Returns to Talent and the Finance Wage Premium*

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Abstract

We study the role of talent in the distribution of pay in the finance industry since the 1980s. We exploit a special feature of the French educational system to build a precise measure of talent that we match with compensation data for graduates of elite French institutions. We document that wage returns to talent are three times higher in the finance industry than in the rest of the economy, and that they have increased threefold since the 1980s. These results illustrate how the finance wage premium has been disproportionately and increasingly allocated to the most talented workers in this industry.

Keywords: Finance, Compensation, Talent, Wage Distribution, Wage Structure

JEL codes: G2, G24, J3, J31, M5

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1 Introduction

Compensation in the finance industry has been higher and more skewed than in other sectors since the beginning of the 1980s. Controlling for education and other individual characteristics, Philippon and Reshef (2012) find that the finance wage premium is, on average, 50% for 2006. The financial sector has largely contributed to the observed gains at the top of the wage distribution since the 1980s (Kaplan and Rauh, 2010; Bakija et al., 2012; Bell and Van Reenen, 2013) and, consequently, has often been criticized as a source of growing income inequality. This public debate, associated with increased regulatory scrutiny, calls for an improved understanding of the drivers of bankers' pay. A growing theoretical literature has been answering this call by modeling the drivers and implications of bankers' pay, using talent as a key ingredient (Acharya et al., 2016; Benabou and Tirole, 2015; Glode and Lowery, 2015; Thanassoulis, 2012).

However, empirically assessing the returns to talent across industries is difficult because it requires accurately observing and measuring worker talent. A unique feature of the French educational system is that prospective engineering students are selected solely based on their performance on a nationwide competitive exam that covers a wide range of subjects in both written and oral formats. We exploit this rigorous, multi-dimensional selection process to build a uniquely granular measure of talent covering the right tail of the population, which we use to address our research question: Are wage returns to talent relatively high in finance compared to the rest of the economy?[1] More broadly, do talent effects drive the cross-section of wages observed in finance?

Our main result is that the finance wage premium is disproportionately and increasingly allocated to the most talented individuals in this sector. We show that the returns to talent are three times higher in the finance industry than in the rest of the economy and that within a highly educated population, the share of the finance wage premium received by the top quintile of talent has increased from 33

[1]For the purposes of this analysis, we define talent as the aptitude to reach an objective in a competitive environment. Talent hence encompasses not only cognitive skills but also non-cognitive skills and personality traits, such as motivation, self-discipline, low cost of effort, and ability to perform in a competitive environment.

An important contribution of our study lies in our measure of talent. We use the selectivity of French engineering schools for the following reasons. First, our research setup offers a unique focus. We analyze talent heterogeneity in a highly educated cohort, on the right tail of the skill distribution where most of the finance premium lies (Philippon and Reshef, 2012; Bell and Van Reenen, 2013). As every individual in our sample has completed a five-year master degree, our setup allows disentangling returns to talent from returns to schooling, which is a traditional challenge for the empirical labor literature. Our highest category of talent corresponds to 0.01% of an age cohort, making our measure significantly more granular than the ones used in other studies.[2] Second, this measure of talent is comprehensive. The national competitive exam for engineering schools incorporates both written and oral sections covering a wide range of subjects. This exam assesses academic, cognitive, and communication skills, and it gauges personality traits such as endurance, commitment, ambition, and ability to perform in a competitive environment.[3,4] The highly selective and competitive environment of preparatory schools prior to the examination, as well as the high stakes of the exam outcome, challenge candidate motivation and resistance to stress. Third, with more than 35 hours of classes, heavy homework loads, and one written and two oral exams per week, the intense workload during these school years ensures that performance is unbiased by personal coaches, exam preparation boot camps, and other support resources that are often used by applicants to US universities. The unique characteristics of our talent measure thus warrant a relatively large explanatory power when accounting for wage differences, four times higher than the one of the standard measures of the literature (Bowles et al. (2001)).

We complement this school-level measure of talent, and control for school treatment

[2]The heterogeneity in talent at the right tail is typically overlooked in discreet population-wide measures, such as SAT scores or IQ tests, while the objective of the engineering school exam is to precisely discriminate among individuals in a highly educated and homogeneous population. In Böhm et al. (2015), the top category of talent corresponds to 4% of an age cohort.

[3]Ors et al. (2013) exploit this specificity of the French educational system for business schools. They find that males' performance dominates that of females in competitive environments, whereas females outperform men on less competitive exams.

[4]French engineering schools confer a generalist degree. The proclaimed objective of the selection process is to identify the most talented individuals in France, and therefore, it goes beyond assessing technical skills.

effects, by also considering the graduation age of engineering school alumni.[5] A student graduating from a top school at age 22 is likely more talented than one that do so at 25.

We match these talent measures to detailed compensation survey data that cover 7% of the total population of French graduate engineers. The survey, which gathers alumni data from 199 of 225 French engineering schools, includes detailed information on education, occupation, family situation, industry, firm type and size, and compensation. It also provides us with the specific job title of the worker. Because engineering, business administration and medicine are the only fields that are selective in the French higher education system, and engineering is the largest of the three, this dataset covers a significant share of the right tail of the skill distribution in the French population. Our dataset spans the period from 1983 to 2011. Each of the 15 repeated cross-sections covers, on average, 30,800 individuals working in France or abroad. We verify the external validity of our setup by replicating existing results from the literature. French graduate engineers in the finance sector are better paid than engineers working in other industries. Finance workers earn a premium of 25% over our sample period, which has increased threefold since the 1980s. This finding is consistent with Philippon and Reshef (2012). In line with Bell and Van Reenen (2014) and Bell and Van Reenen (2013), we also observe relatively high and increasing skewness in the wage distribution in the finance industry.

The central result of our paper is that returns to talent are significantly higher in the finance industry and that the distribution of talent largely maps into the allocation of the wage premium across workers. The main equation in our empirical analysis regresses the log of yearly gross wages on our talent measure and its interaction with an indicator variable for working in finance. Graduating from a school one notch higher in terms of selectivity induces a 6.5% average wage premium in the finance industry, versus a 2% relative premium in the rest of the economy. When we include the interaction between our talent measure and the finance industry indicator, we observe that the coefficient on the finance dummy decreases from 25% to 6%. The least talented engineers are therefore

[5] Age at graduation maps with age at entry. While a large number of students repeat their last year of preparatory classes to improve their ranking, virtually no students skip or repeat a year during engineering school. Gap years are also uncommon in France.

only slightly better paid in finance than in other sectors, meaning that the finance wage premium is disproportionately allocated to the most talented individuals in this industry. Within finance, we interact our talent measure with job title fixed effects and find that returns to talent are even higher for front office jobs, when compared to positions in back office or support departments.

The foregoing result is confirmed when graduation age is used as an alternative measure of talent, thereby allowing all unobserved school-level variables, including potential within-school selection bias into finance, to be absorbed by school fixed effects. We again find that wage returns to talent are more than three times higher in the finance industry than in the rest of the economy. This alternative specification also mitigates concerns over alumni networks or school differences in quality of training or focus on finance as possible explanations for our main result.

Our result is also robust to the introduction of individual fixed effects in a panel regression that estimates the effect on wages of switching into the finance industry from another sector. We track individuals across surveys via detailed socio-demographic variables, such as their father's and mother's occupations and year of birth, and educational variables, such as the name of their engineering school and type of specialization. We find that the wage increase obtained from switching into the finance industry is fully absorbed when we include an interaction between talent and the finance industry indicator. Therefore, our main result is unlikely to be driven by unobserved time-invariant characteristics at the individual level, such as social background or risk aversion. All three results are robust to the introduction of industry-year fixed effects, which absorb any overall shift of wages in finance.

We also observe a trend toward increasing returns to talent. Estimating our main equation separately over each of the three decades of our sample period reveals that returns to talent in finance have increased nearly threefold over the 1980–2011 period. The most talented individuals in finance have thus received most of the increase in the wage premium over the past decades. Our results shed new light on the wage growth in finance since the 1980s documented in the literature. Increasing returns to talent are also associated with an increasing share of talented individuals going into finance.

Finally, we show that the share of variable compensation is positively correlated with returns to talent.[6] Our findings thus point to an interaction between the returns to talent and the structure of pay, variable compensation acting as a screening device or as an incentivizing scheme.

Alternative explanations for our results are difficult to reconcile with our data. Our results hold across the whole distribution of talent, hence mitigating concerns over potential within-school selection biases. A battery of specific tests precludes network effects, social background factors and compensating wage differentials as potential drivers of our results. For example, we find that returns to our talent measure are even higher for first-generation graduates, the children of parents without university degrees. Favorable social backgrounds or personal relations are unlikely to play an important role for this subsample of graduates.

We then discuss the implications of the significantly higher and increasing returns to talent we observe in the finance industry. These higher returns may result from either optimal contracting in a competitive market, or from powerful managers setting their own pay and extracting rents from their employers.[7] Optimal contracting may result in high returns to talent if banks need to compete intensely for talented workers or if talented workers are more costly to monitor or incentivize. A growing theoretical literature investigates the effects of competition for talent (Acharya et al., 2016; Benabou and Tirole, 2015; Glode and Lowery, 2015; Thanassoulis, 2012) and moral hazard (Axelson and Bond, 2015; Biais et al., 2015) on finance worker compensation. While our results are difficult to reconcile with the managerial power view, they are supportive of optimal contracting. Both mechanisms, competition for talent and moral hazard, are likely to interact (Benabou and Tirole (2015)).

Our results also raise the question of talent allocation in the economy. We document

[6] We calculate the variable wage from a survey question on compensation structure.

[7] In this paper, we do not address the question of whether finance as a whole is extracting rents from the economy. If talented workers are better at extracting rents as in Bolton et al. (2016), it is optimal for their employer to compensate them more.

an increase in the share of the most talented individuals going into finance, which points to returns to talent playing a significant role in career decisions of these individuals. The magnitude of this effect, however, is relatively modest in regard to the large gap in returns to talent we observe between the finance industry and the rest of the economy. This magnitude suggests that there are significant frictions in the allocation of talents across industries, which is in line with the findings of Shu (2015) and Böhm et al. (2015) based respectively on MIT students, and the entire Swedish population. Finally, our results contribute to the understanding of the well-documented rise in income inequalities. Talented individuals in certain industries are receiving an increasing share of the total wage bill, which fosters an increasing dispersion of income in the economy.

Our work expands on the recent empirical literature that has identified a high level of compensation in the finance industry relative to the rest of the economy and high skewness at the top of the wage distribution. Philippon and Reshef (2012), Oyer (2008), and Goldin and Katz (2008) – based on data from the Census Population Survey, a Stanford MBA survey, and a Harvard alumni compensation survey, respectively – find that the finance premium varies from 40% (in Philippon and Reshef (2012)) to more than 100% (in Oyer (2008), and Goldin and Katz (2008)). Philippon and Reshef (2012) documents a post-1980s increase in compensation in finance relative to the rest of the private sector after controlling for education, and Kaplan and Rauh (2010), Bakija et al. (2012) and Bell and Van Reenen (2014) show that the financial sector share at the top end of the income distribution has significantly increased. The main contribution of the present paper is to attribute these wage distribution patterns in the finance industry to higher and increasing returns to talent.

