"SINCE YOU'RE SO RICH, YOU MUST BE REALLY SMART": TALENT AND THE FINANCE WAGE PREMIUM*

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Abstract: Wages in the financial sector have experienced an extraordinary increase over the last few decades. A proposed explanation for this trend has been that the demand for skill has risen more in finance compared to other sectors. We use Swedish administrative data, which include detailed cognitive and non-cognitive test scores as well as educational performance, 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 has improved, neither on average nor at the top of the talent and wage distributions. A changing composition of talent or their returns cannot account for the surge in the finance wage premium. While these findings alleviate concerns about a "brain drain" into finance at the expense of other sectors, they also suggest that finance workers are capturing substantial rents that have increased over time.

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I Introduction

Since the 1980's, relative pay in the finance industry has increased dramatically in the United States, the United Kingdom, and many other developed countries (e.g., Philippon and Reshef, 2012; Bell and Van Reenen, 2014; Boustanifar, Grant, and Reshef, 2017). In Sweden, the country we study, average earnings of finance employees rose from 120% of average private sector earnings in 1990 to almost 170% in 2014. The rise was even more dramatic among the highest paid employees, where the top percentile of finance earners increased from 150% to over 250% of the corresponding percentile outside of finance. A significant part of the rising income inequality observed in many countries has been attributed to this surge in finance wages (e.g., Kaplan and Rauh, 2010; Guvenen, Kaplan, and Song, 2014; Bell and Van Reenen, 2014; Lemieux and Riddell, 2015).

In a competitive labor market, wages should rise if the marginal productivity of workers increases. A leading explanation for the surge in finance pay has thus been that finance workers have become relatively more productive compared to other sectors over this period. This, in turn, would imply an increased demand for talent by the financial industry, and a corresponding increase in relative wages. Philippon and Reshef (2012) propose that a combination of new technology, financial deregulation, and globalization of financial markets has increased the productivity of high-skilled workers in finance relative to other sectors. Consistent with this explanation, they document that, since the 1980's, the increase in relative finance wages in the U.S. has gone hand-in-hand with a contemporaneous increase in the fraction of workers with higher education in finance relative to other sectors. Similarly, Goldin and Katz (2008), Oyer (2008), Shu (2016), and Célérier and Vallée (2017) document that a rising fraction of students from elite universities have taken up jobs in the financial industry in recent decades. Célérier and Vallée, who focus on career outcomes of French engineering graduates, also show that the increase in relative finance pay has been particularly pronounced for students graduating from the very top universities.[1] If the most talented workers are drawn to finance, productivity in the non-finance sector may suffer, with potentially negative consequences for economic growth (see Baumol, 1990; Murphy, Shleifer, and Vishny, 1991).[2]

[1] For examples voicing this concern, see e.g., Krugman (2009), Terkel (2011), and Shiller (2013).

[2] Kneer (2013a) and Kneer (2013b) provide empirical evidence suggestive of such "brain drain" effects. Hsieh, Hurst, Jones, and Klenow (2013) quantify the misallocation of talent's effect by occupation on U.S. economic growth during 1960–2010.

In this paper, we examine whether the evolution of finance wages is consistent with an increased demand for talent, using population-wide administrative records from Sweden between 1990 and 2014. Our data contain both uncensored information on individual earnings from tax records, as well as a number of unique measures of talent. Our main talent measure consists of estimates of cognitive and non-cognitive abilities from military aptitude tests, which are available for the majority of Swedish males. In addition, we use detailed information on secondary education, including high-school grades and track, to impute corresponding talent measures for women. Although the exact skills that determine worker productivity are not directly observable, we believe that our talent measures capture an individual's ability to acquire such skills. Unlike other aspects of skill, such as years of education or work experience, our talent measures are largely innate and pre-determined before an individual chooses their sector of employment, and have a distribution that is constant over time, which alleviates concerns about endogeneity and compositional changes. Our measures are also sufficiently granular to allow us to analyze the right tails of the earnings and talent distributions.

We first examine the evolution of talent in the finance sector over time. If the increase in finance wages is due to an increased demand for talent, the talent level should have improved in finance relative to other sectors, given that finance's share of overall employment remained roughly constant. While we find that finance workers are more talented *on average*, talent levels in finance *did not improve* in the period 1990-2014 for any of our measures, neither in absolute terms nor relative to other sectors. Our results are robust in a large number of alternative tests, including restricting the sample to the right tails of the talent or earnings distributions, focusing on recent entrants into the labor market, and by comparing finance to other talent-intensive sectors like Law, Consulting and Accounting (LCA) or Information Technology (IT). Across the board, we find a large increase in relative finance pay, but no corresponding increase in the relative talent of finance workers over time.[3] We also estimate sectoral choice regressions, controlling for other skill determinants such as education, age, and other socio-economic variables, and find no evidence that talent has become a more important determinant of an individual's

[3] Using data from labor force surveys, we find that even though finance workers work long days, working hours have not increased over time during our sample period. This also implies that a comparison of hourly wages across sectors yields a similar upward trend in the finance premium as for yearly earnings. We therefore use the terms "wages" and "earnings" largely interchangeably in the paper.

decision to enter the finance industry over time.

We then consider the relation between compensation and talent in more detail. While talent is positively and significantly related to earnings *on average* for both finance and non-finance workers, *changes* in the return to talent cannot explain the dynamics of relative finance pay. The increasing trend in the finance premium remains in wage regressions, where we control for standard Mincer variables as well as fixed effects on the individual or individual-firm level. We also show that the finance wage premium did not increase more for higher-talent than for lower-talent individuals over our sample period, which should have been the case if the growth in finance pay had been driven by increased competition for talent. Although we cannot rule out that increases in the return to other, unobserved dimensions of skill or talent have contributed to the increase in relative finance wages, our results imply that such dimensions would have to be uncorrelated with our observable talent measures and not absorbed by individual-firm fixed effects.

When we examine the 30 most common occupations in finance we find that relative compensation has risen over time in almost all of them, regardless of skill requirements and income level, and without any significant improvement in the relative talent among workers holding these jobs. The increase in relative finance wages has thus been an industry rather than an occupational phenomenon, and has been present also in generic jobs that are unlikely to require finance-specific skills.

Since we do not have data on individuals once they emigrate from Sweden, one might worry that emigration of talented finance workers to other countries (such as the U.K. or the U.S.) might obscure a relationship between talent and relative finance wages. We show, however, that overall migration rates are quantitatively too small to be able to affect the talent distribution to any significant degree. Following Philippon and Reshef (2012), Goldin and Katz (2008), Oyer (2008), Shu (2016), and Célérier and Vallée (2017), we also consider the career choices of university graduates over our time period. While the share of university-educated workers has increased more in finance than in other sectors (as in Philippon and Reshef, 2012), the share of university graduates has also increased in the overall population, which has lead to a decrease in average talent among university graduates. Holding talent constant, we do not find any significant increase in the fraction of top university graduates entering the finance industry for most educational fields. One exception is engineering, where we, similar to Célérier and Vallée (2017), find an increase in top engineering graduates entering finance over our sample period. During the period we study, however, there was an order of magnitude larger increase of top engineers going into the IT sector, and a correspondingly large decrease of engineers in the manufacturing industry. This suggests that the increase of top engineers in the finance sector is more a consequence of the decline of manufacturing over the last three decades than increased competition for engineering talent from the finance industry.

Our paper contributes to the recent and growing literature on the causes and consequences of compensation in the financial industry. Apart from the papers mentioned above, these include theoretical contributions by Axelson and Bond (2015), Glode and Lowery (2016), and Bolton, Santos, and Scheinkman (2016), and empirical work by Kneer (2013a), Kneer (2013b). Our results suggest that competition for talent is not a main cause of the increase in relative finance wages over the last three decades, and that the increase in finance wages is unlikely to have caused negative externalities on the supply of talent to other sectors. Our results rather point towards other explanations for the increase of relatives compensation in finance, such as increasing excess profits in the sector, which in turn are being shared with workers, e.g., because of moral hazard reasons (Axelson and Bond, 2015; Biais and Landier, 2015), fairness concerns, (Akerlof and Yellen, 1990) or poor governance (Bebchuk, Cohen, and Spamann, 2010; Bivens and Mishel, 2013).[4]

Our results also contribute to the debate about rising inequality. One long-standing view has been that increases in wage inequality largely stem from shifting productivity of skill, due to skill- or task-biased technological change (e.g., Katz and Murphy, 1992; Acemoglu and Autor, 2011), international trade and offshoring (Autor, Dorn, and Hanson, 2013; Hummels, Munch, and Xiang, 2016), or rising superstar economies (Gabaix and Landier, 2008). At the same time, a recent literature has shown the important role of individual firms in determining wages (see Card, Cardoso, Heining, and Kline, 2018). The wage premium in the finance sector has risen significantly since the 1980s, and has persisted even after a historically severe financial crisis, and this is the case also for finance workers well below the top of the skill distribution. Our results suggest that at least part of the increase in inequality, originating from the rising finance industry wage

[4]The growth of profits (and profit share) of the financial industry has been documented by Greenwood and Scharfstein (2013) and Philippon and Reshef (2013). Potential explanations for the relative growth of financial markets include Gennaioli, Shleifer, and Vishny (2014) and Philippon (2015).

premium, is not due to increased productivity of skills.[5] They point more in the direction of imperfect competition leading to industry rents, which are being shared with workers.

Finally, our results have bearing on the literature on labor market sorting. Recent studies argue that matching higher-wage workers with higher-wage firms explains part of the increase in between-firm inequality (e.g., Card, Heining, and Kline, 2013; Song, Price, Guvenen, Bloom, and von Wachter, 2016). In contrast, we obtain no evidence for increased entry of talented workers into the financial sector as relative wages have increased. This sheds some doubts on the effectiveness of the price mechanism to allocate talent, at least between finance and other sectors

In the following section we describe the Swedish financial sector and the overall patterns of finance wages. Section III outlines the Talent-Competition hypothesis for explaining the finance wage premium, and discusses its testable predictions. We then test these implications for the talent selection into finance (Section IV) and for the evolution of relative finance wages (Section V). Section VI reports the main robustness checks, including an analysis of migration and education. The last section concludes and discusses some alternative explanations for the finance pay surge. In a separate appendix we provide a more detailed description of the data, additional tests, a detailed comparison to the United States (showing that finance wage trends are very similar to Sweden), and a theoretical model deriving our testable predictions more formally.

II Relative Finance Wages in Sweden

In this section we describe the Swedish Financial Sector, and document the evolution of finance wages over time. A detailed comparison between the Swedish and U.S. evidence can be found in Appendix D.

II.A The Swedish Financial Sector

Our analysis focuses on the Swedish financial sector, where we have detailed data on earnings and talent of individuals. Although this raises the issue of external validity, the Swedish financial sector is in many ways similar to that of the U.S. and the U.K.. All

[5]Key studies on industry wage differences include, among others, Gibbons and Katz (1992) and Abowd, Kramarz, and Margolis (1999).

three countries experienced significant financial market deregulation in the early 1980s (see Englund, 2015), setting off a substantial expansion of financial activity and (as we will show) a surge in relative wages.

Figure I shows the evolution of the financial sector in terms of employment and GDP share, using data from Statistics Sweden. Appendix D provides statistics on equity market growth, as well as corresponding numbers for the U.S. The finance sector is smaller in Sweden, with the U.S. finance employment share being about 1.5 times the Swedish one (and the difference in GDP share being slightly larger). The evolution over time is quite similar, however. In both countries, the employment share in finance (in terms of hours as well as of number of employees) has been relatively stable over time, while the GDP share has been increasing from the mid 1990's and onwards. In terms of subsectors, both Sweden and the U.S. have experienced a decreasing share of workers in banking and insurance, and an increasing share of workers in asset management over the 1990–2014 period (see A4 in Appendix D for details).

Sweden did have a somewhat different financial crisis experience compared to the U.S. and the U.K.. Following the post-financial deregulation boom, Sweden was hit by a severe banking crisis in the early 1990s, contributing to a drop of Swedish GDP by almost 4% between 1990 and 1993. In contrast, the Swedish financial market emerged relatively unscathed from the 2008–2009 financial crisis compared to the U.S. and U.K.[6]

II.B Evolution of Swedish Finance Wages

Our main data source for worker information is the *Longitudinal Integration Database for Health Insurance and Labor Market Studies* (LISA), provided by Statistics Sweden (SCB). LISA contains employment information (such as employment status, the identity of the employer, and occupation), tax records (including labor and capital income) and demographic information (such as age, education, and family composition) for all individuals

[6]The early 1990s crisis, which also severely hit Norway and Finland, was the result of a series of events that included a general rise in international interest rates (following the fall of the USSR and the reunification of Germany), a 1990 tax reform that significantly increased the after-tax borrowing costs for individuals, a large decrease in real estate prices starting in 1990, and the European-wide currency (ERM) crisis, which eventually led to Sweden abandoning its fixed exchange rate regime in November 1992. The crisis culminated in government bailouts of three of the five major Swedish banks in 1991 and 1992. In contrast, none of the major Swedish banks failed during 2008–2009, although the government did take significant measures to stabilize the banking sector following the Lehman bankruptcy, including guarantees for bank borrowing and doubling the deposit insurance limit. Also, the largest independent Swedish investment bank, Carnegie Investment Bank, was taken over by the government in November 2008.

16 years of age and older, domiciled in Sweden, starting in 1990. In LISA, the sector where an individual works is reported according to the Swedish Standard Industrial Classification (SNI) code at the level of the establishment at which they are employed.

To make our results comparable to Philippon and Reshef (2012) and other previous research, we exclude individuals with yearly labor income below the threshold that qualifies a worker for public pensions (36,400 SEK or approximately 4,500 USD in 1998), as well as farming sector, public sector, and self-employed workers. We have confirmed, however, that including these observations do not significantly change our results. We also exclude observations with incomplete data on gender, age, or sector of employment. This results in a sample of about 82.7 million individual-year observations.

We define the relative finance wage as the ratio of average labor income of finance workers to that of workers in the non-financial, non-farming private sector. Our main classification of a finance worker is an indicator for whether the SNI code of the individual's working establishment is in the "Financial Intermediation"group (SNI codes 65000–67000), which includes banks, finance and leasing companies, insurance companies, security broking, fund management, and pension funds.[7]

For labor income we use reported annual earnings before tax. Importantly, this information is not censored or top-coded, and includes bonus payments, which are a substantial part of compensation for many finance jobs. In robustness tests, we also analyze alternative income measures such as labor plus capital income, after-tax disposable income, and reported hourly wages (details in Appendix C). While we use labor income as our main wage measure throughout the paper, all of our results hold with these alternative income measures. We use the term "relative wages" when referring to relative pay in the financial sector compared to the private, non-financial sector, and refer to the finance "wage premium" as the remaining wage differential once we have accounted for differences in education and other demographic information. Appendix B contains a more detailed description of our data and sample construction. We also extend the relative wage time-series back to 1978 for a representative sample covering between 3% and 4% of the working population, using the *LINDA* data base (see Edin and Fredriksson,

[7] As an alternative definition, we have hand-classified firms into the financial industry based on the *Serrano* data base of Swedish corporations, combined with membership lists from various financial associations. While this method gives very similar results, we stick to the SNI-based definition of a finance worker in the paper.

2000) to capture the time of the deregulation of the Swedish finance industry.

Panel (a) of Figure II shows an extraordinary growth of relative finance wages in Sweden over the last three decades. In the early 1980s, before deregulation, annual earnings in finance were about 10% higher than in the rest of the economy. Relative finance wages begin to rise in 1983, the year when financial deregulation first set off, and steadily increase from this point. [8] By 1990, relative wages had risen to being 20% higher, and continued to grow to become almost 70% higher by 2014. This increase is nearly identical to what Philippon and Reshef (2012, Figure I, p1558) document for the U.S.[9] Appendix F, shows that finance pay still increases when restricting the comparison to other high-skilled sectors, such as Law, Consulting, and Accounting (LCA) and Information Technology (IT).

While finance wages are more cyclical than wages in the rest of the economy, financial downturns only have a temporary effect on relative earnings. Panel (a) of Figure II shows that the 1990–1992 banking crisis is associated with a modest drop in relative finance earnings, and the same was true for the 2000–2001 downturn. Similarly, the global financial crisis of 2008–2010 had only a modest impact, and by 2014 relative finance wages in Sweden were again at an all-time high.[10] Although relative finance pay is substantially higher for males than for females on average (e.g., 37 percent vs. 18 percent in 1990), both genders have experienced a similar increase over time.

With our detailed administrative data, we can precisely estimate the complete distribution of relative wages. Panels (b) and (c) of Figure II plot relative wage percentiles, defined as the earnings at a particular percentile of the finance distribution divided by the earnings at the same percentile of the non-finance distribution. Kaplan and Rauh (2010) and Bell and Van Reenen (2013) show that in the U.S. and U.K. the increase in relative finance wages was particularly dramatic at the top of the income distribution. Again, our Swedish evidence is similar: as the median relative wage increased from around 110% to 140%, the 99th percentile rose from 150% to 250%. That said, there is a significant increase in relative finance pay across all the percentiles of the wage distribution.

[8](Philippon and Reshef, 2012, 2013; Boustanifar, Grant, and Reshef, 2017) also relate the beginning of the finance wage increase to financial deregulation for a large number of countries, including the U.Sȧnd the U.K.

[9]In Appendix D we compute relative finance pay for the U.S. over our sample period using publicly available labor market data from the Current Population Survey (CPS). Note that lower levels of relative finance pay in the CPS are due to it reporting top-coded wages, whereas Philippon and Reshef use Industry Accounts to circumvent this problem (or, alternatively, impute income for U.S. top earners).

[10]Bell and Van Reenen (2014) find that a similar recovery of the finance premium occurred in the U.K. in the years following the Great Recession.

The rise in top finance wages can also be illustrated by considering the representation of finance workers in the highest percentiles of the income distribution. Several recent papers document an increasing share of finance workers in the very top of the income distribution for the U.S., U.K., and Canada over the last three decades.[11] For Sweden, the share of finance workers among the 0.1 percent highest earners rose from 14.7% to 31.1% during the 1990–2014 period (accounting for 15.3% and 32.2% of total earnings in this group, respectively). This compares to an increase from about 17% to 31% between 1981–1985 and 2008–2012 in the U.S.. Cyclical fluctuations are also larger at the top of the distribution, especially for the 95th and 99th percentiles, consistent with what Guvenen, Kaplan, and Song (2014) document for the U.S. This suggests that bonuses and other performance-sensitive pay is particularly important for the top finance earners.

In Appendix D, we analyze employment and wages across different subsectors of the financial industry in Sweden and the U.S.. Trading and asset management ("Securities, brokerage, and investment firms") is the highest-paid sector, and is also the sector with the largest increase in relative wages in both countries. Still, a substantial part of the increase in the overall finance wage is due to a steady relative-wage growth in the banking industry over the last 25 years. Moreover, relative finance wages increased *within all* subsectors between 1990 and 2014, with the exception of savings institutions and credit unions in the U.S., where it stayed approximately flat. Aggregating over subsectors for Sweden, we find that employment-weighted relative finance wages in 1990 were 24% higher, and increased to 78% by 2014. Most of this surge is driven by increases in relative pay within sectors over time rather than by compositional changes across subsectors. If the subsector composition of workers in 1990 would have remained constant, implied average finance wages in 2014 would still have been 73% higher than wages in the non-financial sector, which is almost at the level of actual relative wages (78%).

Appendix C.1 contains a number of robustness tests. First, we compare alternative compensation measures. The evolution of relative finance wages is very similar when including capital income or when considering disposable income after taxes and benefits. We further examine the relative finance wages using approximate hourly wages, and find a comparable increase. Consistent with this, working hours in the financial sector have

[11]See Kaplan and Rauh (2010), Kaplan and Rauh (2013), and Bakija, Cole, and Heim (2012) for the U.S. Bell and Van Reenen (2014) for the U.K. and Lemieux and Riddell (2015) for Canada.

not increased relative to the rest of the economy over our sample period, neither for Sweden nor the U.S. (Figure A9). Finally, about 45 percent of overall and 80 percent of top 5% finance earners in Sweden are working in Stockholm.[12] Since Stockholm is an area with higher wages and wage growth compared to the rest of Sweden, this raises the concern that our relative wage comparisons are capturing a Stockholm effect rather than a finance effect. When we restrict the sample to workers in Stockholm, however, the increase in relative finance wages even comes out marginally higher.

To summarize, our results show that wages in the Swedish finance industry have risen dramatically compared to the rest of the economy since the mid-1980s. Trends are very similar to what has been documented for the U.S. and the U.K.. Although the relative wage increase is most pronounced among top earners, it is present across the income distribution and across the different segments of the finance industry.

III Talent and the Finance Wages: Theory and Predictions

A vast literature has documented that the wages of skilled workers (typically classified by having higher education) have increased relative to unskilled workers over the last several decades in many countries. Since educational attainment has also increased over this period, this suggests that the relative demand for skilled labor in the economy has risen. A leading explanation for this trend is that new technology has disproportionately raised the productivity of skilled workers compared to unskilled workers, so-called *skill-biased technological change (SBTC)*. As Acemoglu and Autor (2011) explain, the canonical SBTC model can account for many observed patterns in the wage distribution, such as changes in returns to schooling over the last 100 years (see Goldin and Katz, 2008).[13]

Philippon and Reshef (2012) propose that increasing returns to skill or talent can also help to explain the surge in relative finance wages in the U.S. since 1980. They argue that the deregulation of financial markets made finance jobs more complex, which in turn lead to an increase in the relative productivity of skilled workers. In addition, Kaplan and Rauh (2010) argue that new technology has enabled the most productive finance workers

[12]These (top) employment shares in finance are comparable to London's share in the UK (Bell and Van Reenen, 2014).

[13]Acemoglu and Autor (2011) also argue, however, that the canonical model needs to be extended by adding endogenous assignment of skills to tasks, in order to explain other salient patterns, such as job polarization.

to apply their talents to a larger capital base, giving rise to superstar effects (Rosen, 1981) and particularly high wage increases at the top of the talent distribution (similar to what Gabaix and Landier (2008) argue for CEO compensation). A faster increase in the productivity of talented workers in the financial industry compared to other sectors should raise the relative demand for such workers in finance. This increased demand for talent should drive up the relative wages of talented workers in finance, both compared to less talented workers and to workers in other sectors. The focus of our study is to test whether the data is consistent with this *Talent-Competition Hypothesis*.

Instead of using education level as a measure of skill, as most of the previous literature, we utilize cognitive and non-cognitive test scores, which we refer to as *innate talent*. While innate talent is a more narrow concept than skill, the measures we use have been shown to have significant impact on labor market outcomes in several studies. Also, innate talent is determined before the individual decides on a career path and makes investments in sector- or firm-specific human capital. This circumvents the problem of education being endogenous to career choice, and allows us to better quantify the extent of "brain drain" of talented individuals into finance at the expense of other sectors (see Baumol, 1990; Murphy, Shleifer, and Vishny, 1991).

In addition to our innate talent measures, there could of course be other character traits that determine the productivity of finance workers. Also, some of the skills that are important for finance jobs might only be acquired or discovered on the job (as in Gibbons, Katz, Lemieux, and Parent (2005) and Terviö (2009)). Nonetheless, if talent is correlated with such skills, or makes it easier to acquire them, talent demand should also increase as these other skills become more productive. This implies that our innate talent measures are relevant for addressing the *Talent-Competition Hypothesis* also in richer models.

Appendix A contains a simple model of talent selection into the financial sector, which we use to formally derive testable predictions from the *Talent-Competition Hypothesis*. The predictions can be summarized as follows:

Prediction 1. *If (a) the productivity of talent increases faster in the financial sector compared to the rest of the economy between time $t = 0$ and $t = 1$, and (b) the employment share of the financial sector in the economy is not increasing at the same time, then the average talent level of finance workers will increase between $t = 0$ and $t = 1$ relative to other sectors.*

If productivity of talent is increasing faster in finance, the demand for talented workers increases more in finance than in other sectors, and the finance sector should hire more of these workers. If the finance sector is not growing in terms of employment share, this should lead to a replacement of less talented workers with more talented workers, and average talent should increase. If the finance sector were also growing, there might not be any improvement in average talent, since finance companies will have to move down the talent supply curve in order to fill an increased number of positions. As we showed in Section II, however, the employment share in finance has been roughly constant over the period we study. Hence, the Talent-Competition Hypothesis predicts that average talent should have increased in finance relative to other sectors.

We can also formulate this prediction in terms of employment choice probabilities.

Prediction 2. *If the productivity of talent increases faster in the financial sector compared to the rest of the economy between time $t = 0$ and $t = 1$, then the likelihood of a more talented worker entering finance should increase more between $t = 0$ and $t = 1$ compared to a less talented worker.*

We will test these two predictions in Section IV.

If the Talent-Competition Hypothesis is true, the increase in relative finance wages documented in Section II results from a combination of more talented (and thus more highly paid) workers entering the finance sector, and an increase in the relative wage of more talented workers. This has two implications.

Prediction 3. *If the productivity of talent increases faster in the financial sector compared to the rest of the economy between time $t = 0$ and $t = 1$ and the average talent level of finance workers therefore increases as in Prediction 1, then part of the increase in relative finance wages should be due to that improved talent selection.*

We will test this prediction in using wage regressions in section V.

Finally, if the Talent-Competition Hypothesis is true, the average finance wage premium, i.e., the relative wage differences that remain after controlling for talent and skill, should be driven by wage increases among the most talented finance workers.

Prediction 4. *If the productivity of talent increases faster in the financial sector compared to the rest of the economy between time $t = 0$ and $t = 1$, then the relative wage of talented workers in finance should increase between $t = 0$ and $t = 1$, and this relative wage change should be increasing in the talent level.*

This prediction was tested in Célérier and Vallée (2017) for a sample of French engineers, using the entry exam score needed for acceptance at a given engineering program as a measure of talent. In Section V, we will analyze the relationship between talent and wages using our measures of innate talent.

Note that these predictions are only necessary but not sufficient conditions for the talent-competition hypothesis to be true, and there might be alternative theories yielding similar predictions. For example, even if productivity of talented workers is not increasing, but the potential to earn rents in the sector is, we might still expect that the most talented workers are drawn to the sector to capture these rents, along the lines of Murphy, Shleifer, and Vishny (1991). Hence, while failing to support these predictions leads to a rejection the talent-competition hypothesis (and other theories with similar implications), a confirmation of the predictions would not necessarily rule out such other explanations.

IV Has the Finance Industry Become More Talented Over Time?

In this section, we examine the evolution of talent in finance over time, both relative to the private sector as a whole as well as to other high-skilled sectors.

IV.A Data on Talent

Our main source of talent data are military enlistment tests, which were mandatory for Swedish male citizens before 2007. They were typically taken at the age of 18 or 19 with the purpose of evaluating an individual's potential for military service based on medical, physical, cognitive, and psychological traits. Lindqvist and Vestman (2011) and Dal Bó, Finan, Folke, Persson, and Rickne (2017) provide further details on this data.[14]

Our first talent measure is an individual's cognitive ability score (similar to IQ). Cognitive ability was assessed through subtests covering logic, verbal, spatial, and technical comprehension. The four test results were aggregated into an overall integer score ranging from 1 (lowest) to 9 (highest), according to a Stanine (standard nine) scale that approximates a normal distribution with a mean of 5 and standard deviation of 2.[15]

[14] In Appendix B.2, we present the data and the construction of our talent measures in detail. We also discuss the predictive power of these measures for labor market outcomes as well as individuals' incentives to perform well in these tests.

