock to the (relative) productivity of finance in producing final output (equivalently, one could model it as a shock to consumption demand for finance). This implies $\frac{A_F}{A_R}$ rises and thus the relative marginal product of finance rises in (18). This raises the relative task price $\frac{\Pi_F}{\Pi_R}$ and $I_F(\mathrm{S}) = 1[\Pi_F S^{\beta_F} \mathrm{M}_F \mathrm{E}_F > \Pi_R S^{\beta_R} \mathrm{M}_R \mathrm{E}_R]$ will be fulfilled for (weakly) more workers. The relative finance input $\frac{F}{R} = \frac{\mathrm{L}_F}{\mathrm{L}_R}$ into final production rises.

The new equilibrium will be characterized by a higher relative finance input $\frac{F}{R}$ as well as a higher relative task price $\frac{\Pi_F}{\Pi_R}$. Thus, as argued in the main text, a higher relative marginal product of finance, which may stem from higher productivity of- or consumption demand for finance, raises the relative intercept $\tilde{\alpha} = \tilde{\pi}$. This relative intercept will only not rise in the extreme case where labor supply to finance is perfectly elastic, so that all of the adjustment of (18) is borne by $\frac{F}{R}$ and employment in finance increases strongly. Conversely, if labor supply to finance is perfectly inelastic, only $\tilde{\pi}$ will rise.

Now consider a shock to the relative skill bias in finance. First of all, $\tilde{\beta}$ in the relative wage equation $\widetilde{w} = \tilde{\alpha} + \tilde{\beta} s$ rises. We test for this in our choice regressions and our wage regressions. Moreover, $I_F(\mathrm{S}) = 1[\Pi_F S^{\beta_F} \mathrm{M}_F \mathrm{E}_F > \Pi_R S^{\beta_R} \mathrm{M}_R \mathrm{E}_R]$ will more likely be fulfilled for high-skill workers (s above zero) and less likely be fulfilled for low-skill workers (s below zero). This is discussed in more detail in the previous appendix section and we test for improving talent selection into finance extensively in the paper. Finally, depending on all the parameters of the model, the relative production of the finance good in equilibrium $\frac{F}{R} = \frac{\mathrm{L}_F}{\mathrm{L}_R}$ may rise, stay constant, or fall. Hence, the finance sector size may change to some extent as well as the intercepts in the wage and the choice regressions. Our empirical methods in the paper allow for this.