Our paper contributes to the literature that investigates the dramatic growth in top executive pay and earning inequalities observed since the 1980s. This literature includes theories of managerial power (Bebchuk and Fried (2004)), social norms (Piketty and Saez (2006); Levy and Temin (2007)), incentives, and competition for talent or managerial skills (Murphy and Zábojník, 2004; Frydman, 2007; Guadalupe, 2007; Gao et al., 2015; Geerolf, 2015). Our results are consistent with the evolution of wages reflecting a change in market returns to talent, magnified in recent decades by scale effects (Gabaix and Landier, 2008; Kaplan and Rauh, 2013; Greenwood and Scharfstein, 2013), skill-biased technological change (Katz and Murphy, 1992; Garicano and Rossi-Hansberg, 2006), and deregulation (Boustanifar et al., 2016).

Our paper also provides new evidence on the interaction between competition for talent and the structure of compensation. Lemieux et al. (2009) show that wages are more closely related to worker production in performance-pay than in non-performance-pay jobs, and Cuñat and Guadalupe (2005) show that a higher level of product market competition increases the performance pay sensitivity of compensation schemes. Reliance on incentive pay may be higher for talented workers because of higher monitoring costs (Biais and Landier (2015)), higher productivity of effort, or better outside options (Giannetti and Metzger (2013)), but causality may also occur in the opposite direction: performance pay may be used as a sorting mechanism to attract talented workers (Benabou and Tirole (2015)).

Finally, our results on the increasing returns to talent and talent allocation effects raise questions concerning the externalities that might be generated by high returns to talent in the finance industry. By offering relatively high wages for the same level of talent, the finance sector may lure talented individuals away from other industries (Murphy et al., 1991; Philippon, 2010; Bolton et al., 2016) or from financial regulation (Shive and Forster, 2016; Bond and Glode, 2014). We find evidence suggestive of a brain-drain towards the finance sector, but of lower magnitude than the difference in returns to talent would suggest, which is broadly consistent with Shu (2015) and Böhm et al. (2015). Böhm et al. (2015), using data on the entire Swedish population, find no evidence that the selection of talent into finance has increased or improved.[8] Competition for talent may also generate inefficient risk taking (Acharya et al., 2016), lead to excessive overbids

[8] Böhm et al. (2015) find, however, that rising returns to talent explain only a small part of the increase in wages. We reconcile our results with this study as follows. First, our analysis is conducted at the extreme right tail of the distribution of talent: as engineer studies attract the most quantitative people and represent 3% of an age cohort in France, our full sample would almost be nested within the top level of talent of this study. Second, our measure is likely to capture aspects of talent that is overlooked by an IQ test or 20 minute personality interview. Finally, the Swedish financial industry might not be large or profitable enough to generate the compensation dynamic that we document.

(Glode and Lowery, 2015), increase the fragility of banks (Thanassoulis, 2012), or shift effort away from less contractible tasks, resulting in efficiency losses (Benabou and Tirole, 2015).

The paper proceeds as follows. In Section 2, we describe how we measure talent. In Section 3, we provide summary statistics for our dataset and assess the representativeness of the sample. We present our results in Section 4. In Section 5, we consider alternative explanations for our results on the returns to talent in finance. Section 6 discusses the implications of our results. Section 7 concludes.

2 Measuring Talent

Comparing returns to talent between industries is challenging because of how difficult it is to accurately observe talent. Disentangling talent from confounding factors, such as social backgrounds or schooling, especially at the top of the talent distribution, is also difficult. Endogenous industry-worker matching represents a final challenge for measuring the returns to talent.

The ideal experiment for our study would therefore cover a highly and homogeneously educated population wherein talent and pay are perfectly observable to the econometrician. In addition, workers should be randomly assigned to a given industry.

We argue in this section that the French educational system provides us with the closest feasible setup to the ideal experiment, as it differs from this ideal setup along only two dimensions and in a moderate manner. First, although talent is not perfectly observable, the selection process of the French education system allows us to build a comprehensive and robust proxy for talent within a highly and homogeneously educated subpopulation. Second, although allocation to a sector is not random, each sector is represented for each level of talent, which allows us to build robust counterfactuals.[9]

[9]See Table A8 in the online appendix.

2.1 French Engineering Schools' Selection Process

We use the selection process of French engineering schools to build a measure of talent for the entire population of engineers. To earn the official title "graduate engineer", students in France need to graduate from a master's program in any field of engineering offered by one of 225 selective, small-scale institutions.[10] These so-called "Grandes Ecoles d'Ingénieurs" select students on the basis of their ranking on a national competitive exam that includes both written and oral tests. Student performance on this exam reflects strong cognitive and academic skills as well as personality traits such as motivation, self-discipline, low cost of effort, and ability to work under pressure. Figure 1 summarizes the selection process of French engineering schools.

First, written tests covering a wide range of subjects assess a large set of cognitive and academic skills, including mathematics, physics, programming, French literature, and foreign language sections. Candidates also select an optional topic from among biology, chemistry, engineering, or computer science. More than 80 hours of testing is involved over a three-week period (see Figure 1 for coefficients and exam lengths for each topic). The candidates are then ranked nationally, and they access oral examination with schools depending on their ranking.

The second phase of the competitive exam includes a series of 20-minute oral exams, which assess presentation, communication, and interaction skills. Candidates solve problems in the same set of subjects in a limited time and present their solutions to a jury of professors.

The process ends with the assignment of a final national ranking that gives to applicants their priority position to choose a school. Students favor reputation over field expertise or location in their selection of schools, and deviations are quite rare, especially for top schools. Admitted students study on campus for three years before being awarded a graduate degree.

[10] Thirty thousand students graduate each year in Engineering in France. Engineering, which is considered a generalist education, has traditionally been the main pathway to obtaining management or leadership positions in France.

The two years that students spend preparing for the exam at highly selective institutions (*Classes Préparatoires*) are a fundamental part of the process. These preparatory schools are mainly public; they are free of tuition and provide subsidized housing. They select students on the basis of superior academic performance in high school, independently of their social or geographic origin.[11] Top high school students are highly encouraged to apply to *Classes Préparatoires.* These two years of study, as well as the three years of engineering school, are virtually free, which limits concerns about selection on family wealth.

Success in *Classes Préparatoires* requires a set of personality traits that have been proven to matter professionally, such as high motivation, self-discipline, low cost of effort, and ability to work under pressure. First, the workload is deliberately heavy, with more than 35 hours of classes per week, one written and two individual oral exams every week, and a large amount of compulsory homework. Second, students have the option to switch into the non-selective French university system at any time. Third, students are ranked quarterly, and they are excluded after the first year if their performance is too low (Ors et al., 2013).

INSERT FIGURE 1

2.2 School Ranking and Talent Measure

We arrive at our main talent measure by classifying engineering schools into ten selectivity categories based on the nationwide competitive exam. Group 1, which enrolls, on average, the most talented students, includes the most selective school, while Group 10 includes the least selective schools. We use these bins to make our analysis easier to read, and because they roughly correspond to a lognormal distribution of talent. In the interest of clarity, we define our measure of talent as *10 minus School Rank.* We use *1 minus Selection Rate* throughout our analysis as an alternative specification for robustness purpose.

[11] The average selection rate Classes Préparatoires in the science and engineering fields is approximately 15% for those who hold a scientific *Baccalauréat. Source: www.data.gouv.fr.*

We compute a school's selection rate by dividing the rank on the national exam of the last admitted student by the total number of enrolled students nationwide. Information on the rank of the marginal student and on the total number of enrolled students is public and available for the 2002–2012 period.[12] The precise methodology for this calculation is described in the online appendix.

Selection rates for each category of our main talent measure are reported in columns (1) and (2) of Table 2. The highest category includes the Ecole Polytechnique, which recruits the top 1.5% of students. The second highest category includes Mines de Paris, Ecole Centrale Paris, and Ecole des Ponts et Chaussées. The lowest category includes mainly schools that admit students directly after high school. The bottom part of Figure 1 plots the admission rate across the groups of our talent measure. Table A8 in the online appendix lists the rank and the selection rate of all schools in our sample.

The main advantage of our talent measure is its focus on the right tale of the distribution, which captures most of the talent premium (Philippon and Reshef, 2012). Our measure covers, with high comparability owing to consistent ranking, the total population of French engineers since 1980, a highly and homogeneously educated population. All engineers have the same level of education and years of schooling – a five year master degree -, and they followed the same educational path. The heterogeneity in talent at the right tail is typically overlooked in discreet population-wide measures, such as SAT scores or IQ tests, while the objective of the engineering school exam is to precisely discriminate among individuals in a highly educated and homogeneous population. Our highest category of talent hence corresponds to 0.01% of an age cohort.

Second, our talent measure is comprehensive, and maps most of the requisite traits for successful careers. Beyond academic, cognitive, and communication skills, the national competitive exam indeed gauges personality traits such as endurance, commitment, ambition, and ability to perform in a competitive environment. The literature shows that personality traits are important determinants of wages (Heckman, 1995; Bowles et al., 2001; Heckman and Kautz, 2012). The highly selective and competitive environment

[12] http://www.scei-concours.fr/.

of preparatory schools prior to the examination, as well as the high stakes of the exam outcome, test candidate motivation and resistance to effort and stress.

Finally, the admission process to French engineer schools ensures that our talent measure is as accurate as possible. The admission process is designed to limit distortions due to networking, social background, reputation, and donations, as the written exam is completely anonymous and there is no use of letters of recommendation. The heavy workload imposed on all students during the two years of preparation limits the potential benefits of additional resources, such as tutors or exam preparation boot camps. A typical week in a preparatory class includes 35 hours of class, two or three one-hour oral examinations, one four-hour written examination, and several at home assignments. In terms of social prestige, and even pay-offs (as students from the top school are eligible for stipends), the stakes of the competitive exam are very high and comparable to those associated with a professional career. Each student self selects, with respect to personal investment, to sit for the toughest of exams, despite guaranteed admission to a French university in any year following their high school graduation.

2.3 Controlling for Treatment Effects: A Non-school-specific Measure of Talent

We also use the student's age at graduation as an alternative measure of talent, which enables us to control for school treatment effects by differentiating among graduates within each school. For instance, schools might offer training of varying quality or a more specific focus on finance or related skills. In the French educational system, high-performing students, on average, graduate at a relatively younger age both because they skip a year and because less talented students often repeat years, typically to improve their ranking at the national exam. Hence, a student who graduates from a top school at the age of 22 will be more talented, on average, than a student who graduates from the same school at an age of 25. Age at graduation, which is not school specific, enables us to introduce school fixed effects in our analysis. Figure A4 in the online appendix plots the distribution of graduation age in our sample. We define the variable *Age at Graduation* as follows: it takes value of 1 for alumni that graduated at age 21 or 22, value of 0 for the ones that graduated at age 23 or 24, and value of -1 for the ones that graduated at age 25 or 26.

2.4 Industry- and Job-Employee Matching

Another advantage of using the French engineering schools' selection process to measure the returns to talent across industries is that a small fraction of graduates of *each* school go into the financial sector, which allows the building of credible counterfactuals both across industries for the same level of talent and across levels of talent for the same industry.[13]

In addition, our setup is immune to concerns over self-selection into finance of the best-ranked graduates within a given level of talent. By construction of the selection process, the "bottom" graduates of a given talent level are indeed more talented, as measured by the competitive exam, than the top graduates of the level below.

Another potential concern would be that, within a talent level, a specific subgroup, for instance, the most social students (as suggested by Shu's (2014) results), are going into finance, whereas in lower talent groups, the opposite selection effect occurs, i.e., the least social individuals are going into finance. Such a selection effect could only drive our results over 10 groups of talent if it is itself highly correlated with our measure of talent, which seems unlikely. Including specifications with individual fixed effects also mitigates these concerns.

Finally, endogenous matching may also happen at the job level, as talented people are more likely to obtain certain jobs. We address this issue by also conducting our analysis at the job title level.

