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

Talent and the finance wage premium

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Abstract

Relative pay in the financial sector has experienced an extraordinary increase over the last few decades. A proposed explanation for this pattern has been that demand for skilled workers in finance has increased more than in other sectors. We exploit Swedish administrative data, which include detailed cognitive and non-cognitive test scores for individuals, 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. Finance does not become more skill-biased and changing composition of skills or their returns cannot account for the surge in the finance wage premium. These findings alleviate concerns about a “brain drain” into finance at the expense of other sectors, but they also suggest that rents in finance are high, increasing, and largely unexplained.

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1 Introduction

Since the 1980’s, relative wages in the finance industry have risen dramatically in many countries around the world (e.g., Boustanifar et al., 2014). Moreover, Kaplan and Rauh (2010), Philippon and Reshef (2012), and Bell and Van Reenen (2013) show that financial sector employees represent a substantial, and increasing, fraction of top percentile earners in the U.S. and the U.K. Consequently, finance pay has accounted for a substantial part of the increase in overall wage inequality and much of the increase of top wage inequality in these countries over the last few decades.\(^1\) To explain 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. In support of this argument, they show that the relative rise in finance pay compared to other industries closely relates to a relative rise in the skill-intensity of finance, where skilled workers are defined as those with strictly more than a high-school education.

These findings raise important issues about the competition for talent across sectors and its implications for allocation of talent in the economy, which we aim to address in this paper. First, the results of Philippon and Reshef (2012) suggest that the increase in finance wages is due to the increase in the marginal productivity of talented workers in finance. This leads to increased competition for talented workers who need to be paid higher wages to be attracted to the finance sector. Whether the rising wages in finance are explained by a rising demand of financial firms for talented workers, as opposed to an increase in rents captured by workers in finance due to moral hazard, asymmetric information, and/or governance problems, has important implications for social welfare and optimal policy responses.\(^2\)

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\(^1\) Atkinson et al (2011) summarize evidence showing that top income shares have increased substantially in many countries over the last thirty years, particularly in English-speaking countries like the U.S. and the U.K. Following Katz and Murphy (1992), several papers have tied the increase in inequality to the increasing disparity of wages between skilled and unskilled workers, due to skill-biased technological change. See Acemoglu and Autor (2010) for a review and critical discussion of this literature.

\(^2\) See Myerson (2012), Biais and Landier (2012), and Axelson and Bond (2014) for models of moral hazard rents; Bolton et al (2014) and Glode and Lowery (2013) for models of asymmetric information rents; and Bebchuk et al (2010), Bell and Van Reenen (2013), and Zingales (2015) for arguments relating to governance problems and rent seeking in finance. E.g. Bell and Van Reenen (2013) write: “...there seems to be substantial evidence of rents within the [finance] sector – a result of imperfect competition or arising from the implicit and explicit guarantees and subsidies that the sector receives from the government due to the ‘too- big-to-fail’ problem.”
Second, to the extent higher wages draw talent to the financial sector from other sectors of the economy, this could have negative effects on the productivity of these other sectors (Baumol, 1990; Murphy et al, 1991). For example, Murphy et al (1991) write: “The flow of some of the most talented people in the United States today into law and financial services might then be one of the sources of our low productivity growth.” Consistent with talent being drawn into the finance sector, Goldin and Katz (2008), Oyer (2008), Shu (2013), and Célérier and Vallée (2014) document that a large fraction of students from top universities have gone into the finance sector in recent decades.

Although previous literature has provided some suggestive evidence on these issues, existing research has suffered from a lack of data on talent or skill at the individual level, and to the extent such measures have been available they are usually very coarse. For example, Philippon and Reshef (2012) and Boustanifar et al (2014), define skill as having more than a high-school or a college degree, respectively. Using such coarse measures to address the effect of competition for talent of wages is potentially problematic given that competition for talent should be particularly strong at the very top of the distribution (Rosen, 1981; Gabaix and Landier, 2008). Consistent with this, Kaplan and Rauh (2010) and Bell and Van Reenen (2013), show that the increase in the finance wage premium is concentrated at the top percentiles of the wage distribution.

Another problem is that the distribution of education varies over time and across cohorts. In most developed countries, including the U.S., the fraction of university graduates has increased substantially over time, which means that the estimated relationships between skill and wages can be confounded by composition effects (Lemieux, 2006).

We are able to get around these problems by examining population-wide data from Sweden over the period 1990-2010, which includes individual-level information on both wages and talent. Our

3 For example Kneer (2013a,b) argues that financial deregulation let to a flow of talent into finance, which resulted in a reduction in productivity in non-finance skill intensive industries.

4 Similarly, Juhn et al (1993) and Lemieux (2006) show that wage inequality has increased substantially within the group of college-educated workers.

5 This problem is acknowledged in Philippon and Reshef (2014), who write: “although education is a good indicator of human capital, it is far from perfect. There is significant variation in human capital within educational groups and the meaning of any particular level of education may not be stable over time. For example, high school graduation indicated relatively more human capital before the expansion of college education than after.”
talent measures - high-school grades and scores from IQ and personality tests - are much finer than the simple education measures used in previous research, and our wage data is uncensored and does not suffer from top coding. As a result, we are able to simultaneously examine the tails of both the talent and wage distributions. The distribution of our talent measures is likely to be constant over time (or can be easily scaled to achieve this), avoiding composition effects. Moreover, our talent measures are determined ex ante, before the worker enters higher education and/or the labor force, and (with the exception of high-school grades) they are likely to measure intrinsic talent, which alleviates problems of endogeneity and reverse causality.6

One potential issue is whether our results on Swedish data are generalizable to countries such as the U.S. and U.K.7 We believe that they are. Although Sweden has a smaller finance sector than these countries, it is still sizable compared to many other countries. Moreover, similar to the U.S. and the U.K., the Swedish financial market was deregulated in the mid-1980’s and the growth of the industry has been very similar. More importantly, we show that the time-series of both relative wage and relative education in the finance sector look remarkably similar in Sweden and the U.S. in our data.8

We use this data to test two predictions of the skill demand hypothesis. First, if the demand for talent in finance increased, we should see more talented workers entering this sector over time. Workers should also base their decision to enter finance more on how talented they are. Second, if competition for talent is driving the rise in the finance premium, we should see that the return to talent or skill in finance increased simultaneously with relative wages. We find little evidence for either of these predictions. This suggests that the competition for talent and skill-bias in finance has not increased over time, and that the increase in relative finance wages is more likely

6 We are currently in the process of matching individuals with firm financials, as well as other socio-economic characteristics, which enables us to test additional hypotheses in the next version of the paper.
7 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.
8 Another potential issue is whether the talent measures we use, based on high-school grades and military test scores, are actually informative about talent and labor market outcomes. Previous research employing similar Swedish data has shown, however, that these talent measures are strong predictors of future income, as well as other socio-economic outcomes such as unemployment, health, divorces, illicit activities, or the likelihood of becoming a CEO (see e.g. Lindqvist and Vestman, 2011; Häkanson et al, 2012; and Adams et al, 2014), and we confirm many of these results in our sample.
driven by other factors, such as increasing rents. Moreover, there is no evidence for finance wages leading to negative “brain-drain” externalities on other sectors.

More specifically, we examine the evolution of wages and talent for a sample of about 65 million individual-year observations of Swedish workers over the period 1991-2010. Over this period, the finance wage premium, defined as premium in the average annual wage of an employee in the finance sector relative to other sectors, increased from around 30% in 1991 to 65% in 2010, compared to an increase from 20% to almost 50% in the U.S. over the same period (see Figure 1). The relative wage increase in finance is particularly pronounced at the top of the wage distribution. Comparing the top percentile of earners in finance to the top percentile in other industries, the premium was 75% in 1991, and grew to over 200% by 2010 (having gone down from over 250% before the financial crisis in 2008-2009). Looking at the composition of the top percentile of Swedish earners, in 1991 nine percent of these worked in the finance sector, compared to fifteen percent in 2010.

Similar to Philippon and Reshef’s (2012) result for the U.S., we also find that the fraction of college graduates has increased faster in the finance sector over this period of time (see Figure 2). Between 1991 and 2010, the percentage of workers in the finance sector with college education was two percent higher than in the rest of the economy and this premium increased to almost fifteen percent. In contrast, when using our fine-grained talent measures – cognitive and non-cognitive skills from military tests, and high-school grades – we find that the average talent across all our measures has remained more or less constant in the finance industry over the sample period. Probit regressions also do not indicate that talent or skill increasingly determines workers’ choice to enter finance over time.

These results hold regardless of whether we examine the average talent across all individuals in the sector or the fraction of top talent; and whether we examine all workers at a given point in time or focus on the cohort of 30-year olds (which we use as a proxy for recent entrants into the sector). 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 graduates from the Stockholm School of Economics, the highest-ranked business school in Sweden. We find negligible changes in the fraction of these graduates going into finance over our
time period. Hence, there is no evidence of the increase in finance wages leading to an increased flow of talented workers into that sector.⁹

One concern is that we are missing part of the brain-drain because of talented Swedes emigrating to take finance job abroad. Although we do not observe the destination industry for emigrants in our sample, we show that the fraction of talented workers emigrating does not show any clear trends, and that the quantitative impact of emigration on the fraction of talent going into finance is very small, even under aggressive assumptions about the fraction of emigrants going into finance jobs.