[15] A score of 5 is reserved for the middle 20 percentiles of the population taking the test, while the scores of 6, 7, and 8, are given to the next 17, 12, and 7 percentiles, and the score of 9 to the top 4 percent of

The second talent measure, the non-cognitive ability score, was assessed through a 25-minute semi-structured interview by a certified psychologist. The individual was graded on his willingness to assume responsibility, independence, outgoing character, persistence, emotional stability, and power of initiative. The psychologist would weigh these components together and assign an overall non-cognitive score on a 1 to 9 Stanine scale.

Individuals who scored sufficiently high on the cognitive test would also be evaluated for leadership ability, again on a 1 to 9 Stanine scale. The leadership score is meant to capture the suitability to become an officer. Since leadership was only assessed for a subset of individuals, we focus on cognitive and non-cognitive ability in our analysis.[16]

Since military enlistment scores are only consistently available for men, our analysis will mostly focus on male workers, but we also construct an alternative talent measure based on high-school grades that covers both genders. Since high school programs vary in length and difficulty, we first regress, for each high-school graduation year separately, the cognitive military test score of males on a third order polynomial of high-school grades interacted with high-school track and age at graduation. The predicted score has a correlation of 0.644 with the actual cognitive score. We then use the estimated parameters to calculate predicted cognitive ability for both genders. We standardize the measure to percentiles (1 to 100) within each graduation year and for each gender, to account for possible grade inflation and the fact that females have higher grades on average.

Appendix B provides summary statistics of all the talent measures as well as the other main variables used in the analysis. Military test scores are consistently available for almost 90 percent of males across most birth cohorts in our sample. Availability of high school grades increases for younger cohorts, as a result of increasing high-school attainment, and reaches 80 percent for cohorts born after the early 1970s.

An advantage of the cognitive and non-cognitive test scores over alternative measures, such as education, is that they are stable over time and not sensitive to compositional changes.[17] While cognitive and non-cognitive ability may not be completely innate

individuals (scoring below 5 is symmetric). See Dal Bó, Finan, Folke, Persson, and Rickne (2017).

[16]Non-cognitive ability and leadership ability are also highly correlated (Lindqvist and Vestman, 2011); in our data the correlation is 0.856, while the correlation of cognitive and non-cognitive is 0.357.

[17]Appendix Figure A2 shows that the distribution of the talent measures is stable over the period 1990-2014 and thus comparable across the sample period. This allows us to select a specific talent percentile of interest and compare it over time. The stability of the military test scores is partly due to standardization by the enlistment authority, but the underlying distribution of cognitive ability is arguably stable over time as well. Although Flynn (2000) reports improvements in average intelligence during the mid-20th century, these

(Hansen, Heckman, and Mullen (2004) and Heckman, Stixrud, and Urzua (2006)), they are largely exogenous and predetermined to the career choices of individuals, since they are measured before individuals enter post-secondary training and/or the labor market.

Importantly, these scores have been shown to significantly predict future labor market outcomes, such as wages and unemployment, in previous research (see, e.g., Lindqvist and Vestman, 2011), and we verify that cognitive, non-cognitive, and predicted cognitive ability are highly significant predictors of wages in our sample (see Appendix B.2, Table A3). Aghion, Akcigit, Hyytinen, and Toivanen (2017) show that similar cognitive military test scores strongly predict whether an individual becomes an inventor in Finland, showing that the allocation of individuals with respect to our talent measures could have first-order consequences for innovation and productivity.

IV.B Education as a Measure of Talent

Most previous studies on wage skill premia have used education as a proxy for worker productivity. Philippon and Reshef (2012) show that the increase in the finance premium in the U.S. has coincided with a relative increase in education level among finance workers compared to the rest of the economy. Boustanifar, Grant, and Reshef (2017) find that this relationship is present in a broader sample of developed countries. In Appendix B.6, we reproduce these results for Sweden and show that the fraction of finance workers with a post-secondary education went from being about 2 percentage points higher in 1990, to being 16 percentage points higher in 2014, relative to the rest of the economy.

Although such findings seem to support the Talent-Competition Hypothesis, the evidence is at best suggestive. Relative education is difficult to compare over time, since the fraction of individuals with at least a post-secondary degree has been increasing substantially. In addition, the choice to pursue higher education is likely endogenous to an individual's sectoral choice. In particular, many finance jobs that in the past were dominated by workers with only a high-school degree today require at least a post-secondary degree. In Appendix B.6 we show that during 1990–2014, post-secondary attainment rose from 21 to 37 % among males. This was accompanied by a decline in average cognitive

gains are likely to have petered out for most of the individuals in our sample. Sundet, Barlaug, and Torjussen (2004) find that 18-year-old Norwegian male conscripts born after the mid-1950s had rapidly decreasing gain rates with a complete cessation of the Flynn effect for birth cohorts after the mid-1970s. Similar findings exist for Danish conscripts and for Swedish 13 year olds born 1947-1977 including girls.

ability in the post-secondary group by .4, or more than a fifth of a standard deviation among the working population. These results are similar for females and university or Ph.D. graduates. Carneiro and Lee (2011) and most recently Bowlus, Bozkurt, Lochner, and Robinson (2017) present related evidence for the U.S., and show that higher college attainment leads to a decline in the average quality of college graduates.[18] Hence, the fact that relative education is increasing is not necessarily a sign that relative talent (measured as cognitive ability, for instance) has been increasing in the finance sector.

IV.C Evolution of Average Talent in Finance Versus the Rest of the Economy

Motivated by these limitations of education for making inferences about changes in relative skill over time, we focus on the innate talent measures from military test scores (and the predicted cognitive talent measure based on high-school grades) in our analysis.

To test Prediction 1, we examine the evolution of relative talent, defined as the difference in average talent between finance and non-finance workers. In Figure III, we plot relative talent in finance for workers across all ages. For males we use the cognitive, non-cognitive, and leadership scores from military tests, and for females we use the predicted cognitive score based on high-school grades.

We first observe that relative talent are positive across all years and talent measures, showing that finance workers are more talented than other private-sector workers on average. The difference, ranging from 0.66 for leadership to 0.85 for cognitive skill, corresponds to more than a third of a standard deviation.[19] Although this implies that finance is a high-talent profession, we show in Appendix F that workers in the LCA and IT sectors are even more talented on average, at least in terms of cognitive ability.

According to Prediction 1, if the rise in relative finance wages were driven by increasing productivity of talented workers, then the mean relative talent in finance should have risen concurrently. Unlike relative education, however, Figure III shows no improvement in relative talent over time. For males, relative talent is flat or decreasing over our sample

[18] The bottom panel of Figure A3 illustrates the problems with compositional changes in our Swedish data, plotting the male post-secondary share in Sweden against average cognitive ability among those who attained post-secondary education.

[19] The quantitative difference is not straightforward to interpret, however, given the approximate bell shape of the Stanine scale (i.e. a difference at the tail is more significant than the same difference around the mean). In section 4.4, we consider relative changes across the whole talent distribution, which are more easily interpretable.

period for cognitive, non-cognitive, and leadership ability. For females, using grade-based predicted cognitive ability, we do not find any evidence of an increase in talent either.

In Appendix C.1, we show the corresponding results for recent male entrants (30 year olds), among whom a change in relative demand for talent should be the easiest to detect. For this subsample of recent entrants, we find that relative talent was actually higher in 1990 than in 2014 for all three measures, opposite to the prediction of the Talent-Competition hypothesis. In Appendix F, we further show that finance talent has not increased compared to the high-skilled LCA sector either, despite finance wages having increased significantly also relative to this sector. For the IT-sector, there is only a minor improvement of average talent in finance, despite a tripling of employment in IT during the 1990's (while the employment share in finance remained constant).

To test Prediction 2, we run regressions analyzing the choice of a male worker entering the financial sector. We focus on the subsample of 30-year olds in order to capture recent entrants and ensure that every individual enters the sample only once. We estimate cross-sectional linear probability models (LPMs) separate for each year of the form

$$F_i = a + b'\theta_i + c'X_i + e_i \tag{1}$$

where F_i is a dummy variable for individual i working in finance at age 30, θ_i is the measure of talent, and X_i is a vector of control variables, including years of schooling and dummies for whether an individual's parents have worked in the finance industry. The results are shown in Table I. We split the sample into five 5-year periods in order to examine the evolution of the coefficients over time.[20] In the first three columns, the stanine talent score enters linearly, while in the fourth and fifth column we allow for a non-linear relationship (which we will discuss in the next subsection).

Column (1) of Table I indicates that while an individual's choice to enter the finance sector is positively related to both cognitive and non-cognitive talent, the effect is if anything decreasing over time (especially for non-cognitive talent). When including years of schooling in Columns (2) and (3), cognitive ability no longer predicts entry into finance, and the coefficient actually turns negative. Consistent with the previous discussion, the

[20]We refrain from making assumptions about the distribution of e_i throughout the paper, but probit regressions yield qualitatively similar findings. We also obtain very similar results when we use more and shorter time-periods, but focus on 5-year periods in order to make the table more readable.

importance of relative formal education for entering finance rises over time. Column (3) adds dummies for whether an individual's father and mother ever worked in finance during the sample period. These dummies are substantially more important than talent or education in determining whether an individual chooses finance.[21] The importance of having parents in finance for sectoral choice also seems to be increasing over time. In Appendix Table A6 we show corresponding evidence for women, using predicted cognitive talent to predict entry into finance, with similar results. Although predicted cognitive talent predicts the entry of female workers into finance, the effect has been decreasing over time, contrary to the prediction of the Talent-Competition hypothesis.

IV.D Evolution of Top Talent in Finance

Even though relative talent in finance has not improved on average, we might be more interested in what happens at the tail of the distribution. Kaplan and Rauh (2010) argue that technical change has particularly benefitted the productivity of "superstars" (in the sense of Rosen (1981)), i.e. workers at the very top of the talent distribution. They attribute much of the increase in relative wages to finance sector workers (as well as CEOs, lawyers, and athletes) to rising compensation levels among the exclusive group of top talents.

An increase in top talent might not be visible in average talent if there is a concurrent increase in the fraction of low-talent workers. This might well be the case, since computers have replaced many mid-level workers performing routine tasks, leading to the phenomenon of *job polarization* (see Acemoglu and Autor, 2011). As shown by Autor, Katz, and Kearney (2008) and others, the replacement of workers involved in routine tasks by computers has coincided with an increase in the (relative) demand for both abstract tasks (which are complementary to IT and require relatively high-skilled labor) and services tasks (which only require relatively low-skilled labor).[22] The observed in-

[21] Even conditional on the other parent's affiliation, a father or mother in finance during 2010–2014 raises the probability of working in the sector by more than 100% (i.e., from around 3 to 6 percent). In unreported tests, we also include the father's income and the share of individuals in finance in the municipality where the individual grew up. While the father's income is insignificant conditional on the parents having worked in finance, the municipality share in finance is another significant predictor for an individual entering finance (adjusted R-square rises substantially, although the effect of parental affiliation declines). We have also included the share of past students of the individual's high school who work in the finance sector, with similar results as for the municipality finance share. These results suggest that social networks might be at least as important as talent and skills for determining the selection of workers into the financial sector.

[22] Several papers, including Böhm (2017), have shown that cognitive ability is higher among workers performing abstract tasks, while non-cognitives correlate positively with both abstract and service tasks.

crease in finance wages might then be driven by an increased productivity of superstars in performing abstract tasks, which might not be visible in average talent because of a decreasing fraction of mid-talent finance workers performing routine tasks.

To investigate this possibility, Figure IV depicts the relative share of each talent group in the financial sector compared to the rest of the economy for the median talent scores and up, in the sample of male workers. Top cognitive talent, i.e., with score 9, represent roughly five percent of finance workers, as opposed to four percent of the working population overall, resulting in a ratio of 1.2. While this shows that top cognitive talent is overrepresented in finance, this ratio has remained more or less constant over the 1990–2014 period, inconsistent with the superstar version of the Talent-Competition hypothesis. The cognitive talent groups that are the most overrepresented are the 7's and 8's, and the relative representation of these groups in finance has fallen over time, while the representation of median cognitive talent (5's) has increased.

In terms of non-cognitive skills, top talent ("9s") comprise a much higher fraction of male workers in finance (around 5% in 1990) compared to the rest of the workforce (around 2% in 1990). This concentration of top non-cognitive talent in finance has decreased somewhat over time, however, from a ratio of 2.5 in 1990 to just above 2.0 in 2014. There is also a modest decrease in the relative share of "8s", the second most talented group. Appendix E presents corresponding results for females, using the predicted cognitive score. In contrast to male workers, the most talented women are underrepresented in finance compared to other sectors (despite a slight upward trend after 2004).

Columns (4) and (5) of Table I report linear probability choice regressions predicting entry into finance for 30-year old male workers using dummies for bottom (omitted), upper middle (scores 5–8), and top (score 9) talent groups, interacted with the time period. Column (5) also includes years of schooling. The regression results largely confirm the patterns in Figure IV, showing no indication that the coefficient on top talent is increasing over time, despite a large increase in the finance premium over this period. The exception is an increase in the coefficient on cognitive talent for males during the post-crisis period 2010–2014, when relative finance wages stayed relatively constant, as seen from Figure II.

In Appendix C.2 we report another test that could potentially uncover superstar effects, namely the evolution of average talent among the very top earners in finance. Although the average cognitive, non-cognitive, and leadership talent of top 5% and 1%

earners in the finance sector is high (about two standard deviations above the mean of the population), it is not increasing. Instead, there is a slight decline over time, although the confidence bands are too wide for statistical significance.[23]

To summarize, we find no support for the hypothesis that top talent has increased in the financial sector compared to other sectors, inconsistent with an increased demand of "superstar" workers driving the rising relative wages in finance.

V Analysis of Wages in the Financial Sector

Even though we do not find support for Predictions 1 and 2, it is still possible that the increase in relative finance wages is concentrated among more talented workers, consistent with wage increases being driven by an increased productivity of talent. This could happen if, for some reason, the supply of talented labor was not very responsive to changes in relative wages across sectors. While the predictions of the Talent-Competition hypothesis for the evolution of relative talent were relatively straightforward to test, the predictions for relative wages are more difficult to identify econometrically, because of self-selection based on unobservable characteristics (Heckman, 1979). In Appendix A.2 we decompose the relative finance wage into observable and unobservable selection, overall return to talent, finance-specific return to talent, and a remaining, unexplained wage premium. To disentangle these effects, we perform our analysis in steps.

We begin by estimating wage regressions, controlling for selection on observable talent and other observable characteristics, such as education, gender, and work experience (Prediction 3 of the Talent-Competition Hypothesis). We then include individual fixed effects to control for (correlated and uncorrelated) time-invariant unobservable components of skills, as well as individual-firm and individual-sector fixed effects to control for time-invariant finance-specific components of skills. Next, we allow the return on talent to vary over time, to account for the economy-wide change in the return to talent. We end by explicitly introduce changing finance-specific returns to talent (Prediction 4). In the last part of this section, we also compare the evolution of relative wages across the most common occupations in finance, which are likely to differ in their degree of

[23] In terms of *relative* talent finance workers are marginally more talented than the rest of the economy's top earners and less talented than the top earners in the LCA and IT sectors. There is no upward trend in relative talent for top earners here either.

finance-specific skill requirements.

V.A Wage Regressions

Figure V displays results from wage regressions for the subsample of males by plotting the finance premium that remains after controlling for talent and other characteristics (Prediction 3). Figure A11 shows corresponding tests for females, with similar results.

The top panel of Figure V plots three versions of the estimated finance premium $(\exp(\hat{\tilde{a}}_t) - 1)$ from the following wage regression:

$$w_{it} = a_t + F_{it}\tilde{a}_t + b'\theta_i + c'X_{it} + v_{it}, \tag{2}$$

where w_{it} is the log wage of individual i at time t, F_{it} is an indicator for whether individual i works in the finance industry at time t, θ_i is observable talent for individual i, X_{it} is a vector of control variables, and a_t is a time fixed effect. $\tilde{a}_t$ captures the part of relative finance wages that is not explained by talent and other control variables. The solid red line shows the finance premium among males with non-missing test scores, controlling for a quadratic in potential experience (defined as age minus 6 years of education). Over our sample period, this premium increased from 25 to almost 60 percent.[24] The dashed blue line plots the estimated finance premium after controlling for cognitive and non-cognitive talent θ_i in addition to potential experience. Finally, the dotted green line graphs the remaining finance premium when years of education is also included among the controls. Cognitive and non-cognitive talent explain roughly 10 percentage points of the premium for men, and adding schooling another 5 percentage points. Still, the increase in the finance premium remains, so the fact that finance workers are more talented and educated cannot by itself explain the rise in relative wages.

Next, we add individual and individual-firm fixed effects (λ_i and λ_{im}, with m indicating a worker's firm) to the specification in 2. Individual fixed effects account for all time-invariant components of worker skills that affect wages, even unobserved ones that are uncorrelated with our talent measures. The panel dimension of the data also permits including individual-firm fixed effects, which are finer than individual-sector fixed ef-

[24]Conditioning on having data on talent and other controls reduces the sample of male workers from 83 million to 40 million individual-year observations, primarily due to missing data for older cohorts. Nonetheless, the increase in relative finance wages remains very pronounced, as seen from Figure V.

fects and can account for time-invariant employer-specific skills.[25] The middle panel of Figure V takes the richest specification from the top panel (controlling for observable talent, experience, and education), and then adds the two different versions of fixed effects. This makes the finance premium negative at the start of the sample period, suggesting that finance has a positive selection of workers both in terms of observable talent and unobservable characteristics. The increase in the finance premium over time is still present, and even slightly stronger than before, showing that time-invariant unobservable individual characteristics cannot account for the rise in relative finance wages either.

The bottom panel of Figure V allows for time-varying (but not sector-specific) returns to observed talent, i.e., b_t and c_t are allowed to vary with t. Previous research has established that the returns to education and skill have increased in most Western countries over the last couple of decades, motivating the skill-biased technical change hypothesis (Katz and Murphy, 1992; Acemoglu and Autor, 2011). Since we have shown that finance attracts relatively talented individuals, rising returns to talent in the overall economy should account for at least part of the increase in relative finance wages. The last row of Figure V plots $\tilde{a}_t$ with and without time-varying coefficients for talent and controls. While the line becomes a little flatter, sector-invariant time-varying returns to talent explain only a small fraction of the overall increase in relative finance wages.[26] Thus, economy-wide skill-biased technical change cannot account for the increasing finance premium.

The four left columns of Table II summarize the results from regressions combining time-varying returns and fixed effects (for males, females, and both genders), i.e.,

$$w_{it} = a_t + F_{it}\tilde{a}_t + b_t'\theta_i + c_t'X_{it} + \lambda_{im} + v_{it}. \tag{3}$$

To make the table more readable, we split our sample into five-year periods, and we interact all regressors with these period dummies. In Column (1), we see that the finance premium, controlling for talent, experience, and education, increased from 16–20 log

[25]To identify firms, we use organization numbers from the Swedish organization registry. Since sectors are determined by the establishments where an individual works, and establishments are subunits of firms, individual-firm and individual-sector fixed effects capture somewhat different notions of specific skills and yield slightly different results. Neither finance-specific or employer-specific skills cannot account for the rising relative wages in this sector, however (see Table II below; unreported individual-establishment fixed effects give the same results).

[26]Appendix Figures A13 and A14 corroborate this result by showing that finance wages strongly increased compared to Accounting, Law, and Consulting as well as Information Technology, sectors which attract workers who are equally or more talented than finance.

points in 1990–1994 to about 28–33 log points towards the end of the sample. Controlling for individual, individual-sector, or individual-firm fixed effects diminishes the level of the premium, but the increase is actually steeper. This confirms the results from Figure V and Prediction 3 of the Talent-Competition Hypothesis is not borne out in the data.

V.B Allowing for Sector-Specific Time-Varying Returns to Talent

Even if a rising return to talent in the overall economy cannot explain increase in relative finance wages, it could still be that the talent premium has been increasing more in finance compared to other sectors. This version of the Talent-Competition hypothesis leads to Prediction 4, which posits that the relative wage of more talented workers *relative to* less talented workers in finance should increase over time. Testing this prediction is complicated due to selection on unobservables, but if we assume unobserved selection is constant over time, we can test it by examining the differences in the change of relative finance wages across workers with different observed talent. (This assumption might not be unreasonable, given that our earlier analysis shows that observable talent has remained roughly constant in finance.) We can then run a regression of the form

$$w_{it} = a_t + F_{it}\tilde{a}_t + b_t'\theta_i + F_{it}\tilde{b}_t'\theta_i + c_t'X_{it} + v_{it} \tag{4}$$

and estimate the *changes* (but not the levels) in the finance-specific return to talent and the residual wage premium from the differences in the coefficients, $\tilde{b}_t - \tilde{b}_0$ and $\tilde{a}_t - \tilde{a}_0$ (see Appendix A.2 for details).[27]

We start non-parametrically. Figure VI plots relative finance earnings for males by talent level from median talent and up (Stanine score 5 through 9), that is, $\exp(\tilde{b}_t^j)$, where $\tilde{b}_t^j = E(w_{it} \mid F_{it} = 1, \theta_i = j) - E(w_{it} \mid F_{it} = 0, \theta_i = j)$, for $j \epsilon \{5, 6, 7, 8, 9\}$. If the return to talent has risen faster in finance than in the rest of the economy, we expect the differences across the talent levels to be increasing over time (i.e., the lines for the different groups should "fan out" to the right). The top panel shows results for cognitive talent. Relative finance wages for males line up roughly by cognitive talent, and the differences widen during market peaks i.e., around 2000/01 and 2007/08, especially for the top

[27] In this fully interacted specification, $\tilde{\alpha}_t$ is not separately identified and $\tilde{b}_t^j$ is in fact the finance premium for individuals with talent score j.

cognitive talent group. The finance premium increases significantly over time across all talent groups, however, and there is little indication that the finance wage premium has increased faster for the more talented groups compared to the mid-talented groups over the long run. The results are similar for non-cognitive talent (Panel (b)) and for females using predicted cognitive talent (Figure A12).

In the rightmost two columns of Table II we report regression estimates of Equation (4) for males with time-interacted controls X_{it} for schooling and potential experience. To account for selection on unobserved characteristics, the last column includes individual-sector fixed effects. We again split workers into bottom talent (omitted), upper middle talent (scores 5–8 or percentile 41–95), and high talent (score 9 or percentile >95). Column (4) shows that the finance wage premium for the bottom talent group rises by 7.9 percentage points over the sample period. As seen in Figure VI, the difference in the finance premium for middle and high talent workers peaks in 2000–2004, but over the whole sample period it does not rise (economically or statistically) significantly more than for the bottom talent group (except for middle non-cognitive talent). When we include individual-sector fixed effects (Column (5)), the finance premium relative to the bottom decreases for most talent groups, except for middle non-cognitive talent (but the increase for the high group is again smaller than for the bottom talent). The corresponding results for females (Table A7) are similar. Overall, we find no evidence that returns to talent have risen more in the finance sector compared to the rest of the economy, inconsistent with Prediction 4 of the Talent-Competition hypothesis.

V.C Evolution of the Finance Wage Premium by Occupation

Another way to adress Predictions 3 and 4 of the Talent-Competition Hypothesis is to analyze the evolution of relative talent and wages in finance across different occupations. If relative demand for talent or skill is rising in finance, the increase in relative wages should only be present in the professions that require such skill.

Table III reports employment shares, talent, and relative wages for the 30 largest occupations in the Swedish financial sector; using 4-digit Swedish Standard Classification of Occupations (SSYK) codes.[28] These 30 occupations make up about 90 percent of finance employment in our sample. Since information SSYK codes are missing for 1991–2000 (and

[28]There are 354 different SSYK codes in total.

classification changes in 2014), we focus on comparing 1990 and 2010 for this analysis.[29]

In Panel A, occupations are ordered by their relative finance premium in 2010 compared to the average wage in the rest of the economy (Column (1) of the table). Most of the top 30 finance occupations are also present outside the financial sector. The three exceptions include "Banking associate professionals", "Insurance representatives", and "Securities and finance dealers and brokers". Consistent with the finance wage premium documented earlier, 25 out of the 30 professions in finance earn more in 2010 than the average worker in the rest of the economy.

According to column (3) the most common occupations in finance are "Banking associate professionals" (with more than 30% of finance employment in 2010) and "Insurance representatives" (representing 11–12%). Some of the highest paid occupations, such as "Securities and finance dealers and brokers" and "Computing professionals" have gained employment share over time, while the largest decrease is is for the middle-skilled "Banking associate professionals" occupation (see Column (4)).

The wage ranking of Column (1) lines up fairly well with average predicted cognitive ability (Column (5)). While several high-skill occupations (in terms of wages and talent) are prevalent in finance, many medium-skilled (e.g., bookkeepers or secretaries) and low-skilled (e.g., doorkeepers and clerks) occupations are common, too. In 27 out of the 30 occupations, finance workers have a predicted cognitive score higher than the population average (i.e., above 50). Moreover, comparing finance to non-finance workers *within* each occupation, in about two thirds of the occupations, finance workers are on average more talented than non-finance workers in the same occupation (Column (7)).

Column (9) shows that finance sector workers also earn more than non-finance workers with the equivalent job for 25 out of 27 occupations (excluding the three occupations only present in finance). Hence, the finance premium does not seem to be driven by the composition of occupations or tasks.

To address the rise in the finance wage premium, we focus on consider changes rather than levels. In Column (2) of Panel A, the finance premium compared to the average of workers across all occupations increased for 25 out of the 30 occupations, with exceptions

[29]The choice of 2010 as the ending year is somewhat arbitrary, but results are not sensitive to using any ending years between 2005 and 2013. We pool both genders in Table III, Panel A, and therefore use predicted cognitive ability. Panel (b) also shows cognitive and non-cognitive correlations, and the overall results in panel (a) are similar for the subsample of males using actual rather than predicted talent scores.

being low-skilled occupations that have experienced a declining employment share. The overall premium in Column (2) also rises more strongly for high-skill occupations than for middle- and low-skill occupations. “Securities and finance dealers and brokers” experience the largest relative wage increase, with pay rising from 1.5 to more than 4 times the average non-finance wage. In contrast, there is no visible trend in talent, which increases for half of these occupations and decreases for the other half (Column (6)).

Column (10) of Panel A reports the change in the within-occupation finance premium, which has increased in all occupations but one.[30] There is no consistent relation between the required talent of the occupation (Column (5)) (or the “finance-specificity” of the job) and the increase in relative pay over time. For example, in 1990, a doorkeeper working for a financial firm earned 7% more than a doorkeeper in a non-financial firm. This wage difference grew dramatically over the next two decades, and by 2010, the finance-employed doorkeeper made on average 43% more than his or her non-finance peer. Similarly, other low-paid and non-specific occupations, such as teller clerks and switchboard operators, experienced a positive and increasing finance premium between 1990 and 2010.

Panel B shows there is a positive and significant correlation between wage premia and talent (cognitive, non-cognitive, and predicted cognitive) across occupations (Column (1)), i.e., the highest paying jobs also have the more talented workers, consistent with talent being predictive of future labor market outcomes. At the same time, the within-occupation correlation is about zero and not significant (Column (2)). That is, the finance premium for a given occupation is not significantly related to the difference in talent between finance and non-finance workers in this occupation.

Columns (3) and (4) of Panel B show that the correlation between the change in talent and wages relative to the rest of the economy is generally small and insignificant.[31] Column (5) shows that the within-occupation changes in relative wages and talent are also uncorrelated.[32] Appendix Table A5 reports very similar results for the 30 largest

[30]The one occupation where this is not the case, “Directors, CEOs and managers in small business services enterprises”, is a quite heterogenous group, since it contains both directors and chief executives of large corporations, as well as managers of small business services enterprises (including many tiny firms with fewer than five employees). For this reason, Statistics Sweden started separating these two groups in 2010, but for consistency over time, we merge them back together.