[13]See Table A9 in the online appendix for the distribution of respondents across industries and talent levels.

3 Data

3.1 Survey

We empirically analyze the results of a detailed wage survey consisting of 324,761 observations of engineering school graduates from 1983 to 2011. The survey, conducted by the French Engineering and Scientist Council (IESF), a network of alumni organizations representing 199 of the 240 French engineering schools, or 85% of the total population of French graduate engineers in 2010, solicits the latest yearly gross wages, as well as detailed information on the demographics, education, career, job position, and employer, of each graduate.[14,15]

The survey explicitly asks for the yearly gross wages available on the latest December pay sheet and for the employer's five-digit industry code. Yearly gross wages include cash bonuses but exclude compensation as stocks or options. Incentives to misreport due to tax concerns are low, as in France, firms directly declare wages to the tax authority, and the survey is anonymous. In addition, we retain only observations accompanied by a valid industry code to ensure that respondents actually consulted their pay sheets when answering the survey. This conservative approach maximizes the accuracy of wage data and limits measurement error. We further mitigate concerns over systematic misreporting by looking at reported wages with round numbers, as they are more likely to have been misreported. The share of respondents that declare a multiple of 100 as wage amounts to 24%, is comparable in the finance industry and in the rest of the economy (27%), and is also not correlated with our talent measure and the level of wages (see Column (8) in Table 2).[16]

Overall, filtering the survey data leaves us with 247,201 observations.[17]

[14] http://www.iesf.fr/.

[15] Source: French Education Ministry.

[16] Our results are robust to dropping all the respondents that declare a multiple of 100 as wages. See columns (6) and (7) of Table A4 in the online appendix.

[17] We apply the following filtering: we retain only respondents between the ages of 20 and 65 who are full-time employees, possess a valid industry code, and have more than one year of experience. We also exclude respondents whose compensation is less than the legal minimum wage, and for each sector and year, we drop compensation above the top 1% of the distribution. We do not trim the data at the

Our analysis benefits from several key features of the IESF survey. Its provision of the name of the engineering school from which each respondent graduated is essential to the implementation of our talent measure. Its access to unique wage data, including information on the variable share, is key to our analysis. Finally, the substantial information the survey provides on demographics, the specialization, job positions, employers, and work locations (including engineers working outside of France, for example, in London or New York) enables our analysis to control for a broad set of variables.

3.2 Summary Statistics

Table 1 provides key variable summary statistics together with information on the scope of the survey. Its frequency progressively increased from every five years until 1986 to annually beginning in 2004. The filtered number of respondents per survey averages 17,885, and each survey represents, on average, 6.9% of the total population of French engineers. The response rate is 18.8%, as the survey is sent only to alumni whose names and addresses are known to the association. Selection effects would bias our analysis if and only if alumni participation to the survey varied with both their talent level and their industry. If anything, we would expect these selection effects to bias our results downward. Talented individuals working in industries with high returns to talent would have indeed fewer incentives to respond to the survey because their opportunity cost is higher.

INSERT TABLE 1

The wage distribution among French graduate engineers has become increasingly skewed over the past three decades. Whereas the average wage, in constant euros, decreased slightly in our sample, from 63,000 euros in the 1980s to 58,000 euros in the 2000s,

total sample level so that highly paid sectors are not overrepresented in the affected subsample. Our results, however, are robust to using the total sample without dropping any observation (see Table A4 in the online appendix). Finally, all nominal quantities are converted into constant 2005 euros using the French National Price Index (IPCN) from the French National Statistical Institute (INSEE). The data are available at http://www.imf.org/external/datamapper/index.php.

due to composition effects, the wages at the 99th percentile increased by more than 14% over the same period.[18] This result is in line with recent research showing that inequality has increased in most OECD countries, mainly at the very top of the wage distribution (Piketty and Saez, 2003, 2006).

We define 48 industries based on the official industry classification codes respondents provided. Table 1 details the percentage share of respondents in the highest-paying industries (i.e., finance, oil, chemical, and consulting). Finance accounts for approximately 2% of the total sample.[19]

Table 1 also includes summary statistics on demographics, jobs, careers, employers, work locations, and compensation structures. The decrease in respondents' average age is likely driven by the change to an e-survey format. The increase in the share of female respondents is in line with the evolution of the composition of the engineer population nationwide. The share of respondents working outside of France has dramatically increased, which is consistent with the improved mobility of highly qualified workers.[20]

3.3 The Talent Measure

Table 2 reports the selection rate (column (2)) and the number of schools and students (columns (3) to (5)) by talent category. Our talent measure is available for 226,846 observations. By construction of our talent measure, a larger number of respondents is associated with a lower level of talent. Based on column (6), which reports the share of respondents that graduated at least one year earlier than the standard age by talent category, the share of early graduates appears to be correlated with the school rank. Its focus on a highly educated population notwithstanding, our sample offers considerable heterogeneity with respect to talent.

INSERT TABLE 2

[18]The slight decrease is due mainly to the decrease in the age of the average respondent.

[19]See Table A8 in the online appendix for a detailed list of, and the distribution of workers across, all industries.

[20]See the online appendix for a list of the questions asked in the 2008 survey.

We confirm that our talent measure is correlated with individual productivity by focusing on a specific field for which proxies for productivity are available: academic research. We proxy output using citation counts from Google Scholar. We collect the information for all alumni from the top 16 French engineering schools who work as academics in US universities, which correspond to the four top levels of our talent measure. We use *LinkedIn* and searches of top university departments to identify these alumni. Column (7) of Table 2 provides the predicted citation count for the four highest levels of our talent measure. The predicted values result from an OLS regression that controls for the research field, gender, experience, experience squared and experience cubed. We observe that the number of citations increases significantly with our talent measure.

3.4 Representativeness of the Sample

We implement two checks to assess potential selection effects in our survey data. First, we benchmark our worker survey data to employer survey data from Towers Watson covering the French engineer population. Second, we compare the patterns of compensation in the finance industry observed in our data to those found in the literature. In both cases, we find highly similar statistics. In addition, we find that the demographic characteristics of respondents have evolved over time in a similar way in finance and in other sectors. These characteristics are also similar to those obtained by the French Statistics Institute (INSEE) in the French employment survey whose sample is randomly selected.

Figure A1 in the online appendix plots the median starting salary from both our worker survey and the Towers Watson employer survey by industry and level of talent.[21] We observe that wages are similar for both surveys along these two divisions of the data. If anything, employers seem to report slightly higher wages than workers.

In addition, engineering schools alumni represent a sizable share of the finance industry in France, especially in corporate and investment bank divisions. For instance, 40% of employees of Credit Agricole's investment bank are engineers graduate.[22] This large

[21] We can only compare our data to the survey for starting salaries.

[22] `http://www.usinenouvelle.com/article/les-competences-des-ingenieurs-valent-de-l-or.`

representation of engineers is consistent with employers viewing the engineering degree as a label of talent.

We then replicate the main stylized facts from the literature on bankers' pay using our data. Figure 2 plots the evolution of the coefficient of the finance sector dummy in quantile regressions estimated at the 10^{th}, 50^{th}, and 90^{th} percentiles in the 1980s, 1990s, and 2000s samples. The skewness in wages in our sample increases significantly over the past decades, as already documented in Philippon and Reshef (2012) and Bell and Van Reenen (2014).[23]

INSERT FIGURE 2

We confirm this observation by estimating the annual wage premia in the finance industry via the following equation:

$$w_{i,t} = \alpha \times Talent_i + \beta \times F_i + \gamma \times X_i + \mu \times D_t + \lambda_{i,t}, \tag{1}$$

where $w_{i,t}$ is the log of yearly gross wages, $Talent$ is the talent measure, F_i represents the indicator variable for working in the finance industry, D_t is the vector of year dummies, X_i is a vector of individual characteristics, and α represents the average returns to talent in the economy.[24] This estimation controls for our talent measure as well as for demographic, occupation, job, and employer characteristics.[25,26]

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[23]See Figure A3 in the online appendix for a description of the evolution of wages at the 10^{th}, 50^{th}, and 90^{th} percentiles of the earnings distribution in the finance, oil, chemical, and consulting industries.

[24]For the purposes of clarity, and so that it increases with worker skill, $Talent$ is defined in our main measure as 10 minus the rank of the school from which a respondent graduated.

[25]Acemoglu and Autor provide evidence of the strong explanatory power of occupational categories in wage regressions.

[26]Demographic controls include years of experience, experience squared, experience cubed, gender, marital status, and gender×marital status. We control for occupation using nine dummies (production, logistics, development, IT, commercialization, administration, executive, education) and for employer type using five dummies (self-employment, private sector, state-owned company, public administration, and other (e.g., non-governmental organizations)), and for firm size with four dummies (fewer than 20, from 20 to 500, from 500 to 2,000, and more than 2,000, employees). Job characteristics are represented by an "Ile de France" dummy (Paris area), a working abroad dummy (as well as country dummies for the United States, the United Kingdom, Germany, Switzerland, Luxembourg, China, and Belgium from 2004), and four hierarchical responsibility dummies from no hierarchical responsibility to chief executive. Table A1 in the online appendix displays the coefficient of these control variables.

The results are displayed in column (1) of Table 3. The average wage premium in finance over the 1983–2011 period in our sample is 25%, compared to 14%, 13%, and 7% in the next best paying industries, consulting, oil and chemistry, respectively. Our finding that finance industry workers are the best paid is consistent with the results reported by Philippon and Reshef (2012), Oyer (2008), Goldin and Katz (2008). Our estimation of the finance wage premium is in the lower range of recent estimations reported in the literature, which is likely due to our rich set of controls, most importantly, our talent measure, and to the educational homogeneity of our sample. In addition, the explanatory power of our talent measure is relatively large compared to the usual measures in the literature, such as the principal component of the US Armed Services Vocational Aptitude Battery (ASVAB) tests or the Armed Forces Qualifying Test (AFQT).[27]

INSERT TABLE 3

The external validity of our sample is further supported by Table A2 in the online appendix, which replicates Table 6 from Bell and Van Reenen (2014). The first column shows that the finance wage premium has increased from 7%, on average, in the 1980s, to more than 30%, on average, over the 2004–2011 period, and the premium is much higher at the 90$^{\text{th}}$ than at the 10$^{\text{th}}$ and 50$^{\text{th}}$ percentiles of the wage distribution. The last row of the table shows the average annualized increase in the premia to be more than 2.8% at the 90$^{\text{th}}$, less than 0.7% at the 50$^{\text{th}}$, and 0.3% at the 10$^{\text{th}}$, percentiles. Our finding that the finance wage premium has increased dramatically since the 1980s and that it is concentrated among top earners is also consistent with Philippon and Reshef (2012).

[27] After controlling for experience and education, we indeed find that adding our talent measure induces an increase in the R^2 four times higher than that induced by the usual talent measures (Bowles et al., 2001).The change in the R^2 is 2.8% in our specification versus a median value of 0.7% in the literature. This gap is likely to be underestimated because of our precise control for education. This relatively large explanatory power is likely due to the inclusion of personality traits, which are an important and increasing determinant of wages (Heckman, 1995; Bowles et al., 2001; Heckman and Kautz, 2012; Deming, 2015).

4 Results

4.1 Heterogeneous Returns to Talent across Industries

We report here our central result that returns to talent are significantly higher in the finance industry and therefore that top talents receive a disproportionate share of the wage premium in this industry.

Graphical evidence of this result is provided in Figure 3, which plots respondents' predicted wage by industry over the ten categories of our talent measure using a non-parametric estimation of equation (1).[28] While wages are an increasing function of talent in each industries and in the whole economy, the magnitude of this relationship is significantly higher in the finance industry. For example, moving from the bottom category of talent to the top category translates into a wage increase for finance workers of 105%, while in the oil industry it is only 35%. The relationship between our talent measure and wages in finance appears to be convex.