We then turn to testing the relationship of finance wages and talent directly, and run regressions of wages on our talent measures, time, and controls (including education and experience). We start with running specifications where the return to talent is restricted to be the same across sectors, to examine the extent to which finance wages can be explained by changes in composition of talent across sectors. We are also able to include individual and individual-employer fixed effects in this regression, thanks to the rich panel structure of our data. Consistent with talent remaining fairly constant within the finance sector, we find that changes in talent composition (as well as education) cannot explain the increase in finance wages since 1991.

We also run specifications of the wage equation allowing for time-varying, sector-specific returns to talent. Although there is some evidence that the return to talent in a simple OLS regression has increased more in the financial sector, compared to other sectors, it fails to explain the increasing wage premium over our sample period. Heckman-corrected wage regressions, which account for the fact that the workers that we observe in each sector are self-selected, indicate no increase in the (relative) return to talent in finance.¹⁰ Hence, we conclude that rising productivity of talent or skill in the finance sector cannot explain the increase in the wage premium from 1991 to 2010.

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⁹ One important caveat is that workers who emigrate drop out of our sample, which would be a problem if a substantial number of talented workers enter the finance sector abroad, e.g. in New York or London. We are in the process of collecting migration data, and we will analyze this issue in the next version of the paper. At this point, however, we still observe that the magnitude of emigration by talented workers would have to be very (and implausibly) large to significantly change our overall results.

¹⁰ One problem with the current version of the selection model is that we do not have a good exogenous instrument for the selection into finance, and therefore have to rely on the underlying distributional assumptions of the Heckman
Finally, one might argue that our results are still consistent with an increasing productivity in finance of unobserved skill components that are orthogonal to our talent and education measures. However, to the extent that fixed effects on different levels capture these skill components, this is accounted for in the analysis. In addition, the residuals in the Heckman-corrected regressions capture sector-specific unobserved orthogonal skills and their returns. These also do not increase in finance over time.

Our paper is organized as follows: Section 2 discusses the related literature. Section 3 explains our data and establishes the main stylized facts in the finance sector in Sweden comparing it to the evidence in the U.S. and the U.K. Section 4 introduces our empirical model and Section 5 analyses the skill selection and talent composition in finance. Section 6 studies whether changing composition of- or returns to talent can account for the finance wage premium. The last section concludes.

2 Related literature

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

Combining data from the U.S. Census and the Current Population Survey, Philippon and Reshef (2012) document that relative wages are higher in finance overall, and increased significantly over the period 1985-2005. They propose an explanation for this based on the mid-1980s financial deregulation together with technological developments in IT, which increased the demand for skilled labor in the financial sector, resulting in higher salaries for skilled workers. Consistent with this explanation they also find that relative education in finance followed a similar pattern to relative wages over this period (higher and increasing); while the size of the model to identify the selection effect. In the next version of the paper, we will use socio-economic variables, such as peer effect and geographical instruments, to try to better identify this model.
financial sector, measured by the employment share, remained relatively flat. They estimate that finance sector can explain 8% of the increase in the college premium over this period.\(^{11}\)

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

Boustanifar et al (2014) extend Phillipon and Reshef’s analysis to international data, examining relative finance wages for 22 industrialized and transition economies over the period 1970-2005. They use the EU KLEMS database, which has aggregate wage data by industry and education level (college vs. not) for each sector over time. Boustanifar et al (2014) report significant heterogeneity in the evolution of wages across countries, with about half the countries experiencing an increase in relative wages over their sample period. Consistent with Phillipon and Reshef, they find that finance was a main contributor to the increases in the wedge between skilled and unskilled labor for many countries, and that the finance wage premium is driven more by changes in skilled vs unskilled wages rather than a changes in the educational composition in finance. They also suggest deregulation as a main factor causing increases in relative wages in finance, while IT played a relatively minor role.

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

\(^{11}\) Related to this, Juhn et al (1993) and Lemieux (2006) show that wage inequality has increased substantially within the group of college-educated workers in recent decades.
The unique feature of data set we use in our analysis is that we observe direct measures of different dimensions of human capital (e.g., cognitive and non-cognitive skills) whose distributions are stable over time and are not based on outcomes (e.g., share of top-earners (Philippon and Reshef, 2012)). In addition, there is considerably more dispersion in our talent measures compared to simple education measures, which enables us to test the correlation between talent and wages at the top of the distribution. This is important given that increases in finance wages have been found to be particularly pronounced in the right tail. Moreover, our data set includes matched worker-firm data, which enables us to test new predictions regarding several other potential determinants of the finance wage premium. We can also use the rich panel structure of our data to examine hypotheses related to earnings risk.

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

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

The research that is closest to ours in that spirit is Lindley and Macintosh (2014), who examine data on numeracy skills from the British Cohort Study (BCS) and the National Child

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12 The proportion is actually declining from about 12% in 2006 to about 4% in 2012 which she attributes to the financial crisis.
Development Study (NCDS) in the UK. Lindley and Macintosh find that finance college workers have not become relatively more numerate over time, but that instead their numeracy slightly declined. These results rely on a very small sample, however, as there are only 378 finance workers in the BCS, and covers only two cohorts, makes it more difficult to account for composition effects.

We also contribute to the literature that studies negative externalities of high wages in the financial sectors for the allocation of skills (“brain drain”), either within a country and between different sectors (Baumol (1990); Murphy, Shleifer, and Vishny (1991); Shu (2013) and Kneer (2013b)) or between different countries (see Kneer (2013a) and Boustanifar, Grant, and Reshef (2014)). Using an indirect approach, Kneer (2013b) finds that labor productivity in non-finance sectors falls after the relaxation of US interstate banking restrictions. She attributes this to more talented people moving into finance and concludes that the financial sector absorbs talent at the expense of the real economy. On the contrary, Shu (2013) does not find any increase in talented workers going into finance for her sample of MIT graduates between 2006 and 2012. Exploiting the recent financial crisis as an exogenous shock to the number of vacancies in the financial sector, Shu presents further evidence suggesting “that finance does not attract the most productive scientists and engineers from MIT”.

3 Data and Stylized Facts

3.1 Sample Construction

Our basic sample is the longitudinal integration database for health insurance and labour market studies (LISA) provided by Statistics Sweden (SCB). The database presently holds annual registers since 1990 and includes all individuals 16 years of age and older that were registered in Sweden as of December 31 for each year. The dataset contains employment information (such as employment status, the identity of the employer and wages) as well as demographic information (such as age or family composition).

13 We also find a slight decrease of some dimensions cognitive over time. This trend is, however, neither economically nor statistically significant.
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). To compare wages across time, we deflate all wages using the CPI.

We supplement the initial sample with various items that are also provided by SCB: We obtain information on education (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. No aggregation is necessary for the financial sector.

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.

3.2 Skill Measures

Following Philippon and Reshef (2012) we use education groups as a first measure of skill. We assign individuals education groups based on their highest level of education. Our main groups of interests are “post-secondary education”, “university degree”, and “PhD” which are classified in the same way as in Philippon and Reshef (2012).

14 We lose the observations for 1990 in our analysis because our wage measure is not available for that year.
Similar to in the U.S., the fraction of people with college education has increased in most countries in Western Europe 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 that sector.\textsuperscript{15} 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 measures of innate abilities (e.g., cognitive and non-cognitive skills), 2) the distributions of these measures within the population are stable over time,\textsuperscript{16} and 3) they are elicited at age 18 or 19 and thus our measures of skill that are determined 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 extraordinarily at the top, this is of special interest.

Our proxies of skill measure different aspects of cognitive and non-cognitive ability and they originate from the Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for persons enlisted between 1983 and 2010 and from the Military Archives (Krigsarkivet) for persons enlisted between 1969 and 1983. Lindqvist and Vestman (2011) provide a detailed description of the data and its collection.

The test on cognitive skills consists of four different parts (logic, verbal, spatial, and technical comprehension) of which each is constructed from 40 questions. 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 skills. This standardized variable ranges from 1 (lowest) to 9 (highest) and

\textsuperscript{15} To illustrate this point, consider the following example. Suppose the financial sector is always recruiting the 20% smartest people of all workers. Furthermore, suppose that in 1991 only the 10% smartest got a college degree. This would imply that half of the workers in finance had a college degree, the other half did not have one; no worker outside finance had a college degree. The relative education in finance is $10/20 - 0/80 = 0.5$. Now, suppose that in 2010, due to expansion in education the top 40% of the population have a university degree. Still assuming that finance is recruiting the top 20% of the skill distribution, the relative education in finance went up to $20/20 - 20/80 = 1 - 0.25 = 0.75$. Hence, we observe increased relative education in the data, while the relative innate skills have not improved at all.

\textsuperscript{16} Average intelligence in the population has been documented to increase over the generations ("Flynn Effect"). This is however modest and in particular it petered out over the last decades for male conscripts in Nordic countries (e.g, see http://en.wikipedia.org/wiki/Flynn_effect, last visited 2015-03-09).
follows a Stanine scale that approximates a normal distribution. While our main analysis is based on the aggregated variable, we also examine at the raw scores in parts of the analysis. Since 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 skills ranging from 1 to 9, following a Stanine scale as well. The score is based on a 25-minute semi-structured interview by a certified psychologist. The non-cognitive score is associated with willingness to assume responsibility; independence; outgoing character; persistence; emotional stability; and power of initiative (Swedish National Service Administration (SNSA) referenced by Lindqvist and Vestman (2011) and Lothigius (2004)).

As a third dimension 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 and follows a Stanine scale.