[31]There is a positive and significant correlation of about 0.4 between pay increase (relative to the average non-finance worker) and change in predictive cognitive talent. This is largely driven by “Securities and finance dealers and brokers”, and the correlation decreases to 0.17 when this one occupation is excluded (Column (4)). Pay increases and talent change is more or less uncorrelated for the other two talent measures.

[32]Another indication that occupation demand (e.g., via job polarization) is unlikely to explain much of the

finance occupations in the United States.

To summarize, we do not find support for the prediction that the increase in relative finance wages is present only for the highest-paid finance professions that employ the most talented workers. Rising wages are not related to talent increases within finance occupations. Rather, finance wages have increased broadly across occupations regardless of task content, required talent, or finance sector-specificity.

VI Robustness Tests

VI.A Elite University Graduates

We have focused our analysis on using cognitive and non-cognitive scores as measures of talent or (the ability to acquire) skill. These measures have the advantages that (1) their distribution in the population is stable over time, (2) they are pre-determined with respect to career choice, and (3) they are able to capture the right tail of the talent distribution. Nevertheless, in order to compare our findings with other studies on skill demand and wages in the finance sector, we also examine whether educational achievement has evolved differently in finance over our sample period.

In section IV.B we reported that the fraction of Swedish workers with a university degree increased more in finance than in the rest of the economy, similar to what Philippon and Reshef (2012) documented for the U.S.. This finding cannot simply be interpreted as an increase in talent demand, however, since overall educational attainment increased substantially over time, and the average talent of university graduates (as measured for example by cognitive ability) has decreased as a result.

Instead of overall educational attainment, Goldin and Katz (2008), Oyer (2008), Shu (2016), and Célérier and Vallée (2017), consider the fraction of graduates from elite universities going into finance. Although compositional changes can be an issue for these studies as well, e.g. if the size of elite programs has increased over time, the problem

evolution of finance wages is that the correlation between the change in employment share and the change in occupational finance premia is very low: 0.13 for the wage growth relative to non-finance workers across all occupations, 0.10 for the wage growth relative to non-finance workers in the same occupation. Both are statistically insignificant. The increase in finance occupations' relative wages is also not significantly related to their abstract task content. We further find that the employment structure in the finance sector has not polarized more (in terms of abstract and manual task content relative to routine) than other high-skilled sectors such as LCA and IT or the rest of the economy. These results are not explicitly reported for brevity but available upon request.

might be less severe than for studies focusing on educational attainment more broadly. Goldin and Katz (2008) and Oyer (2008) study Harvard undergraduates and Stanford MBAs, respectively, and find that the fraction of graduates going into finance was significantly higher for cohorts graduating around 1990 compared to 20 years earlier. Célérier and Vallée (2017) show that the percentage of engineering graduates working in finance from elite schools (those with students performing in the top 2% on national entry exams) increased from 3% to 8% between 1985 and 2010. The corresponding percentage for engineers across all schools increased much less, from 2% to 4%. They also show that relative wages increased significantly more for the elite engineers in finance compared to the others, which they view as support for the Talent-Competition hypothesis.

Due to the structure of Swedish higher education, elite universities are not as easily identified as in the U.S. or France. We choose to define top graduates as university graduates with a cognitive score of 9. The upper panel of Figure VII shows the fraction among 30-year old male graduates with a top cognitive score who hold a degree in business and engineering for the years 1990 and 2014. Engineering attracts a large fraction of top cognitive male graduates, ranging from 55% to 65% over our sample period. Majors in business constitute around 6% to 9% of top cognitive male graduates.

The middle panel of Figure VII shows the fraction of 30-year old men with top cognitive ability and a degree from business and engineering that work in finance over the same period. The fraction among top cognitive business majors who choose finance is significantly higher than the fraction among top cognitive engineering majors (20% compared to 3% in 2014). The latter is smaller than the fraction of finance workers across all study fields. The fraction of top male business majors working in finance is higher in 2014 than in 1990, and most of this increase took place after 2001. In contrast, the fraction of top business majors going to finance decreased between 1990 and 2000, a period accounting for the bulk of the finance wage premium increase 1990–2014 (Figure V). Hence, there is no consistent evidence that rising finance wages coincided with an increase of top business graduates working in finance.

Similar to Célérier and Vallée (2017), however, we do observe a steady rise in the fraction of top engineers entering finance, from around 1% in 1990 to 3% in 2014. Although this is a significant increase relative to the baseline, the economic magnitude is modest. To put this in perspective, we can observe that the fraction of top engineering talent going to the IT sector increased from less than 10% in the early 1990s to almost 30% in the early 2000s and has remained at this level ever since.[33] The bottom panel of Figure VII shows that the average non-cognitive and leadership skills of the most cognitively talented university graduates are declining over time. This decline is substantial (ca 25-33% of a standard deviation) and might be a result of compositional changes following the expansion of university programs (including elite ones), which we discussed previously.

Finally, in Figure VIII, we repeat the analysis of relative wages by talent from Figure VI but condition the sample on holding a university degree, having a business major, or having an engineering major. Except for university graduates with higher talent earning higher relative wages in finance during market peaks, there is little evidence that the wage difference across talent groups has increased over time.

To summarize, adding education as another dimension of talent does not provide much additional support for the predictions from the Talent-Competition Hypothesis. But these results do help us to reconcile our evidence with the seemingly different conclusion of Célérier and Vallée (2017). We show that their finding that increasing fraction of elite engineers have gone to the finance sector is also true for Sweden. We find that the fraction seems too small, however, to have any significant impact on the talent allocation and evolution of the finance premium in the overall economy.

VI.B Migration

Major financial centers, such as the City of London or Wall Street, tend to attract a significant number of foreign workers. Using data on bilateral migration flows between 16 OECD countries (including Sweden, the U.S., and the U.K.) for the year 2000, Boustanifar, Grant, and Reshef (2017) show that the wage gap in finance between two countries predicts emigration of financial workers from the lower- to the higher-wage country, and this relationship is particularly strong for workers with a university education. This suggests that the Talent-Competition Hypothesis might receive more empirical support if migration is taken into account. In particular, it may be the case that demand for talent has indeed increased in finance but that the most talented finance workers have been hired by employers outside of Sweden. The surge in Swedish financial wages might then have been exacerbated by Swedish financial firms raising compensation levels to prevent

[33]The figure is not included for brevity, but we are happy to provide them upon request.

their most talented workers from being poached away by foreign employers.

Unfortunately, our main dataset, LISA, only contains information on individuals while they are residents of Sweden. As a result, we might not detect an increase in the relative talent of finance workers if the most talented individuals take up finance jobs outside of Sweden. To investigate the importance of emigration for our results, we first identify individuals who emigrate using Statistics Sweden's migration register. We observe that a substantial fraction of emigrants disappear from LISA a few years before their official migration date, which suggests that migration status is registered with a lag. We therefore use the first year after the emigrant last appears in LISA as our proxy for migration year. Although the migration register reports the destination country, we do not observe where (and whether) an individual is employed after emigrating. To proxy for the post-migration sector of employment, we use the last sector in which the individual worked before migrating. We then assume that an emigrant works in the financial sector abroad if he or she worked in finance in Sweden before migrating.[34]

In order to assess the quantitative impact of emigration on the relative talent distribution, we then add back emigrants to the worker panel for the years they stay abroad and repeat the tests of Section IV.D using this new sample.[35] Figure IX reveals that financial sector's relative talent distribution remains essentially unchanged. In particular, when comparing the share of each group of cognitive and non-cognitive ability among finance workers to the rest of the economy, we find no increase in the representation of high talent individuals (levels 6 to 9).

There are two reasons for why the relative talent results do not change compared to before. First, the group of emigrants is relatively small and they therefore only have a very minor effect on the overall talent distribution. Second, even though finance emigrants are on average more talented, the relative finance versus non-finance share emigrating from

[34]As a robustness check, we assume that individuals who have worked in finance at any time during the last three years before migrating obtain a position in the financial sector abroad. One advantage of this approach is that we also include university graduates whose first full-time job is in the non-Swedish financial sector to the extent to which they have had finance work experience in Sweden before graduating, such as a paid summer internship or part-time job.

[35]We make the simplifying assumption that emigrants keep working in the sector of their last employment until they either retire or return to Sweden. We observe that between 15,000 and 20,000 Swedes emigrate each year (about 1 in 200 of the working population). While the propensity to emigrate is relatively low in a given year, the flow of emigrants accumulates to a substantial stock over time, amounting to approximately 4% of the Swedish workforce living abroad at any given point in time. This number decreases to about 3% if we classify emigrants based on the official migration year rather than the year after leaving LISA.

each talent group is fairly constant over time.

It also seems unlikely that foreign competition for talented labor is the main driver of the increasing Swedish finance premium. Table III showed that relative finance wages have increased across most occupations, including jobs (e.g. doorkeepers, teller clerks, and office secretaries) that should not be subject to talent poaching concerns.[36]

VI.C Sweden versus the U.S.

In Appendix D, we replicate our Swedish evidence for the U.S. to the extent available data permits. We analyze U.S. finance sector growth, evolution of relative wages and employment share (including the gender composition), working hours, subsector composition and pay, and wage dynamics across finance occupations. The analysis reveals that the patterns in the U.S. and Sweden are very similar, which we believe strengthens the external validity of our results.

VII Discussion and Conclusion

This study was motivated by the dramatic increase of relative finance wages over the last couple of decades. We have addressed one of the leading candidates for explaining this increase, which we denote the "Talent-Competition Hypothesis". According to this explanation, the productivity of the most talented workers rose more in finance than in other sectors, which lead to an increased demand for talent from the financial sector and pushed up wages. Using Swedish population-wide register data, with individual-level measures of cognitive and non-cognitive skill and uncensored wage information, we do not find any support for this explanation. Relative talent of workers in the financial industry has not increased, neither on average nor at the top of the talent distribution. At the same time, relative wages in the financial sector have surged across the entire talent distribution, and there is no sign that the wage gap between more and less talented workers has widened. We also show that many lower-level jobs in the financial sector,

[36]In addition or as an alternative to Swedish finance workers emigrating, there could also be foreigners increasingly entering finance jobs in Sweden. If they arrive after age 18 or 19, we would have no talent information from military enlistment or high school for these individuals. The analyses of Section V, including fixed effects estimations and detailed occupational tests, however apply and yield the same results when we do not condition the sample on early talent measures. More generally, if the (relative) labor supply to Swedish finance increases over time due to immigration, we would expect to see rising employment, falling wages, and probably rising talent in this sector – exactly the opposite of what is observed in our data.

where competition for talent seems less likely, have experienced significant increases in relative wages. Apart from being inconsistent with the Talent-Competition Hypothesis, these findings alleviate concerns about a "brain drain" into the financial sector at the expense of other sectors.

One potential criticism against the talent measures we employ is that they might not be able to capture the characteristics that are relevant for worker productivity in the financial industry. For instance, the characteristics that make someone a great trader or investment banker might not be well measured by cognitive or non-cognitive skill, or by high-school grades. Moreover, these relevant skills might only be acquired or discovered "on the job", as in Gibbons, Katz, Lemieux, and Parent (2005) and Terviö (2009). While this possible, we believe a few comments are in order. First, our results indicate that the aspects of talent we measure are indeed highly valued in finance: individuals with high cognitive and (even more so) with non-cognitive abilities are overrepresented among finance workers, and relative wages are positively related to talent. The lack of support for the Talent-Competition Hypothesis comes from the fact that these differences should be *increasing* over time, which they are not. Second, if the increase in the relative wages in the financial sector is driven by some other unobserved and/or acquired skill, which is becoming increasingly rewarded over time, this skill would have to be uncorrelated with our observable talent measures.[37] In that case, however, "brain drain" to the financial sector (along the lines of Murphy, Shleifer, and Vishny, 1991) would be much less of a concern, since demand for this characteristic would not increase the competition for the cognitive and non-cognitive talents that makes a worker productive in other sectors. Moreover, as Terviö (2009) shows, when talent is industry-specific and only revealed on the job, the financial sector can end up with a sub-optimally low talent pool, i.e., the opposite of the "brain drain" prediction.

A related concern is that people might deliberately underperform on their military aptitude tests, which would make our talent measures less informative. We showed, however, that our measures predict both whether an individual enters finance as well as his relative compensation. Hence, the cognitive and non-cognitive scores we use contain rele-

[37]When discussing our results with a high-level manager at one of the Nordic banks, he commented: "I have been thinking about what the most successful people in our bank have in common. They are not the smartest people. They are not the nicest people. But they are the ones who really, really like to make money." Such a characteristic might of course be uncorrelated with our talent measures.

vant information about characteristics valued in the labor market, consistent with earlier literature using these scores (e.g., Lindqvist and Vestman, 2011). We believe that there are good reasons for this. In Sweden, military service assignment was one of the factors that potential employers considered in hiring decisions. The most attractive and prestigious positions, which were the most highly valued in the labor market subsequently, required top scores on cognitive and non-cognitive tests. In addition, many of these prestigious military service positions – e.g. serving as a reserve officer in the navy – are particularly common among public company CEOs and other top business people in Sweden, and are likely to provide important networks that help forward a person's future career. While we cannot rule out that some individuals still deliberately performed badly, to change the interpretation of our results it would have to be that (1) faking it is more common among people ending up working in finance, and (2) faking would have to increase as wages increase. We find these assumptions quite implausible, especially since networks might be particularly important for landing a finance job, as we discuss below.

While the presence of unobserved skills is hard to test empirically, alternative explanations for the rising relative finance wages might be easier to address. One such explanation is that finance jobs have become less attractive over time, e.g., due to longer hours, unpleasant side effects on health or happiness, or increased earnings risk, which forces financial firms to compensate workers with higher wages. In ongoing work (Böhm, Metzger, and Strömberg, 2017), we test some of the implications from this hypothesis, but find weak support. When looking at measures of earnings risk, such as earnings volatility or likelihood of unemployment, we find no indication that finance has become riskier over our sample period, similar to what Bell and Van Reenen (2013) found for the U.K. While finance wages are more dispersed than non-finance wages, we find that this is driven by a higher likelihood of unusually high earnings growth, while the risk of unusually low earnings growth or unemployment risk is actually lower in finance than in other sectors. We also consider other life outcomes, such as marriage and divorce rates, number of children, and days of sick leave, and find these measures to be stable (or improving) in the financial sector compared to the rest of the population.

A remaining explanation that is consistent with our results is that increasing excess profits of financial firms have resulted in rents being shared with workers, e.g., because of moral hazard (Axelson and Bond, 2015; Biais and Landier, 2015), fairness concerns, (Akerlof and Yellen, 1990) or poor governance (Bebchuk, Cohen, and Spamann, 2010; Bivens and Mishel, 2013).[38] In other words, when financial firms experience higher profits, a fraction of these profits are shared with the employees of these firms, regardless of their productivity. This rent-sharing explanation still raises the question of why talented workers are not increasingly drawn to the sector, as predicted by Murphy, Shleifer, and Vishny (1991). One reason could be that individuals are not very sensitive to wages when choosing their career. Another reason could be that individuals are not able to freely enter the financial sector. For example, it could be the case that interested candidates need to have the right contacts or belong to certain networks in order to land a job in the financial sector. The finding that individuals with parents in the financial sector are more likely to enter finance themselves seems be consistent with this explanation. This interpretation is supported by the findings in Chuprinin and Sosyura (forthcoming) that mutual fund managers with rich parents are more likely to be promoted, despite underperforming those with poor parents on average. We believe that the analysis of wages, firm profits, and networks in the financial sector is a promising area for future research.

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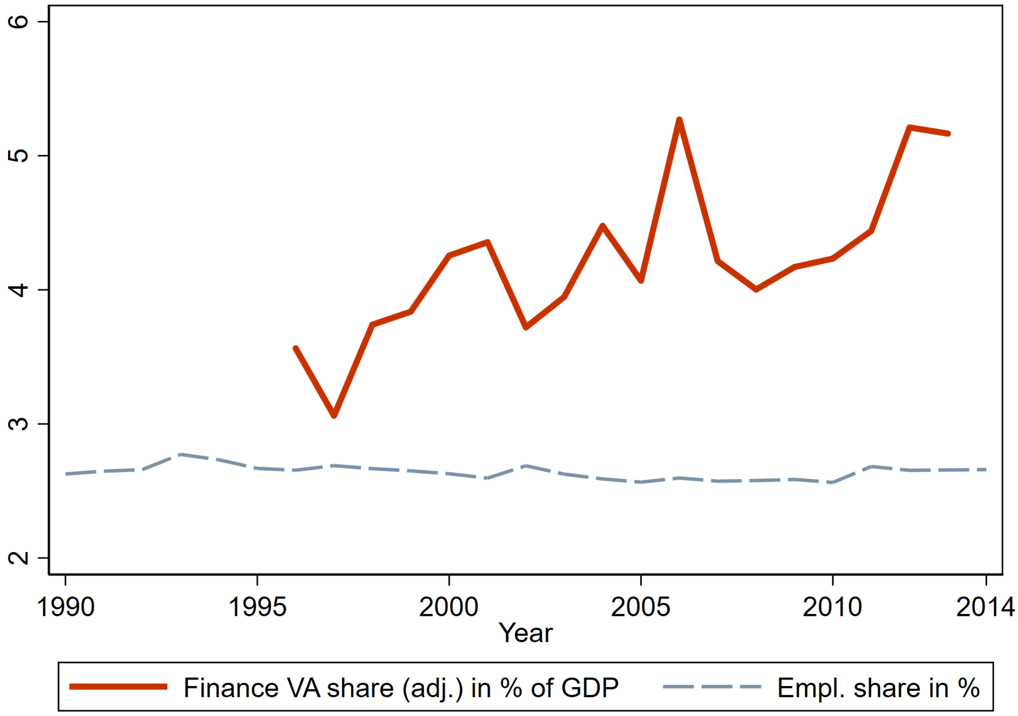
VIII Figures

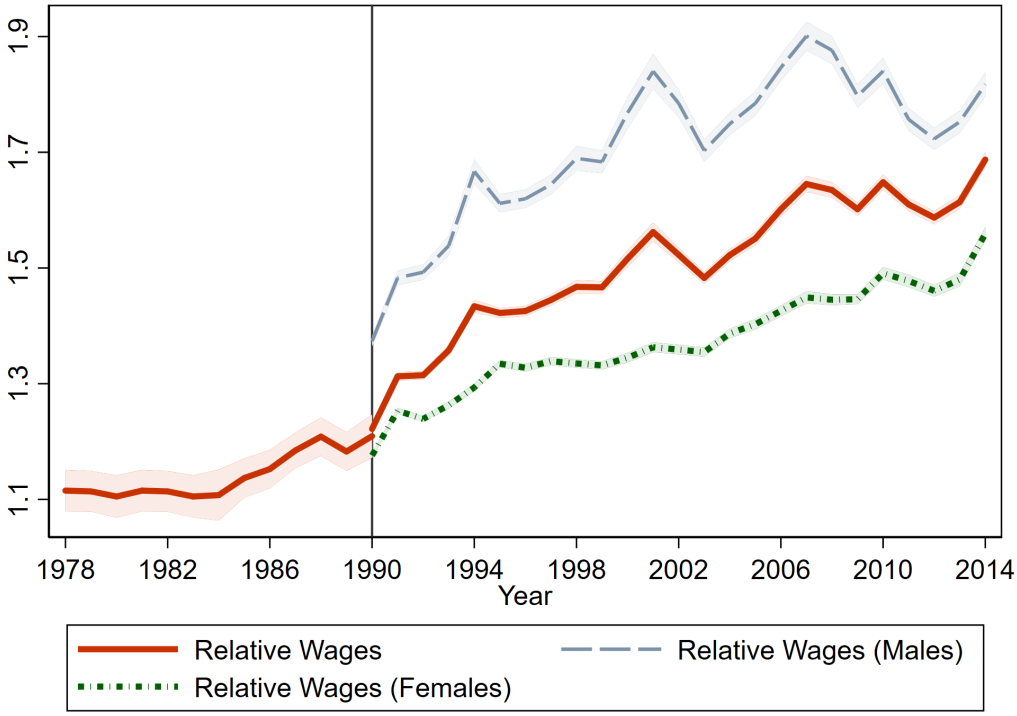
Figure I: Value Added and Employment Share of the Financial Sector



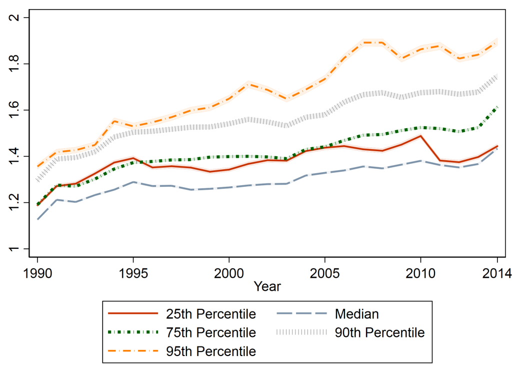
The figure describes the evolution of value added as a percentage of GDP and the employment share in finance, defined as the ratio of the number of employees in the financial sector to the number of employees in the non-financial, non-farming private sector. Value added has been adjusted as described in Bazot (2017). Sources: Swedish population data LISA and national accounts / operating income of banking subsector from Statistics Sweden.

Figure II: Relative Wages in the Financial Sector

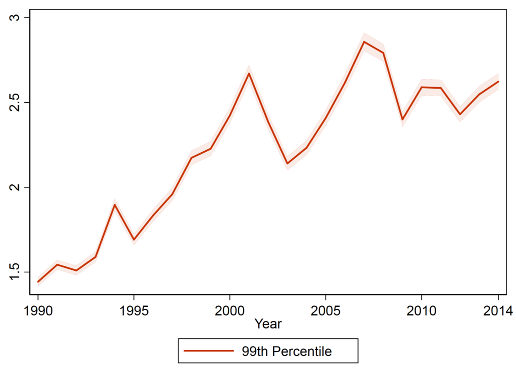
(a) Relative Wages



(b) Relative Wages (Percentiles)

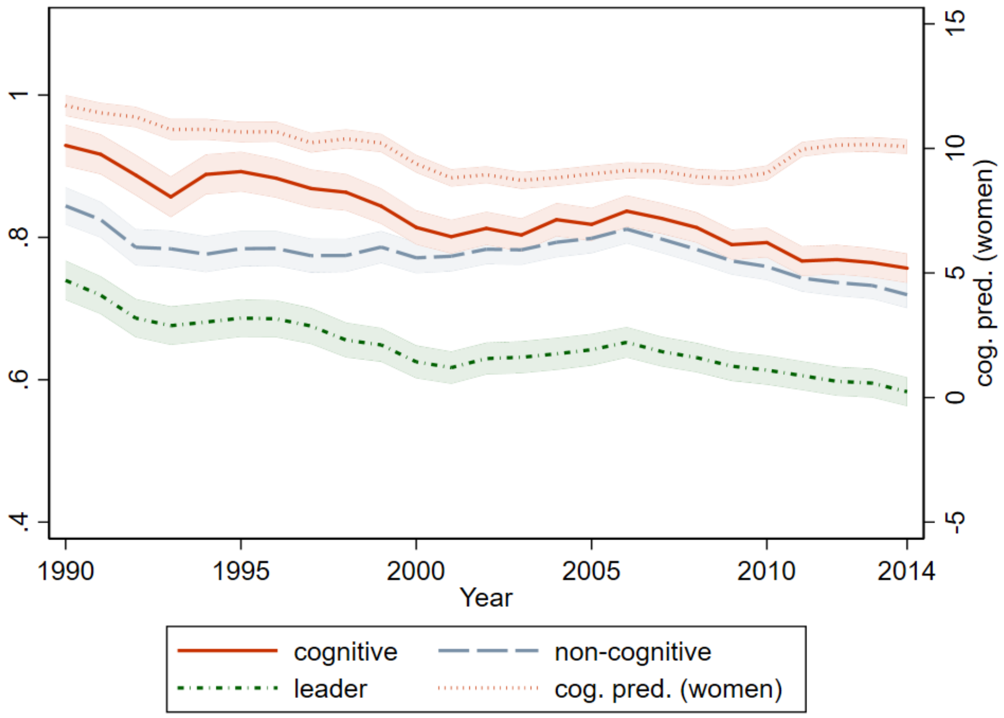


(c) Relative Wages (99th Percentile)



The figures describe the evolution of relative wages in finance, defined as the ratio of wages in finance to wages in the non-financial, non-farming private sector. Panel (a) shows relative average wages during 1978–2014. The period between 1978 and 1989 uses a representative administrative sample of 3–4% of the Swedish population (LINDA). The period between 1990 and 2014 uses the full Swedish population data (LISA). Gender-specific relative wages are displayed for the full sample. Panel (b) depicts the relative quantiles of the wage distribution in the Swedish financial sector, i.e., the ratio between the percentile in finance and the respective percentile in the non-financial, non-farming private sector. The 99th percentile is displayed with a different scale in Panel (c). Sources: Swedish population data LISA and 3–4% sample LINDA. 95 percent confidence intervals are shaded.