INSERT FIGURE 3

We specifically test whether and to what extent wage elasticity to talent is high in finance by including an interaction between talent and the indicator variable for working in finance in equation (1):

$$w_{i,t} = \alpha \times Talent_i + \beta \times F_i + \overline{\eta} \times F_i \times Talent_i + \gamma \times X_i + \mu \times D_t + \lambda_{i,t}, \qquad (2)$$

where $\overline{\eta}$ is the finance-specific component of returns to talent (the other variables are the same as in equation (1)).

Column (2) of Table 3 reports the results. The positive and significant coefficient of the interaction term between the finance dummy and talent measure shows returns to talent to be significantly higher, three times higher in fact, in the finance industry than in the rest of the economy. Moving one notch up our talent scale yields a 6.3% increase in

[28]This non-parametric estimation decomposes our talent measure with one coefficient for each talent level.

wages for a finance worker vs. 2.0% for a worker in the rest of the economy. Table A3 in the online appendix runs the same analysis for the ten highest-paid industries including finance. The consulting industry offers returns to talent twice as high as in the rest of the economy. Conversely, returns to talent are significantly lower in the oil and chemical industries than in the rest of the economy, likely because of strong physical constraints that limit the scalability of talent in these sectors.

The magnitude of the finance wage premium varies closely with the level of talent. When we include the interaction term $F_i \times Talent_{i,t}$ in our specification, the finance premium drops to 6.2% (column (2)). This result is strongly supportive of the finance wage premium being largely allocated according to workers' talent. This finding is robust to including industry-year fixed effects (column (3)) and to using our alternative talent measure *1 minus selection rate* (columns (5) and (6)).[29]

Returns to talent are also stronger for engineers who work in finance outside of France. Column (4) displays the coefficient on a triple interaction term between the talent measure, an indicator variable for working in finance, and an indicator variable for working outside of France. The coefficient on this interaction term is positive and both economically and statistically significant, evidencing that returns to talent are 32% higher for engineers who work in finance abroad. The majority of engineers working in finance do so in London or in New York (more than 50% in our sample), which suggests that returns to talent are even higher in these geographic zones.

We complement this result by implementing a Blinder-Oaxaca decomposition of the finance wage premium. Figure 4 displays both endowment and coefficient effects for the following determinants of wages in finance: social background, gender, experience, and talent. Differences in returns to talent appear to explain by far the largest share of the finance wage premium, whereas differences in returns to other characteristics are limited.

INSERT FIGURE 4

Finally, Table A5 in the online appendix investigates whether returns to talent are

[29] The results are also robust to using the total sample (rather than the trimmed sample), as shown in Table A4 in the online appendix.

higher in finance within each type of occupation and level of hierarchy. For example, we compare returns to talent for IT employees in finance versus IT employees in other sectors, and for top managers in finance versus top managers in other industries. We find that returns to talent are more than twice higher in finance across each category.

4.2 Controlling for Treatment Effects with School Fixed Effects

Our result is robust to the inclusion of school fixed effects, which is possible when using the graduation age as a measure of talent. Columns (7) and (8) of Table 3 report the regression coefficients when we interact the *Age at Graduation* talent measure with the finance indicator variable. We find that, among alumni from the same school, those who graduate earlier in life are paid relatively more and that this effect is significantly stronger in finance. The effect is amplified when we control for industry-year fixed effects (column (8)). This result suggests that neither treatment effects during school nor school-specific alumni network effects drive our previous findings.[30]

We also control for differences in what students learn in engineering schools by including specialization fixed effects. Higher returns to talent could be driven by a larger share of students opting for a specialization in economics or finance in top schools. These students would get identified, recruited into finance and paid higher wages (see Lemieux (2014)). Table A3 in the online appendix shows that including a control for economics or finance specialization, as well as an interaction term with working in finance, only decrease the finance premium by 1%, and does not affect returns to talent in the finance industry (column (5)).[31]

[30]The lower economic magnitude we find for this measure of talent is likely to come from its lower dispersion, as well as a potential confounding effect: a subgroup of the students that repeat years to improve their ranking are likely to do so out of high ambition.

[31]In our sample, 1.6% of engineers have opted for a economics or finance major, and 34% of them work in the finance industry. They account for only 13.5% of the engineers working in finance.

4.3 Controlling for Individual Fixed Effects

We further confirm our results by estimating panel data regressions with individual fixed effects that absorb any time-invariant unobserved characteristics. Returns to talent are similar to the ones estimated in the cross-section and almost fully absorb the wage variation when a worker switches into or out of the financial sector.

To include individual fixed effects, we convert our repeated cross-section data into panel data. We identify unique individuals across time using 16 variables: year of birth, nationality, sex, name of the engineering school, year of graduation, type of specialization, additional degree (PhD degree, double degree in management, double degree in science, second engineer degree), father's and mother's occupations and nationalities, number of children, number of firms the individual has been working in.[32] This high number of dimensions minimizes the likelihood of matching observations from different individuals. We also use the answer to a survey question on job mobility to comfort the robustness of our matching. This constructed panel covers the 2000–2010 period, includes 13,366 individuals who appear at least twice, among which 3,275 individuals switch sectors over the period, 126 of whom are entering and 74 of whom are exiting the finance industry.

We identify the impact of switching sectors on wages using the following regression:

$$w_{i,t} = \alpha_i + \beta \times F_{i,t} + \mu \times D_t + \gamma X_{j,t} + \lambda_{i,t}, \tag{3}$$

where α_i represents the vector of individual fixed effects, $I_{i,t}$ is the vector of sector fixed effects t, D_t is the vector of year dummies and $X_{j,t}$ is a vector of job characteristics, including firm type, size, level of hierarchical responsibilities and occupation dummies. The results are reported in Table 4.

The 24% wage increase enjoyed by a worker who joins the finance industry is close to the level of the finance wage premium estimated using the cross-section for the same sample (31%) and is significantly larger than the wage increase obtained by workers who

[32]Because number of children and number of firms are not permanent variables, we use their non decreasing property to distinguish among individuals that are identical on the other dimensions

join other sectors.[33]

To test whether an individual obtains higher returns to its talent when joining the finance industry, we include the interaction of the finance indicator variable with talent in this panel specification:

$$w_{i,t} = \alpha_i + \beta \times F_{i,t} + \gamma X_{j,t} + \overline{\eta} \times F_{i,t} \times Talent_i + \mu \times D_t + \lambda_{i,t}, \tag{4}$$

Column (3) in Table 4 displays the results for this specification. We find that talent fully describes the wage increase obtained by a worker who joins the finance industry, and the coefficient of the finance industry dummy decreases down to zero. Most importantly, the elasticity of talent is significantly higher in finance than in other sectors, and is of the same magnitude as the one we estimate in the cross-section. This point estimate relies on both entry and exit from the finance sector, is robust to including industry-year fixed effects (column (4)). and to restricting the sample to individuals who switch sectors (columns (5) and (6)). This latter specification allows precisely controlling for the standard pay increase workers obtain when changing job.

INSERT TABLE 4

4.4 Controlling for Job Fixed Effects

We exploit the granularity of our data to ensure that the potential selection of graduates from top schools into relatively high paying jobs within the finance industry does not drive our result. Some finance occupations, such as Traders, pay much more, on average, than other finance jobs.

We reject this endogenous matching explanation by introducing exact job title fixed effects into equation (1) while restricting the sample to finance workers only. This enables us to compare, for the same role (e.g., Trader, Quant, Audit, IT), the wages of the alumni

[33]This result is consistent with Gibbons and Katz (1992), who find that the wage change experienced by a typical industry switcher closely resembles the difference in the industry wage differentials estimated in the cross-section.

of top and lower ranked schools.[34]

Our main result is robust to this constrained specification. Column (1) in Table 5 reports the returns to talent for the subsample of individuals for which we possess a job title without the job titles fixed effects. Moving one notch up our talent scale yields a 7.3% increase in wages for a finance worker, which is close to the level found in our full sample (column (2) of Table 3). When we include job title fixed effects in column (2), we still find that returns to talent in the finance industry are more than twice as high as those in the rest of the economy: moving one notch up our talent scale yields a 4.8% increase in wages after controlling for job fixed effects. This means that a talented trader, all else equal, earns significantly more than a less talented one.

INSERT TABLE 5

We complement this analysis by exploring whether returns to talent are higher for certain job categories or for engineers working in finance outside of France. Columns (3) and (4) in Table 5 show that returns to talent are significantly higher in front office jobs (which include Trader, Quant, Structurer, Sales, Asset manager, and Investment Banker) compared to other jobs in finance (IT, Audit, Middle and Back office, other support functions).

Finally, Figure 5 displays the estimated returns to talent for each job category in the finance industry. We observe that returns to talent are more than twice as high for front office jobs such as Sales, Asset managers, Traders or Quants than for Auditors or IT workers.

INSERT FIGURE 5

[34]Respondents are asked to give their job title in the 2006–2010 surveys. We manually sort self-described job titles into 9 main job categories for finance workers: back office, support, IT, auditing, middle office, corporate finance, asset manager, trader, sales, and quant.

4.5 Increasing Returns to Talent in the Finance Industry, and Allocation Effects

We show that returns to talent have increased over time, which sheds new light on the increase in the finance premium since the 1980s documented by Philippon and Reshef (2012). These increasing returns to talent are associated with an increasing share of talented individuals working in finance.

Columns (2), (4), and (6) of Table 6 report the OLS coefficients of equation (1) over three sub-periods: the 1980s, the 1990s, and the 2000s. We find that the returns to talent in the finance industry have increased three folds between the 1980s and the 2000s. In the 1980s, a one-notch increase on our talent scale translated into an increase in wages for a finance worker of 2.8% (column (2)). In the 2000s, the same difference in talent generates a 7.5% increase in wages in finance (column (6)). We obtain results of the same magnitude when using *1 minus Selection Rate/100* as an alternative talent measure (see Table A6 in the online appendix). Returns to talent thus increase in line with the finance wage premium.[35]

INSERT TABLE 6

These increasing returns to talent in finance are contemporaneous to a change in the allocation of talent. The left-hand side of Figure 6 plots the evolution of the share of graduate engineers from our sample working in finance for the whole sample and for the top three levels of our talent measure.[36] We observe that French graduate engineers have been increasingly working in finance and that this pattern is significantly more

[35]A possible explanation for this increase in returns to talent in finance would be that the number of students in top schools have not increased in line with the total population. Top schools would have therefore become more selective over the years and the increasing returns to talent we observe would reflect increasing talent within schools. This explanation does not hold for two main reasons: first, top schools have been increasing their number of students over the sample period. Hence, the number of graduating engineers from state engineering schools has increased from 25,000 in 1990 to 40,000 in 2008. The data source can be found at $http://media.enseignementsup-recherche.gouv.fr/file/2009/19/4/RERS2009_119194.pdf$. Second, this would not account for the increasing gap in returns to talent between finance and the rest of the economy.

[36]The pattern is similar if we use only the top level or the top two levels.

pronounced for the most talented individuals. While 4% of this group worked in finance in 1986, finance workers represent more than 10% of this subsample in 2011.[37] The share of highly talented graduates choosing finance, however, might still seem low relative to the significantly higher returns to talent we observe.