One caveat of the skill measures provided by the recruitment agency is its gender selection. While almost all men are required to do these enlistment tests when they turn 18 or 19 years old, women are usually not tested. For this reason, we employ the high school grade point average as an alternative measure of skill. Moreover, though it has been shown that cognitive and non-cognitive skills have been positively associated with performance in school, grades at school capture additional dimensions of skills that are potentially relevant for job success.\(^{17}\) Hence, we believe that grades are also partly complementary to the enlistment test results.

We collect information on the final high school grade, graduation year, and the type of program the person was enrolled in. We construct our variable graderank by sorting students into grade percentiles (1 to 100) within each cohort, that is, a graderank of 100 means that a person was

\(^{17}\) Almlund et al. (2011, p 103-104) report that conscientiousness is an important component of high-school grades. Also, they cite studies which find that grades are better predictors of performance in college than are standardized test scores (which are closer to cognitive skills).
graduating in the top 1% of the grade distribution of her cohort. As a result we obtain a fine-grained relative and early skill measure that is stable across years. This approach accounts for potential grade inflation over time as well as for changes in the scale of GPAs.

One remaining issue that we face with respect to the graderank variable relates to the comparability of programs chosen in high school. Swedish students can choose between several programs ("Linjer") which are of different length and difficulty. As our principal graderank measure, we only consider the main programs that lead to university admission. 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. However, as a robustness check, we also pool all programs, with similar results.

### 3.3 Stylized Facts: The Swedish Case

We start our analysis by comparing stylized facts of the evolution of the Swedish financial sector with those in the US and the UK. The motivation behind this exercise is twofold: First, we are interested in the Swedish case in itself given that nobody has analyzed these facts with such high quality data for Sweden yet. Second, we want to understand to which extent the Swedish financial sector looks similar to the US or UK one. A positive answer to this second question will give us more confidence in the applicability of our findings to other countries.

Following the literature we focus on relative pay, pay dispersion (in particular compensation at the top), and relative education of the financial sector. We use our Swedish registry data for the period from 1991 to 2010 and CPS data as in Philippon and Reshef (2012) for the US.

We start with relative finance wages over time in Figure 1. These are defined as the ratio of the average wage in finance to the average wage in the non-financial, nonfarm private sector. In our sample of Swedish registry data in Panel A (1991-2010) we observe that workers in the financial sector earn about 30% more in 1991. This pay premium increases over time to about 65% in 2010. The only occasions when it drops is after the crises around 2000 and 2007, but it recovers and overtakes the previous level quickly. In Panel B, the picture looks similar in the US (CPS data). Considering our period of interest, the US pay premium also starts at a relatively low level of about 20% in 1991 and then surges to 50% in 2010. Interestingly, year-to-year fluctuations are
also strikingly similar between Sweden and the U.S., with both countries experiencing drops in the finance premium after the tech crash in 2000 and the financial crisis in 2008, followed by relatively quick recoveries.

Two reasons for the somewhat lower level of the finance premium in the U.S. data is that (1) the CPS survey is top-coded and (2) only surveys workers for hourly or weekly wages, which do not include end-of-year bonuses and other payments.\textsuperscript{18} While the trends in both datasets are very similar, our Swedish wage data is therefore a more accurate measure of the overall finance pay premium.

Working with uncensored data, which includes all compensation such as bonus payments, is particularly important since the rise in the finance premium has been shown to be particularly large at the top of the wage distribution. For the U.S., 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 (combining data from the U.S. census and ACS).\textsuperscript{19} Using U.K. administrative record data, Bell and Van Reenen (2012) show that almost the entire increase in the share of top earners between 1999 to 2008 is due to the finance sector.

Figure 2 depicts the finance pay premium for Sweden, for different quantiles of the wage distribution. We calculate the quantile premium as relative quantile of finance pay compared the respective quantile in the rest of the economy. Panel A of Figure 2 shows that the finance premia rise for all percentiles of the wage distribution over the period we study. The difference between quantiles also increases over time, with the top percentiles experiencing the largest increases. The top percentile of finance earners also experiences the largest year-to-year fluctuations in the relative wages, suggesting that bonus payments are particularly important for this group (similar

\textsuperscript{18} For the wage premium, Philippon and Reshef (2012) actually do not use the CPS but Industry Accounts of the US for exactly these reasons. The trend and the fluctuations are the same as in Panel B of Figure 1, while the level of the premium at the end of their sample in 2006 is almost exactly the same as we find for Sweden in that year.

\textsuperscript{19} For the U.S., Kaplan and Rauh estimate 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% of earnings. 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 U.S. 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, which is the second highest fraction (after Services) among the 9 industries they consider.
to what Bell and Van Reenen, 2013, document). Panel B of Figure 2 plots the finance premium for each quantile normalized at its 1991 level. While the median finance earner experiences a 10% increase in their pay relative to the existing premium in 1991, the top percentile increase is over 70%

These results imply that 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. Consequently, we compute that the share of finance workers among the top 1 (0.1) percent earners in Sweden rises from 9 (16) percent to 15 (28) percent between 1991 and 2010. This striking increase of pay at the very top is in line with the evidence reported for the US and the UK, two countries usually associated with significantly more wage inequality than Sweden.

In addition to rising pay in finance, several studies have documented high and rising relative skill levels in the finance sector (e.g., Lindley and McIntosh for the U.K., Philippon and Reshef for the U.S.), using relative education (college vs. not) as the measure of skill. In the left panel of Figure 3 we use 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) 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 shown in the right panel, the level differences in relative education are somewhat smaller but the trend is very similar. For the U.S. post-secondary education increases from 14% to 18%, relative university education increases from about 11% in 1991 to about 16% in 2010.

Overall, we conclude from these analyses that the main stylized facts, and especially the trends, about the financial sector in Sweden are similar to the ones documented in the literature for the US and the UK. Relative finance pay rises strongly and it rises extraordinarily at the top of the wage distribution. At the same time, relative education levels in finance increase as well. The following sections will analyze whether this evidence implies that the relative demand for skill in the financial sector increased, potentially most strongly so at the top, and whether this has led to extreme finance wages on the one hand and a brain drain into the financial sector on the other hand.
4 Empirical Model

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.\footnote{Our results on skill selection below do not depend on the model and stand on their own. For illustrative purposes we abstract from skills being completely sector-specific, i.e., possessing an index $k$. However, all our predictions go through for this more general case.}

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 $s_{it}$:\footnote{The model can easily be extended to more than two sectors. The binary choice regressions proposed below would then simply become multinomial choice regressions.}

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

Changes in $\alpha_{kt}$ correspond to percentage changes in the wage that are independent of the level of skill, while changes in $\beta_{kt}$ translate into percentage changes of wages depending on the skill of the workers. These wages may, but do not need to, be determined competitively according to workers’ marginal product in sector $k$. Workers have preferences over wages and job characteristics. Hence, utility from working in sector $k$ is given by:

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

where $v_{kit} = \mu_{kt} + \epsilon_{kit}$ is the worker’s preference for the job with $\mu_{kt}$ the population mean and $\epsilon_{kit} \sim iid$ 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:

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

$$\bar{U}_{it} \equiv U_{Fit} - U_{Rit} = \bar{\alpha}_t + \bar{\beta}_t s_{it} + \bar{\mu}_t + \bar{\epsilon}_it \quad (4)$$

Illustration 1 plots these relative wages and utilities against workers’ skills for the expositionally convenient case of $\bar{\mu}_t=0$. 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 side of Illustration 1 shows the case in which finance is a 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 demand in finance is captured by an increase of the relative $\tilde{\beta}_t$ in equation (3) over time. That is, relative wage offers – and the marginal product under competitive wage determination – for high skill workers rise compared to low skill workers. Illustration 1 (right) illustrates this by the steeper $\tilde{w}_{it}$ 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.$^{22}$

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

$$E(s_{it}|\tilde{U}_{it} > 0) = E(s_{it}|\tilde{\varepsilon}_{it} > -(\tilde{\alpha}_t + \tilde{\beta}_t s_{it} + \tilde{\mu}_t))$$  \hspace{0.5cm} (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 rises (e.g., see Mulligan and Rubinstein 2007). $^{22}$ This immediately leads to the rising relative wages in finance that we observe in the data. In addition, wage inequality in finance will rise when the increase in $\tilde{\beta}_t$ dominates the effect of a potentially more homogenous (high-)skill selection into finance.

$^{22}$
II.B.). Concurrently, the selection of skill into the rest of the economy \( E(s_{it}| \bar{U}_{it} < 0) \) declines. Our first empirical test will, therefore, be based on sectoral skill composition by checking whether

\[
E(s_{it}| \bar{U}_{it} > 0) - E(s_{it}| \bar{U}_{it} < 0) \quad (6)
\]

rise over time. Philippon and Reshef (2012) also analyze how relative skills (in their case, the relative share of workers who have attained strictly more than high-school) between the financial sector and the rest of the economy, that is, \( E(s_{it}| \bar{U}_{it} > 0) - E(s_{it}| \bar{U}_{it} < 0) \), evolve over time.

One case in which skill selection into the financial sector may not improve even under standard assumptions is if there are many new entrants on the margin. In Illustration 1 (right) we can see a small triangle spanned by the \( \bar{w}_{i1} \), \( \bar{w}_{i0} \) lines and the x-axis. If there is enough mass of workers within this triangle and their skill is sufficiently low, \( E(s_{it}| \bar{U}_{it} > 0) \) may actually not increase. In that case, however, overall employment in the financial sector will rise.