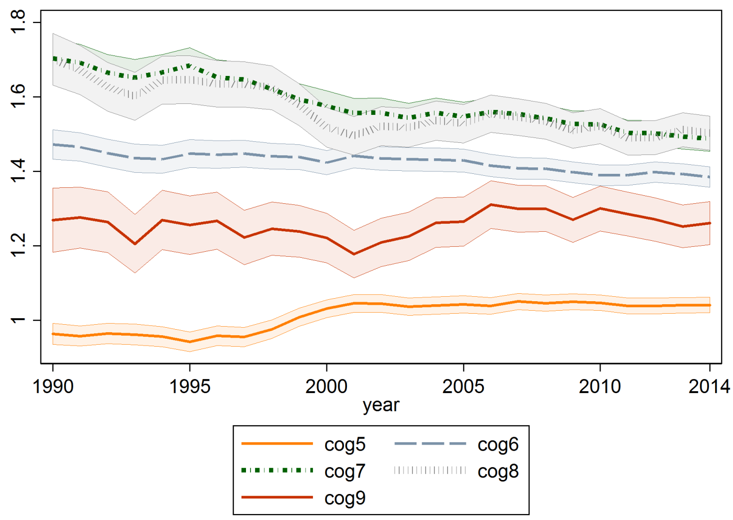
Figure III: Relative Talent in the Financial Sector



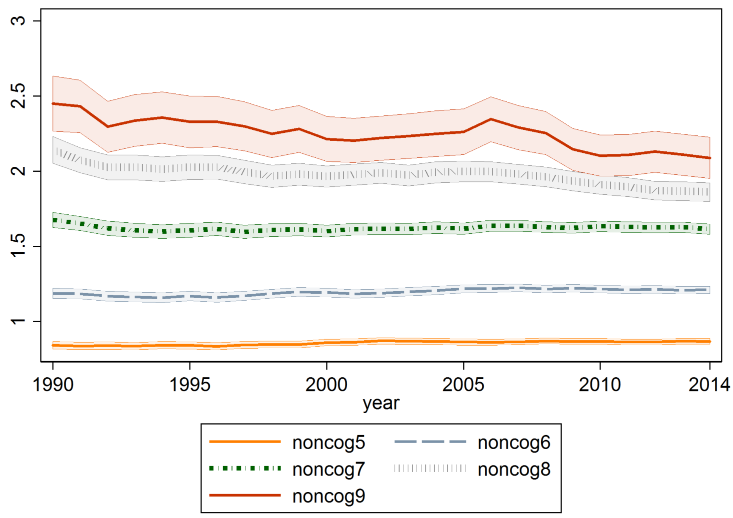
The figure shows the evolution of relative talent in finance, i.e., average talent in finance minus the corresponding average in the rest of the economy, during 1990 to 2014. The left y-axis displays the relative talent for cognitive ability, non-cognitive ability, and leadership for men, while the right y-axis displays relative predicted cognitive ability for women. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

Figure IV: Relative Distribution of Talent in the Financial Sector

(a) Cognitives



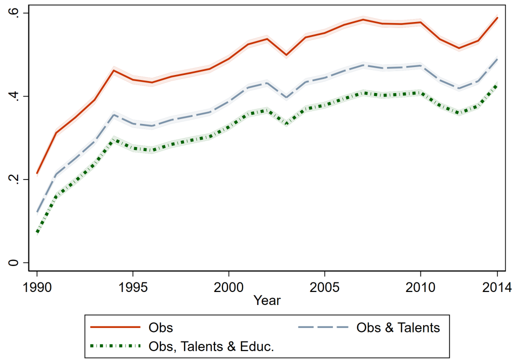
(b) Non-Cognitives



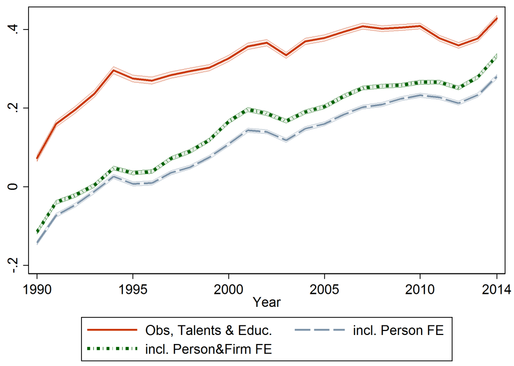
The figure shows the evolution of relative shares of medium and high talent levels in the financial sector during 1990 to 2014. Relative shares are calculated as the share of individuals with a specific talent level in finance divided by the corresponding share in the rest of the economy. Panel (a) employs cognitive ability as a talent measure, while Panel (b) uses non-cognitive ability. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

Figure V: Wage Premium of the Financial Sector

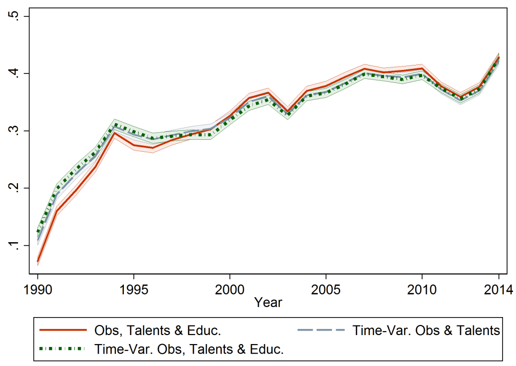
(a) OLS (Males)



(b) Fixed effects (Males)



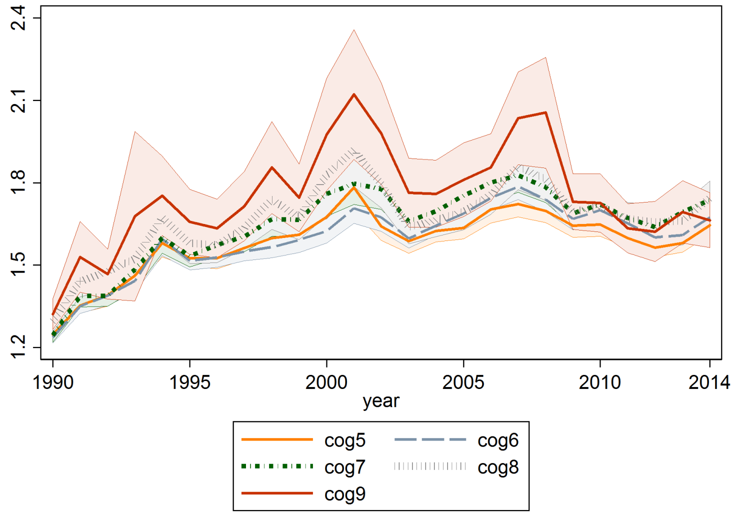
(c) Time-varying OLS (Males)



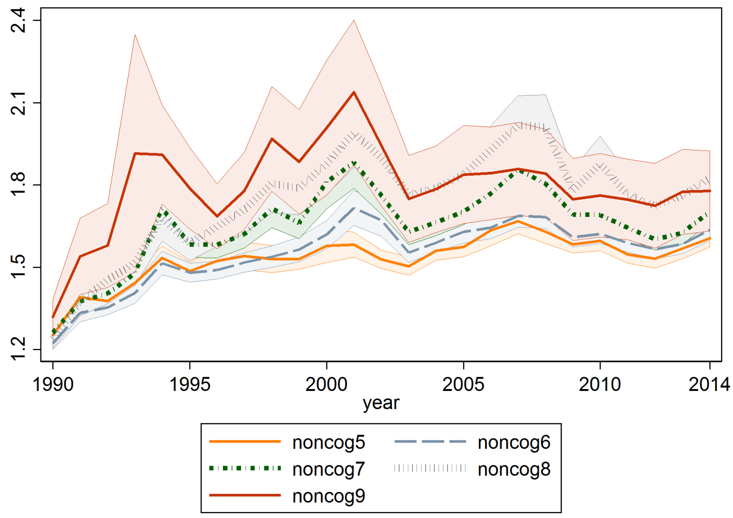
The figure in Panel (a) shows the remaining finance wage premium after controlling for observed and unobserved skills as well as for other variables in linear regressions. Three models are estimated: (i) controls for potential experience, (ii) controls for potential experience and talent, and (iii) adds education (years of schooling). The sample consists of males only, and talent is measured by cognitive and non-cognitive test scores. Panel (b) adds individual fixed effects and individual-firm fixed effects to (iii). Panel (c) allows for time-varying returns to experience, talent, and education. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency. 95 percent confidence intervals are shaded.

Figure VI: Relative Wages in the Financial Sector by Talent Group

(a) Cognitive Skills (Males)



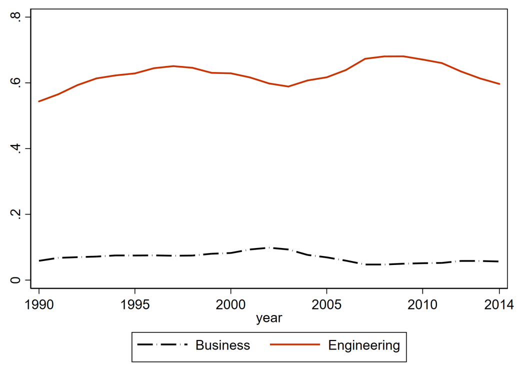
(b) Non-cognitive Skills (Males)



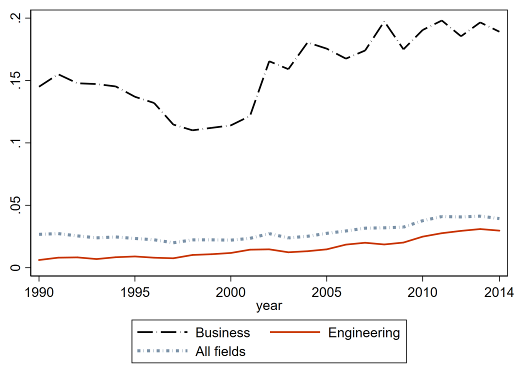
The figure shows relative finance wages by cognitive and non-cognitive talent group for medium and high talent males during 1990–2014. Relative finance wages are defined as the average wages in finance of the respective talent score divided by the average wages outside finance of the same talent score. Panel (a) shows results for cognitive skills and Panel (b) for non-cognitive skills. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency. 95 percent confidence intervals are shaded.

Figure VII: Fields at University

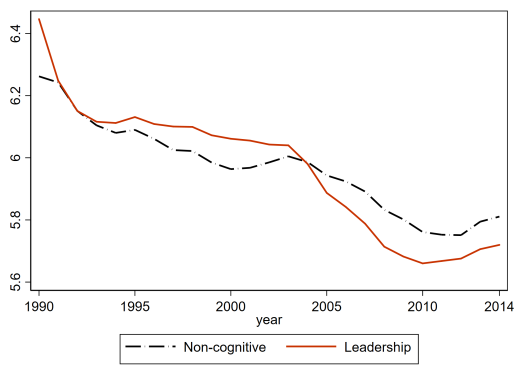
(a) Fields at University



(b) Financial Sector Workers



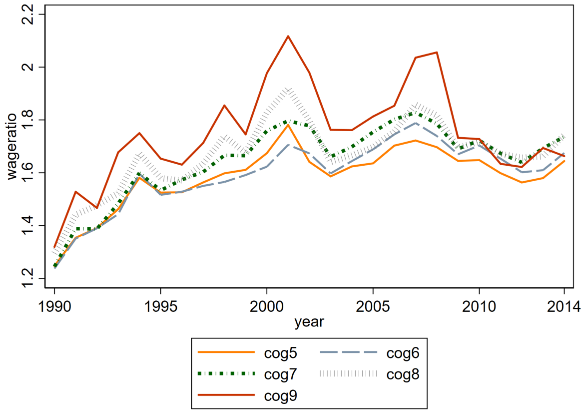
(c) Average Non-cognitive and Leadership Skills



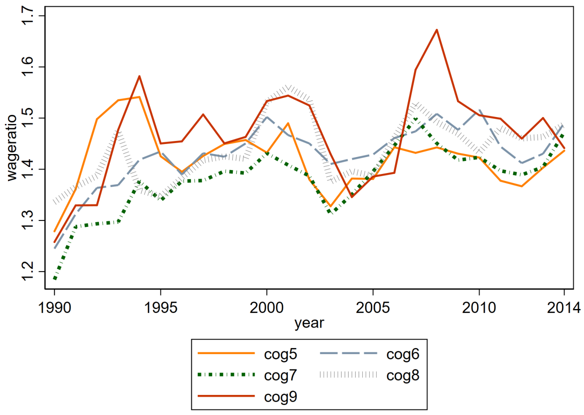
The figure depicts the study fields and sectors of employment for 30 year old male university graduates with highest cognitive ability (score of 9) during 1990 to 2014. Panel (a) shows the fraction of these individuals with a degree in "Engineering" or "Business Studies". Panel (b) displays the fraction of highest cognitive graduates (across all fields, from engineering, and from business studies) who are working in the financial sector. Panel (c) shows the average non-cognitive and leadership skills of these individuals over time. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish university register.

Figure VIII: Relative Wages in the Financial Sector by Talent Group and Field at University

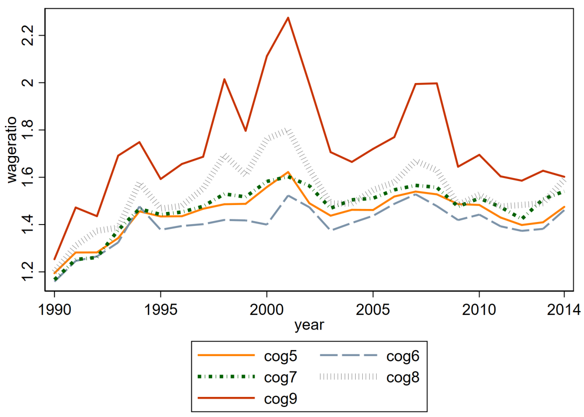
(a) All Fields



(b) Engineering



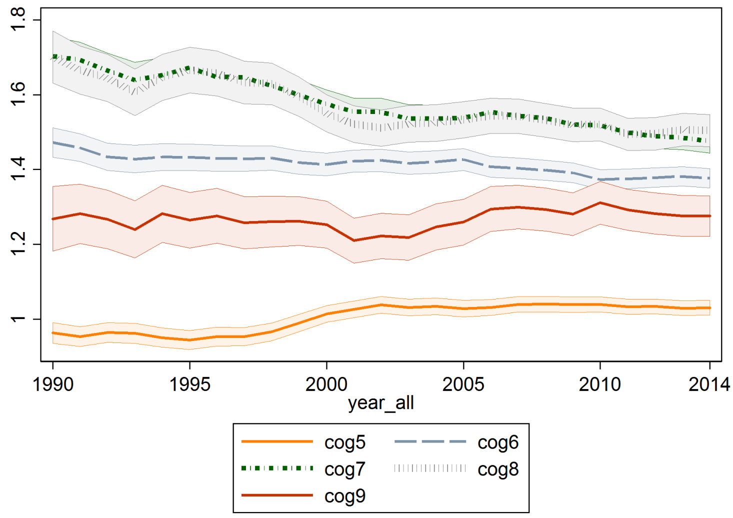
(c) Business Studies



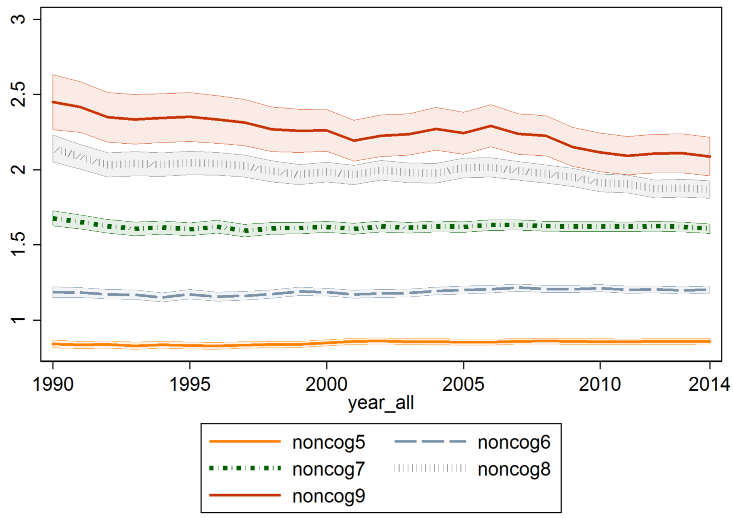
The figure shows the finance earnings premium of medium and high talent males over the period 1990 to 2014 for graduates from different fields at university. Panel (a) includes all university graduates regardless of their fields. Panel (b) focuses on graduates with an engineering degree and Panel (c) on those with a degree in business studies. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish university register.

Figure IX: Distribution of Relative Talent in Financial Sector Including Emigrants

(a) Cognitives (Men)



(b) Non-Cognitives (Men)



The figure shows the evolution of relative shares of medium and high talent levels in the financial sector during 1990 to 2014. Relative shares are calculated as the share of individuals with a specific talent level in finance divided by the corresponding share in the rest of the economy. Panel (a) employs cognitive ability as a talent measure, while Panel (b) uses non-cognitive ability. Emigrating workers are added back to the sample. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency. 95 percent confidence intervals are shaded.

IX Tables

Table I: Linear Probability Sector Choice Regressions (Males, 30 Years Old)

Linear in talent	**(1)**	**(2)**	**(3)**	**By talent group**	**(4)**	**(5)**
Years of School (1990-94)		**0.671***	**0.381***	**Yrs of Sch (1990-94)**		**0.720***
difference in 1995-99		-0.020	0.047	diff. in 1995-99		-0.045
difference in 2000-04		0.083	0.215*	diff. in 2000-04		0.019
difference in 2005-09		0.057	0.210*	diff. in 2005-09		0.000
difference in 2010-14		0.209*	0.305*	diff. in 2010-14		0.138*
Cognitive Talent (1990-94)	**0.345***	**-0.034**	**-0.028**	**Mid cogn talent (5-8)**	**1.92***	**0.81***
difference in 1995-99	-0.075*	-0.085*	0.024	diff. in 1995-99	-0.16	-0.08
difference in 2000-04	-0.073*	-0.158*	-0.320*	diff. in 2000-04	-0.44*	-0.63*
difference in 2005-09	-0.043	-0.073	-0.208*	diff. in 2005-09	-0.23	-0.31*
difference in 2010-14	-0.001	-0.083	-0.205*	diff. in 2010-14	-0.40*	-0.56*
Non-cogn. Talent (1990-94)	**0.650***	**0.504***	**0.276***	**High cogn talent (9)**	**0.92***	**-1.84***
difference in 1995-99	0.001	-0.001	-0.033	diff. in 1995-99	-0.17	0.02
difference in 2000-04	-0.102*	-0.124*	0.034	diff. in 2000-04	0.02	-0.01
difference in 2005-09	-0.072	-0.058	0.088	diff. in 2005-09	0.20	0.53
difference in 2010-14	-0.220*	-0.197*	-0.035	diff. in 2010-14	1.08*	1.26*
Father Ever in Finance			**1.733***	**Mid non-cogn t (5-8)**	**1.46***	**0.95***
difference in 1995-99			0.204	diff. in 1995-99	-0.05	-0.02
difference in 2000-04			1.566	diff. in 2000-04	-0.07	-0.12
difference in 2005-09			2.617*	diff. in 2005-09	0.07	0.09
difference in 2010-14			3.299*	diff. in 2010-14	-0.32*	-0.25
Mother Ever in Finance			**0.306**	**High non-cogn t (9)**	**4.33***	**3.07***
difference in 1995-99			1.317	diff. in 1995-99	-0.93	-0.81
difference in 2000-04			1.885*	diff. in 2000-04	-1.28	-1.17
difference in 2005-09			2.529*	diff. in 2005-09	-1.17	-0.87
difference in 2010-14			2.020*	diff. in 2010-14	-2.09	-1.64
N	808,213	807,590	417,429	**N**	808,213	807,590
R-sq	0.007	0.014	0.039	**R-sq**	0.006	0.014
adj. R-sq	0.007	0.014	0.039	**adj. R-sq**	0.006	0.014
Father & Mother Total Inc.	No	No	Yes	**Fthr & Mthr Total Inc.**	N/A	N/A
Graduation Municip. FE	No	No	Yes	**Grad. Municip. FE**	N/A	N/A

Notes: The table shows linear probability regressions of choosing finance (indicator multiplied by 100) for 30 year old males over time. The left panel uses as regressors linear cognitive and non-cognitive talent interacted with 5-year period dummies. Column (2) adds years of schooling and Column (3) adds dummies for whether the individual's father and mother ever worked in finance during the sample period, their total annual income, and fixed effects for the individual's municipality of residence when they graduated from high-school. The right panel uses dummies for low (1–4; base group), (upper-)middle (5–8), and high (9) cognitive and non-cognitive talent groups. Robust standard errors are clustered on individual (not reported for brevity, significance at 1% level indicated by a single *).

Table II: Finance Premium Overall and By Talent Group (All Ages)

	Overall (1)	(2)	(3)	(4)	By talent group (Males Only)	(5)	(6)
Fin Prem (log pts; Male)	**20.3***	**-1.2***	***absorbd***	**1.2**	**Fin. Prem. (log pts)**	**15.9***	***absorbd***
difference in 1995-99	5.2*	5.8*	6.5*	6.5*	diff. in 1995-99	0.8	5.3*
difference in 2000-04	8.9*	13.1*	13.7*	14.1*	diff. in 2000-04	0.6	9.2*
difference in 2005-09	12.4*	17.8*	17.9*	18.4*	diff. in 2005-09	4.7*	11.7*
difference in 2010-14	12.3*	20.4*	19.8*	20.8*	diff. in 2010-14	7.9*	16.0*
Fin Prem (log pts; Fmle)	**16.7***	**-2.3***	***absorbd***	**3.1***	**Fin×Mid cogn (5-8)**	**3.7***	***absorbd***
difference in 1995-99	3.5*	4.3*	5.3*	5.5*	diff. in 1995-99	1.6	-0.3
difference in 2000-04	7.2*	10.5*	11.3*	11.4*	diff. in 2000-04	4.6*	0.6
difference in 2005-09	10.5*	14.7*	14.8*	15.1*	diff. in 2005-09	3.3*	-0.2
difference in 2010-14	11.2*	17.4*	15.8*	16.5*	diff. in 2010-14	1.9	-1.6
Fin Prem (log pts; Both)	**17.7***	**-3.0***	***absorbd***	**1.0**	**Fin×High cogn (9)**	**10.3***	***absorbd***
difference in 1995-99	4.0*	4.9*	5.8*	5.8*	diff. in 1995-99	0.2	-3.8
difference in 2000-04	7.7*	12.2*	13.1*	13.1*	diff. in 2000-04	5.3*	-2.5
difference in 2005-09	11.0*	17.2*	17.7*	17.5*	diff. in 2005-09	2.6	-4.5
difference in 2010-14	10.8*	20.4*	19.9*	19.7*	diff. in 2010-14	-3.5	-9.1*
					Fin×Mi n-cog (5-8)	**1.2**	***absorbd***
					diff. in 1995-99	4.1*	2.3*
					diff. in 2000-04	6.0*	6.0*
					diff. in 2005-09	6.8*	9.0*
					diff. in 2010-14	4.6*	7.9*
					Fin×Hi non-cog (9)	**12.8***	***absorbd***
					diff. in 1995-99	4.6	1.8
					diff. in 2000-04	4.0	1.0
					diff. in 2005-09	2.7	1.1
					diff. in 2010-14	1.2	-2.0
Years of School	Yes	Yes	Yes	Yes	**Years of School**	Yes	Yes
Pot. Exp. (Quadratic)	Yes	Yes	Yes	Yes	**Pot. Exp. (Quadr)**	Yes	Yes
Fixed Effects	No	Ind.	Ind.×Sec	I.×Firm	**Fixed Effects**	No	Ind.×Sec
N (in million; Male)	24.9	24.9	24.9	24.1	**N (million; Male)**	24.9	24.9
N (in million; Fmle)	18.6	18.6	18.6	17.8			
N (in million; Both)	39.4	39.4	39.4	37.9			

Notes: The table shows results from regressing log earnings (multiplied by 100) on a finance dummy interacted with 5-year period dummies ("the finance premium in log points") for individuals of all ages. The left panel uses as controls linear cognitive and non-cognitive talent (or predicted cognitive ability plus gender dummy where appropriate) and adds individual (Column (2)), individual interacted with sector (Column (3)), and individual interacted with firm (Column (4)) fixed effects. The right panel computes the premium interacted with low (1–4; base group), (upper-)middle (5–8), and high (9) cognitive and non-cognitive talent groups for males. Robust standard errors clustered on individual (not reported for brevity, significance at 1% level indicated by a single *).

Table III: Occupational Employment, Talent, and the Finance Wage Premium in Sweden (30 largest 4-digit occupations in finance)

Panel A

	Rel.pay (/ all workers)		**Fin. empl. share (%)**		**Pred.cognitive score**		**Rel.pred-cogn (/ same occ)**		**Rel.pay (/ same occup)**	
	2010	*2010-1990*	*2010*	*2010-1990*	*2010*	*2010-1990*	*2010*	*2010-1990*	*2010*	*2010-1990*
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Securities and finance dealers and brokers	4.12	2.64	2.04	1.86	72.4	9.0	N/A	N/A	N/A	N/A
Directors, CEOs, or managers of business services enterprises	3.44	0.68	3.66	-0.11	68.9	0.9	1.01	-0.12	1.17	-0.09
Sales and marketing managers	3.29	1.04	0.60	0.41	68.4	4.1	1.03	-0.01	1.36	0.20
Finance and administration managers	3.14	0.87	0.67	-0.03	73.6	1.2	1.05	-0.01	1.39	0.13
Business professionals not elsewhere classified	2.96	1.28	4.41	1.81	74.1	1.1	1.04	-0.03	1.82	0.60
Corporate legal officers	2.44	0.71	0.99	-0.04	79.8	2.5	1.01	0.01	1.29	0.40
Organisational analysts	1.91	0.12	0.80	0.66	72.2	9.4	0.97	0.08	1.10	0.03
Market research analysts and related professionals	1.85	0.03	1.56	0.95	67.1	-3.2	0.99	-0.05	1.23	0.10
Technical and commercial sales representatives	1.84	0.53	2.04	1.61	59.6	-2.6	1.15	0.03	1.33	0.32
Computing professionals not elsewhere classified	1.83	-0.01	3.51	2.93	70.8	1.6	1.07	0.13	1.22	0.09
Accountants	1.83	0.30	1.91	1.28	68.7	-5.9	1.00	-0.02	1.28	0.21
Personnel and careers professionals	1.79	0.34	0.66	0.27	66.3	-0.8	1.12	-0.01	1.48	0.24
Computer systems designers, analysts and programmers	1.66	0.08	3.23	0.88	68.9	-2.9	0.95	0.01	1.13	0.05
Authors, journalists and related professionals	1.57	0.08	0.60	0.32	67.9	-2.4	0.99	0.00	1.35	0.18
Finance and sales associate professionals	1.54	0.37	0.56	0.29	61.4	-3.5	1.20	0.10	1.28	0.23
Insurance representatives	1.47	0.12	11.71	-1.39	54.9	-3.7	N/A	N/A	N/A	N/A
Computer assistants	1.46	-0.06	1.89	1.54	55.5	-9.2	1.02	0.10	1.22	0.14
Bookkeepers	1.43	0.46	1.34	1.05	66.1	-0.9	1.12	-0.01	1.32	0.31
Computer equipment operators	1.42	0.26	0.66	-0.21	60.9	8.6	1.14	0.16	1.22	0.13
Banking associate professionals	1.34	0.30	32.23	-12.69	61.5	-1.0	N/A	N/A	N/A	N/A
Office secretaries	1.28	0.27	0.84	-1.53	54.0	1.4	1.28	0.17	1.57	0.40
Administrative secretaries and related associate professionals	1.26	0.06	2.10	0.78	57.7	-0.7	1.05	0.03	1.26	0.15
Appraisers, valuers and auctioneers	1.23	-0.02	5.18	2.20	52.5	-6.5	0.94	-0.04	1.17	0.16
Public service administrative professionals	1.07	0.00	0.91	0.67	58.3	5.1	0.91	0.07	0.94	0.00
Numerical clerks	1.06	0.04	1.23	-0.26	53.9	-3.7	1.11	0.07	1.20	0.08
Doorkeepers and related workers	0.99	0.12	0.52	-0.15	42.1	-3.5	0.97	-0.12	1.43	0.36
Other office clerks	0.93	0.09	2.30	-4.26	54.7	6.4	1.14	0.05	1.13	0.09
Telephone switchboard operators	0.75	-0.03	0.72	-0.08	47.8	4.7	1.11	0.08	1.12	0.07
Tellers and other counter clerks	0.64	-0.11	1.76	-0.75	58.6	1.6	0.98	-0.13	1.15	0.26
Helpers and cleaners in offices, hotels, etc	0.52	-0.03	0.21	-0.64	43.8	0.5	1.40	0.05	0.87	0.00

Panel B

	Correlation relative pay and talent in 2010		**Corr. of changes in relative pay and talent 1990-2010**		
Talent measure	*wage relative to all non-fin. workers*	*finance wage premium within occupation*	*relative to all non-fin. workers*	*all excl "Dealers and Brokers"*	*within occupations*
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Cognitive	0.622	-0.046	0.102	0.055	0.092
	(0.000)	(0.820)	(0.592)	(0.778)	(0.648)
Non-cogn.	0.807	-0.088	-0.089	-0.093	-0.098
	(0.000)	(0.663)	(0.638)	(0.631)	(0.628)
Predicted cognitive	0.742	0.009	0.378	0.166	-0.124
	(0.000)	(0.966)	(0.039)	(0.390)	(0.534)

This table shows employment, talent, and earnings of the 30 largest (4-digit SSYK96 codes, 354 in total) occupations in finance, constituting 90.65 percent of finance employment on average between 1990 and 2010. Each occupation's share of finance employment, average and relative predicted cognitive ability, relative pay versus all workers and workers in the same occupation outside finance, as well as their changes between 1990 and 2000, are reported. Source: Swedish census and population data LISA from Statistic Sweden. Panel B shows pairwise correlations, with p-values in parentheses.