The right-hand side of Figure 6 displays the evolution of the share of graduate engineers from our sample that work outside of France in finance and in the rest of the economy. While this share has been increasing for the whole population in line with an increase in the international mobility of qualified workers, this trend is significantly more pronounced in finance than in the rest of the economy, especially for the most talented engineers.[38]

INSERT FIGURE 6

4.6 Returns to Talent and the Structure of Compensation

We next investigate the relationship between returns to talent and the structure of pay. We show that variable pay and returns to talent are closely related; a higher level of talent is associated with a larger share of variable compensation, and this is even more pronounced in sectors such as finance and in occupations such as trading in which the returns to talent are especially high.

Column (3) in Table 7 shows that variable compensation represents a significantly larger share of total wages in finance than in other sectors and that more talented workers have a larger share of variable pay. Column (4) includes the interaction between the talent measure and the finance sector dummy. The coefficient of the interaction indicates that relation between talent and variable pay is much stronger in finance than in the rest of

[37] One concern, as with any survey data, is that the allocation of respondents across industries may not be perfectly representative of the whole population. However, this concern is mitigated by the fact that we consider the relative evolution across talent levels and industries. If anything, we should expect that talented finance workers have reduced incentives to answer the survey, as the opportunity cost of answering the survey increases.

[38] The survey has been e-mailed since 2002, whereas it was previously mailed, which is likely to have increased participation from alumni working abroad across all sectors. We therefore focus on the evolution of the share of finance workers working abroad.

the economy, and the decrease in the coefficient on the finance dummy, which is divided by three.

INSERT TABLE 7

Using the detailed information we have on the exact job title of respondents from 2006 to 2009, we also explore whether the returns to talent and the structure of compensation are correlated at the job level within finance. Figure A5 in the appendix plots returns to talent over the share of variable compensation for the main occupation categories in finance. We observe a strong positive correlation: occupations with the highest returns to talent also pay the largest share of variable compensation.

5 Alternative Channels

This section discusses alternative explanations for our results, which are not related to talent effects.

5.1 Elite Network Effects

Our results could be driven by elite network effects rather than by talent. More precisely, the high returns to school ranking we observe in finance might come from alumni networks being more influential, or degree prestige more important, in finance than in the rest of the economy.[39] However, after excluding individuals from the most elite schools, i.e., the Ecole Polytechnique and related schools from our sample, the returns to talent are still three times higher in the finance industry than in the rest of the economy (column (1) in Table 8).[40]

INSERT TABLE 8

[39]Recent studies on networks insist on their importance in labor market processes, such as hiring, promotion, and compensation setting (Butler and Gurun, 2012; Engelberg et al., 2013; Shue, 2013)

[40] Graduates of these schools are over-represented among top executives and CEOs (Kramarz and Thesmar, 2013). The excluded schools are Ecole Polytechnique, Mines de Paris, Ecole des Ponts, Supelec, AgroParisTech Grignon, Supaero, INP-ENSEEIHT, Supoptic Orsay, ESPCI Paris, and Chimie Paris et Telecom Paris. We also exclude Centrale Paris because its selection rate is equivalent.

In addition, our specification using age at graduation as a measure of talent and including school fixed effects controls for school-specific network effects, and therefore identifies on variation "within the club". Assuming that alumni networks do not discriminate by age of graduation, the fact that our main result is robust to this specification is not consistent with network effects driving the level of wages in the finance industry.

Finally, column (7) in Table 2 shows that our talent measure is highly correlated with the productivity of French graduate engineers who work as academics in the United States, as measured by the number of citations. Academic paper citations are unlikely to be driven by the network or prestige of the undergraduate engineering school of any of the authors. Our talent measure is therefore unlikely to capture network effects or prestige alone.

5.2 Social Background

Our results might be driven by the social backgrounds of graduates if both the share of students with well-connected parents is higher in top schools and these connections are particularly valuable in the finance industry. We conduct two distinct tests to rule out this hypothesis. First, in columns (2) of Table 8, we restrict our sample to *First Generation* students whose parents do not possess university level educations and are therefore less likely to be well connected. We find that our results are robust to this subsample; in fact, they are actually strengthened, as the coefficient on the interaction between talent and finance is significantly higher than for the benchmark sample (column (3)).[41] Second, in columns (4), we restrict our sample to graduates of non-French nationality, following the rationale that their parents are likely to be less integrated into French social networks. We find that our main result remains robust to this specification, making our data difficult to reconcile with a social background explanation.

[41] The benchmark sample includes the period for which we have information on alumni parents.

5.3 Compensating Wage Differential

A final alternative explanation would be that higher compensation in finance aims to offset tougher working conditions or higher income risks. More talented workers deserve a higher compensation differential because they work relatively harder or because their health, income or employment are more at risk. However, Philippon and Reshef (2012) and Oyer (2008)'s estimates of the lifetime pay premium in finance explicitly control for hours worked, wage risk, career length, and the risks of exiting the finance sector.

We nevertheless conduct additional tests to rule out this possibility using data on job satisfaction and hours worked, controlling for both stress and excessive workloads in equation (2).[42] We use a dummy variable equal to one if a respondent reports suffering from stress and zero otherwise. We also introduce a variable that indicates whether a respondent works overtime occasionally, 5 to 10 hours, or more than 10 hours.[43] We find no significant downward impact of these variables on talent returns in the finance industry. The results are reported in Table A7 in the online appendix.

We employ two strategies to control for unemployment and income risks. We first observe the fraction of layoffs in the total population of French employees for each sector as a measure of unemployment risk, and we find that this risk is not higher in finance.[44]

Second, we restrict our wage regression to the fixed portion of workers' compensation packages in columns (1) and (2) of Table 7 and find that finance workers also earn a

[42] We do not control for stress or excessive workloads in our main results, as this information is not available for the entire sample.

[43] Note that self-reported level of stress and job security might be biased. Indeed, if individuals who work in finance are those who choose risky, high-pressure environments, they might not report different levels of stress or perceived job security even if a neutral observer would see a large difference. However, in equilibrium, these individuals should not receive such a large a compensating premium if they do not suffer from their working conditions. Therefore controlling for workers' perceptions seems adequate in our setup.

[44] Source: 2009 labor turnover data from the French Ministry of Labor, Employment and Health. http://travail-emploi.gouv.fr/etudes-recherches-statistiques-de,76/statistiques,78/emploi,82/les-mouvements-de-main-d-oeuvre,272/les-donnees-sur-les-mouvements-de,2268/les-donnees-sur-les-mouvements-de,2633.htmlWe find a negative correlation between wages and industry unemployment risk: unemployment risk has been constant in the financial sector over the 1999–2011 period (layoff rate = 1.7%), and the finance sector has one of the lowest layoff rates (whole economy average = 2.9%). Second, we use a survey question that asks if interviewees experience low job security as an additional control, which leaves our main result unchanged (see Table A7 in the online appendix).

premium on fixed pay, which presents low, if any, income risk. In addition, the level of talent explains the level of fixed compensation in the financial sector.

5.4 Endogenous Sorting into Finance by Talent Level

Endogenous sorting into finance by talent level may bias our estimates upwards if it is positively correlated with school rank, e.g. more talented students sort into finance in top schools, while in bottom schools the less talented go into this sector.[45] This hypothesis is hard to reconcile with our data. First, our result holds across the whole distribution of talent within our sample, as evidenced by figure 3. Within schools of rank i of talent, it should roughly be their decile i of graduates going into finance. However the finance wage premium is positive even for schools of the lowest rank, and should therefore foster the best graduates to apply at every school rank. [46] Second, our results are robust when using the within-school measure of talent. Finally, our finding is robust to including job fixed effects, which ensures the comparability of the tasks within finance, and therefore mitigates concerns over selection over different skills by school rank.

6 Discussion

Our result on the returns to talent sheds some new light on the debate of the determinants of pay at the top of the wage distribution. Executive compensation has been increasing dramatically since the 1980s. The literature (see Frydman and Jenter (2010) for a review) has been investigating whether this high level of pay results from optimal contracting in a competitive market, or from powerful managers setting their own pay and extracting rents from their employer.[47] We address this question from the angle of the finance

[45] In our data, we do not observe the grades at the competitive exam, and therefore cannot rank students within school.

[46] Anecdotally, in the top school, endogenous sorting is likely to bias against our result, as the best graduates typically enter top civil servant tracks rather than going into finance.

[47] In this study, we do not address the question whether bankers use their talent to extract rents from society, as for example in Bolton et al. (2016) and Biais and Landier (2015). If high skilled workers are more talented at extracting rents from society, higher wages may be the result of optimal contracting with their employer.

industry. We have shown in the previous section that the finance wage premium is disproportionately and increasingly allocated to talented individuals. Identifying which mechanism leads to this empirical fact has important implications in terms of firm value, talent allocation and wage inequality.

6.1 Competitive Pay or Rent Extraction?

Optimal contracting in a competitive labor market might generate high returns to talent if firms compete intensively for talent, as in Rosen (1981), Gabaix and Landier (2008) and Glode et al. (2012), and/or if talented workers are more costly to incentivize (Axelson and Bond, 2015). Conversely, high returns to talent may result from rent extraction by powerful managers if talented individuals are more prone to entrenchment (Bebchuk and Fried, 2004).

We interpret our set of results as most consistent with the finance premium resulting from a competitive pay-setting process rather than managerial entrenchment. First, in line with the predictions of a "superstar"-like model of pay, the wage distribution in the finance industry is highly skewed and returns to talent are higher at the top of the wage distribution. Second, in the time series, returns to talent have been increasing over the years along with scale effects. Skill-biases technological change (Katz and Murphy, 1992; Garicano and Rossi-Hansberg, 2006) and deregulation (Philippon and Reshef, 2012; Boustanifar et al., 2016) may have magnified scale effects over the years.[48] Third, returns to talent are higher in jobs where talent is likely to be more easily scaled, such as front office jobs, than in risk management or back office jobs, and in more competitive labor markets, such as in the United Kingdom and the United States. Finally, in the optimal contracting view the positive correlation between returns to talent and incentive pay we observe can be interpreted as evidence that variable compensation is used to attract talented workers when talent is not perfectly observable (Benabou and Tirole, 2015).

[48]Kaplan and Rauh (2010) estimate that capital per employee in the top U.S. security firms has increased substantially from $124,000 (in 2004 dollars) in 1972 up to $1,789,000 in 2004. They also observe a twenty-three-fold increase in capital per managing director since the 1970s.

Our result might also stem from optimal contracting if talented finance executives are more costly to incentivize. This theory of incentives would also predict a positive correlation between the share of variable compensation and returns to talent, which is what we observe in our data. Talented workers may be more costly to incentivize in the finance industry either because of better outside options, if banks compete relatively intensively for talent, or because of a more severe moral hazard problem. Talented workers may perform innovative tasks that are often opaque and complex, which makes their exact effort more difficult to monitor (Biais et al., 2015; Biais and Landier, 2015). Employee marginal effort, on the other hand, may be more critical in finance than in the rest of the economy because of the large amounts of capital at risk. Moral hazard is likely to be especially acute in front office jobs, where we observe the higher returns to talent.

On the other hand, our results are difficult to reconcile with the *managerial power hypothesis* (Bebchuk and Fried, 2004). To be consistent with our results, this theory first requires that more talented individuals are better at extracting rents from their employer, and even more so in the finance industry than in any other industry. Second, our study is based on easily observed compensation, which is less associated with entrenchment. The managerial power theory indeed predicts that much of the rent extraction occurs through forms of pay that are less observable or more difficult to value, such as stock options, perquisites, pensions, and severance pay.[49] Third, finance executives from our sample do not hold top management positions, and are therefore unlikely to be in a position to set their own compensation. In addition, to reconcile the increasing returns to talent we observe with this theory, we would need to make a convincing case that corporate governance has been significantly deteriorating in finance relatively to other sectors over our sample period.