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. In Illustration 1 (right) this would constitute a shift up of the relative wage curve instead of- or in addition to a rotation along the y-axis. We test for this below.

The second empirical test of increasing skill demand in finance is based on workers’ choices. The probability that a worker with skill \( s_{it} \) chooses finance is given by

\[
Pr(\bar{U}_{it} > 0) = Pr(\tilde{\varepsilon}_{it} > -(\tilde{\alpha}_t + \tilde{\beta}_t s_{it} + \tilde{\mu}_t)) \quad (7)
\]

If we are willing to approximate the skill composite \( s_{it} \) by a linear combination of our measures and an unobserved component

\[
s_{it} = \gamma_1 \text{cog}_{it} + \gamma_2 \text{noncog}_{it} + \ldots + s_{it}^n \quad (8)
\]

we can use choice regressions to identify the changing slope \( \tilde{\beta}_t \) and intercept \( \tilde{\alpha}_t + \tilde{\mu}_t \) over time. For example, we can estimate this in a probit model when \( \tilde{\varepsilon}_{it} \) and \( s_{it}^n \) are jointly normally distributed. If we are unwilling to make a particular distributional assumption, a linear probability
model can still estimate the changing marginal effects of the skill measures for occupational choice over time.

Our third test of the increasing skill demand hypothesis in finance is based on sectoral wage regressions and we defer deriving it to our wage regressions in section 6.

5 Skill Selection into Finance

5.1 Has finance become more skill-intensive?
As a first step, we test non-parametrically, whether the relative talent in finance has increased over time. Figure 4 plots average and relative talent measures in finance and the rest of the economy as defined in equation (5) between 1991 and 2010. Each figure displays the average levels of the different dimensions of talent for the financial sector (finance) and the rest of the economy (real economy) on the left y-axis, as well as the relative level of skills (relative skill) on the right y-axis.

In the top row we show the aggregate measures of the enlistment tests for men (cognitive and non-cognitive skills, and leadership). In the second row, we show results on the subtests on logic and verbal skills, which are two major components of cognitive skills, as well as high school grades (normalized though our “graderank” variable), which is also available for women.

Throughout all dimensions of talent we find that employees in the financial sector are more talented compared with the rest of the economy. This is consistent with finance being a skill-biased sector. Interestingly, and in stark contrast to relative education, we do not find that relative talent has improved over time. 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 dashed relative average talent line.

As robustness check, we redo the previous analysis for the subpopulation of 30-year old workers. The reason for this is twofold. First, we would expect the effect of an increased demand for talent in finance on the allocation of talent to be most obvious in the group of recently hired workers. Second, the share of 30-year old male workers for whom we have military test scores is quite
constant at around 80-90 percent over the whole sample period. For both genders at age 30, the coverage of the high-school grade variable is constant at around 60-70 percent. In contrast, for all age groups the coverage of these variables is substantially lower at the beginning of the sample period (i.e., for the older cohorts). If the differential coverage is non-random, this may induce a bias, which can be avoided by focusing on 30-year olds. Our findings for this subsample, remain unchanged.

In addition, in unreported results we further decompose the rise in relative education in finance reported in Section 3 into increased attainment versus increased skill selection into finance for a constant rate of attainment. In the U.S. data, if we condition on males born during the 1950s and 1960s when college attainment was (almost) flat, relative skill selection into finance does not rise.

This suggests that the increase of relative education in finance workers in the U.S. (as well as in Sweden) is due to an increase in college attainment for the types of workers who have always been likely to choose finance, rather than an improvement of fundamental talent among finance workers over time. To the extent that our talent measures are valid measures of workers’ skills, our results therefore suggest that average as well as relative average skill selection into finance did not improve over the two-decade period when (relative) wages rose sharply in that sector.

One caveat to this conclusion is that rising demand for skill may coincide with an overall increase in employment in the sector. In this case, average skill 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. Figure 5 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.

This contradicts the idea that, despite an increase in \( \tilde{\beta}_t \), the entry of relatively low-skilled workers on the margin keeps down relative skill in finance. It is also not consistent with an interpretation
of increased finance labor demand based on a rise in $\tilde{a}_t$.\textsuperscript{23} The right panel of Figure 5 shows that the finance employment share has been roughly stable in the U.S. as well. Note that the levels are quite different though: while the finance employment share is about 5-5.5% in the US, it is only 3.4% in Sweden.

To complement the graphical evidence, we also test the hypothesis of an increased skill demand parametrically. As shown in equation (7), the skill demand hypothesis predicts that workers’ sectoral choice should depend more on their relative skill over time, i.e., the coefficient estimate of $\tilde{\beta}_t$ should rise.

Table 2 reports the results for probit regressions estimating the likelihood of a worker choosing the finance sector as a function of our cognitive and non-cognitive talent measures, controlling for years of schooling as a measure of education. The first column shows our baseline case for males, where we have cognitive and non-cognitive skill measures. The coefficients on the interaction terms between time (year) and skills (cognitive and non-cognitive), representing changes of $\tilde{\beta}_t$ between two consecutive years, are very small in economic terms. For instance, the coefficient on cognitive skills changes less than 0.05 percent per year in relative terms.

The large number of observations in the Swedish data set allows us to estimate these coefficients quite precisely, despite the small economic magnitudes. The point estimates of the time interaction with cognitive skills (negative) and non-cognitive skills (positive) are highly statistically significant, with t-statistics of 11.93 and 3.23, respectively.

The second column of Table 2 also includes years of schooling as a control variable. The levels and the interactions on cognitive and non-cognitive skills are of the same magnitude as our baseline regression, confirming the result that $\tilde{\beta}_t$ is essentially unchanged over time.

Columns three and four of Table 2 uses the subsample of 30 year old males in order to address concerns about the changing composition of workers for whom we observe military test scores as discussed above. Again, the trends of the coefficients on cognitives, non-cognitives, and years of schooling are small compared to their levels. In fact, for 30 year olds, all the trend coefficients

\textsuperscript{23} We discuss below that the only way the increased skill demand model can be consistent with our evidence is if an increase in $\tilde{a}_t$ is exactly offset by a decline in the relative non-pecuniary attractiveness of finance $\tilde{\mu}_t$. 

22
are significantly below zero while the increased skill-bias hypothesis predicts that they should be positive.

Table 3 does a similar exercise to the one presented in Table 2 for both males and females and with high-school grades as a talent measure instead of cognitive and non-cognitive test scores. We see that the time trends in the talent effects, which can be interpreted as the changes in $\tilde{\beta}_t$, are again tiny while the signs are partly positive and partly negative. Overall, the same picture as in Table 2 emerges.

Finally, we have checked for the robustness of the results in Tables 2 and 3 using logit and linear probability models for the choice regressions. In addition, instead of summarizing the change in $\tilde{\beta}_t$ by a linear time trend we have also ran regressions where we have fully interacted the talent and skill measures with year dummies. The results from these robustness checks are very similar, and fail to find any time trend in talent selection into finance over time (results available upon request).

5.2 Skill selection at the top and job polarization

The results presented in the previous section consistently show that the average skill selection into the financial sector has not improved, despite an increase in relative wages. Workers also do not increasingly base their sectoral choice on their talent or skill as the increased skill-bias hypothesis for finance would suggest.

In this section we examine whether the selection or the sectoral choice of top talent into finance may have changed. In particular, the extreme increase of the finance pay premium at the very top of the wage distribution that has been documented in the literature (e.g., Kaplan and Rauh 2010 for the U.S., Bell and Van Reenen 2013 for the U.K.) and that we computed for Sweden in Figure 2, suggests that most of the action of skill selection and compensation may have taken place at the very top.

Consistent with this idea, Philippon and Reshef (2012) 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 only plausible that there are superstar effects
arising in the financial sector that have become stronger over time. Increased financial globalization, skill-biased technological change, and financial innovation are likely to have contributed to a situation where highly productive individuals can manage more and more assets as well as subordinates over time, 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 in our model from Section 4 is depicted in Illustration 2 (left).

Illustration 2

In addition to the superstar effect, 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 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 secretarial jobs 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.). Illustration 2 (right) plots the relative polarized skill demand in finance for our model of Section 4.

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24 Superstars models of CEOs proposed by Terviö (2008) and Gabaix and Landier (2008) can readily be applied to top financial professionals.

The two theoretical mechanisms depicted in Illustration 2 are potentially consistent with an on average unchanged relative skill-bias in finance, as well as with the increasing inequality and surging top wages in finance that we observe in the data. Therefore, our analysis in the following concentrates on talent selection and sectoral choice at the top.26

We start the analysis of top talent selection into finance by examining the destinations of top performers in cognitive and non-cognitive tests as well as the top performers in terms of high-school grades. Figure 6 (left) considers the share selecting into the two sectors of males who score the highest (9 out of 9) in the cognitive test, representing a fraction of around 4.5 percent. Similarly, the figure in the middle focuses on individuals who score at least 9 in the non-cognitive test, representing only 2 percent of individuals. A first observation is that a higher fraction of finance workers (around 5% for cognitive skills and 4% for non-cognitive skills) can be found in these top groups, compared to other industries. Still, for both of these measures, the average and relative selection into finance does not trend upward. The corresponding shares of top talent restricting the sample to 30 year olds is plotted below and show a similar picture.