“Since you’re so rich, you must be really smart”: Talent and the Finance Wage Premium External Appendix

Michael Böhm, Daniel Metzger, and Per Strömberg

This version: February 2018

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A Simple Model of Talent Selection and Wages

This appendix discusses a simple model of selection into the finance sector which can be used to motivate key steps in our empirical analysis.

Assume there are two sectors, finance and the real economy, denoted by $k \in \{F, R\}$, that produce under a constant returns production function with one input, labor. Under perfect competition in labor and output markets, worker i's potential (log) wage in sector k at time t is equal to his marginal productivity:

$$w_{kit} = \alpha_{kt} + l_{kit} = \alpha_{kt} + \beta'_{kt}\theta_i + \varepsilon_{ki} \tag{5}$$

where α_{kt} is sector k's (log) labor productivity and l_{kit} are (log) efficiency units of labor that i can provide to that sector. We specify l_{kit} as a function of the vector of the worker's talents θ_i mapped into efficiency units in the sector via β_{kt} plus an error ε_{ki}. This error may contain transitory deviations from expected output, as well as the effect of unobserved components of talent. To simplify the discussion, we assume that $\varepsilon_{ki} \sim iid(0, \sigma_\varepsilon^2)$ is uncorrelated with θ_i, but this can be relaxed. First, parallel to the main text's analysis of talent selection, we focus on the coefficients β_{kt}, which can be interpreted as sector k's "talent"or "skill-bias". As we will see, a rising skill-bias of finance over time leads to the *Talent-Competition Hypothesis* and the empirical predictions presented in Section III. We return to α_{kt}, which can be interpreted as the sector's "wage premium", in relation to the main text's analysis of wages.

A.1 Predictions on Talent Selection

Worker i's utility from working in sector k is the sum of the wage plus a sector-specific non-pecuniary payoff, $U_{kit} = w_{kit} + \mu_{kt}$.[39] It will be convenient to define workers' relative wages and utilities in finance:

$$\begin{aligned} \tilde{w}_{it} \equiv w_{Fit} - w_{Rit} &= \tilde{\alpha}_t + \tilde{\beta}_t\theta_i + \tilde{\varepsilon}_i && (6) \\ \tilde{U}_{it} \equiv U_{Fit} - U_{Rit} &= \tilde{\mu}_t + \tilde{w}_{it} && (7) \end{aligned}$$

We assume that the labor market is frictionless (i.e., no barriers or costs to enter

[39]For simplicity, we assume all individuals have the same preferences over a given sector.

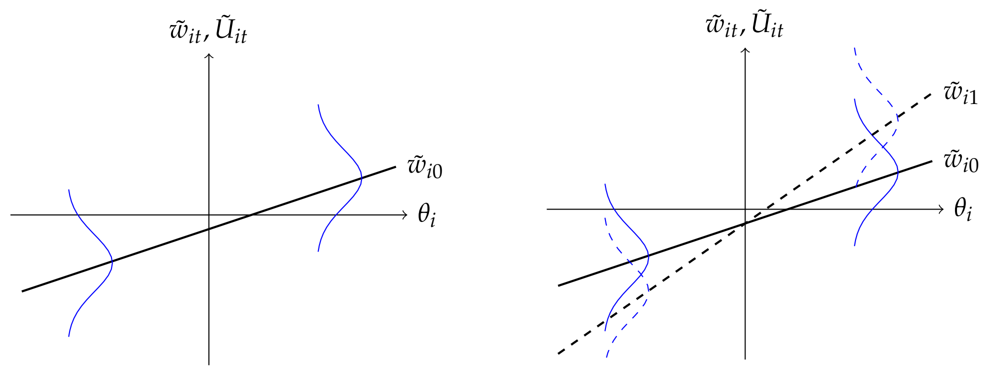
sectors and perfect information) and that workers maximize utility. Given this, we can define the choice indicator for entering finance:

$$F_{it} \equiv I\{\tilde{U} > 0\} = I\{\tilde{\mu}_t + \tilde{\alpha}_t + \tilde{\beta}_t\theta_i + \tilde{\varepsilon}_i > 0\} \tag{8}$$

where I is an indicator function.

Now, assume θ_i is a scalar (e.g., an individual's cognitive ability), normalized to a deviation from its population average. In other words, $E(\theta_i) = 0$, and $\theta_i > 0$ are relatively high-talented workers while $\theta_i < 0$ are relatively low-talented workers. Figure A1 plots the relative wages and utilities from Equations (6) and (7) against workers' talent (for $\tilde{\mu}_t = 0$). In the left panel, the two curves around the relative wage line indicate the distribution of individual-specific relative errors $\tilde{\varepsilon}_i$. The finance sector is chosen when workers' relative utility is positive. The left panel of Figure A1 shows the case in which finance is relatively skill-biased, as the relative wage line is upward-sloping (i.e., $\tilde{\beta}_t > 0$). In this case, high-talent workers are (relatively) more likely to enter the finance sector than are low-talent workers, and average talent in finance is higher than in the rest of the economy.

Figure A1: Relative Wages and Utilities in Finance (Model)



Lemma 1. *If* $\tilde{\beta}_t > 0$*, then* $E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0) > 0$.

Proof: See subsection A.3 below.

We examine Lemma 1 in the main text using different talent measures as proxies for θ_i.

The idea of an increasing skill-bias in finance is captured by an increase of the relative $\tilde{\beta}_t$ over time. This implies that relative productivity, and potential wages, in finance should rise over time for high-talented workers compared to low-talented workers. Figure A1 (right panel) depicts this by the steeper $\tilde{w}_{i1}$ line, leading to a larger share of the high-talented and a smaller share of the low-talented workers entering the finance sector. This leads to a more formal statement of the main text's Prediction 1:

Prediction 1′. *If $\triangle\tilde{\beta}_t > 0$, then either*

$$\triangle\, E(\theta_i \mid F_{it} = 1) > 0 \tag{9}$$

or

$$\triangle\, S_t \equiv E(F_{it} = 1) > 0 \tag{10}$$

or both (9) and (10) are true, where $\triangle$ indicates the change between time $t-1$ and t and S_t is the finance sector's share of total employment.

Proof: See subsection A.3 below.

Equation (9) formalizes the intuition from the right hand side of Figure A1 that a rising relative skill-bias of finance $\tilde{\beta}_t$ leads to a better selection of workers into that sector. However, one case in which skill selection into finance may not improve or even decline is if there are many new entrants on the margin. In Figure A1 (right panel) we can see a small triangle spanned by the $\tilde{w}_{i1}$, $\tilde{w}_{i0}$ lines and the x-axis. If there is enough mass of workers within this triangle and their skill is sufficiently low, expression (9) may not be true. Prediction 1′ captures this by stating that (9) and (10) or both of them need to be true.

As shown in Section II, the employment share in finance has been roughly constant over our sample period ($\Delta S_t \approx 0$). We thus focus in Section IV on examining Equation (9) using different candidate variables for θ_i. Following Philippon and Reshef (2012), we analyze the equivalent prediction:[40]

$$\Delta[E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0)] > 0. \tag{11}$$

Finally, we also use combinations of the θ_i measures together in choice regressions based

[40] Since the distribution of talent measures and sector sizes are constant over time ($\Delta E(\theta_i) = 0$ and $\Delta S_t = 0$), both (9) and (11) yield the same results, i.e., $\Delta E(\theta_i \mid F_{it} = 1) > 0$ implies $\Delta E(\theta_i \mid F_{it} = 0) < 0$. In the case of examining relative education as in prior literature, (9) and (11) are different because educational attainment is trending in the population over time.

on Equation (8). When we run these choice (and later wage) regressions, we also control for other productivity determinants x_i, such as a workers' experience and education. That is, $l_{kit} = \beta'_{kt}\theta_i + \gamma x_i + \varepsilon_{ki}$, where γ is time- and/or sector-specific across the different tests. But we expect from the skill-bias hypothesis that at least some elements of $\tilde{\beta}_t$ rise over time because the talents θ_i should affect productivity in the sector under any reasonable interpretation of the idea of rising skill-bias. Therefore, we also test Prediction 2, which is stated more formally here:

Prediction 2'. *If (elements of) $\Delta\tilde{\beta}_t > 0$, the respective coefficients from a choice regression based on Equation* (8) *should also be positive and increasing over time (i.e., $\Delta\hat{\tilde{\beta}}_t > 0$).*

A.2 Predictions on Wage Components and Identification

Section V of the main text examines wages in finance in relation to the selection of- and return to talent. We motivate the respective analyses more formally here.

We start by decomposing the contemporaneous difference in average (log) earnings between finance and the rest of the economy into changes (between now and some initial $t = 0$) in overall returns to talent, changes in sector-specific returns to talent, and selection effects:

$$
\begin{aligned}
&E(w_{it} \mid F_{it} = 1) - E(w_{it} \mid F_{it} = 0) = \\
&E(\alpha_{Ft} + \beta'_{Ft}\theta_i + \varepsilon_{Fi} \mid F_{it} = 1) - E(\alpha_{Rt} + \beta'_{Rt}\theta_i + \varepsilon_{Ri} \mid F_{it} = 0) = \\
&\tilde{\alpha}_t + \beta'_{Rt}[E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0)] + E(\varepsilon_{Fi} \mid F_{it} = 1) - E(\varepsilon_{Ri} \mid F_{it} = 0) + \tilde{\beta}'_t E(\theta_i \mid F_{it} = 1) = \\
&\underbrace{\tilde{\alpha}_t}_{\text{(1) wage premium}} + \underbrace{\beta'_{R0}[E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0)]}_{\text{(2) observable selection}} + \underbrace{E(\varepsilon_{Ri} \mid F_{it} = 1) - E(\varepsilon_{Ri} \mid F_{it} = 0)}_{\text{(3) unobservable selection}} \\
&+ \underbrace{\tilde{\beta}'_0 E(\theta_i \mid F_{it} = 1) + E(\tilde{\varepsilon}_i \mid F_{it} = 1)}_{\text{(4) sector-specific selection}} + \underbrace{\Delta\beta'_{Rt}[E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0)]}_{\text{(5) changing overall return to talent}} \\
&+ \underbrace{\Delta\tilde{\beta}'_t E(\theta_i \mid F_{it} = 1)}_{\text{(6) changing sector-specific return to talent}}
\end{aligned}
\tag{12}
$$

where Δ indicates the change between time 0 and time t. A change in the relative return to talent generally has two types of effects on average earnings: a direct effect through the changing returns to talent, and an indirect effect through the changing selection of talented workers into different sectors.

First, if finance is a skill-biased sector, it should have a baseline higher return to talent ($\tilde{\beta}_0 > 0$) and, according to Lemma 1, a more talented selection of workers ($E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0) > 0$). Second, if finance becomes more skill-biased over time, the relative return to talent in finance increases ($\Delta\tilde{\beta}_t > 0$) and, according to Prediction 1′, the relative selection of talent into finance should improve over time ($\Delta[E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0)] > 0$).

We can capture the first part in a more formal version of Prediction 3:

Prediction 3′. *If the productivity of talent increases faster in the financial sector compared to the rest of the economy between time $t = 0$ and $t = 1$, and therefore the average talent level of finance workers increases as in Prediction 1, then the wage premium $\tilde{\alpha}_t$ should decline when accounting for components (2), (3), and (4) in Equation (12).*

In the empirical analysis we sequentially control in wage regressions for talent and other observable characteristics such as education and experience (2) as well as unobservable selection using individual fixed effects (3) and individual with sector- or firm-specific interacted fixed effects (4).

A **corollary** of Lemma 1 is component (5) of Equation (12): a general increase of the return to talent in the overall economy ($\Delta\beta'_{Rt} > 0$) may also affect the finance premium without any change in relative talent, simply due to finance having more talented workers to begin with. In Section V.A we therefore also control for changing returns over time to talent θ_i and compare the rising wage premium to other high-skilled sectors which should also be affected by a generally rising return to talent.

Finally, we arrive at Prediction 4 from the main text:

Prediction 4′. *If the productivity of talent increases faster in the financial sector compared to the rest of the economy between time $t = 0$ and $t = 1$, then component (6) in Equation (12) should be positive and $\tilde{\alpha}_t$ should decline when accounting for it.*

The finance sector-specific return to talent $\tilde{\beta}_0$ and its change over time $\Delta\tilde{\beta}_t$ are generally difficult to identify in wage regressions because of the self-selection of individuals into the sector based on unobservables, i.e., ε_{Ri} and $\tilde{\varepsilon}_i$ (Heckman, 1979). We address this problem with two approaches in Section V.B. We run wage regressions (4) on talent interacted with sector and time controlling for observable X_{it} variables such as education and potential experience, and also add individual×sector fixed effects. In addition, we plot the raw finance premia by discrete talent levels, which provides the correct *change in* these premia if the selection of unobservables (and X_{it}) into finance does not change over time. To see this, compute the difference of Equation (12) in times t and 0, assuming that component (3) as well as $E(\tilde{\varepsilon}_i \mid F_{it} = 1)$ in (4) does not change over time:

$$\Delta\left[E(w_{it} \mid F_{it} = 1) - E(w_{it} \mid F_{it} = 0)\right] =$$

$$\underbrace{\Delta\tilde{\alpha}_t}_{\text{(1) wage premium}} + \underbrace{\beta'_{R0}\Delta[E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0)]}_{\text{(2) observable selection}} + \underbrace{\tilde{\beta}'_0\Delta E(\theta_i \mid F_{it} = 1)}_{\text{(4) sector-specific \textit{observable} selection}}$$
$$+ \underbrace{\Delta\beta'_{Rt}[E(\theta_i \mid F_{it} = 1) - E(\theta_i \mid F_{it} = 0)]}_{\text{(5) changing overall return to talent}} + \underbrace{\Delta\tilde{\beta}'_t E(\theta_i \mid F_{it} = 1)}_{\text{(6) changing sector-specific return to talent}} \quad (13)$$

All of these components are accounted for by wage regression (4)[41] and by the *changes in* the differences across talent groups plotted in Figure VI.

A.3 Proofs

To conduct the proofs, a couple of definitions are in order. We first normalize the overall mass of workers to 1, i.e.,

$$\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} g_{\theta,\tilde{\varepsilon}}(\theta,\tilde{\varepsilon})\, d\theta d\tilde{\varepsilon} = \int_{-\infty}^{+\infty} g_{\theta}(\theta)\, d\theta \int_{-\infty}^{+\infty} g_{\tilde{\varepsilon}}(\tilde{\varepsilon})\, d\tilde{\varepsilon} = 1,$$

where we can separate the joint distribution $g_{\theta,\tilde{\varepsilon}}$ into marginals because θ and $\tilde{\varepsilon}$ are assumed independent.

We also define finance's share of employment (and the number of employees in finance given the normalization) as:

$$S_t \equiv E(F_t = 1) = \int_{-\infty}^{+\infty} g_{\theta}(\theta) Pr(\tilde{\varepsilon} > -\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t\theta)\, d\theta \quad (14)$$
$$= 1 - \int_{-\infty}^{+\infty} g_{\theta}(\theta) G_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t\theta)\, d\theta \quad (15)$$

Finance employment rises (ceteris paribus) with the finance wage premium

$$\frac{\partial S_t}{\partial \tilde{\alpha}_t} = + \int_{-\infty}^{+\infty} g_{\theta}(\theta) g_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t\theta)\, d\theta > 0,$$

[41] That is, $b'_t\theta_i$ corresponds to components (2) and (5) in Equation (13), $F_{it}\tilde{b}'_t\theta_i$ to (4) and (6), and $F_{it}\tilde{a}_t$ to the change in the wage premium (1).

but it is ambiguous with respect to finance's relative skill bias

$$\frac{\partial S_t}{\partial \tilde{\beta}_t} = + \int_{-\infty}^{+\infty} g_\theta(\theta) g_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t \theta)\theta \, d\theta, \tag{16}$$

as low-skilled workers earn relatively less in the sector when pay more sharply depends on skill. That is, the integrand in Equation (16) is negative for $\theta < 0$.

Proof of Lemma 1. The average talent in finance is:

$$E(\theta | F_t = 1) = \int_{-\infty}^{+\infty} \theta \frac{g_\theta(\theta)[1 - G_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t \theta)]}{S_t} \, d\theta \tag{17}$$

We compare the density of θ with and without conditioning on $F_t = 1$, i.e., compute the relative density $\frac{g_{\theta|F_t=1}}{g_\theta} = \frac{[1 - G_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t \theta)]}{S_t}$. Differentiating this w.r.t. θ gives:

$$\frac{\partial \frac{g_{\theta|F_t=1}}{g_\theta}}{\partial \theta} = + \frac{g_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t \theta)\tilde{\beta}_t}{S_t} > 0 \text{ for all } \theta \text{ if } \tilde{\beta}_t > 0.$$

This implies that the talent distribution of skill-biased finance ($\tilde{\beta}_t > 0$) first order stochastically dominates the unconditional skill distribution in the overall population. Using

$$E(\theta) = S_t E(\theta | F_t = 1) + (1 - S_t) E(\theta | F_t = 0), \tag{18}$$

we get $E(\theta | F_t = 0) < E(\theta) < E(\theta | F_t = 1)$. More generally, finance's skill distribution dominates that of the rest of the economy in every quantile. □

Proof of Prediction 1′. We can rewrite the average talent in finance (17) as

$$E(\theta | F_t = 1) = \frac{1}{S_t} \underbrace{[E(\theta) - \int_{-\infty}^{+\infty} \theta g_\theta(\theta) G_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t \theta) \, d\theta]}_{\equiv \mathcal{X}_t}, \tag{19}$$

with

$$\frac{\partial \mathcal{X}_t}{\partial \tilde{\beta}_t} = + \int_{-\infty}^{+\infty} \theta^2 g_\theta(\theta) g_{\tilde{\varepsilon}}(-\tilde{\mu}_t - \tilde{\alpha}_t - \tilde{\beta}_t \theta) \, d\theta > 0.$$

Therefore,

$$\frac{\partial E(\theta | F_t = 1)}{\partial \tilde{\beta}_t} = \underbrace{- \frac{1}{S_t} \frac{\partial S_t}{\partial \tilde{\beta}_t} E(\theta | F_t = 1)}_{\text{marginal, >0 or <0}} + \underbrace{\frac{1}{S_t} \frac{\partial \mathcal{X}_t}{\partial \tilde{\beta}_t}}_{\text{inframarginal, >0}} . \tag{20}$$

The second, inframarginal effect is always positive. That is, given a fixed sector size, increased relative skill-bias improves talent in finance. The first effect depends on the marginal workers that may enter or leave the sector when relative skill-bias changes. If the finance sector size rises ($\frac{\partial S_t}{\partial \tilde{\beta}_t} > 0$) and the additionally entering workers are sufficiently low-talented to dominate the inframarginal effect, average talent in finance may deteriorate. In contrast, if the finance sector size stays constant or declines, both effects work together and average talent in finance always improves ($\frac{\partial E(\theta|F_t=1)}{\partial \tilde{\beta}_t} > 0$).

For us, the latter is the empirically relevant case, since $\Delta S_t \approx 0$. Using Equation (18) from above in differences we get: $\Delta[E(\theta|F_t = 1) - E(\theta|F_t = 0)] > 0$ if $\Delta\tilde{\beta}_t > 0$. $\square$

B Data

B.1 Income Data and Definition of the Financial Sector

Our main data source is the *Longitudinal Integration Database for Health Insurance and Labor Market Studies* (LISA), provided by Statistics Sweden (SCB). LISA contains employment information (such as employment status, the identity of the employer, and job classification), tax records (including labor and capital income) and demographic information (such as age, education, and family composition) for all individuals 16 years of age and older, domiciled in Sweden as of November 1 each year, starting in 1990.

Our main measure of earnings is the annual labor income from the largest source of income, in case somebody has multiple employers. One advantage of having annual earnings compared to hourly wages is that they include bonus payments that are likely an important part of compensation in finance.[42] As alternative compensation measures, we consider total taxable income, including capital gains as well as labor income, and disposable income from all sources after deducting taxes and adding benefits.[43] None of the income measures is top-coded or censored. When analyzing wage levels, we deflate all earnings using the official Swedish consumer price index.

To arrive at our analysis sample, we first restrict the dataset to workers whose declared labor income exceeds the minimum amount of earnings that qualifies to the earnings related part of the public pension system, following Edin and Fredriksson (2000). In 1998, this amount was 36,400 SEK per year, approximately 4,500 USD in contemporary exchange rates. We then drop all observations with incomplete data (e.g., missing

[42]Our preferred Swedish earnings measure, declared annual labor income (*deklon*), is not available in 1990. For this year, the data includes a related measure, labor income reported by employers (*loneink*). The difference is that the latter excludes additional income that an individual chooses to self-report. As might be expected, these two measures are highly correlated, and we use the relationship between them for the years 1991–1993 to construct a predicted *deklon* for 1990.

[43]Results in Figure A4. The main reason for considering labor plus capital income is that it would capture any equity-based compensation accruing to the worker. Employee stock option programs are rare in Sweden because of identical tax treatment to regular wages (see Henrekson and Sanandaji, 2014, 2018). As a result, in the largest Swedish banks and insurance companies, incentive pay is almost exclusively in the form of bonuses, which are included in labor income. Smaller private companies and partnerships, which are particularly prevalent in asset management and private equity, are often employee-owned, however, and a substantial part of the compensation for the highest paid workers may come in the form of equity income from the shares they own in their company. Although this would be an argument for including capital income when calculating the finance wage premium, the bulk of capital income for most individuals comes from returns on savings, and including these would introduce noise in the compensation measure. Finally, Sweden has higher marginal tax rates than the U.S., and differences in after-tax relative wages across sectors might be smaller than differences in pre-tax wages. This goes in favor of calculating finance wage premia based on disposable income (i.e., after tax, including transfers) rather than pre-tax income.

gender information, age, or sector of employment). Finally, to be in line with Philippon and Reshef (2012), we drop farming sector, public sector, and self-employed workers (although including them does not significantly change our results). This results in a final sample of about 82.7 million individual-year observations.

We follow Bazot (2017) when calculating the GDP share of the financial sector. He shows that the omission of banks' capital income in the value added share from national accounts leads to underestimation of the finance industry's growth over the last decades for several European countries. To calculate the GDP share of finance for Sweden we therefore adopt the approach of Bazot (2016) and replace value added (from Swedish national accounts) with operating income (before depreciation) for the banking subsector. Unfortunately, bank income statistics are only available for Sweden starting in 1996.

In LISA, the sector where an individual works is reported according to the Swedish Standard Industrial Classification (SNI) code at the level of the establishment at which they are employed.[44] Our main classification of a finance worker is an indicator for whether the SNI code of the individual's working establishment is in the "Financial Intermediation"group (SNI codes 65000–67000), which includes banks, finance and leasing companies, insurance companies, security broking, fund management, and pension funds.

LISA also reports a unique company identifier for an individual's employer, a so-called organization number, which we use to construct an alternative classification of finance workers. We first collected lists of finance companies using annual membership rosters from various financial industry associations, including the Swedish Banker's Association (*Bankföreningen*), Insurance Sweden (*Svensk Försäkring*), the Swedish Securities Dealers Association (*Svenska Fondhandlareföreningen*), the Swedish Investment Fund Association (*Fondbolagens Förening*), and the Swedish Venture Capital Association (*Svenska Riskkapitalföreningen*) from 1990 and onwards. With the help of Swedish company registry (*Bolagsverket, processed by Serrano*), we obtained organization numbers for these firms as well as their subsidiaries, parent companies, and related companies. We then classified a finance worker as an individual in LISA working in one of these companies, matched

[44] The SNI classification is based on the European Union's NACE standard. Our sample years are covered by the SNI1992 (1990–2001), SNI2002 (2002–2010), and SNI2007 (2011–2014) classification. We construct a balanced SNI industry code for the years 1990–2014 based on the SNI2002 by aggregating non-unique mappings between SNI1992, SNI2002, and SNI2007.

by organization number. This alternative classification method also allows us to divide finance workers into more detailed sub-sectors, beyond what the SNI codes allow.

Table A1: Descriptive Statistics for the Two Sample Definitions Used

All Employed	**obs (m)**	**mean**	**sd**	**p5**	**p25**	**p50**	**p75**	**p95**
Age	82.7	41.3	12.6	22.0	31.0	41.0	51.0	62.0
Female	82.7	0.5	0.5	0.0	0.0	0.0	1.0	1.0
Labor Income (SEK '00's)	82.7	274.6	209.2	68.4	169.0	250.0	333.1	558.8
Predict. Cogn. Ability	39.4	50.0	28.5	5.6	25.5	49.6	74.5	94.7
Post-Second. Degree	82.3	0.3	0.5	0.0	0.0	0.0	1.0	1.0
University Degree	82.3	0.2	0.4	0.0	0.0	0.0	0.0	1.0
PhD Degree	82.3	0.0	0.1	0.0	0.0	0.0	0.0	0.0
Yrs Potent. Experience	82.7	22.3	12.6	3.0	12.0	22.0	32.5	43.0
Males (Non-miss cogn)								
Age	26.2	36.44	10.11	21	28	36	44	55
Labor Income (SEK '00's)	26.2	325.2	255.5	79.4	216.5	292.4	382.5	647.7
Predict. Cogn. Ability	18.3	49.7	28.4	5.9	25.3	48.9	74.3	94.4
Post-Second. Degree	26.2	0.31	0.46	0.00	0.00	0.00	1.00	1.00
University Degree	26.2	0.16	0.37	0.00	0.00	0.00	0.00	1.00
PhD Degree	26.2	0.01	0.10	0.00	0.00	0.00	0.00	0.00
Yrs Potent. Experience	26.2	17.6	10.1	3	9	17	25	36
Cognitive Ability	26.2	5.16	1.90	2	4	5	6	8
Non-cog. Ability	25.0	5.12	1.69	2	4	5	6	8
Leadership Ability	16.4	5.30	1.65	2	4	5	6	8
Logic Score Pct	20.6	50.5	28.7	5.4	26.3	50.9	75.1	94.9
Verbal Score Pct	20.5	50.1	28.6	5.3	25.5	48.7	74.1	94.9
Spatial Score Pct	20.5	50.3	28.7	5.3	25.6	50.3	75.2	94.7
Technical Score Pct	20.3	50.3	28.7	5.3	25.8	51.2	74.6	95.2

Table A1 provides summary statistics for our dataset. The average individual in the sample is 41 years old and earns a yearly labor income of SEK 274,600, approximately 35,090 US Dollars (both deflated to 2014). Our two methods for classifying finance workers both give a finance share of around 2.6%, or slightly more than two million individual-year observations.

B.2 Data on Talent

In order to test the predictions from Section A, we would like to find empirical proxies for θ_i, which fulfill the following criteria:

1. They are comparable over time, i.e., their distribution in the population should be the same across cohorts.

2. They are largely exogenous of (and not jointly determined with) the outcome of interest, i.e., the decision to work in finance.

3. They are sufficiently detailed to allow us to analyze the upper percentiles of the talent distribution.

4. They are predictive of future outcomes in domains such as education, employment, earnings, family, health, innovation, and leadership.

Our first set of talent measures come from Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for cohorts enlisted between 1983 and 2010 and the Military Archives (Krigsarkivet) for cohorts enlisted between 1969 and 1983. Military enlistment tests were mandatory for Swedish male citizens and typically taken at the age of 18 or 19. Sweden had a conscription army until 2010, and the tests were used to determine the military placement of an individual. There are two potential issues with these test scores. Starting in the early 2000s, Sweden required fewer and fewer males to do military service, and mandatory military service was abolished completely in 2010. Up until 2006, however, all males were required to do the military enlistment tests. Hence, in order to ensure that we have talent measures for a representative sample of the male population, we restrict our analysis to individuals born before 1985. Also, there might be a worry that a certain individual would deliberately perform badly on these tests in order to get a shorter military service or avoid it all together. There are, however, many reasons to believe this is not a major problem, including the fact that potential employers usually put considerable weight on military service performance. Also, anecdotal evidence suggests that some positions – like being an officer in the navy – were important for the networks individuals would obtain, and a substantial fraction of individuals working at high positions in Swedish society went to these military service assignments. Consistent with this, military test scores have been shown to significantly predict future wages, managerial positions, and incidence of unemployment (see, e.g., Lindqvist and Vestman, 2011).