[49] Although we cannot rule out that some of this compensation is simultaneously taking place, the hypothesis cannot explain our result.

6.2 Returns to Talent and the Allocation of Talent in the Economy

With 6 million jobs in the US, the financial sector has the potential to lure a large share of talented workers through higher compensation. Our results suggest that the finance wage premium has an impact on the allocation of talent across sectors. In line with the prediction of Roy (1951)'s model, we document a positive correlation between the evolution of returns to talent in finance, and the share of talented individuals working in this sector. These talent allocation effects also have a cross-border dimension possibly driven by returns to talent within the same industry differing significantly across countries.[50]

Our results, however, are also illustrative of significant frictions in the allocation of workers across industries. In a frictionless world, talent allocation should be primarily driven by the heterogeneous returns to talent across industries (Roy, 1951). Increasing returns to talent in finance should lead to a massive flow of top talent workers to the finance industry, whereas we document a relatively modest one. However, compensation may only partly explain career decisions of talented individuals, because of heterogeneous preferences across workers (Shu, 2015) or due to the acquisition of industry-specific skills that are complementary to talent. Switching costs increase rapidly with experience when workers acquire industry-specific knowledge, such as product knowledge or a professional network. If this industry-specific knowledge is complementary to individuals' innate talent, the pool of talents banks are willing to compete for is limited, which increases the value of talented individuals within the industry and restricts talent entry.[51]

6.3 Income Inequalities and Regulation

Our results contribute to the understanding of the well-documented rise in income equality (Piketty and Saez, 2003, 2006)). We identify that a specific population, i.e. the talented individuals in certain industries, is receiving an increasing share of the total wage

[50]Boustanifar et al. (2016) find also evidence of migration.

[51]See Terviö (2009) for a model of competition for talent when industry-specific skills are progressively revealed on the job.

bill, hence contributing to an increasing dispersion of income in the economy. While this outcome might result from optimal contracting in a competitive labor market and be both meritocratic and economically efficient in the short run, this trend might not be socially and politically sustainable in the long run. This relates to the recent debate on income and wealth inequalities, and raises the question of regulating banker's pay.

However, regulating bankers' pay may not be efficient if the level and structure of their pay result from competitive market forces. A cap on wages would likely encourage the development of an opaque and complex retribution process. Regulating the structure of pay, on the other hand, would lead to inefficient risk taking and/or an increase in fixed pay (see Benabou and Tirole (2015)).

7 Conclusion

The main contribution of this paper is to show that high and increasing returns to talent in finance explain the distribution of bankers' pay and its evolution since the 1980s. To estimate returns to talent calls for an appropriate measure of talent. We exploit for this purpose the results of a competitive examination among highly educated candidates that captures not only cognitive skills but also personality traits such as motivation, self-discipline, and low cost of effort.

Our results are supportive of compensation in finance resulting from optimal contracting, but raise questions over talent allocation and income inequalities.

References

Acharya, V., M. Pagano, and P. Volpin (Forthcoming, 2016). Seeking Alpha: Excess Risk Taking and Competition for Managerial Talent. *Review of Financial Studies*.

Axelson, U. and P. Bond (2015). Wall Street Occupations. *Journal of Finance 70*(5), 1949–1996.

Bakija, J., A. Cole, B. T. Heim, et al. (2012). Jobs and Income Growth of Top Earners and the Causes of Changing Income Inequality: Evidence from US tax Return Data. *Unpublished manuscript, Williams College*.

Bebchuk, L. and J. Fried (2004). Pay Without Performance: The Unfulfilled Promise of Executive Compensation. *Harvard University Press*.

Bell, B. and J. Van Reenen (2013). Extreme Wage Inequality: Pay at the Very Top. *American Economic Review: Papers and Proceedings 103*(3), 153–157.

Bell, B. and J. Van Reenen (2014). Bankers and Their Bonuses. *Economic Journal 124*(574), F1–F21.

Benabou, R. and J. Tirole (forthcoming, 2015). Bonus Culture: Competitive Pay, Screening, and Multitasking. *Journal of Political Economy*.

Biais, B. and A. Landier (2015). Endogenous Agency Problems and the Dynamics of Rents. *Working Paper, Toulouse School of Economics*.

Biais, B., J.-C. Rochet, and P. Woolley (2015). Dynamics of Innovation and Risk. *Review of Financial Studies 28*(5), 1353–1380.

Bolton, P., T. Santos, and J. A. Scheinkman (2016). Cream Skimming in Financial Markets. *The Journal of Finance 71*(2), 709–736.

Bond, P. and V. Glode (2014). The Labor Market for Bankers and Regulators. *Review of Financial Studies 27*(9), 2539–2579.

Boustanifar, H., E. Grant, and A. Reshef (2016). Wages and Human Capital in Finance: International Evidence, 1970-2011. *Working Paper*.

Bowles, S., H. Gintis, and M. Osborne (2001). The Determinants of Earnings: A Behavioral Approach. *Journal of Economic Literature 39*(4), 1137–1176.

Butler, A. W. and U. G. Gurun (2012). Educational Networks, Mutual Fund Voting Patterns, and CEO Compensation. *Review of Financial Studies 25*(8), 2533–2562.

Böhm, M., D. Metzger, and P. Strömberg (2015). "Since You're So Rich, You Must Be Really Smart": Talent and the Finance Wage Premium. *Working Paper*.

Cuñat, V. and M. Guadalupe (2005). How does product market competition shape incentive contracts? *Journal of the European Economic Association 3*(5), 1058–1082.

Deming, D. J. (2015). The Growing Importance of Social Skills in the Labor Market. *NBER Working Paper Series* (21473).

Engelberg, J., P. Gao, and C. A. Parsons (2013). The Price of a CEO's Rolodex. *Review of Financial Studies 26*(1), 79–114.

Frydman, C. (2007). Rising Through the Ranks. The Evolution of the Market for Corporate Executives, 1936-2003. *Working Paper*.

Frydman, C. and D. Jenter (2010). CEO Compensation. *Annual Review of Financial Economics 2*, 75–102.

Gabaix, X. and A. Landier (2008). Why Has CEO Pay Increased so Much? *Quarterly Journal of Economics 123*(1), 49–100.

Gao, H., J. Luo, and T. Tang (2015). Effects of Managerial Labor Market on Executive Compensation: Evidence from Job-Hopping. *Journal of Accounting and Economics 59*(2-3), 203–220.

Garicano, L. and E. Rossi-Hansberg (2006). Organization and Inequality in a Knowledge Economy. *Quarterly Journal of Economics 121*(4), 1383–1435.

Geerolf, F. (2015). A Static and Microfounded Theory of Zipf's Law for Firms and of the Top Labor Income Distribution. *Working Paper*.

Giannetti, M. and D. Metzger (2013). Compensation and Competition for Talent: Talent Scarcity or Incentives? *Working Paper*.

Gibbons, R. and L. Katz (1992). Does Unmeasured Ability Explain Inter-industry Wage Differentials? *The Review of Economic Studies 59*(3), 515–535.

Glode, V., R. C. Green, and R. Lowery (2012). Financial Expertise as an Arms Race. *The Journal of Finance 67*(5), 1723–1759.

Glode, V. and R. Lowery (Forthcoming, 2015). Compensating Financial Experts. *Journal of Finance*.

Goldin, C. and L. Katz (2008). Transitions: Career and Family Life Cycles in the Educational Elite. *American Economic Review: Papers & Proceedings 98*(2), 363–369.

Greenwood, R. and D. Scharfstein (2013). The Growth of Finance. *Journal of Economic Perspectives 27*(2), 3–28.

Guadalupe, M. (2007). Product Market Competition, Returns to Skill, and Wage Inequality. *Journal of Labor Economics 25*(3), 439–474.

Heckman, J. J. (1995). Lessons From the Bell Curve. *Journal of Political Economy 103*(5), 1091–1120.

Heckman, J. J. and T. Kautz (2012). Hard Evidence on Soft Skills. *Labour economics 19*(4), 451–464.

Kaplan, S. and J. D. Rauh (2010). Wall Street and Main Street: What Contributes to the Rise in the Highest Income? *Review of Financial Studies 23*(3), 1004–1050.

Kaplan, S. N. and J. D. Rauh (2013). Family, Education, and Sources of Wealth among the Richest Americans, 1982-2012. *American Economic Review 103*(3), 158–62.

Katz, L. F. and K. M. Murphy (1992). Changes in Relative Wages, 1963–1987: Supply and Demand Factors. *Quarterly Journal of Economics 107*(1), 35–78.

Kramarz, F. and D. Thesmar (2013). Social Networks in the Boardroom. *Journal of European Economic Association 11*(4), 780–807.

Lemieux, T. (2014). Occupations, Fields of Study and Returns to Education. *Canadian Journal of Economics 47*(4), 1047–1077.

Lemieux, T., W. B. MacLeod, and D. Parent (2009). Performance Pay and Wage Inequality. *Quarterly Journal of Economics 124*(1), 1–49.

Levy, F. and P. Temin (2007). Inequality and Institutions in 20th Century America. *NBER Working Paper Series* (13106).

Murphy, K., A. Shleifer, and R. Vishny (1991). The Allocation of Talent: Implications for Growth. *Quarterly Journal of Economics 106*(2), 503–530.

Murphy, K. J. and J. Zábojník (2004). CEO Pay and Appointments: A Market-Based Explanation for Recent Trends. *American Economic Review 94*(2), 192–196.

Ors, E., F. Palomino, and E. Peyrache (2013). Performance Gender-Gap: Does Competition Matter? *Journal of Labor Economics 31*(3), 443–499.

Oyer, P. (2008). The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income. *Journal of Finance 63*(6), 2601–2628.

Philippon, T. (2010). Financiers versus Engineers: Should the Financial Sector be Taxed or Subsidized? *American Economic Journal: Macroeconomics 2*(3), 158–182.

Philippon, T. and A. Reshef (2012). Wages and Human Capital in the U.S. Finance Industry: 1909-2006. *Quartlery Journal of Economics 127*(4), 1551–1609.

Piketty, T. and E. Saez (2003). Income Inequality in the United States, 1913-1998. *Quarterly Journal of Economics 118*(1), 1–41.

Piketty, T. and E. Saez (2006). The Evolution of Top Incomes: A Historical and International Perspective. *American Economic Review 96*(2), 200–205.

Rosen, S. (1981). The Economics of Superstars. *American Economic Review 71*(5), 845–858.

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers 3*(2), 135–146.

Shive, S. and M. Forster (2016). The Revolving Door for Financial Regulators. *Working Paper*.

Shu, P. (2015). Are the "Best and Brightest" Going into Finance? Skill Development and Career Choice of MIT Graduates. *HBS Working Paper* (16-067).

Shue, K. (2013). Executive Networks and Firm Policies: Evidence from the Random Assignment of MBA Peers. *Review of Financial Studies 26*(6), 1401–1442.

Terviö, M. (2009). Superstars and Mediocrity: Market Failures in the Discovery of Talent. *Review of Economic Studies 72*(2), 829–850.

Thanassoulis, J. (2012). The Case for Intervening in Bankers' Pay. *Journal of Finance 67*(3), 849–895.