The Figure 6 (right) considers males and females who score above the 95th percentile in terms of high-school grades. There is in fact an upward trend for the average as well as the relative grades of finance sector workers of all ages over time. However, this may be due to improving grades overall among the employed in combination with a changing age composition of individuals for whom we observe this score. When we condition on 30 year olds below, to rule out such compositional effects, there is no upward trend in the (relative) share of high-grade individuals in finance.

Thus, the evidence reported in this section indicates that finance skill selection at the top did neither improve on average nor in relative terms between 1991 and 2010. Finally, in unreported evidence we include results from sectoral choice regressions focusing on these top talent measures, and the results show no increase in the propensity of top talent to enter finance, consistent with the regressions on average skill in the previous subsection.

26 Analytically, one could model these hypotheses by modifying equation (3) to

\[ \bar{w}_{it} \equiv w_{fit} - w_{Rit} = \bar{a}_t + \bar{\beta}_{ht} H_{it} + \bar{\beta}_{mt} M_{it} + \bar{\beta}_{lt} L_{it}, \]

where \( J_{it} \in \{H, M, L\} \) is an indicator for being a high-, middle-, or a low-skilled worker. The superstar hypothesis implies that \( \bar{\beta}_{ht} \) rises while the polarization of skill demand implies that \( \bar{\beta}_{mt} \) falls compared to \( \bar{\beta}_{ht} \) and \( \bar{\beta}_{lt} \).
5.3 Brain Drain: Career Choices of High-Skilled Workers

In the discussion of possible “brain drain” into finance, one concern is that the most talented people, and in particular graduates from Science, Technology, Engineering, Mathematics (STEM) and related subjects, are drawn into the sector because of the extraordinary earnings opportunities. Since these talented individuals have skills that would have been highly valuable in other “more productive” sectors, such as science and engineering, the brain drain externality is argued to be particularly damaging for this group.

We therefore examine whether there is evidence for “brain drain” by examining the career choices of important populations at risk of being absorbed by the financial sector. We take a dynamic perspective, and analyze the sector choices of 30-years old employees.

As a first subsample, we look at all 30-years old that belong to the top 5% in the talent distribution in Figure 7. High talent is defined as having cognitive skills of 9 (first column), belonging to the top 5% of the grade rank distribution (second column) or belonging to the top 5% of the grade rank distribution of science programs only (last column). The first row of Figure 7 show the top 3 destinations (measured in 2010 employment) of these top talent employees, while the bottom row depict the corresponding graph for finance only. We report more detailed results of these career choices across multiple sectors in the appendix.

With respect to finance, there are two important facts to note. First of all, there is no obvious strong trend over time. In the case of cognitive skills the fraction of high talent people choosing finance is fluctuating between 1.5% and 3.0% until 2005. In the last five years it fluctuates between 2.5% and 4.0%. Using grades as a metric for talent (second and third columns) the fraction of people going into finance remains flat across almost all years. Exceptions are 2002 (middle) and 2007 (right), when the fraction sharply decreases (increases) before it sharply reverses in the following year.

Second, the fraction of high-talent people in the workforce that chooses a career in finance is relatively small. Depending on the measure, 2.0 to 5.5% of the most talented people choose a career in the financial sector. This level is a bit higher than the overall employment size of the
finance sector of around 2.5 to 3.5% (see Figure 5), consistent with the previous finding that average talent is higher in the financial sector.

We then analyze at the destinations of 30 years old STEM graduates over time. Figure 8 shows the industry destination for high talent STEM graduates (cognitive skills equal to 9) in the top row and for lower talent graduates (cognitive skills smaller or equal to 7) in the bottom row. Only between 0.5 to 3% of high talent STEM graduates go to the financial sector. The fraction is relatively flat in the first half of the sample (0.5%-1.0% between 1990 and 2000). In the second half it fluctuates between 1.0% and 3.0%. Still, the average is about 1.6% and, thus, the financial sector does not seem to be a very significant destination for high-talent STEM graduates. The percentage is even smaller for lower-skilled STEM graduates in terms of magnitude: less than 1% end up in the financial sector, although there is an visible upward trend (from 0.6% to 1.2%).

As a side note, it is interesting to observe that the destinations of top talent and lower talent STEM graduates appear to be very different. Figure 8 reveals that the fraction of high talent STEM graduates that goes into Business Services, which includes the IT and software sectors, nearly doubles between 1990 and 2010. The increase is not only big in relative terms but also in absolute magnitude. Business Services constitutes the largest sector of employment for these graduates, representing about 50%. At the same time, the share of high skilled graduates working in manufacturing falls from about 40% to about 25% in 2010. For lower skilled STEM graduates the picture looks quite different. Manufacturing is the largest sector of employment for these graduates and it does not decrease much over time. The corresponding fraction is about 40% in 1991 and slightly below 40% in 2010.

Finally, we look at graduates from selective universities. We focus on students from the Stockholm School of Economics (SSE) (whose high-school grades are in the top 3% on average) and graduates from the Royal Institute of Technology (KTH). Figure 9 reveals that the fraction of students who enter the financial sector is much higher compared to the previous analyzed groups of interest: between 20% and 25% of SSE’s graduates work in the financial sector at the age of 30. However, consistent with our general findings, there is no obvious upwards trend detectable. Analyzing the most popular two sectors (business services and finance) there are two interesting points to note. More than 2/3 of all students work in only these two sectors. It seems that the
sectors are strongly negatively correlated to each other, suggesting that students see them as substitutes (depending on available positions for instance). The picture for KTH graduates looks similar to the general trend of STEM students. The fraction of students who go into finance fluctuates between 1 and 3% in the first half of the sample and between 2.5 and 4% in the second half of the sample. Finance belongs to the least attractive sectors; the most attractive sector is business services that grow from about 30% to almost 50% in 2010.

5.4 International Migration

The results of the last section showed no evidence that different high-skilled groups of interest are more likely to enter the financial sector over time. One remaining concern is that talented people move abroad to work in the financial sector in London, Frankfurt, or New York, for instance, which would effectively increase the fraction of talented people drawn into finance. The richness of our data allows us to address this hypothesis in the following way. As a first step, we identify 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. Given that our data ends in 2010, we can only identify these “leavers” for the period between 1990 and 2007.

If there exists high-skilled “brain drain” into the financial sector abroad, we would expect to see that i) more high-skilled people are moving abroad (disappearing) and/or ii) an increasing fraction of these leavers works in the financial sector. Unfortunately, we do not have information on the potential job abroad. However, we do observe the last position of a leaving individual, which we use as a proxy for her next job. In our analysis we focus on individuals between 20 and 35 years of age. The idea is that it is more likely to move abroad earlier in a person’s career.27 Given that it is rare that people move into the financial sector later in their career after having worked in a different sector (see Oyer, 2008; Axelson and Bond, 2014), emigrating from a finance job should be a good proxy for taking a finance job abroad. We confirm this pattern in our data. In Table A.2 in the appendix we analyze the transitions between industries. We focus

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27 Another reason for restricting the analysis to relatively young individuals is that people disappearing from the sample in later years are more likely to have passed away rather than having emigrated. We are currently in the process of obtaining additional data with direct measures of emigration (as well as mortality). Still, we have repeated the analysis including additional age groups with qualitatively similar results.
on high-skilled individuals between 35 and 55 years who start a new job with a new employer in the financial sector. We exclude transitions of younger individuals as we want to exclude transitions by students who may have had various part-time jobs in different sectors while studying. For these individuals we look at the industry of the last job. Panel A shows the results for individuals with cognitive skills of 8 and higher, panel B shows the corresponding results for individuals with a grade rank (university) of 90 and higher. The results look remarkably similar. About 60% of the job starters have worked in the finance sector before. Another 20% comes from business consulting and accounting, IT, or other services.

In Figure 10 we analyze emigration of workers. The figure on the left (first row) depicts the fraction of the population that leaves our sample for at least 2 years in every year, split between high-skilled individuals (top 5% in terms of grade rank) and the remaining part. The average fraction of individuals disappearing from our panel is about 6%. In most years, the share of high-skilled individuals is slightly higher than the corresponding share of the rest of the economy. However, there is no obvious upward trend over time. We also do not observe any trend in the fraction of people who previously worked in the finance sector emigrating over time. Rather, the fraction of leavers from the financial sector is quite cyclical. For instance, the fraction of high-skilled leavers from the financial sector increased during the dot-com bubble and decreased after it burst; it picked up again after 2003. The level as well as the cyclicity is lower for individuals who do not belong to the top-5%. Moreover, considering these two panels together, we observe that the fraction of talented individuals moving into finance jobs abroad is very small. Multiplying the percentage of talented workers who leave (around 6%) with the percentage of talented leavers previously working in finance (around 5%) gives us an estimate of 0.3% of talented workers emigrating to take finance jobs abroad. Recall that the percentage of the top-5% (in terms of grades) going into the finance sector fluctuated between 1.5-2.5%, accounting for emigration would make a small difference quantitatively. The takeaway from these results is that even if we would account for talented workers who join the finance sector in other countries, there is no evidence that the fraction of top talent going into the financial sector has increased in any meaningful way over time.
In the second row, we look at the fraction of graduates from the Stockholm School of Economics who emigrate. The levels are substantially higher than the population average (about twice as high). However, there is no visible upward trend, which is further evidence that skilled emigration into finance has not increased over time.