The enlistment process for military service spans two days and evaluates a person's medical and physical status as well as cognitive and mental abilities. We employ the cognitive and the non-cognitive score as two of our three main talent measures. The leadership score and the constituent subtests of the cognitive score are used in robustness checks. Lindqvist and Vestman (2011) and Dal Bó, Finan, Folke, Persson, and Rickne

(2017) provide further details on this data and its collection.

The test of cognitive ability consists of four different parts (logic, verbal, spatial, and technical comprehension), each of which each is constructed from 40 questions. The test is arguably a good measure of general intelligence and it thus has a stronger fluid IQ component than the American AFQT, which focuses more on crystallized IQ.[45] We obtain both the raw results of the subtests as well as a transformed discrete variable, aggregating the individual results into one score of cognitive ability. This standardized variable ranges from integer values 1 (lowest) to 9 (highest) and follows a Stanine (standard nine) scale that approximates a normal distribution with mean/median 5 and standard deviation 2.[46] In our (self-selected) analysis sample of workers in the private and non-farming sector the mean is 5.2 and the standard deviation 1.9. While our main analysis is based on the aggregated variable, we also examine the raw scores on logic, verbal, spatial, and technical comprehension in robustness checks (Figure A5(b)). We convert these more detailed scores to percentiles (1-100) with mean 50 and standard deviation 29 in the population (approximately mean 50.5 and standard deviation 28.6 in the analysis sample).

We obtain a standardized score for non-cognitive ability following a Stanine scale as well.[47] The score is based on a 25-minute semi-structured interview by a certified psychologist. It is designed to elicit, among others, willingness to assume responsibility, independence, outgoing character, persistence, emotional stability, and power of initiative (Swedish National Service Administration referenced by, among others, Lindqvist and Vestman (2011)). Following the interview, the psychologist assigns one final score out of 1-9, weighing the different components of the tests. The means are 5 and 5.1 and the standard deviations are 2 and 1.7 in the population and the analysis sample, respectively. Lindqvist and Vestman (2011), on p. 109, argue that the non-cognitive score is related to but also different from other measures often used in the literature on personality and labor market outcomes. Rather than assessing a specific trait, the non-cognitive score assesses the ability to function in a very demanding environment (military combat), which

[45]See Lindqvist and Vestman (2011). The important thing for our analysis is that these scores capture abilities correlated with an individual's labor market productivity.

[46]A score of 5 is reserved for the middle 20 percentiles of the population taking the test, while the scores of 6, 7, and 8, are given to the next 17, 12, and 7 percentiles, and the top score of 9 to the uppermost 4 percentiles (scoring below 5 is symmetric; Dal Bó, Finan, Folke, Persson, and Rickne (2017)).

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

they find is rewarded in the labor market.

The psychologist also scores an individual's leadership ability, again on a 1 to 9 Stanine scale. Leadership is meant to capture the suitability for a career as an officer and is conducted only for those who scored at least the mean in cognitive ability test (score of 5 or higher). The leadership score is designed to capture four personality traits: social maturity, psychological energy, intensity, and emotional stability (Dal Bó, Finan, Folke, Persson, and Rickne, 2017). Leadership has mean 5.3 and standard deviation 1.7 in the analysis sample. Non-cognitive ability and leadership ability are relatively highly correlated (Lindqvist and Vestman (2011); in our data the correlation is 0.856, while the correlation of cognitive and non-cognitive is 0.357). Since leadership is not available for all test takers, cognitive and non-cognitive ability will be our main measures of talent.

The second set of talent variables that we employ is from secondary schooling. We collect information from the high school register on the school, final grade, graduation year, and the track the person took from 1973 (birth cohort 1955) onward. Compared to the military enlistment scores, these measures have the advantage that they are available for both genders (while required for men, only a small fraction of women voluntarily did the military test). High-school grades have also been shown to reflect a combination of cognitive achievement and personality traits such as conscientiousness (Almlund, Duckworth, Heckman, and Kautz, 2011, p. 103–104).

It may be problematic in terms of comparability to pool raw grades across all the high school tracks of varying length and difficulty that Swedish students may have completed. Therefore, although all our results are the same when using the raw measures, we employ two strategies in our main analyses to ensure comparability. First, we only consider students attending tracks that lead to university admission and compute their percentile rank (*graderank uni*; mean 49.7 and standard deviation 28.7 in the analysis sample).[48] We further restrict our grades sample to the science track in high-school, which traditionally enrolls the most able students (*graderank science*; mean 49.6 and standard deviation 28.9 in the analysis sample). These measures hone in on the most talented groups of individuals, which are of particular interest for us, but they carry the limitation that by definition they are only available for a selection of students. Therefore, we construct predicted cog-

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

nitive ability as our main measure of talent when we analyse females or both genders together. In particular, we regress cognitive ability of males on a third order polynomial of high-school grades interacted with track and the age at graduation for each graduation year. We then use the parameters from this regression to predict individual cognitive ability for both genders. This predicted talent measure alone explains more than 40 percent (corr=0.644) of the variation in males' actual cognitive score in the analysis sample (including school dummies gives similar results). Finally, we standardize the measure to percentiles (1 to 100) within graduation year and gender to account for possible grade inflation and for the fact that females on average have better grades in high school. As a result, we obtain a fine-grained relative and early talent measure for both genders that is stable across years (mean 50.0 and standard deviation 28.5 in our analysis sample).

We believe that our main talent measures fulfill the four requirements set out in the beginning of this section. First, Figure A2 shows that the distribution of the talent measures is stable over the period 1990-2014, which allows us to select a specific talent percentile of interest and compare it over time. The stability of the military test scores is partly due to standardization by the enlistment authority, but the underlying distribution of cognitive ability is arguably stable over time as well.[49] Figure A2 also shows that military conscription information is recorded for almost 90 percent of males born after 1951. Availability declines after the birth years of the early 1980s due to the gradual abolition of military service, but it remains above 70 percent for all cohorts that we use in our analysis.[50] High school grades, in contrast, are increasingly common for younger cohorts mainly as a result of increasing high-school attainment, with availability of raw grades and predicted cognitive ability reaching 80 percent for both genders born after the early 1970s.

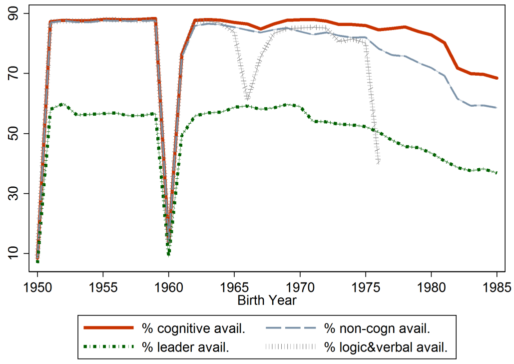
Although there is no evidence for this in previous literature, one might be concerned that the selection of test takers changed with less stringent conscription in the 2000s or that the incentive to perform well in the military tests weakened. We therefore verified

[49] Flynn (2000) reports improvements in average intelligence during the mid-20th century. These gains seem to have petered out in the Nordic countries for a large part of our study population, however. For example, Sundet, Barlaug, and Torjussen (2004) find that 18-year-old Norwegian male conscripts born after the mid-1950s had rapidly decreasing gain rates with a complete cessation of the Flynn effect for birth cohorts after the mid-1970s. Similar findings exist for Danish conscripts and for Swedish 13 year olds born 1947–1977 including girls.

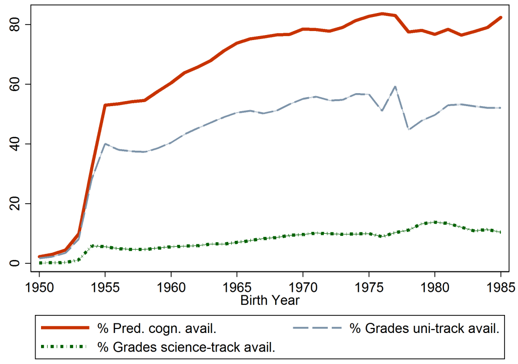
[50] The drop in the availability of the military measures in 1960 is due to the fact that the enlistment files for that birth cohort were burned in an incident.

Figure A2: Distribution of Talent Measures by Birth Cohort and Over Time

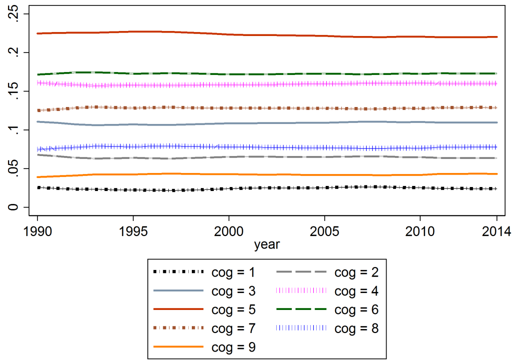
(a) Males' Talent Availability



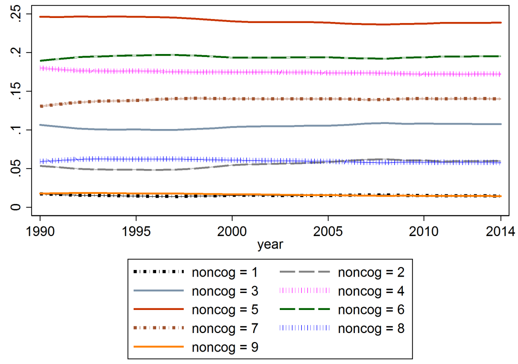
(b) Females' Talent Availability



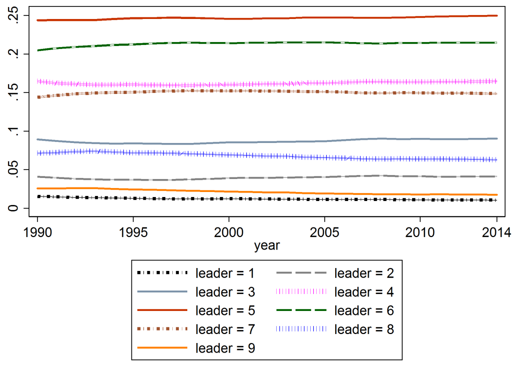
(c) Males' Cognitive Scores



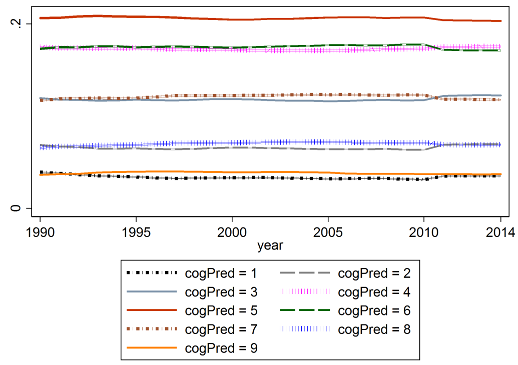
(d) Males' Non-Cognitive Scores



(e) Males' Leadership Scores



(f) Females' Predict.Cognit. (Stanine Scaled)



The top row shows the fraction of males (left panel) and females (right panel) for whom we observe the respective talent measures. The middle and the bottom row depict the distribution of cognitive, non-cognitive, leadership, and predicted cognitive test scores (i.e., share of each test score in the sample) over time. For this purpose, we discretized the predicted cognitive percentiles to a Stanine scale as well. Source: Swedish Defence Recruitment Agency (Rekryteringsmyndigheten) for persons enlisted between 1983 and 2010, Military Archives (Krigsarkivet) for persons enlisted between 1969 and 1983, Swedish high school register, Swedish population data LISA from Statistics Sweden.

Table A2: Relationship Between Talent Measures from High-School and Military Enlistment for Different Birth Cohorts

	HS-Grades	HS-Grades	HS-Grades	Pred.Cog.	Pred.Cog.	Pred.Cog.
Coeff on cognitive talent (1955-59)	**5.23**	**5.72**		**8.97**	**9.65**	
	0.000	0.000		0.000	0.000	
difference for 1960-64	0.88	1.05		0.73	0.91	
	0.000	0.000		0.000	0.000	
difference for 1965-69	1.39	1.59		0.92	1.11	
	0.000	0.000		0.000	0.000	
difference for 1970-74	1.31	1.56		0.60	0.87	
	0.000	0.000		0.000	0.000	
difference for 1975-79	1.91	2.04		0.55	0.55	
	0.000	0.000		0.000	0.000	
difference for 1980-84	1.93	1.85		0.29	0.03	
	0.000	0.000		0.000	0.571	
difference for 1985-90	1.56	1.76		-0.45	-0.54	
	0.000	0.000		0.000	0.000	
Coeff on non-cog talent (1955-59)	**1.75**		**3.38**	**2.41**		**5.21**
	0.000		0.000	0.000		0.000
difference for 1960-64	0.63		1.26	0.67		1.46
	0.000		0.000	0.000		0.000
difference for 1965-69	0.93		1.85	0.94		1.96
	0.000		0.000	0.000		0.000
difference for 1970-74	0.81		1.62	0.84		1.62
	0.000		0.000	0.000		0.000
difference for 1975-79	0.30		1.15	-0.18		0.34
	0.000		0.000	0.000		0.000
difference for 1980-84	-0.40		0.34	-1.04		-0.76
	0.000		0.000	0.000		0.000
difference for 1985-90	0.36		1.01	-0.62		-0.56
	0.000		0.000	0.000		0.000
Regression R-squared (1955-59)	**0.141**	**0.131**	**0.041**	**0.381**	**0.362**	**0.095**
difference for 1960-64	0.052	0.047	0.022	0.069	0.064	0.033
difference for 1965-69	0.09	0.083	0.032	0.115	0.106	0.045
difference for 1970-74	0.097	0.088	0.039	0.111	0.1	0.057
difference for 1975-79	0.124	0.12	0.034	0.074	0.077	0.018
difference for 1980-84	0.088	0.092	0.008	-0.01	0.003	-0.025
difference for 1985-90	0.081	0.076	0.029	-0.047	-0.039	-0.013
N	1,138,662	1,138,662	1,138,662	1,136,924	1,136,924	1,136,924
R-sq	0.22	0.206	0.067	0.439	0.419	0.118
adj. R-sq	0.22	0.206	0.067	0.439	0.419	0.118
Sample	Men	Men	Men	Men	Men	Men

Notes: Outcome is standardized percentile within gender. P-values are under the coefficients.

that our results are robust to dropping the test scores for males born after 1979 (as in Dal Bó, Finan, Folke, Persson, and Rickne, 2017). Also, the incentives to do well in high school should not have declined, and we find qualitatively similar results using high school grades rather than military test scores as our proxy for talent. Table A2 shows that the relationship between the military enlistment scores and high-school grades for the test takers born in the 1980s is not substantially weaker than for other cohorts.

Second, the talent measures are largely exogenous or predetermined with respect to individuals' career choices. Military enlistment tests as well as grades are measured at the end of high school, before individuals enter post-secondary training or the labor market. Whereas cognitive and non-cognitive ability are not exclusively innate (Hansen, Heckman, and Mullen (2004) and Heckman, Stixrud, and Urzua (2006)), they are very hard for an individual to manipulate. While these scores could have been influenced by schooling, this is less of an issue for our paper, as long as test scores and high-school grades are (1) related to labor market outcomes and productivity θ_i and (2) exogenous to these future labor market outcomes.

The test scores are also sufficiently detailed to examine relatively high percentiles of the talent distribution. The highest code of 9 represents the top 4% cognitive and non-cognitive ability in society, respectively. The grade percentiles or predicted cognitive talent measures are in principle even more detailed. See Table A3 below for relationship between wages and talent levels overall as well as within the finance sector.

Finally, previous research employing similar Swedish talent measures has shown that these are strong predictors of future income, as well as other socio-economic outcomes such as unemployment, health, divorces, illicit activities, and becoming a manager, or winning political office (e.g., Lindqvist and Vestman, 2011; Dal Bó, Finan, Folke, Persson, and Rickne, 2017). Cognitive performance in particular is among the most important predictors of innovation (e.g., Aghion, Akcigit, Hyytinen, and Toivanen, 2017). While research on the validity of high-school grades as a talent measure is more sparse, some studies have documented that these are even better predictors of performance in college than are standardized test scores (which are closer to cognitive skills; see Almlund, Duckworth, Heckman, and Kautz (2011)). We also verify in our sample that cognitive, non-cognitive, and predicted cognitive ability are significant predictors of wages in the overall labor market as well as within finance (Table A3).

B.3 Swedish Labour Force Survey for Data on Hours Worked

For our analyses on hours worked and approximate hourly wages we supplement the LISA sample with data from the Swedish Labour Force Survey (SE-LFS). The SE-LFS is

Table A3: Returns to Talent Measures

Panel A: Cognitive and Non-cognitive skills (Men)

	All	All	Finance	Finance
Cognitive premium relative to level 1				
2	**2.1**	**1.9**	-5.9	-6.7
3	**4.0**	**3.5**	-1.9	-3.2
4	**5.9**	**5.1**	5.7	3.2
5	**8.6**	**7.0**	7.2	3.7
6	**12.6**	**9.9**	11.4	6.5
7	**16.2**	**12.3**	**17.2**	11.3
8	**20.4**	**15.3**	**22.7**	**15.7**
9	**23.0**	**16.6**	**24.1**	**16.7**
Non-Cogn. premium relative to level 1				
2	**7.0**	**6.8**	-4.6	-4.8
3	**12.3**	**11.9**	-1.3	-2.0
4	**17.8**	**17.1**	2.1	1.1
5	**21.5**	**20.5**	5.1	3.8
6	**25.8**	**24.4**	11.6	9.5
7	**30.4**	**28.4**	**18.5**	**16.0**
8	**34.8**	**32.4**	**27.6**	**24.9**
9	**38.5**	**35.9**	**34.5**	**31.3**
Premium relative to less than High-School				
High-School		**4.2**		3.4
Some Post-secondary		**2.3**		-1.2
University Graduate		**14.8**		**17.5**
PhD Graduate		**9.1**		6.3
N	808,213	807,590	20,412	20,409
R-sq	0.215	0.221	0.184	0.201
adj. R-sq	0.215	0.221	0.182	0.199
Sample	Men 30yo	Men 30yo	Men 30yo	Men 30yo

Panel B: Predicted cognitive skills (Both)

	All	All	Finance	Finance
Male pred.Cogn.premium relative to level 1				
2	**7.1**	**7.1**	4.4	3.4
3	**11.2**	**11.2**	9.1	7.5
4	**14.2**	**14.1**	**12.4**	**10.4**
5	**17.0**	**16.7**	**22.9**	**19.1**
6	**23.6**	**23.0**	**33.3**	**26.9**
7	**32.3**	**31.4**	**44.0**	**35.5**
8	**39.3**	**36.5**	**50.2**	**40.3**
9	**47.1**	**43.0**	**74.4**	**63.2**
Female pay penalty at Pred.Cog.=1	**-38.1**	**-37.9**	**-34.3**	**-34.4**
Fmle pred.Cogn.premium relative to male				
2	**-2.5**	**-2.6**	-1.6	-1.2
3	**-3.7**	**-3.9**	-2.9	-2.1
4	**-2.7**	**-3.2**	-1.6	-1.4
5	-0.5	**-1.2**	-7.1	-6.6
6	-0.2	**-1.3**	-9.5	-8.4
7	-0.2	**-1.8**	-11.5	-10.8
8	0.8	0.5	-8.0	-7.3
9	**4.5**	**4.3**	**-16.9**	**-16.7**
Premium relative to less than High-School				
High-School		**35.9**		-23.0
Some Post-secondary		**30.6**		-26.1
University Graduate		**41.7**		-9.7
PhD Graduate		**32.2**		-32.3
N	1,438,648	1,438,603	48,119	48,118
R-sq	0.292	0.295	0.321	0.33
adj. R-sq	0.292	0.295	0.321	0.33
Sample	Both 30yo	Both 30yo	Both 30yo	Both 30yo

This table shows returns to talent measures for 30 year olds across all sectors and within finance. The predicted cognitive ability measure is discretized to Stanine scale in Panel (b). Year dummies control for time effects. Statistical significance at the 5% level is indicated with bold font.

a monthly survey of about 30,000 individuals representative of the Swedish population aged 16–64 (later 15–74) capturing areas such as background characteristics, (un)employment, labor force participation, job search, and – crucially for us – hours worked per week. We use actual hours worked in main job (variable "HuFaktTim") for our analysis, but total hours ("TotFaktTim") in all jobs yield similar results.

Unfortunately, between 2006 and 2008, the sample size in the SE-LFS (at least the data that we received from Statistics Sweden) drops by ninety percent. Therefore, the working hours results in Figure A9 become very imprecise at that point and we actually had to cut off the hourly wages series in Figure A4(a).

B.4 LINDA Data for Relative Wages in Finance During the 1980s

In order to extend the relative wage time-series to the 1980s, we use the *Longitudinal Individual Database* (LINDA), also provided by Statistics Sweden. LINDA is a representative sample covering 3–4% of the Swedish working population (details in Edin and Fredriksson, 2000). We process LINDA similarly to our main LISA dataset (e.g., dropping the farming and public sector) and compute relative finance wages for the years 1978 to 1990 in Figure II.

B.5 U.S. Current Population Survey and Census/ACS Data

For comparison with the United States financial sector, we use the Current Population Survey (CPS) as well as Census and American Community Survey (ACS) data provided by Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2017). We process both datasets as closely as possible to Philippon and Reshef (2012). We use non-farm private sector employment in the March CPS and the Census/ACS. Earnings are measured by total pre-tax wage and salary income for the previous year ("INCWAGE" variable), adjusted for top-coding by multiplying with 1.75 until the mid-1990s (after that IPUMS replace top-coded wages themselves with an average in the group), deflated by PCE deflator of the Bureau of Economic Analysis (BEA), and in the CPS divided by hours and weeks worked to generate hourly wages.

Top-coding and measurement error in wages, bonuses, and hours/weeks worked (e.g., due to recall error) are likely to bias our estimates of the relative U.S. finance wages downward compared to the Swedish tax records, especially so at the top of the income distribution. Accordingly, Philippon and Reshef (2012, Figure I, p1558) use Industry Accounts of the United States to circumvent this problem (alternatively, they impute income for U.S. top earners), which yields a remarkably similar relative wage series to Figure II in this paper.

Our results for the CPS are shown in Figures A8–A9 and Table A4 of Section D. We also employ the Census in 1990 and pool the ACS years 2008–2012 for 2010 in order to have sufficiently many observations for an analysis of detailed occupations (Table A5).

B.6 Relative Education as Evidence of Increasing Skill Intensity

In addition to the rising pay in finance, several studies have documented relatively high and rising formal education levels in this sector (e.g., Philippon and Reshef (2012) for the US; Boustanifar, Grant, and Reshef (2017) for a sample of developed countries). Following these studies, we assign individuals to groups based on their highest level of education and use them as a first proxy for talent or skill. Our main groups of interest are *post-secondary education* and *university degree*, which are defined as in Philippon and Reshef (2012). More formally, we examine theoretical Prediction 1 by plotting

$$E(c_{it} \mid F_{it} = 1) - E(c_{it} \mid F_{it} = 0) \tag{21}$$

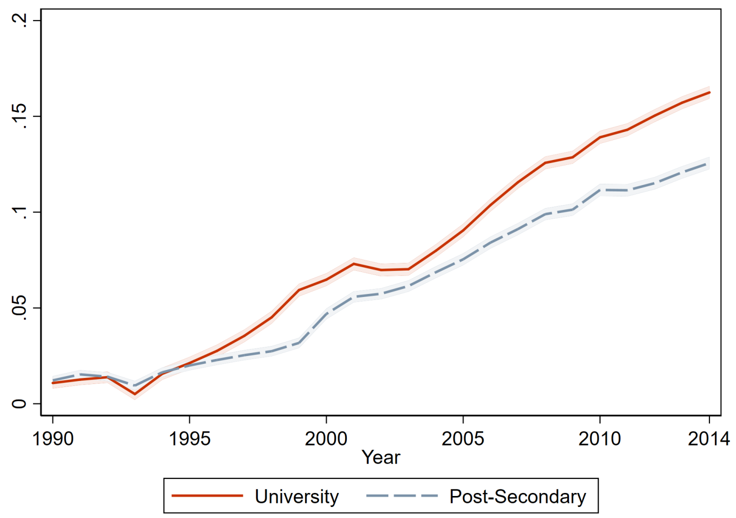
over time, where c_{it} is an indicator variable for post-secondary or college education. The t-subscript indicates that the distribution of c_{it} in the population may (and in fact does) change over time.

In the top panel of Figure A3, we use our Swedish data to plot Equation (21) for the relative share of individuals who attained more than a high-school degree (*Post-Secondary*) and for those who attained a university degree (*University*). We see that an increase in relative education is present also in Sweden, with the fraction of post-secondary (university) finance workers rising from about 2% (2%) higher than in the rest of the economy to 16% (12%) higher in 2014. For the US (using CPS data), the level differences are larger and the increase for post-secondary education is less clear-cut, but overall the trend is similar (Figure A8, Panel (f)).[51] The difference in post-secondary education share

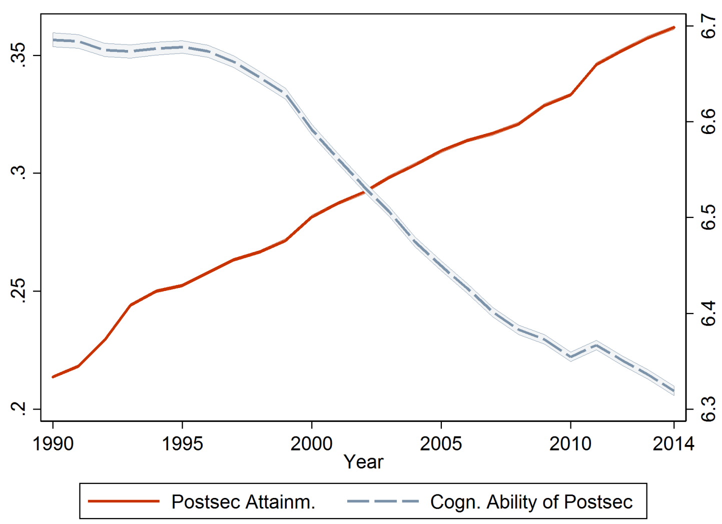
[51]The different level shares in Sweden and the US are due to different educational systems: American

Figure A3: Relative Education in the Financial Sector

(a) Relative education in Sweden



(b) Post-secondary education & average cognitive ability (men)



The top row shows the evolution of relative education in the financial sector compared to the rest of the economy for Sweden between 1990 and 2014. Relative education is calculated as the share of individuals in finance who attained more than a high-school degree (post-secondary education) and of those who attained a university degree (university education) minus the corresponding shares in the rest of the economy. The bottom panel depicts post-secondary attainment rates and average cognitive ability among men with at least post-secondary attainment. Sources: Swedish population data LISA, high school register, Military Archives and Defense Recruitment Agency. from Statistic Sweden. 95 percent confidence intervals are shaded.

between finance and non-finance workers changes from 14% to 18%, the corresponding measure for university education increases from 11% in 1990 to 19% in 2014. We have corroborated this trend in choice regressions as in Prediction 2 and Table I, using c_{it} and years of schooling instead of talent θ_i.