8 Figures

Figure 1. Selection Process of French Engineering Schools

High School - Science Major

⇓

Preparatory School (2 years, *Selection rate: 15%*)

Subject	**# Hours (per Week)**	**# Exams (per month)**
Mathematics	12	4
Physics and Chemistry	8	2
Industrial Science	2	0
Literature	2	1
Foreign Language	2 to 4	2
Programming	2	0

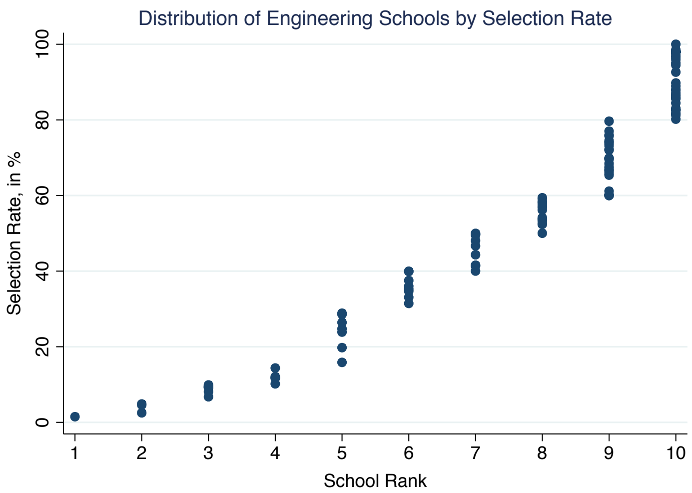
⇓

National Competitive Exam

Written Competitive Exam		**Oral Competitive Exam**	
Subject	**Coefficient**	**Subject**	**Coefficient**
Mathematics 1	8	Mathematics 1	16
Mathematics 2	7	Mathematics 2	16
Physics	6	Physics	20
Industrial Science	6	Industrial Science	15
Literature	6	Literature	8
Foreign Language	6	Foreign Language	8
Computer Science	4	Chemistry	9
		Sports	5

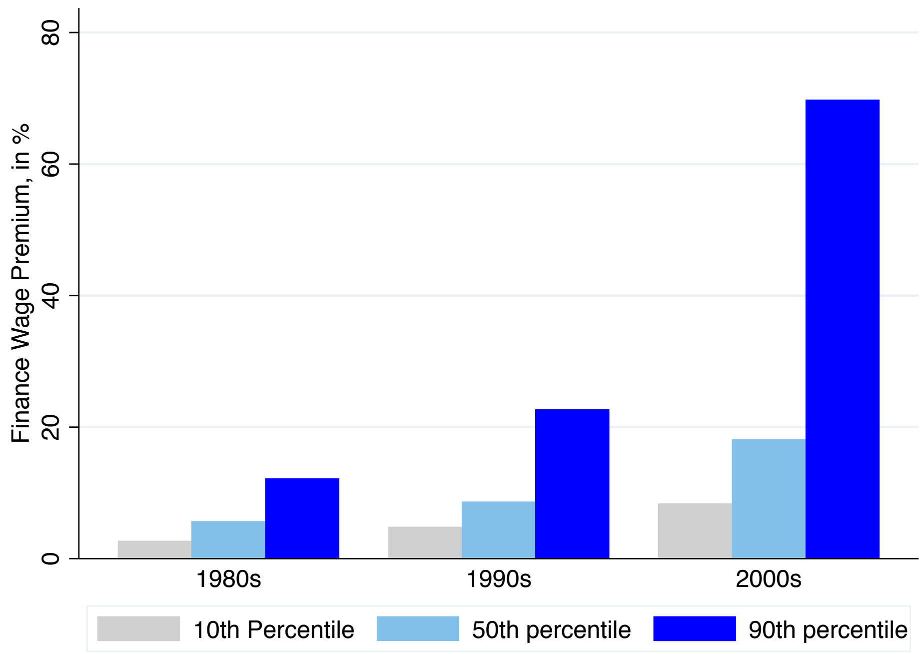
⇓

Final Ranking



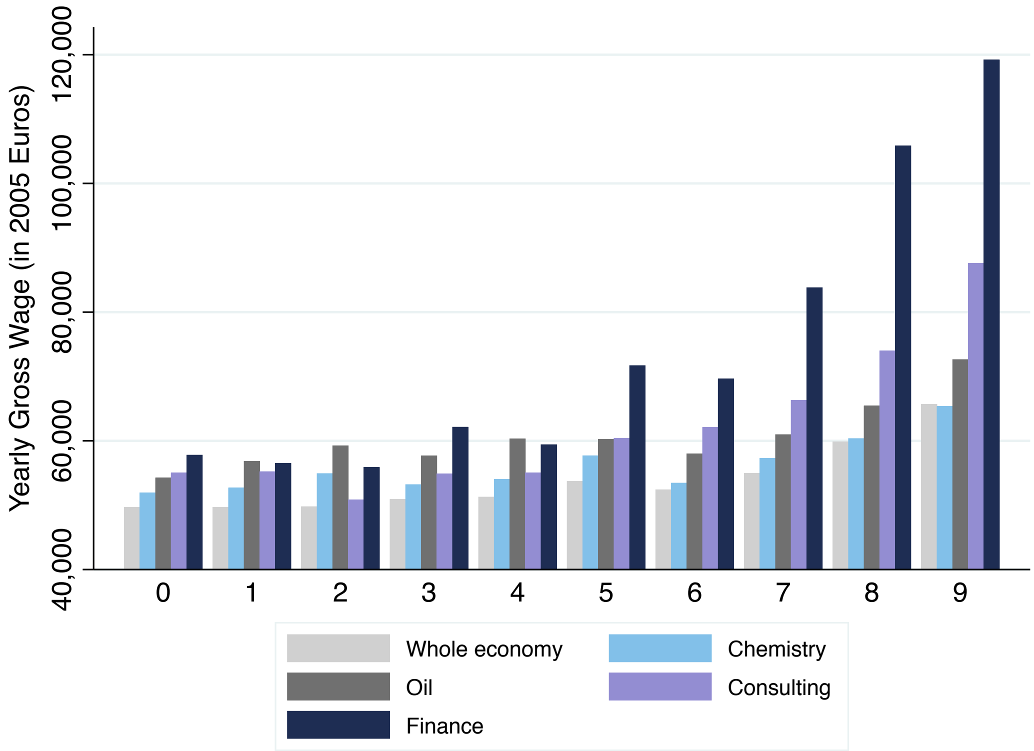
Note: This figure summarizes the selection process to enter in French Engineering Schools and displays the resulting distribution of engineering school selectivity by level of talent. French engineering schools, or "Grandes Ecoles", select students for admission based on their national ranking in a competitive written and oral exam. Schools are sorted on their selection rate, measured as the ratio of the marginal student's rank in the national competitive exam to the total number of competing students.

Figure 2. Evolution of the Finance Wage Premium by Percentile of the Wage Distribution



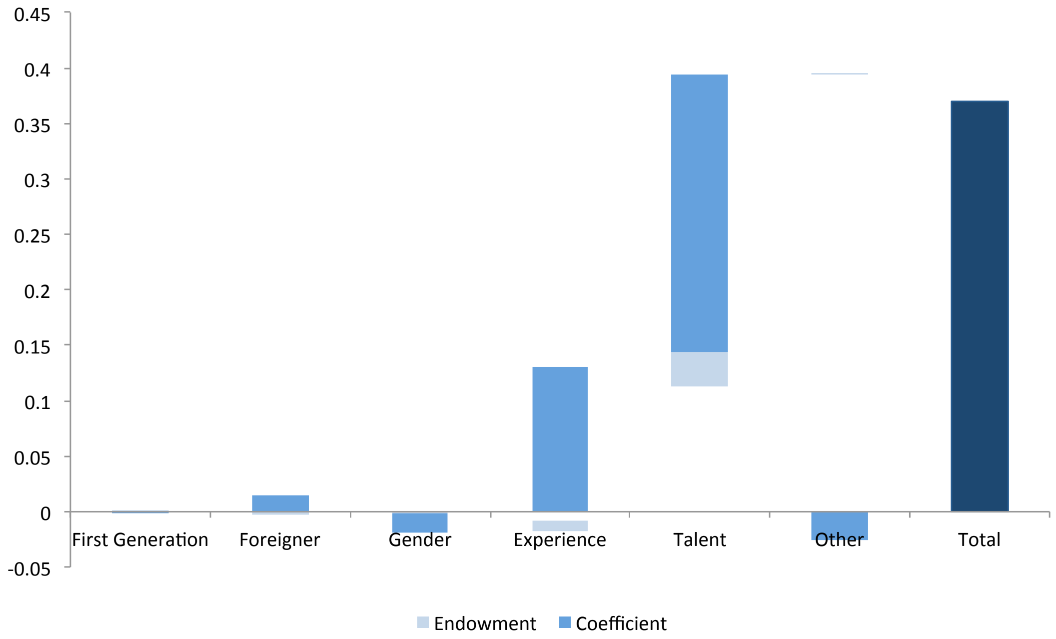
Note: This figure plots the evolution of the coefficient of the financial sector dummy in quantile regressions estimated at the 10th, 50th, and 90th percentiles of the wage distribution, in which the dependent variable is the log of the yearly gross wage. There are 48 industry dummies, with the sum of all industry dummy coefficients being constrained to zero. Each regression also controls for education, gender, marital status, occupation, firm type, firm size, hierarchical responsibilities, working abroad, working in the Paris area, experience, experience squared, and experience cubed.

Figure 3. Predicted Wages by Talent Level (*10 minus School Rank*) and Sector



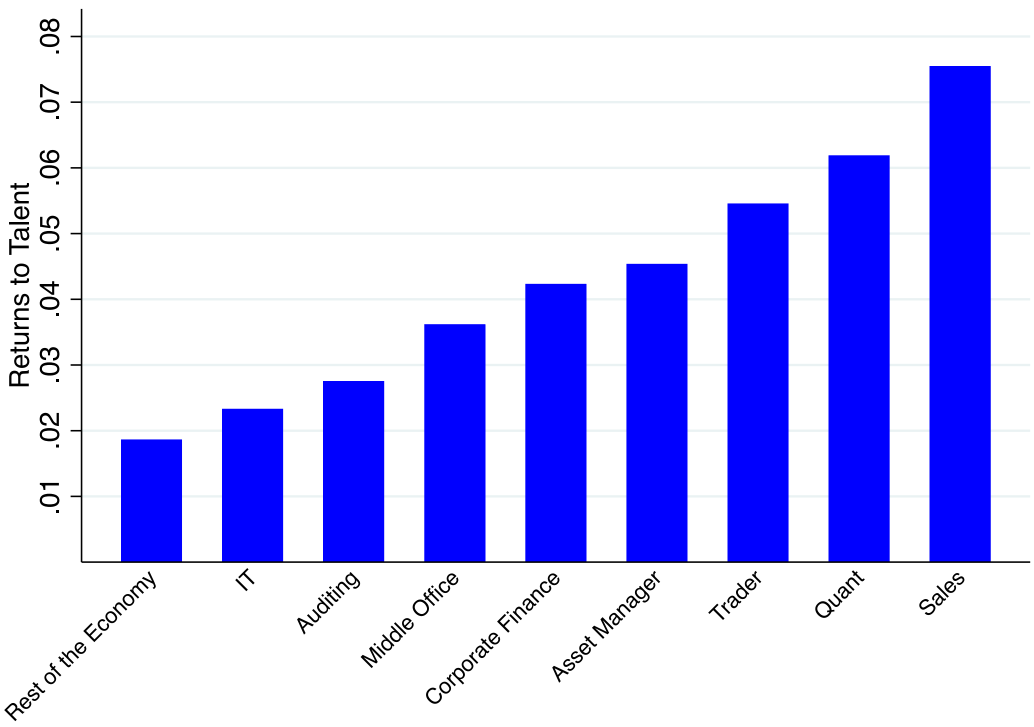
Note: This figure displays the predicted yearly gross wage calculated from the non parametric estimation of an OLS regression with a dummy for each talent level interacted with a dummy for each of the **four highest-paying industries**: oil, finance, chemistry, and consulting. The dependent variable is the log of the yearly gross wage, and the regression is estimated over the 2004-2011 period (198,886 observations). The model includes a female dummy, a married dummy, a female $\times$ married dummy, a Paris area dummy, a working abroad dummy, six country dummies, experience level, squared and cubed, four hierarchic responsibility dummies, nine occupation dummies, four firm size dummies, and four firm type dummies.