A second concern is that the average talent in finance could have increased due to the Swedish finance sector hiring people from abroad, either high-skilled immigrants or returning Swedes. This would be a concern for our estimates of average talent in finance, since we cannot measure the talent of immigrants as they have not done the military enlistment test or graduated from a Swedish high school. An individual is classified as an “appearer” if she appears in our sample for the first time at age 30-45. We focus our analysis on people in this age range as it includes young professionals with some years of experience. The top row of Figure 11 shows the results for this sample of immigrants. The left figure plots the fraction of individuals appearing in our sample. The fraction is about 1% and, consistent with previous results, cyclical without any obvious upward trend. The right figure shows the fraction of individuals starting a job in the financial sector. The level is very low (less than 1%) and below the population average. There is also no trend.

We also look at individuals who re-appear in our panel after having been away for at least 2 years. This group is of interest as it allows us to observe their skill measures as well. The lower row of Figure 11 shows the results. The left figure shows that there is, if anything, a declining trend of people returning to Sweden. This is true for both highly skilled and medium-to-low skilled individuals. Interestingly, the there are fewer high-skilled people who return. This result is even stronger given that more high-skilled people are emigrating at first. The figure on the right shows the fraction of the re-appearing individuals who work in the financial sector. The fraction is fluctuating quite a bit between 1997 and 2007 (2.5 – 4.5%) without any clear trend. The level is slightly higher 2008 and 2009 but decreasing in 2010. For medium and low-skilled individuals there is much less variation and the level is lower.

Overall, our evidence suggests that migration is unlikely to explain the wage premium. There are no obvious trends that are consistent with the dynamics of the wage premium. Moreover, given
the low fraction of emigrants it is unlikely that migration has any significant a quantitative impact on the fraction of talent going into finance.

6 Talent and the finance wage premium

We now turn to the relation between talent and wages in the finance sector. We first run reduced-form wage regressions with the aim to account for the rising wage premium in finance using changing worker skills and changing returns to these skills. We then apply the model from Section 4 explicitly and run structural selection-adjusted sectoral wage regressions to identify the parameters of interest from the data on wages.

6.1 Reduced-form wage regressions

We start with a wage regression that allows for the changing observed and unobserved skill composition in finance to have driven its increasing pay premium, while keeping the return to talent constant across both sectors and time. We then let the returns to skills vary over time. Finally, sector-specific changing returns to skills are permitted, which brings us back to our general time-varying and sector-specific wage equation (1) from Section 4.

Suppose workers’ log wages are determined by the returns to their individual skills and a premium that is paid in sector \( k \in \{F,R\} \):

\[
w_{kit} = \alpha_{it} + F_{it} \tilde{\alpha}_t + \beta s_{it} \quad (9)
\]

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

The two graphs on the left of Figure 12 plots the \( \tilde{\alpha}_t \) from three different regressions over the period 1991-2010. Both sexes are reported in the first row and males only in the bottom row. First, no measures for worker skill \( s_{it} \) are included, that is, \( \tilde{\alpha}_t \) constitutes the raw finance wage premium. Then, the observable component of \( s_{it} = s_{it}^O + s_{it}^U \) contains the standard controls of
years of experience and its square as well as talent measures that are usually unobserved: high-school graderank for both sexes in the left panel and cognitives and noncognitives for males in the right panel. Last, we include years of education in the third specification.

We see that the control variables decrease the level of the finance pay premium. Adding graderank alone explains about 10 percentage points (almost 20% of the premium in 2010) of the premium in the regression including both sexes, while cognitive and non-cognitive skill explains 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, but 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 sexes included), the vast bulk of the increase remains unexplained. This result is not very surprising given our previous finding that the average talent in finance has remained roughly constant over time.

The middle column of Figure 12 tries to account for any time-invariant unobserved component of skill \( s_{it}^u \) by including fixed effects. The rich panel dimension of our data allows us to not only compute worker fixed effects but also worker-firm match-specific fixed effects.\(^{30}\)

We see that the fixed effects bring the level of the finance wage premium down to about zero, which is not surprising since they constitute worker(-firm)-specific intercepts. Yet, they have no impact on the increasing trend in the finance premium. In fact, the surge in the premium is even larger for males when fixed effects are included.

The last column of Figure 12 allows for time-varying (economy-wide) returns to observed components of skill, that is, \( \beta_t \) in equation (9) 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 skills have increased in most Western countries including Sweden over the last

\(^{29}\) The 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 \( k \).

\(^{30}\) 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).
couple of decades. Thus, since finance absorbs relatively high-skilled individuals, the rising returns to their skills should account for some of the trend in the finance premium. Indeed, we see in the last column of Figure 12 that the plot of $a_t$ rotates slightly to the right and becomes flatter. Still, this explains only a very small component of the overall increase in relative finance wages.

To summarize, we find that the changing skill composition of the finance sector and the changing returns to skills in the overall economy can at best only explain a very minor part of the rise in the finance wage premium from 1991-2010. Given the results from section 5, this is maybe not too surprising, since we found there that the skill 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.\footnote{Still, the unobserved component of skill might well be time-varying for at least three reasons. First, the value of these skills in the finance sector, even if constant, may have increased over time. Second, part of these skills may be acquired on the job, and thus increasing with tenure. Third, even if skills do not increase with tenure, they may only be gradually discovered over time, as in Gibbons et al (2005) and Terviö (2009). We will address some of these possibilities in a future version of the paper.}

One remaining possibility, which is the point also made in e.g. Célériér and Vallée (2014), is that the increase in relative finance wages is due to the sector-specific returns to skills in finance increasing over time. Recall our original wage equation (1) from section 4, which we repeat here in a slightly modified formulation:

$$w_{kit} = \alpha_{Rt} + F_{it}{\tilde{a}}_t + (\beta_{Rt} + F_{it}{\tilde{p}}_t)s_{it} \quad (10)$$

Using a sample of French engineers and measuring their talent by the ranking of the school that they graduated from. Célériér and Vallée (2014) estimate equation (10) with OLS. They find that $\tilde{p}_t$ rises strongly while $\tilde{a}_t$ remains largely flat. Célériér and Vallée interpret this as evidence that increasing returns to skill (or skill-bias) in finance account for the surging wage premium in that sector.

In Figure 13 we depict results from a related exercise to Célériér and Vallée (2014) with our skill measures of cognitives, non-cognitives (for males), and graderank (for both sexes). We split the
sample into high-, middle-, and low-skill to also allow for the above-mentioned hypotheses of skill demand only rising at the top or polarizing over time.

We see in Figure 13 that the finance premium for low-skill males increases less than the premium for high- and middle-skill workers when ranking them according to cognitive or non-cognitive talent. However, the premium for the high-skilled does not rise compared to the middle-skilled. When ranking both sexes according to graderank, the premium of middle-skilled over low-skilled does not rise. The premium for the low-skilled is also still rises substantially in all three definitions.

If we interpret these results within the wage equation (10), we therefore find that $\bar{\beta}_t$ neither increases for all comparisons, nor does it polarize or only increase for the high-skill workers. Moreover, the baseline premium $\bar{\alpha}_t$ for low-skilled workers in fact rises considerably over time.

Therefore, our results are not very supportive of the finding in Célérier and Vallée (2014) and the different skill-bias hypotheses. The rising returns to skill in finance can at best explain a fraction of the increased finance wage premium.

6.2 Selection-bias corrected wage regressions

Our results from the skill selection analysis and the choice regressions in section 5 consistently showed that $\bar{\beta}_t$ does not rise at all over time. How does this square with the OLS wage regressions of equation (10) and the results reported in Figure 10? In fact, if we acknowledge that cognitives, non-cognitives, graderank, or school rank as in Célérier and Vallée (2014) are only partial measures of workers’ skills, the OLS results from equation (10) are likely to be inconsistent due to selection bias (Heckman 1979).

To see this, consider workers’ expected wages conditional on their sectoral choice:

$$E(w_{it}|F_{it}) = (\alpha_{Rt} + F_{it}\bar{\alpha}_t) + (\beta_{Rt} + F_{it}\bar{\beta}_t)E(s_{it}|F_{it}),$$

where again $F_{it} \equiv I(\bar{U}_{it} > 0)$ is the indicator for working in finance. If we concede that despite our detailed talent measures there will be unobserved components of skill, i.e., $s_{it} = s^o_{it} + s^{ut}_{it}$, we get:
\[
E(w_{it}|F_{it}) = (\alpha_{rt} + F_{it} \tilde{\alpha}_t) + (\beta_{rt} + F_{it} \tilde{\beta}_t)s_{it}^0 + (\beta_{rt} + F_{it} \tilde{\beta}_t)E(s_{it}^u|F_{it}) \quad (12)
\]

Since sectoral choice also depends on unobserved skill components, we have that \( E(s_{it}^u|F_{it}) \neq E(s_{it}^0) \neq 0 \). Thus, the error term (the last summand) in OLS regression (12) will not have mean zero in a given sector and it is correlated with the regressor \( s_{it}^0 \).

In order to identify the correct finance pay premium \( \tilde{\alpha}_t \) and relative skill-bias \( \tilde{\beta}_t \) we must therefore run selection-corrected wage regressions by sector. One can do this semi-parametrically under an exclusion restriction whereby one or more variables are assumed to only affect sectoral choice but not wages in sectors (i.e., to only affect \( \tilde{\varepsilon}_{it} \) in terms of our model).\(^{32}\) Alternatively, one can structurally estimate (12) identifying the parameters solely from the functional form of the model of sectoral choice.