Although these results are consistent with a positive and increasing relative skill demand of the financial sector, the trends are at best suggestive. The reasons are that these dummies for higher education are rather crude measures of skill, that they are likely to be directly influenced by individuals' career plans, and that they are difficult to compare over time due to compositional changes. In 2014 almost 45 percent of the Swedish working population held a post-secondary degree and 23 percent a university degree, while in the US-CPS data the corresponding numbers are 62% and 33%, (and even higher for recent graduates). In addition, education is likely to be endogenous to an individual's sectoral choice. In particular, individuals who wish to work in the financial sector today need a university degree or at least post-secondary education for most jobs, including relatively low-skilled clerical work, which compromises the exogeneity of the relative education measure.[52]

Most importantly, the relative education measures are difficult to compare over time because of compositional changes. Post-secondary and university attainment has risen strongly during the past decades, resulting in a substantial decline of average talent in the group of post-secondary educated or university graduates. The bottom panel of Figure A3 illustrates this in our Swedish data, plotting males' post-secondary share in Sweden against average cognitive ability among those who attained post-secondary education. During 1990-2014, post-secondary attainment rose from 21 to 37% accompanied by a decline in average cognitive ability of .4, or more than a fifth of a standard deviation in the working population. The results are similar when including both genders (decline of more than six percentiles predicted cognitive ability, i.e., almost a fourth of a standard deviation). They are also qualitatively and quantitatively the same for university

pupils on average graduate about one year earlier from high-school than their Swedish peers, and a larger share of academic as well as vocational training are provided by post-secondary colleges in the US. The high level shares of post-secondary or university education arguably make these less useful measures of talent (especially for the tails of the distribution) toward the end of our sample period. Rapidly rising attainment also induces a comparability problem, as we discuss below.

[52] In the wage regressions of the main text, we estimate the finance earnings premium controlling for education, in order to account for rising relative education and the compensation that may be attached to it. Our results for both genders barely change when including these regressors and do not change at all for the subsample of male workers.

(rises from 12 to 26 percent, 1/3 of a standard deviation decline in ability) attainment in Sweden. Carneiro and Lee (2011) and most recently Bowlus, Bozkurt, Lochner, and Robinson (2017) present similar evidence for the U.S., and show that higher college attainment leads to a decline in the average quality of college graduates. For these reasons, it is difficult to compare the evidence generated using c_{it} instead of θ_i to test Predictions 1 and 2.

C Further Robustness Tests

C.1 Alternative Specifications

Our main measure for wages is labor income but we also consider labor plus capital income and disposable income, i.e., total income after tax plus transfers as alternative measures. See footnote 43 for a detailed discussion of why one might want to consider these alternative income measures. Moreover, we approximate hourly earnings by dividing yearly labor income by weekly hours worked from the Swedish Labour Force Survey (SE-LFS; see Section B.3), assuming that annual weeks worked do not differ across sectors and did not change over time (there is no weeks worked variable in that data). We also cut off the series in 2006 because the dropping number of survey respondents makes this measure highly imprecise after that point in time (although the rough trend is similar). Panel (a) of Figure A4 shows that the patterns look very similar when considering relative wages in the financial sector with these alternative measures. Reassuringly, the basic levels and evolution of relative hourly finance earnings in the SE-LFS are the same as annual earnings in the LISA population data. The finance employment share is also similar to LISA and constant over time (not plotted). This supports the results from the SE-LFS data and makes us more confident that our annual earnings trends in Figure II reflect comparable trends in hourly wages over time.

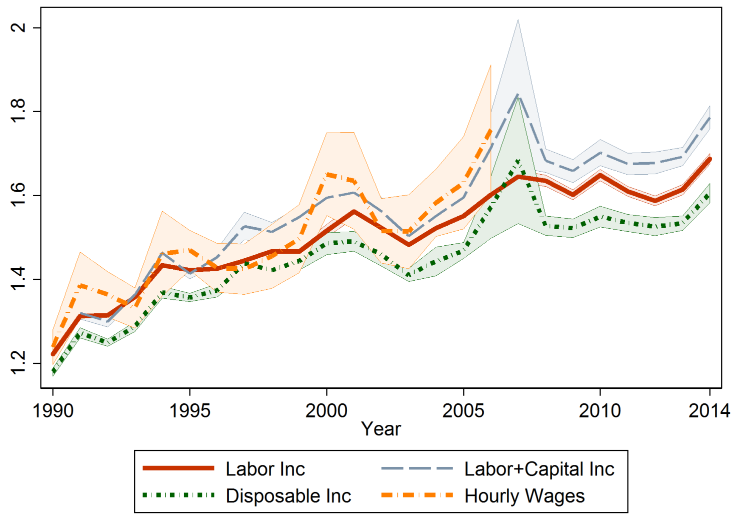
Another potential concern is that the Swedish finance industry is concentrated in the area in and around Stockholm, which is a region with higher wages and prices overall. Panel (b) of Figure A4 depicts the ratio of finance to non-finance wages for the subsample of individuals living in Stockholm. The increase in relative finance wages is slightly larger for this subsample, showing that it is in fact a finance effect rather than a Stockholm effect.

Figure A5 shows some alternative relative talent measures to the ones reported in the main text. Panel (a) depicts relative cognitive, non-cognitive, and leadership scores in finance for 30 year old males as an alternative to Figure III for all age groups (Figure A10(b) reports grades-based measures for 30 year old females). Panel (b) plots the detailed logic, verbal, spatial, and technical comprehension subscores of the cognitive ability test. Finally, the bottom two panels of Figure A5 depict the relative distribution of talent in finance alternatively to Figure IV by subtracting the respective shares instead of dividing.

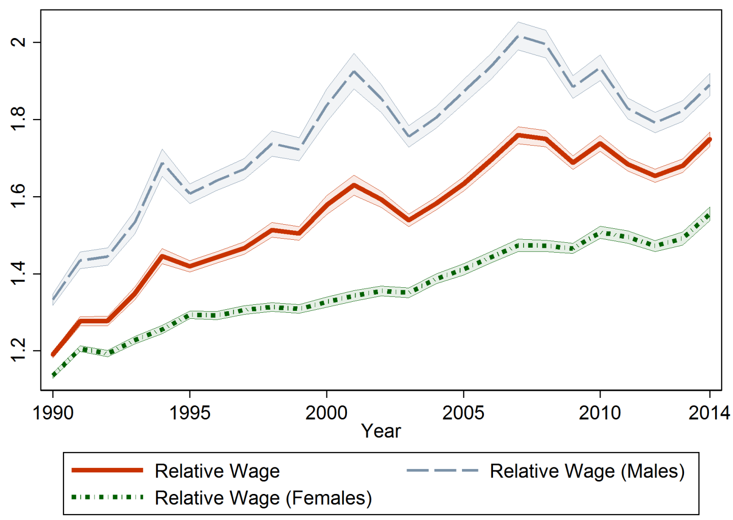
All of the results in this section are consistent with the main text; the relative talent of finance does not increase whereas its relative wages surge.

Figure A4: Relative Wages in the Financial Sector (Robustness)

(a) Different Income Types (Both Genders)

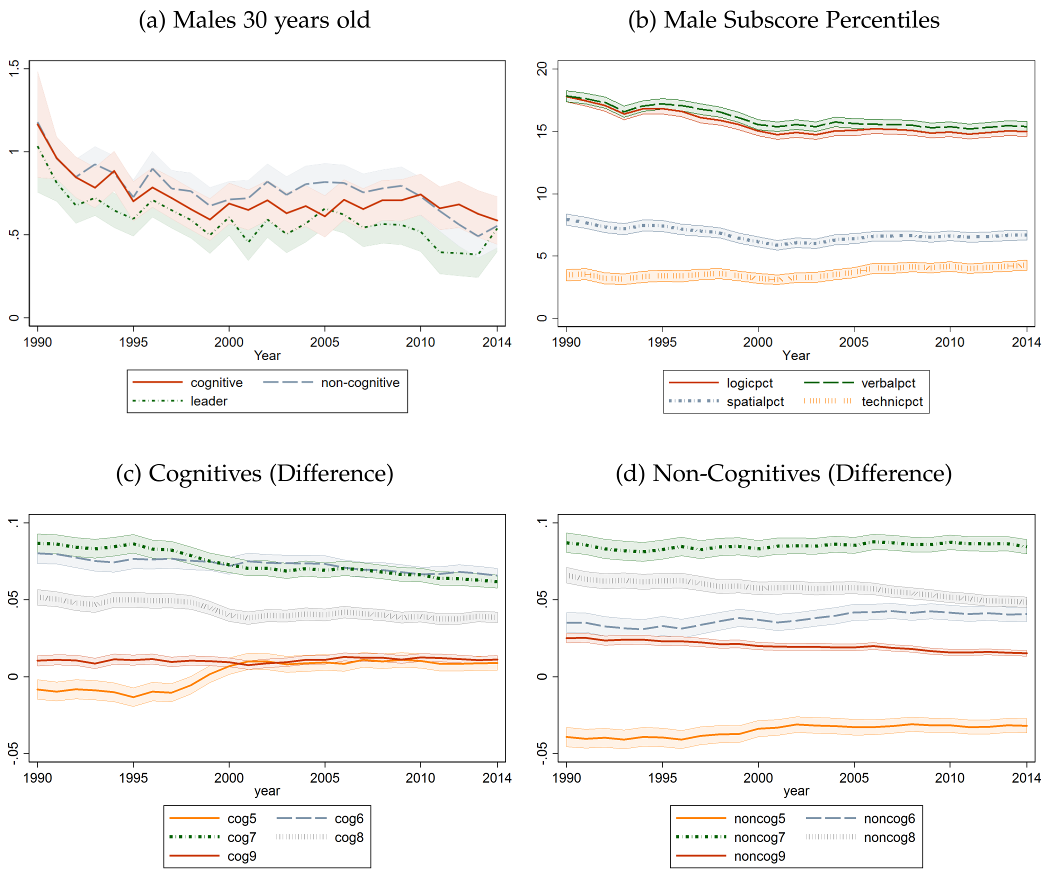


(b) Only Stockholm Area



The figure describes the evolution of relative finance wages for different income measures and samples. Panel (a) shows the relative labor income of the main text next to labor plus capital income, disposable income after taxes and benefits, and hourly wages constructed by dividing yearly labor income with weekly hours worked from the Swedish Labour Force Survey (SE-LFS). Panel (b) depicts relative wages of finance for the Stockholm area only. Sources: Swedish population data LISA and Swedish Labour Force Survey (SE-LFS).

Figure A5: Relative Talent in the Financial Sector (Robustness)



This figure shows the evolution of relative talent in finance, i.e., average talent in finance minus average in the rest of the economy, during 1990 to 2014. The panel on the top left shows the results for 30 year old men. The top right panel shows the the relative levels of logic reasoning, verbal comprehension, spatial ability, and technical understanding. The bottom row shows the evolution of relative shares of medium and high talent levels (measured for cognitive and non-cognitive skills) in the financial sector during 1990 to 2014. Relative share is calculated as the share in finance minus by the share in the rest of the economy. Sources: Swedish population data LISA, Swedish Military Archives and Defense Recruitment Agency. 95 percent confidence intervals are shaded.

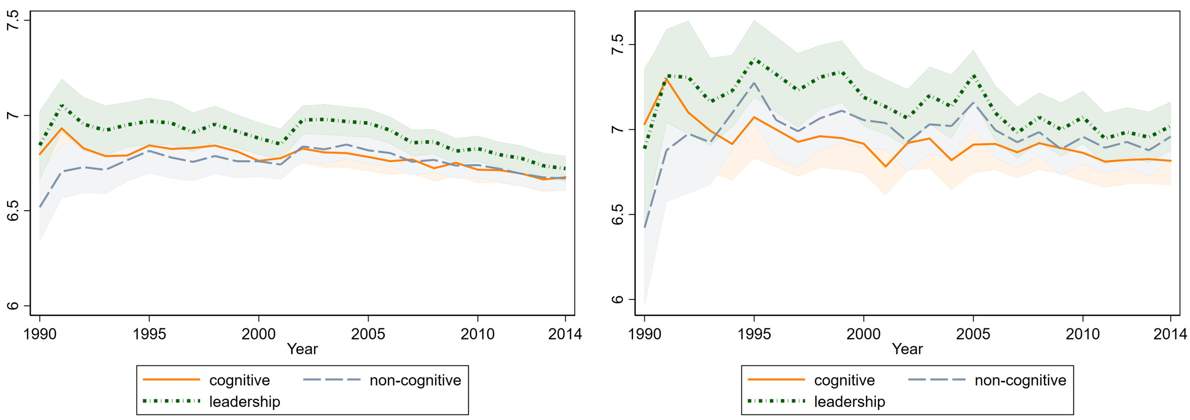
C.2 Top Earners

An alternative test that could potentially uncover an increased selection of top talent is to examine the evolution of talent among the very top earners in finance. Figure A6 shows the average cognitive, non-cognitive, and leadership talent of top 5% or 1% earners in the finance sector over time. The talent of these individuals is high, about two standard deviations above the mean in the population, but it is not increasing. Instead there is a suggestive slight decline over time (the confidence bands are too wide for statistical significance, however). When depicting top finance earners' *relative* talent they are marginally more talented than the rest of the economy's top earners and less talented than LCA and IT top earners, but the trends are the same (not plotted for brevity).

Therefore, consistent with the previous results, we find no indication that the talent of top finance earners has increased over time for any of our talent measures, neither in absolute terms nor relative to the rest of the economy or other high-skilled sectors.

Figure A6: Talent of Top 5% and 1% Earners in the Financial Sector

(a) Top 5% (b) Top 1%



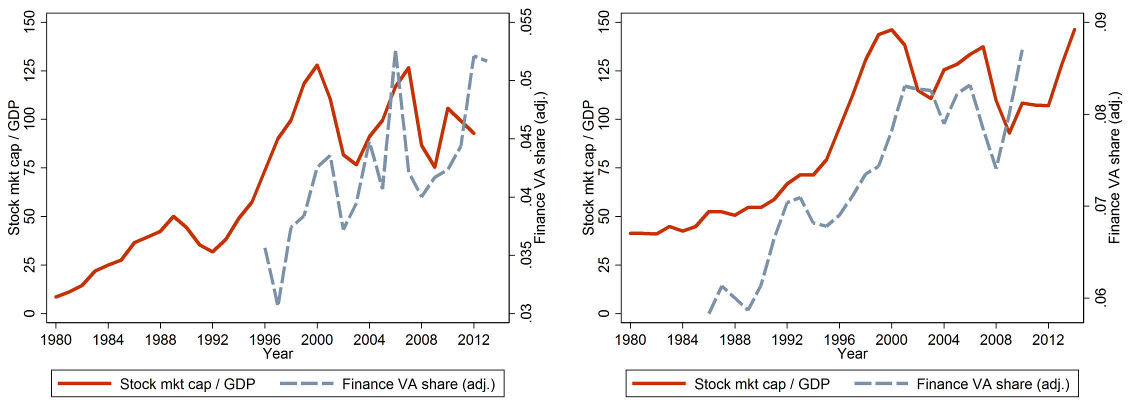
This figure shows average talent of male top 5% and 1% earners in finance (on a yearly basis). Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency. 95 percent confidence intervals are shaded.

D Evidence for the United States

We provide further support for the external validity of our results by comparing the Swedish evidence with U.S. data (see also Section B.5). Figure A7 indicates that financial sector performance in Sweden and the U.S. evolved similarly over time, increasing until the end of the 90s (tech bubble), followed by a short period of decline, and another increase until the most recent financial crisis in 2007-2008. Figure A8 (a) and (b) show that finance's share of overall employment stayed roughly constant in Sweden and the U.S. over our sample period (levels are higher in the U.S. though). Moreover, the gender composition has experienced very similar trends, too. There are relatively more women than men working in the financial sector but this gap is narrowing over time.

Figure A7: Finance as a Percentage Share of the Economy

(a) Sweden (b) U.S.

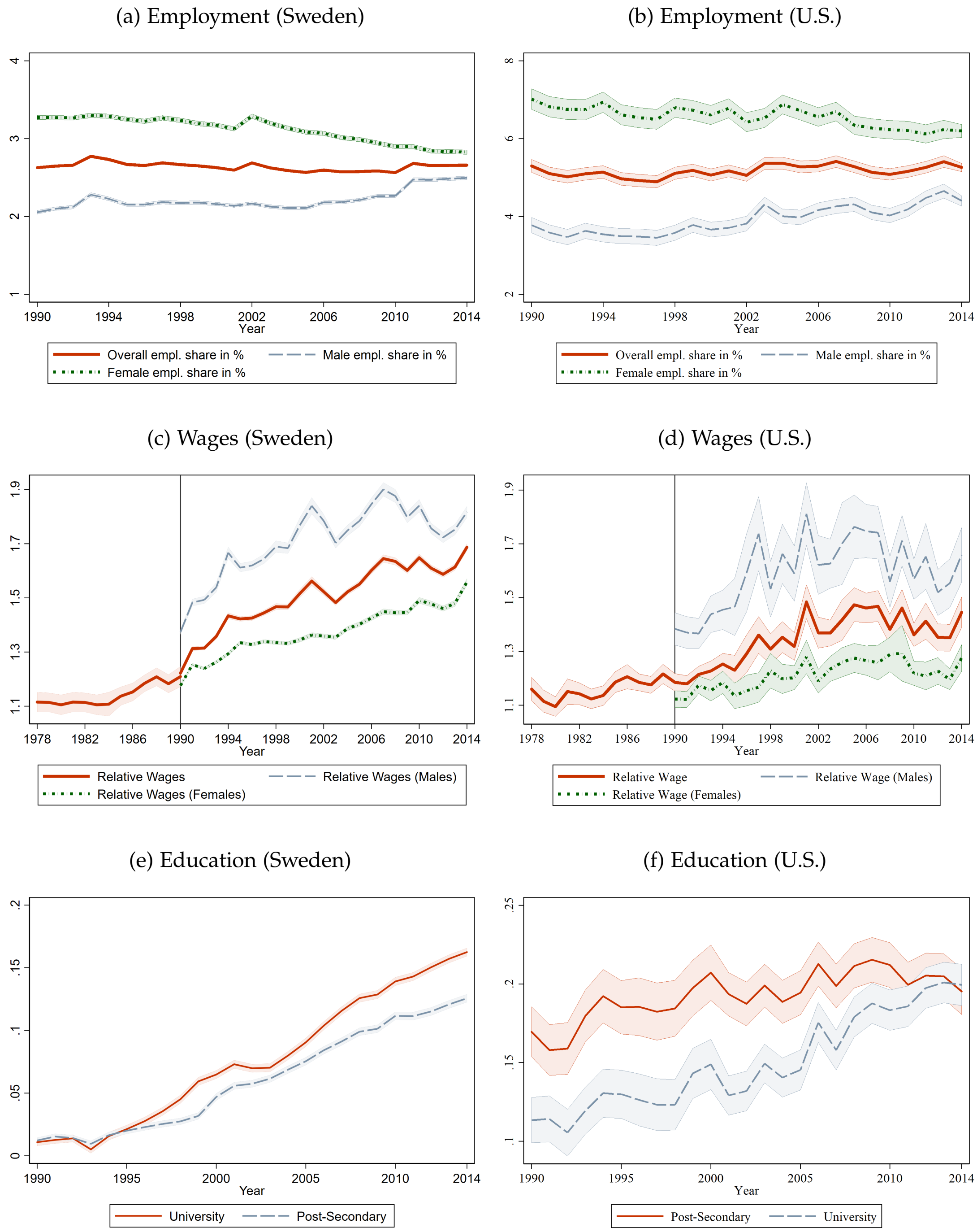


The aggregate series are obtained from Statistics Sweden (Sweden) and World Klems (U.S. value added only available to 2010). The value-added share for Sweden has been adjusted using the methodology of Bazot (2017).

Figure A8 (c) and (d) compare relative finance wages for men and women. Relative wages increased in Sweden and the U.S.; the levels are higher in Sweden which is likely to be explained by top-coded income data in the U.S. Current Population Survey (CPS). In both countries, the increase of relative wages is more pronounced for men than for women. Figure A8 (e) and (f) show that relative education of finance has increased in both countries over the sample period. For the U.S., this has been documented before by Philippon and Reshef (2012).

Table A4 reports information on subsector composition and wages of the financial industry over time. We map our Swedish SNI subsector classification into the classifi-

Figure A8: Finance Relative Employment, Wages, and Education in Sweden and the U.S.

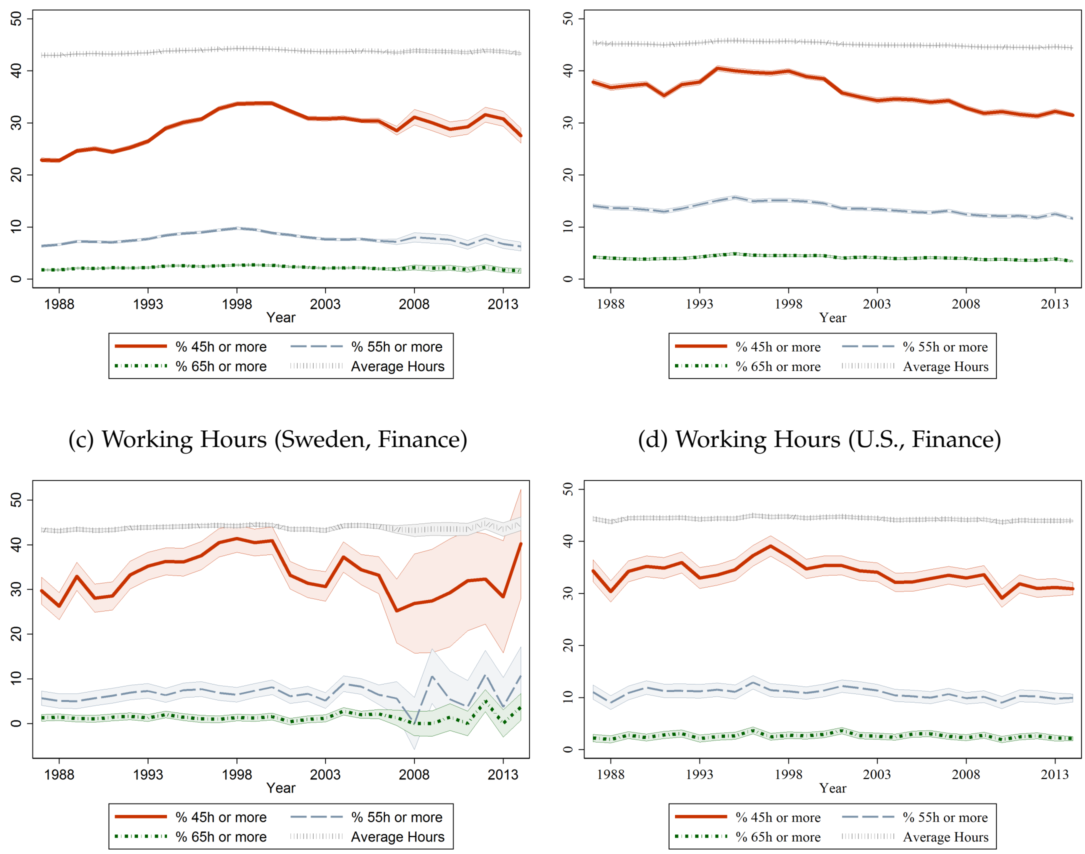


Panels (a) and (b) depict the evolution of finance's relative employment share, defined as the ratio of the number of workers in the financial sector over workers in the non-financial, nonfarm private sector. Panels (c) and (d) depict the evolution of relative pay in the financial sector, defined as the ratio of average pay in finance to average pay in the non-financial, nonfarm private sector. Yearly labor earnings are used for Sweden (left panels) and hourly wages for the US (right panels). Panels (e) and (f) show the evolution of the relative education between the financial sector and the rest of the economy for Sweden (1990-2014, left panel) and the US (1990-2014, right panel). Relative education is calculated as the share of individuals in finance who attained more than a high-school degree (post-secondary education) and of those who attained a university degree (university education) minus the corresponding shares in the rest of the economy. Sources: Swedish population data LISA from Statistic Sweden; Current Population Survey for the US. 95 percent confidence intervals are shaded.

Figure A9: Finance and Non-Finance Working Hours in Sweden and the U.S.

(a) Working Hours (Sweden, RoE)   (b) Working Hours (U.S., RoE)

(c) Working Hours (Sweden, Finance)   (d) Working Hours (U.S., Finance)



This figure shows the distribution of working hours in finance (second row) and the rest of the economy (RoE, first row) for Sweden and the US during 1987–2014 for full-time individuals working at least 40 hours per week. Sources: Swedish Labor Force Survey (SE-LFS), US Current Population Survey (US-CPS). 95 percent confidence intervals are shaded.

cation of the U.S. CPS. Categories that could not be mapped into the CPS classification (e.g., back office or accounting) are summarized by "Other". We see that the subsector composition as well as employment and wage trends are broadly comparable in Sweden and the U.S. (remember that lower relative wage levels in the U.S. are likely due to top-coding). Also, as discussed in the main text, the increase in relative wages takes place across-the-board, and thus is not due to shifting finance employment into different subsectors.

Figure A9 displays the working hours in finance and the rest of the economy for fulltime workers (40 hours or more) using Swedish Labour Force Survey (SE-LFS; see Section B.3) and U.S. Current Population Survey data. We see that hours are longer

Table A4: Subsectors in Finance

Panel A: Sweden

	1990		1996		2002		2008		2014	
	Rel. Wage	**Empl.**	**Rel. Wage**	**Empl.**	**Rel. Wage**	**Empl.**	**Rel. Wage**	**Empl.**	**Rel. Wage**	**Empl.**
Banking	116%	47%	141%	49%	155%	42%	169%	43%	188%	44%
Credit Agencies	132%	11%	161%	5%	152%	6%	153%	6%	151%	7%
Securities, Brokers, Investment Companies	171%	3%	235%	4%	276%	9%	281%	9%	247%	9%
Insurance	134%	23%	151%	24%	148%	22%	153%	24%	153%	23%
Saving Institutions and Credit Unions	101%	4%	110%	5%	112%	5%	119%	5%	130%	5%
Other	131%	12%	156%	13%	146%	16%	158%	13%	173%	11%
Weighted average	124%		149%		160%		170%		178%	
Weighted average (1990 empl. allocation)	124%		148%		153%		163%		173%	

Panel B: USA

	1990		1996		2002		2008		2014	
	Rel. Wage	**Empl.**	**Rel. Wage**	**Empl.**	**Rel. Wage**	**Empl.**	**Rel. Wage**	**Empl.**	**Rel. Wage**	**Empl.**
Banking	111%	34%	112%	29%	113%	27%	122%	28%	139%	28%
Credit Agencies	117%	10%	126%	9%	127%	14%	125%	15%	160%	13%
Securities, Brokers, Investment Companies	152%	12%	196%	14%	197%	18%	191%	19%	186%	20%
Insurance	117%	41%	123%	43%	134%	37%	127%	35%	127%	37%
Saving Institutions and Credit Unions	109%	3%	100%	4%	104%	4%	96%	4%	106%	3%
Weighted average	119%		129%		137%		137%		145%	
Weighted average (1990 empl. allocation)	119%		128%		133%		132%		141%	

The classification of Swedish subsectors in finance is based on annual membership rosters from various financial industry associations (more detail in Section B.1). We map this subsector classification into the classification of the U.S. Current Population Survey (CPS). Categories that could not mapped into the CPS classification (e.g., back office or accounting) are summarized by "Other". Note that lower levels of relative finance wages in the U.S. are likely due to the CPS reporting top-coded wages. Source: Statistics Sweden, Serrano, for Sweden. Current Population Survey for the U.S..

in the U.S. than in Sweden (top panels), but not necessarily in finance than in non-finance (bottom panels) and, most importantly, (relative) working hours in finance do not increase over time. One exception is the subsector of "Securities, Brokers, and Investment Companies", which does feature actual long hours, but again these do not increase over time (not plotted for brevity). We also use SE-LFS data in order to compute approximate hourly wages in Sweden (Figure A4(a)). Overall, there is no indication that increased hours or the resulting hourly wages as opposed to yearly earnings can account for the rising finance premium.

Finally, Table A5 shows employment and relative wages of the 30 largest detailed occupations in finance as well as their changes over time in the U.S.. As in Sweden (Table III), finance wages compared to all workers increased for most occupations during 1990–2010 (Column (4)), and they increased for all except "bill and account collectors" within the same occupation (last column). These within-occupation increases are again not confined to highly-skilled or finance-specific occupations (e.g., consider once more "guards, watchmen, doorkeepers, janitors") and they are not systematically related to occupations' employment growth (Column (2)). Hence, as discussed in the case of Sweden (Section V.C), finance wages have increased across practically all occupations regardless of likely task content, required talent, or sector-specificity.

Overall, we conclude from the evidence in this section that the relevant trends for our study in terms of wages and the financial sector more generally are remarkably similar in the U.S. and Sweden. This makes us quite confident that our main conclusions possess relevancy also for the U.S..

Table A5: Occupational Employment and the Finance Wage Premium in the United States (30 largest 3-digit occupations in finance)

	Finance empl. share (%)		**Relative pay (/ all workers)**		**Rel.pay (/ same occupation)**	
	2010	*2010-1990*	*2010*	*2010-1990*	*2010*	*2010-1990*
lawyers AND legal assistants, paralegals, legal support, etc	1.13	0.25	2.90	0.80	1.20	0.24
financial services sales occupations	4.03	-0.14	2.90	0.34	N/A	N/A
managers and administrators, n.e.c	4.14	-0.66	2.84	0.37	1.34	0.12
managers and specialists in marketing, advertising, and public relations	1.19	0.52	2.70	0.25	1.26	0.10
supervisors and proprietors of sales jobs	3.32	-0.13	2.48	0.14	2.06	0.31
computer software developers	2.16	0.76	2.28	0.65	1.09	0.03
other financial specialists	9.21	2.93	2.23	0.52	1.57	0.44
financial managers	9.74	4.18	2.18	0.11	0.99	0.02
accountants and auditors	4.06	0.23	2.02	0.58	1.27	0.26
computer systems analysts and computer scientists	3.24	2.54	1.94	0.10	1.21	0.23
personnel, hr, training, and labor relations specialists	1.03	0.31	1.71	0.31	1.22	0.19
insurance underwriters	1.52	0.42	1.63	0.22	N/A	N/A
insurance sales occupations	6.06	-2.40	1.51	-0.11	N/A	N/A
management support occupations	0.31	-0.48	1.48	0.44	1.05	0.12
office supervisors	2.72	0.18	1.40	0.17	1.15	0.20
computer and peripheral equipment operators	0.32	-1.50	1.12	0.11	1.16	0.15
insurance adjusters, examiners, and investigators	9.05	3.24	1.07	-0.02	N/A	N/A
administrative support jobs, n.e.c	0.74	-1.18	1.03	0.10	1.18	0.20
interviewers, enumerators, and surveyors	0.86	0.18	0.99	0.22	1.83	0.39
secretaries	3.73	-2.98	0.92	0.14	1.22	0.17
bookkeepers and accounting and auditing clerks	2.03	-1.53	0.92	0.14	1.14	0.09
customer service reps, investigators and adjusters, except insurance	5.78	2.41	0.84	-0.01	1.24	0.34
bill and account collectors	0.96	0.38	0.80	-0.09	1.07	-0.03
general office clerks	1.39	-1.63	0.78	0.06	1.24	0.12
guards, watchmen, doorkeepers AND janitors	0.48	-0.67	0.76	0.06	1.33	0.21
typists	0.49	-1.05	0.73	0.05	1.16	0.08
data entry keyers	0.90	-0.86	0.70	0.03	1.15	0.12
receptionists	1.07	0.13	0.61	0.06	1.26	0.14
file clerks	0.53	-0.42	0.59	0.13	1.13	0.04
bank tellers	7.05	-2.08	0.55	0.01	N/A	N/A

This table shows employment and earnings of the 30 largest (3-digit US Census codes, 380 in total) occupations in finance, constituting 88.77 percent of finance employment on average between 1990 and 2010. Each occupation's share of finance employment relative pay versus all workers and workers in the same occupation outside finance, as well as their changes between 1990 and 2010, are reported. Source: US Census for 1990 and American Community Survey for 2010.

E Females

In our baseline analysis, we restrict the sample to males for whom we observe talent measures from military enlistments tests. For both males and females, we have detailed information from secondary education, such as grades, track, and school characteristics. Based on these information, we construct talent measures for women. Appendix B.2 describes the construction of these variables in more detail.

Figure A10 analyzes Prediction 1 for females by depicting the relative talent of the financial sector, computed as the average talent in finance minus the average talent in the rest of the economy. Panel (a) uses predicted cognitive ability, graderank uni, and graderank science, all measured as percentiles in the population. Consistent with Figure III of the main text, we see the relative talent in finance does not increase according to any of these measures (also raw grades, which are not plotted, do not improve). Panel (b) shows the corresponding graph to Figure A5(b) of 30 year old males. Relative talent of recent female entrants to finance also does not improve. In Panel (c), which corresponds to Figure IV for males, finance's relative share of top 9 females is actually lower than in the overall population and it does trend slightly upward after 2004. In contrast, the relative share of 8s is fairly flat and of 7s and 6s decline.

Table A6 conducts the choice regressions of Prediction 2 for females. As in Table I of the main text, the coefficient on talent for selecting into finance rather declines over time than rises, regardless if we control for schooling or not (Columns (1) and (2)). The role of parents' sector affiliation (and thus maybe networks) again increases over time (Column (3); though imprecise and insignificant here). If we do the analysis by talent group, we find that middle- as well as high-talented females both become less likely to enter finance than low-talented females over time (Columns (4) and (5)). This is once more comparable to Table I of the main text.

Figure A11 moves on to the wage analysis for females, plotting the finance premium from wage regression (2) in order to test Prediction 3. In Panel (a) we control for predicted cognitive talent, a quadratic in potential experience (dashed blue line), and then add years of education (dotted green). In Panel (b), we add individual and individual-firm fixed effects and Panel (c) allows for time-varying (but not sector-specific) returns to observed talent. The results in all three panels are parallel to Figure V of the main text

Table A6: Linear Probability Sector Choice Regressions (Females, 30 Years Old)

Linear in talent	(1)	(2)	(3)	By talent group	(4)	(5)
Years of School (1990-94)		**-0.290***	**0.168**	**Yrs of Sch (1990-94)**		**-0.019**
difference in 1995-99		-0.292*	-0.119	diff. in 1995-99		-0.224*
difference in 2000-04		0.049	-0.377	diff. in 2000-04		-0.127*
difference in 2005-09		0.181*	-0.294	diff. in 2005-09		-0.043
difference in 2010-14		0.288*	-0.221	diff. in 2010-14		0.070
Pred Cogn Talent (1990-94)	**0.057***	**0.070***	**-0.01**	**Mid pred cogn t (5-8)**	**3.45***	**3.48***
difference in 1995-99	-0.001	0.013*	0.011	diff. in 1995-99	0.27	0.69*
difference in 2000-04	-0.028*	-0.030*	0.028	diff. in 2000-04	-1.44*	-1.16*
difference in 2005-09	-0.033*	-0.041*	0.025	diff. in 2005-09	-1.49*	-1.39*
difference in 2010-14	-0.026*	-0.038*	0.027	diff. in 2010-14	-1.30*	-1.43*
Father Ever in Finance			**-0.37**	**High pred cogn t (9)**	**1.24***	**1.31***
difference in 1995-99			6.824	diff. in 1995-99	-1.01*	-0.09
difference in 2000-04			3.278	diff. in 2000-04	-0.91*	-0.44
difference in 2005-09			3.566	diff. in 2005-09	-2.21*	-2.09*
difference in 2010-14			3.555	diff. in 2010-14	-0.97*	-1.19*
Mother Ever in Finance			**-0.35**			
difference in 1995-99			-0.762			
difference in 2000-04			3.783			
difference in 2005-09			5.454			
difference in 2010-14			4.527			
N	657,249	657,234	328,517	**N**	657,249	657,234
R-sq	0.004	0.005	0.021	**R-sq**	0.005	0.005
adj. R-sq	0.004	0.005	0.02	**adj. R-sq**	0.005	0.005
Father & Mother Total Inc.	No	No	Yes	**Fthr & Mthr Total Inc.**	N/A	N/A
Graduation Municip. FE	No	No	Yes	**Grad. Municip. FE**	N/A	N/A

Notes: The table shows linear probability regressions of choosing finance (indicator multiplied by 100) for 30 year old females over time. The left panel uses as regressors linear predicted cognitive talent interacted with 5-year period dummies. Column (2) adds years of schooling and Column (3) adds dummies for whether the individual's father and mother ever worked in finance during the sample period, their total annual income, and fixed effects for the individual's municipality of residence when they graduated from high-school. The right panel uses dummies for low (1–4; base group), (upper-)middle (5–8), and high (9) predicted cognitive talent groups. Robust standard errors are clustered on individual (not reported for brevity, significance at 1% level indicated by a single *).

for men. That is, talent selection, fixed effects, and changing overall returns to talent cannot account for the increasing finance wage premium over time. Table II of the main text already summarized these results for males, females, and both genders together, including further individual-sector fixed effects.

Finally, we examine Prediction 4 for females. First, Figure A12, shows that raw relative wages in finance did not increase more for higher levels of talent. This is in line with Figure VI for males in the main text. Second, Table A7 shows the corresponding regression results controlling for schooling and experience (Column (1)) plus individual-sector fixed effects (Column (2)). Again consistent with the results for males (Table II, Columns (4) and (5)), the finance wage premium did not increase more for mid- or high-talented females than for low-talented ones.

Table A7: Finance Premium By Talent Group (Females, All Ages)

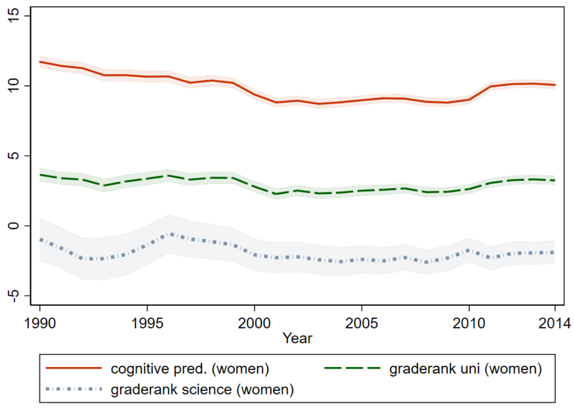
	Females Only	
	(1)	**(2)**
Finance Premium (log points)	**15.5***	***absorbed***
diff. in 1995-99	4.3*	9.1*
diff. in 2000-04	8.6*	15.1*
diff. in 2005-09	9.9*	18.2*
diff. in 2010-14	11.1*	19.3*
Finance × Mid Pred Cogn (5-8)	**2.2***	***absorbed***
diff. in 1995-99	-0.3	-4.3*
diff. in 2000-04	-1.1	-4.2*
diff. in 2005-09	1.7	-3.0*
diff. in 2010-14	1.4	-2.7*
Finance × High Pred Cogn (9)	**0.3**	***absorbed***
diff. in 1995-99	-2.6	-6.7*
diff. in 2000-04	1.3	-2.1
diff. in 2005-09	2.4	-4.7
diff. in 2010-14	1.9	-5.7
N (in million)	18.6	18.6
Years of School	Yes	Yes
Pot. Exp. (Quadr)	Yes	Yes
Fixed Effects	No	Ind.×Sec

Notes: The table reports the finance premium for low (1–4; base group), (upper-)middle (5–8), and high (9) predicted cognitive talent groups. Controls are years of schooling, potential experience, a gender dummy, all interacted by time period, and individual interacted with sector fixed effects (Column (2)). Robust standard errors clustered on individual (not reported for brevity, significance at 1% level indicated by a single *).

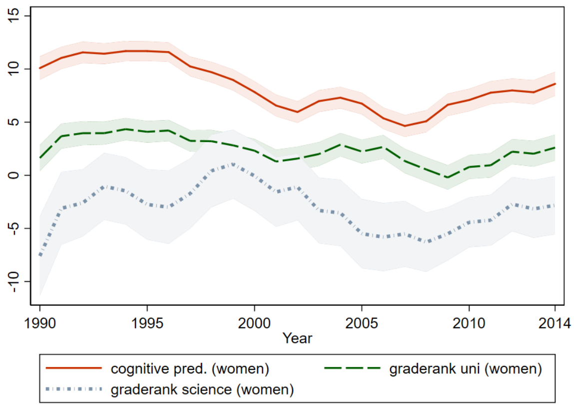
Overall, we therefore find that the conclusions for females' talent selection and wages in the financial sector are very similar to those for males of the main text. We see a strong increase in relative finance wages, but relative talent does not improve and neither selection nor changing returns to talent can account for the wage increase.

Figure A10: Relative Talent in the Financial Sector (Females)

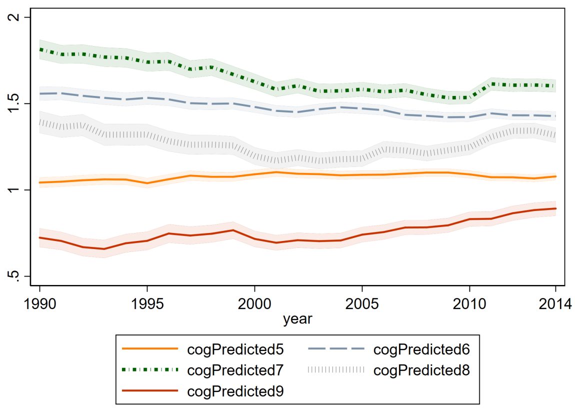
(a) Relative Talent



(b) Relative Talent (30 years old)



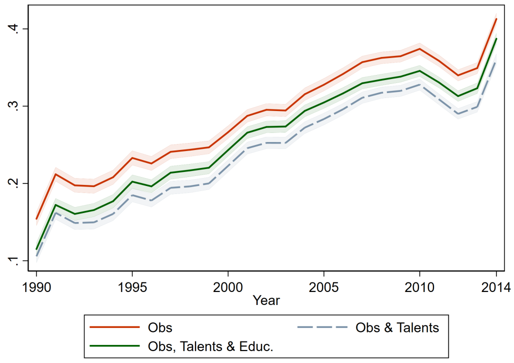
(c) Relative Distribution of Talent



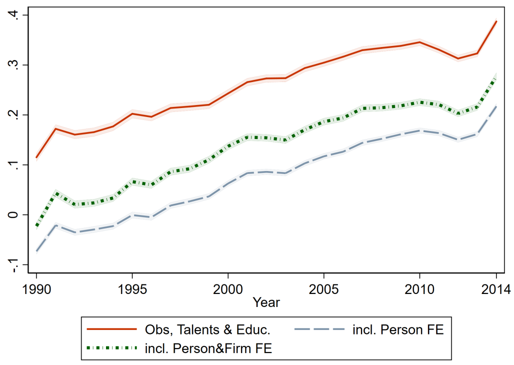
This figure describes the relative talent in finance for females during 1990 to 2014. Panel (a) depicts the average talent in finance minus the rest of the economy, using predicted cognitive ability and grade percentile rank for graduates from high-school tracks that have a science focus or lead to university more generally. Panel (b) shows the same for 30-year olds. Panel (c) depicts the relative shares of medium and high predicted cognitive talent levels, where relative share is calculated as the share in finance divided by the share in the rest of the economy. The predicted cognitive ability measure is discretized to Stanine scale for this purpose. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

Figure A11: Wage Premium of the Financial Sector (Females)

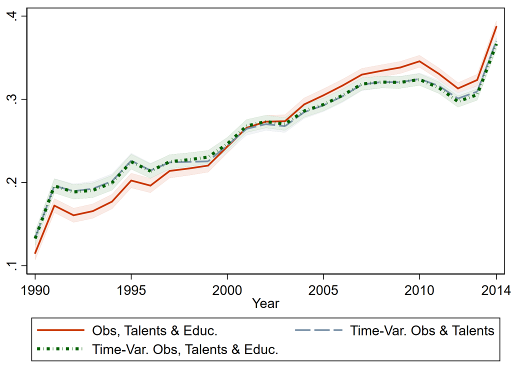
(a) OLS (Females)



(b) Fixed effects (Females)

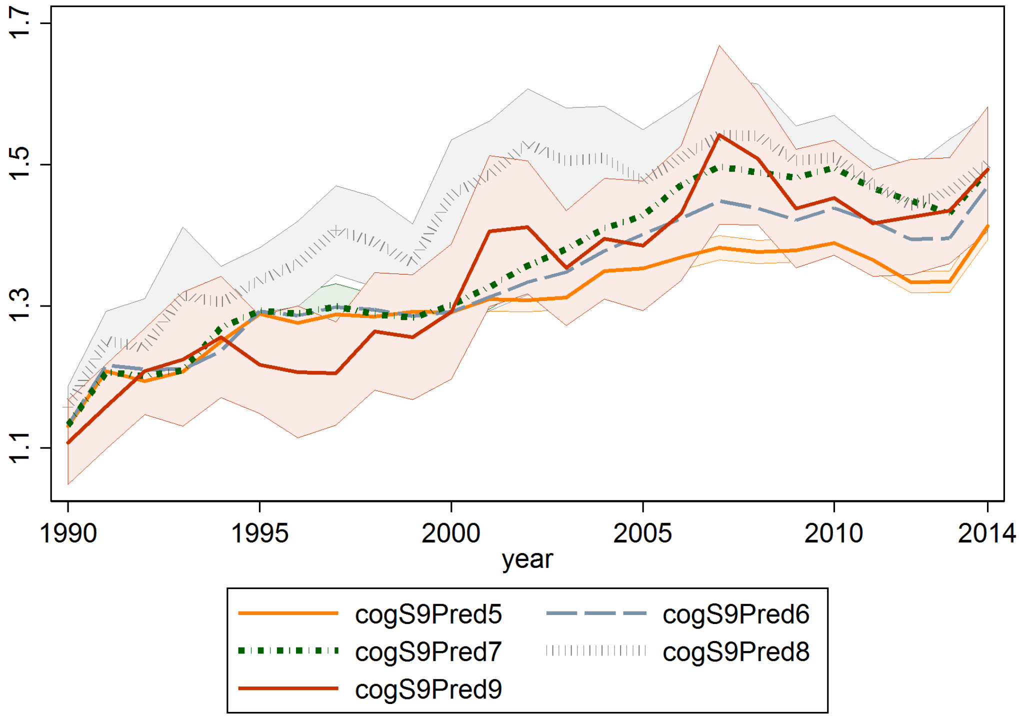


(c) Time-varying OLS (Females)



This figure shows the remaining finance wage premium for females after controlling for talent and other variables in linear regressions. The three models are: (i) controls for potential experience, (ii) controls for potential experience and talent, and (iii) adds education (years of schooling). The sample consists of females only, and talent is measured by predicted cognitive ability scores. The middle row adds individual fixed effects and individual-firm fixed effects to (iii). The bottom row allows for time-varying returns to experience, talent, and education. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

Figure A12: Relative Wages in the Financial Sector by Talent Group (Females)

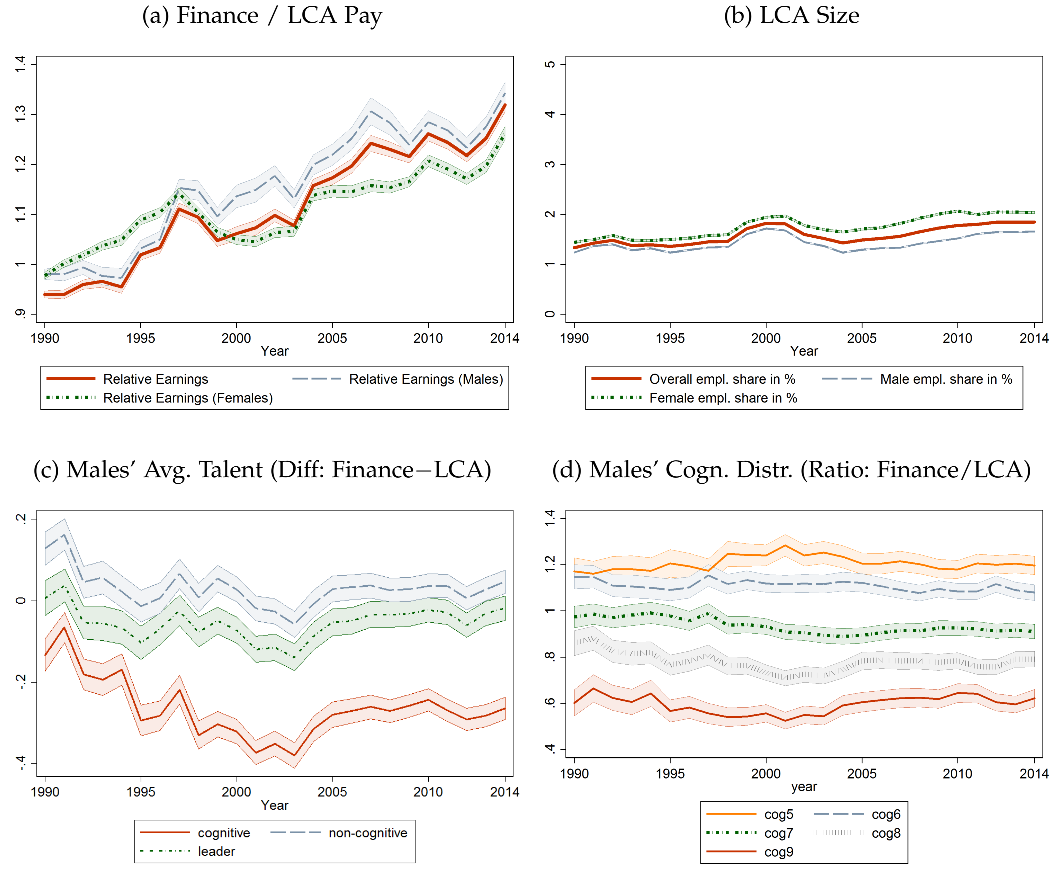


This figure shows relative finance wages by predicted cognitive talent group for medium and high talent levels of females during 1990–2014. Relative finance wages are defined as the average wages in finance of the respective talent score divided by the average wages outside finance of the same talent score. The predicted cognitive ability measure is discretized to a Stanine scale for this purpose. Sources: Swedish population data LISA, Swedish Military Archives and Defence Recruitment Agency, Swedish high school register. 95 percent confidence intervals are shaded.

F Comparison to Other High-Skilled Sectors

Finally, we compare the trends in finance to two other high-skilled and high-earning sectors: Law, Consulting, and Accounting (LCA) and Information Technology (IT). In particular, one concern is that the surge in relative finance wages might be due to a general increase in the demand for labor and/or wages of high-skilled sectors. While we did show that changing overall return to cognitive and non-cognitive talent hardly accounts for any of the increase in the finance wage premium (Figures V(c) and A11(c)), we test this hypothesis here directly.

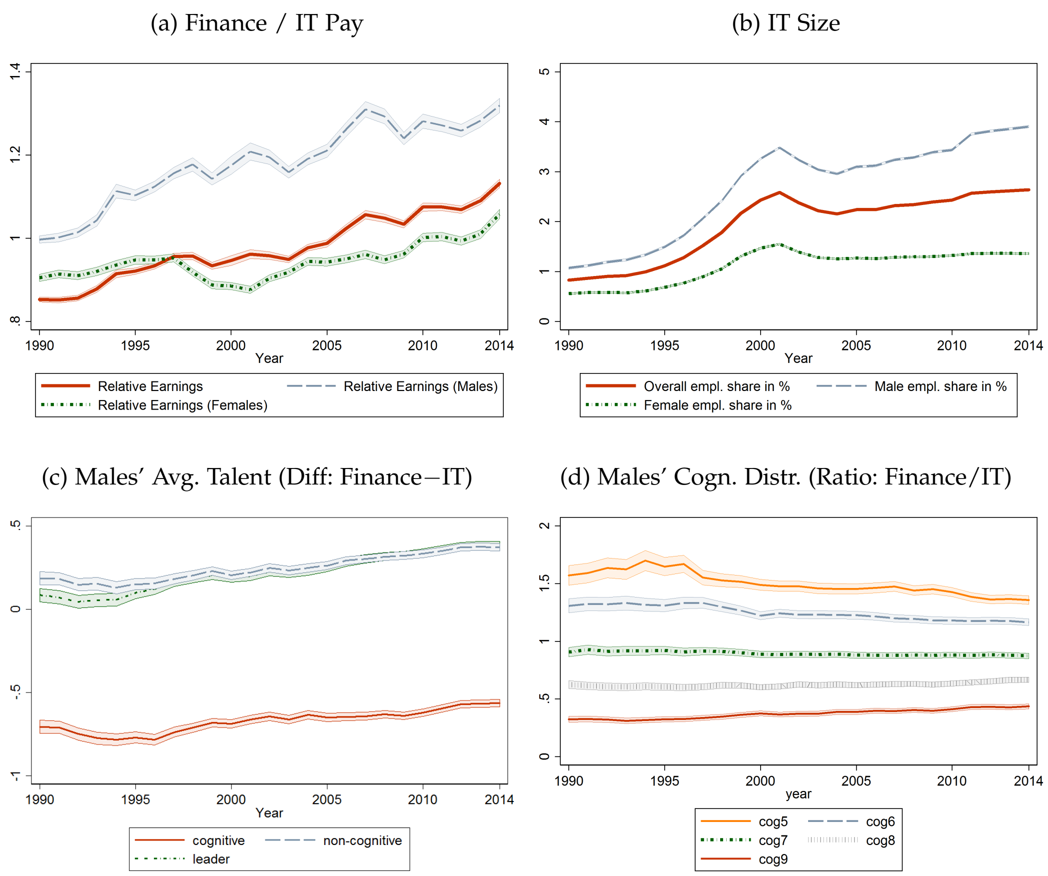
Figure A13: Law, Consulting, and Accounting (LCA)



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

Figures A13 and A14 show that finance is actually less cognitively talented than LCA

Figure A14: Information Technology (IT)



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

and IT (Panels (c)) and that especially the share of top 9 cognitive ability is only about half as high (Panels (d)). In terms of non-cognitive and leadership ability, finance is overall about as skilled as LCA and slightly more skilled than IT.

While relative wages in finance are initially also below both of these sector (Panels (a)), they increase strongly over time, from 0.95 to 1.3 for LCA and from 0.85 to 1.1 for IT.[53] This increase is especially remarkable for LCA, where relative finance talent decreased if anything. In the case of IT, relative finance talent increased modestly after about the mid 1990s. But at the same time the employment share (and probably labor demand)

[53]Part of the reason why average IT wages were higher than finance wages for so long is that there is a significantly larger fraction of women in the finance workforce compared to IT. Restricting the comparison to males, finance wages have been higher than IT wages since the early 1990s.

of IT trebled over the sample period (Figure A14(b)), presumably having to take in a substantial number of less talented workers than the truly exceptional pioneers that were in the IT sector in the beginning of our sample.

Therefore, the comparisons to LCA and IT reinforce our findings of the main text. The increase of finance wages was exceptional, also relative to these other highly skilled sectors and especially when taking into account the change in the relative size and talent composition of its workforce.