In Table 4 we report the results for males from the structural estimation when a normal distribution of \( s_{it} \) and \( \tilde{\varepsilon}_{it} \) is assumed. This amounts to a probit sectoral choice regression in the first-stage as in Table 2 of section 5.

In the first two rows of the table we report these regressions for the finance and the real sector, respectively, when using only cognitive and non-cognitive talent as skill measures. We see that again, as in Tables 2 and 3, the changing sectoral wage returns to talent are tiny compared to the levels. For the cognitive skill measure, the return slightly declines in finance compared to the real sector, that is, \( \tilde{\beta}_t \) falls, while for the non-cognitive skill measure the return rises.

Still, almost the whole increase in the finance pay premium is accounted for by the coefficient on year, i.e. the trend in the \( \tilde{\alpha}_t \). Taking the ca 0.0062 difference between this coefficient in finance and the real sector, predicts a rise of the finance premium of about 12.4 log points. The regressions in columns three and four of Table 4 with years of education and quadratic potential experience as additional regressors yield very similar results.

Finally, Figure 14 plots the residuals from the selection-corrected wage regressions in finance (left panel) and the real sector (right panel) over time. These residuals constitute the last

\(^{32}\)We are currently working with geographic instruments in order to identify the selection equation. We will include these results in a future version of the paper.
summand of equation (12) and should therefore rise (relatively) in finance when either the skill-bias $\tilde{\mu}_t$ increases or the unobserved component of skill in finance $E(s_{it}^t|F_{1t})$ improves.

We see that the level of the residuals is larger in the left panel than the right, which reflects the fact that finance attracts more high-skilled workers than the real sector in terms of unobservable components of skill, similar to observable talent. However, the trend in finance is remarkably flat for the regression without the education and experience controls, and even slightly declining for the one with these controls. Therefore, also the unobservable (sector-specific) component of skill in finance seems to not be improving over time.

To summarize, the evidence reported in this section has to be interpreted with care due to its strong identification assumptions (i.e., identification from the functional form of the choice regression) compared to the choice regressions in section 5. However, it confirms and complements the results from that section in several respects. First, we find here that the (relative) sector-specific return to talent in finance does not rise over time, and this seems to be true for both observable and unobservable components of skill.

Second, recall that in section 5 we estimated that the sum $\tilde{\alpha}_t + \tilde{\mu}_t$ is constant, while we now obtained that $\tilde{\alpha}_t$ rises in the wage regressions. Hence, the only way that a standard competitive model of skill demand and worker choice of sectors could explain the skill selection and wage facts that we find in the data is that the average job amenities in finance $\tilde{\mu}_t$ fall proportionately with the rising $\tilde{\alpha}_t$ over time.

7 Conclusion

In this paper, we study the evolution of skill selection and wages in the financial sector for a sample of 65 million individual-year observations of Swedish workers between 1991 and 2010. Over this period, the finance wage premium, defined as premium in the average annual wage of an employee in the finance sector relative to other sectors, increased from around 30% in 1991 to 65% in 2010, compared to an increase from 20% to almost 50% in the U.S. over the same period. Employing detailed talent measures, which include detailed cognitive and non-cognitive test scores as well as high-school grades, we then examine the implications of this increase in the
finance wage premium on the allocation of talent. 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. Finance has not become more skill-biased over time, and changing composition of skill or increasing returns to skill cannot account for the surge in the finance wage premium. These findings are important as they alleviate concerns about a “brain drain” into finance at the expense of other sectors.

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. However, our findings also suggest that rents in finance are high, increasing, and still largely unexplained. Whether these rising wages in finance are explained 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 we aim to address in a companion paper.
References


9 Figures

Figure 1: Relative Wage in the Financial Sector

This graph shows the evolution of the relative wages between the financial sector and the rest of the economy during 1991 to 2010. Relative wage is defined as the ratio of the average wage in finance to the average wage in the non-financial, 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.
Figure 2: Relative Wage in the Financial Sector (Quantiles)

This graph shows the evolution of the relative wages between the financial sector and the rest of the economy from 1991 to 2010 for different quantiles of the wage distribution. Each line shows the Relative Wage by Quantile defined as the wage in finance compared to the respective quantile in the rest of the economy. The left graph shows the absolute wage premium for the different quantiles. The right graph shows the wage premium normalized to zero in 1991. Source: Swedish population data LISA from Statistics Sweden.
**Figure 3: Relative Education in the Financial Sector**

This 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) 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. Source: Swedish population data LISA from Statistic Sweden; Current Population Survey for the US.
**Figure 4: Relative skills in the Financial Sector**

This graph shows the evolution of relative skills between the financial sector and the rest of the economy during 1991 to 2010. The graphs on the left y-axis plot the average level of skills for the finance sector and for the rest of the economy (other). The graph on the right y-axis plots the difference (Relative Skill). The top row shows the evidence for cognitive skills, non-cognitive skills, and leadership. The bottom row shows the results of the tests on logic and verbal comprehension as well as the grade rank. 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 5: 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 red line shows the case when we include health and education to the nonfarm private sector. The graph on the top shows the evidence for Sweden, the bottom one corresponding evidence for the US. Source: Swedish population data LISA from Statistics Sweden; Current Population Survey for the US.
Figure 6: Share of Top Talent in Finance

These graphs show the evolution of shares of top talent in the financial sector and the rest of the economy between 1991 and 2010. The graphs on the left y-axis plot the share of top talent workers in the finance sector and in the real economy. The graph on the right y-axis plots the difference (Relative Skills, bold dotted line). The top row shows the evidence for the whole population. The bottom row shows corresponding evidence for 30 years old only. Top talent is defined as follows: cognitive skills equal to 9 (about 4.5% of the population, left column), non-cognitive skills equal to 9 (about 2%, middle column), or grade rank greater than 95 (about 4%, right column). 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 sector choices of top talented 30 years old individuals between 1991 and 2010. Top talent is defined as cognitive skills of 9 (left column), a grade rank of above 95 (middle column), and a grade rank in the science track of above 95 (right column). The graphs on the top show the top 3 largest industry sectors in terms of 2010 employment for the group of interest, while the graphs on the bottom show the finance sector in detail. 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 8:** Sector Choices of STEM Graduates

These graphs show the evolution of sector choices of 30 years old STEM graduates (science, technology, engineering, and mathematics) between 1991 and 2010. The top row shows evidence for top talented STEM graduates with cognitive skills of 9. The bottom row shows corresponding evidence for STEM graduates with cognitive skills of 7 and lower. The graphs on the left show the top 3 largest industry sectors in terms of 2010 employment for the group of interest, while the graphs on the right show the finance sector in detail. 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 9: Sector Choices of Graduates from Selective Schools

These graphs show the evolution of sector choices of 30 years old graduates between 1991 and 2010 from Stockholm School of Economics (SSE) in the first row and from the Royal Institute of Technology (KTH) in the second row. The graphs on the left show the top 3 largest industry sectors in terms of 2010 employment for the group of interest, while the graphs on the right show the finance sector in detail. Source: Swedish population data LISA from Statistics Sweden.
Figure 10: Emigration

These graphs show the fraction of individuals between 20 and 35 who leave the sample for at least two consecutive years between 1991 and 2007. Top 5% refers to individuals with a grade rank of 95 and higher, while below top 5% refers to a grade rank below 95. The graph on the left shows the fraction of high-skilled and medium-low skilled individuals who leave the sample. The graph on the right shows the fraction of people who were employed in the financial sector among these leavers. The graph in the second row 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.
**Figure 11: Immigration**

These graphs show the fraction of individuals between 30 and 45 who appear (top row) or re-appear after having been out of the sample for at least two consecutive years (bottom row) between 1991 and 2007. Top 5% refers to individuals with a grade rank of 95 and higher, while below top 5% refers to a grade rank below 95. The graph on the left shows the fraction of individuals who are appearers and re-appearers. The graph on the right shows the fraction among them who were employed in the financial sector. Source: Swedish population data LISA from Statistics Sweden.
Figure 12: 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 \( w_{kt} = \alpha_{kt} + F_{kt} \bar{\alpha}_{t} + \beta s_{kt} \) by OLS. The \( \beta \) is the (economy-wide) return to worker skill, \( F_{kt} \) is an indicator for the financial sector, and \( \bar{\alpha}_{t} \) time-varying finance pay premium in log points. Three different models are estimated. (i) no controls, (ii) controlling for observables (age, gender, potential experience) and talent, (iii) is adding education (years of schooling). The first row reports results for the whole population, the second row for males only. Grade rank is used as a population-wide measure and cognitive and non-cognitive skills for the male subsample. Specifications in the middle row add person fixed effects and person-organization fixed effects to (iii). The specification in the right row allows for time-varying returns to experience, skills, and education.
Figure 13: 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 skills, and grade rank) are used to form three talent groups: Low Talent (cognitive and non-cognitive skills 1-3 or grade rank 0-39), Middle Talent (cognitive and non-cognitive skills 4-8 or grade rank 40-95), and High Talent (cognitive and non-cognitive skills 9 or grade rank 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.
Figure 14: Residuals from the Selection-Corrected Sectoral Wage Regressions for Males in Table 4

These graphs plot the residuals from the selection corrected wage regressions reported in Table 4 between 1991 and 2010. The red line refers to the specification with only cognitive and non-cognitive talent as regressors. The blue line depicts the specification where years of schooling are added to the regressions. 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.
10 Tables

Table 1: Summary Statistics

This table shows summary statistics of the main variables. The definition of variables is in the Appendix. 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

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### Panel B: Men with Non-Missing Cognitive Skills Only

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<td>9.5</td>
<td>16.5</td>
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<td>1,810</td>
<td>2,471</td>
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</table>
Table 2: Occupation Choice and Skills - Males

This table shows the results from probit regressions on choosing to work in finance as opposed to other sectors for males. In the first column cognitive and non-cognitive talent and their interaction with a linear time trend (year) are the regressors. In the second column we add years of schooling. Columns three and four do the same for 30 year olds. Linear and quadratic potential experience as well as a year trend are included as controls in all specifications. 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.

<table>
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<td>cog</td>
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<td>2.076***</td>
<td>1.463***</td>
<td>1.726***</td>
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<td>(12.49)</td>
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<td>4.991***</td>
<td>3.958***</td>
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<td></td>
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Observations 19,245,525 19,245,525 2,055,665 2,054,198
Sample Men Men 30 yo Men 30 yo
Estimation Probit Probit Probit Probit
Pot experience Yes Yes Yes Yes
Year trend Yes Yes Yes Yes
Table 3: Occupation Choice and Skills – Both Genders

This table shows the results from probit regressions on choosing to work in finance as opposed to other sectors for both sexes. In the first column grade rank and its interaction with a linear time trend (year) are the regressors. In the second column we add years of schooling. Columns three and four do the same for 30 year olds. Linear and quadratic potential experience as well as a year trend are included as controls in all specifications. 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.

<table>
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<td>7.804***</td>
<td>0.00384***</td>
<td>15.13</td>
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<tr>
<td></td>
<td>(3.93)</td>
<td>(15.13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year # yearsofschool</td>
<td>-0.000146***</td>
<td>-0.00384***</td>
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<td>30 yo</td>
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<td>Estimation</td>
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<td>Probit</td>
<td>Probit</td>
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<tr>
<td>Pot experience</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year trend</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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Table 4: Selection-Corrected Sectoral Wage Regressions for Males

This table shows the results from selection-corrected wage regressions in the finance sector (columns one and three) and the rest of the economy (columns two and four) for males of all ages. In the first and second column cognitive and non-cognitive talent and their interaction with a linear time trend (year) are the regressors. Columns three and four add years of schooling. Linear and quadratic potential experience as well as a year trend are included as controls in all specifications. 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.

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<td>(42.47)</td>
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<td>(141.67)</td>
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<td>(-2.68)</td>
<td>(35.07)</td>
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<td>(62.68)</td>
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<td>noncog</td>
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<td>-3.488481***</td>
<td>-2.579193***</td>
<td>-2.184809***</td>
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<td>(-22.42)</td>
<td>(-133.20)</td>
<td>(-12.35)</td>
<td>(-94.83)</td>
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<tr>
<td>year # noncog</td>
<td>0.0027281***</td>
<td>0.0017656***</td>
<td>0.0013433***</td>
<td>0.0011087***</td>
</tr>
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<td></td>
<td>(22.99)</td>
<td>(134.92)</td>
<td>(12.87)</td>
<td>(96.31)</td>
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<td>yearsofschool</td>
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<td>-0.305895***</td>
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<td>(-4.88)</td>
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<td>452,090</td>
<td>18,800,000</td>
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<td>Men</td>
<td>Men</td>
<td>Men</td>
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<td>Heckman ML</td>
<td>Heckman ML</td>
<td>Heckman ML</td>
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<td>No</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Year trend</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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## Appendix

### Table A1: Definitions of Variables

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<td>Education</td>
<td>Set of educational dummy variables:</td>
<td>LISA</td>
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<td>2) post secondary (sun2000niva_old&gt;=5)</td>
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<td></td>
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<td></td>
<td>4) two-year highschool (sun2000niva_old&gt;=3)</td>
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<td></td>
<td>5) compulsory schooling (sun2000niva_old&gt;=2)</td>
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<td>Cognitive skills</td>
<td>Cognitive skills measures; discrete variable ranging from 1 to 9 that approximates the normal distribution (Stanine distribution).</td>
<td>Swedish Defence Recruitment Agency and Military Archives</td>
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<td>Non-cognitive skills measures; discrete variable ranging from 1 to 9 that approximates the normal distribution (Stanine distribution).</td>
<td>Swedish Defence Recruitment Agency and Military Archives</td>
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<td>Leadership measure; discrete variable ranging from 1 to 9 that approximates the normal distribution (Stanine distribution).</td>
<td>Swedish Defence Recruitment Agency and Military Archives</td>
</tr>
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<td>Logic test score</td>
<td>Results on logic test; discrete variable ranging from 0 to 40</td>
<td>Swedish Defence Recruitment Agency and Military Archives</td>
</tr>
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<td>Verbal test score</td>
<td>Results on verbal comprehension test; discrete variable ranging from 0 to 40</td>
<td>Swedish Defence Recruitment Agency and Military Archives</td>
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<td>Rank in the grade distribution based on graduation year.</td>
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### Panel B: Demographics and Job characteristics:

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<th>Description</th>
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<td>Age of a worker</td>
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<td>Female</td>
<td>Dummy variable that is equal to 1 if the worker is female</td>
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<td>Income</td>
<td>Total declared yearly labor income (deklon), deflated to 1997 prices. Includes income from closely held businesses from 1994 onward.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Potential experience</td>
<td>Potential experience, calculated as the difference between age and the years of schooling. Years of schooling is approximated from the education variable.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sectors (SNI)</td>
<td>* Finance sector (SNI &gt;= 65110 &amp; SNI&lt;=67202)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>* Consulting&amp;Accounting (SNI &gt;= 74100 &amp; SNI &lt;= 74199)</td>
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<tr>
<td></td>
<td>* IT sector (SNI &gt;= 72100 &amp; SNI &lt;= 72500)</td>
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<td></td>
<td>* Public sector (SNI &gt;= 75111 &amp; SNI&lt;=75300)</td>
<td>SNI==99000)</td>
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<td></td>
<td>* Farm sector (SNI below 5025)</td>
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</table>
Table A2: Transitions into the Finance Sector

This table shows the previous industry of workers who start a new job (new employer) in the financial sector. We focus on high-skilled individuals (cognitive skills $\geq 8$ in Panel A, grade rank (university) $\geq 90$ in Panel B) between 35 and 55 years. We report the top 4 industries and the corresponding percentages.

Panel A: Cognitive skills $\geq 8$

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<th>Previous sector</th>
<th>% of hiring</th>
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<tr>
<td>Financial sector</td>
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</tr>
<tr>
<td>IT</td>
<td>8.29%</td>
</tr>
<tr>
<td>Consulting and Accounting</td>
<td>6.27%</td>
</tr>
<tr>
<td>Other Services</td>
<td>3.72%</td>
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<tr>
<td><strong>Total</strong></td>
<td><strong>80.87%</strong></td>
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Panel B: Grade rank $\geq 90$

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<tr>
<td>Consulting and Accounting</td>
<td>7.91%</td>
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<tr>
<td>IT</td>
<td>6.58%</td>
</tr>
<tr>
<td>Other Services</td>
<td>3.81%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>80.16%</strong></td>
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**Figure A1: Sector Choices of STEM Graduates (Top Talent)**

These graphs show the evolution of sector choices of 30 years old STEM graduates between 1991 and 2010. Top talent is defined as cognitive skills of 9. The graph on the top left shows the destinations of this group, split into 11 different major industries, while the graphs on the right show the finance sector in detail. The row in the bottom shows corresponding figures for the top 3 largest (left) and smallest (right) industry sectors in terms of 2010 employment for the group 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.
Figure A2: Sector Choices of STEM Graduates (Bottom Talent)

These graphs show the evolution of sector choices of 30 years old STEM graduates between 1991 and 2010. Bottom talent is defined as cognitive skills of below 8. The graph on the top left shows the destinations of this group, split into 11 different major industries, while the graphs on the right show the finance sector in detail. The row in the bottom shows corresponding figures for the top 3 largest (left) and smallest (right) industry sectors in terms of 2010 employment for the group 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.
Figure A3: Sector Choices of 30 Year Old High Talent Workers (Males, Cognitive Skills)

These graphs show the evolution of sector choices of top talented 30 years old individuals between 1991 and 2010. Top talent is defined as cognitive skills of 9. The graph on the top left shows the destinations of this group, split into 11 different major industries, while the graphs on the right show the finance sector in detail. The row in the bottom shows corresponding figures for the top 3 largest (left) and smallest (right) industry sectors in terms of 2010 employment for the group 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.
Figure A4: Sector Choices of 30 Year Old High Talent Workers (Both Genders, Graderank)

These graphs show the evolution of sector choices of top talented 30 years old individuals between 1991 and 2010. Top talent is defined as grade rank of above 95. The graph on the top left shows the destinations of this group, split into 11 different major industries, while the graphs on the right show the finance sector in detail. The row in the bottom shows corresponding figures for the top 3 largest (left) and smallest (right) industry sectors in terms of 2010 employment for the group 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.
Figure A5: Sector Choices of SSE Graduates (Both Genders)

These graphs show the evolution of sector choices of 30 years graduates from the Stockholm School of Economics between 1991 and 2010. The graph on the top left shows the destinations of this group, split into 11 different major industries, while the graphs on the right show the finance sector in detail. The row in the bottom shows corresponding figures for the top 3 largest (left) and smallest (right) industry sectors in terms of 2010 employment for the group 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.