Figure 4. Blinder-Oaxaca Decomposition of the Finance Wage Premium



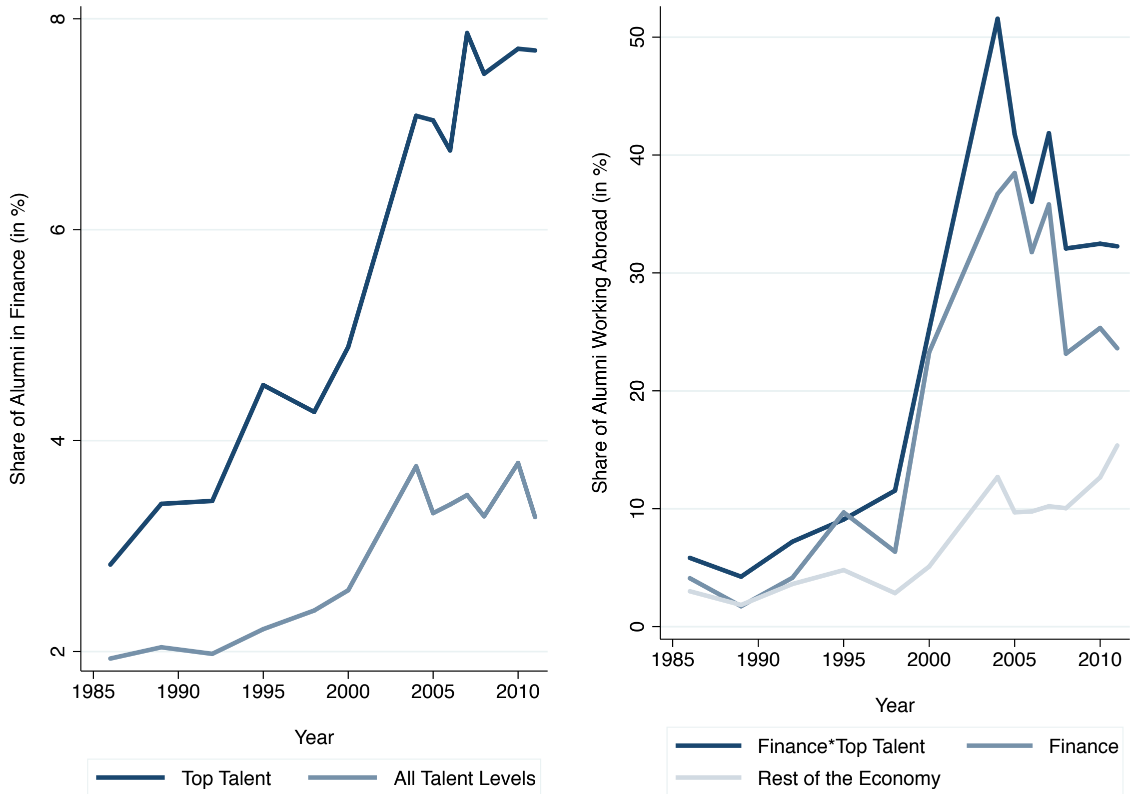
Note: This figures plots the results of the Blinder-Oaxaca decomposition of the difference in the log of the yearly gross wage between finance and non finance workers.

Figure 5. Returns to Talent across Jobs in Finance



Note: This figure displays the estimated returns to talent for each job category in the Finance industry. Self described job titles of individuals from the 2000-2010 surveys have been manually sorted into job categories. Returns to talent are the coefficients on the interaction terms between our talent measure and job category indicator variable, in OLS regressions where the dependent variable is the log of the yearly gross wage. The model includes a female dummy, a married dummy, a female $\times$ married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, and four firm size dummies.

Figure 6. Alumni Allocation in Finance by Talent Level and Geographical Area



Note: The left-hand side of this figure plots the evolution of the share of graduate engineers from our sample working in finance, for the total sample and for the three top levels of our talent measure. The right-hand side of this figure displays the evolution of the share of graduate engineers from our sample that work outside of France, for the whole sample, for engineers working in finance, and for top talented engineers working in finance.

9 Tables

Table 1. Summary Statistics

	1980s	1990s	2000s
Sample Size			
Average number of observations per survey	20,805	15,088	17,776
Number of surveys	3	4	7
Total number of observations	62,415	60,353	124,433
Response rate (%)	21	17	Nd
Coverage of total population of French engineers (%)	9	7.1	6.2
Compensation (in 2005 constant euros)			
Mean yearly gross wage	62,137	62,625	57,983
90^{th} percentile	99,718	101,964	95,598
99^{th} percentile	146,253	169,870	186,438
Standard deviation	27,073	31,827	39,086
Engineers per sector (%)			
Finance	1.9	2.3	3.5
Consulting	0.0	1.5	3.6
Oil	3.1	1.8	0.7
Chemical	3.6	3.8	2.6
Demographics			
Mean age	38.4	38.2	35.1
Percent female	6.1	11.9	15.3
Percent married	77.7	73.6	77.2
Foreigners	-	-	8.6
First Generation	-	-	11.8
Work location			
Percent working outside of France	2.6	4.1	12.1
Percent working in the Paris area	46.9	42.4	39.3
Career			
Mean experience (years)	14.6	13.6	11.9
Percent team manager	32.1	25.2	21.4
Percent department head	15.9	19.2	17.7
Percent top executive	6.5	11.3	7.1

This table reports summary statistics for the main compensation and demographic variables in our dataset. 1980s = graduates from the 1983, 1986, and 1989 surveys; 1990s = graduates from the 1992, 1995, 1998, and 2000 surveys; 2000s = graduates from the 2004, 2005, 2006, 2007, 2008, 2010, and 2011 surveys. Source: IESF Compensation Survey.

Table 2. Measuring Talent

School Rank	Recruitment Level	# Schools	Graduates		% Early Acceptance	# Citations (Academics)	Round Wage
			Number	% Share			% Share
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	Top 2%	1	6,173	2.7	36.0	3,174***	24.5
2	Top 5%	3	12,868	5.7	21.2	1,897***	22.3
3	Top 10%	7	20,119	8.9	14.2	1,623**	20.3
4	Top 15%	5	12,236	5.4	12.9	1,147**	20.7
5	Top 30%	7	12,182	5.4	17.1	-	16.2
6	Top 40%	8	11,468	5.1	11.4	-	19.6
7	Top 50%	14	46,676	20.6	13.0	-	21.2
8	Top 60%	21	20,747	9.1	8.8	-	27.7
9	Top 80%	45	36,615	16.1	11.1	-	27.9
10	100%	85	47,762	21.1	10.2	-	29.4
Total	-	196	226,846	100.0	-	-	24.1

This table reports summary statistics for each level of our talent measure *School Rank*. This talent measure takes a value from 1 to 10 and sorts schools based on their selectivity rate. French engineering schools, or "Grandes Ecoles", select students for admission based on student national ranking in a competitive written and oral exam. Recruitment level (column (2)) is the position of the marginal student for each school in the national ranking. Column (3) reports the number of schools for each level of our talent measure. Columns (4) and (5) give the number and share of students for each level of talent. Column (6) reports the share of respondents that are admitted in an engineering school early (at least one year ahead). Column (7) gives the predicted number of citations (after 9.7 years of experience) of academics that graduated from a school of the corresponding rank. The predicted values result from an OLS regression where the dependent variable is the 1% winsorized number of citations in Google Scholars. The sample consists of the 98 graduates from top engineering schools working in US universities. The control variables are gender, research area, experience, experience squared and experience cubed. Standard errors are clustered at the school level. Column (8) reports the share of respondents that declare a multiple of 100 as wage for each level of talent.

Table 3. Returns to Talent in the Finance Industry

	Log(Wage)							
Talent Measure	10 *minus* School Rank				1 *minus* Selection Rate		Early Graduation Dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Finance	0.248***	0.062***		0.018	0.022		0.234***	
	(0.033)	(0.021)		(0.018)	(0.032)		(0.014)	
Talent	0.021***	0.020***	0.020***	0.020***	0.166***	0.165***	0.006***	0.006***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.026)	(0.026)	(0.002)	(0.002)
***Talent* × Finance**		**0.043*** **	**0.044*** **	**0.034*** **	**0.369*** **	**0.394*** **	**0.025*** **	**0.033*** **
		(0.006)	(0.004)	(0.005)	(0.071)	(0.062)	(0.003)	(0.003)
Talent × Finance × Abroad				0.024***				
				(0.006)				
School FE	-	-	-	-	-	-	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	-	-	Yes	-	-	Yes	-	Yes
Observations	198,886	198,886	198,886	198,886	198,886	198,886	188,931	188,931
R^2	0.698	0.696	0.698	0.700	0.694	0.696	0.711	0.713

This table reports the coefficient of OLS regressions, where the dependent variable is the log of yearly gross wage. Returns to talent in the finance industry amount to the coefficient of *Talent* **plus** the coefficient of the interaction ***Talent* × Finance**. In columns (1) to (4), *Talent* is equal to *10 minus School Rank*, with *School Rank* based on the ranking of the marginal student in the national competitive exam, as defined in Table 2. Column (4) shows the coefficient of the interaction *Talent* × Finance× Abroad, where *Abroad* is equal to one if the alumni works outside of France. The model also includes the corresponding double interactions Finance × Abroad and *Talent* × Abroad. In columns (5) and (6), *Talent* is equal to *1 minus Selection Rate*, where *Selection Rate* is the selection rate of each school. Finally, in columns (7) and (8), *Talent* is a dummy equal to 1 if the individual graduated early, i.e. at 22 or before, and -1 if the individual graduates late, at 25 or after. Highly performing students graduate earlier on average because they often skipped one or two years of education. 12.2% of the students of our sample graduated early, 13% graduated late. Columns (7) and (8) include school fixed effects, and columns (3), (6) and (8) include finance-year fixed effects. All equations include year dummies, a female dummy, a married dummy, a female × married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, nine occupation dummies, four firm size dummies, and four firm type dummies. Standard errors are clustered at the school level in columns (1) to (6) and at the industry level in columns (7) and (8) and reported in brackets, * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Panel Analysis

	Log(Wage)					
Sample	2000-2011 Panel				Switching Individuals Only	
	(1)	(2)	(3)	(4)	(5)	(6)
Finance	0.273***	0.245***	-0.011		0.182***	-0.022
	(0.025)	(0.063)	(0.072)		(0.054)	(0.069)
Talent	0.028***					
	(0.001)					
***Talent* × Finance**			**0.055*** **	**0.056*** **		**0.053*** **
			(0.018)	(0.018)		(0.018)
Individual FE	-	Yes	Yes	-	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	-	-	-	Yes	-	-
Individual Controls	Yes	-	-	-	-	-
Job Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,429	29,429	29,429	29,429	6,992	6,992
R^2	0.412	0.934	0.937	0.937	0.878	0.880

This table reports the coefficient of OLS regressions, where the dependent variable is the log of yearly gross wage. Yearly gross wage includes both fixed and variable compensation. *Talent* is equal to *10 minus School Rank*, with *School Rank* based on the ranking of the marginal student in the national competitive exam, as defined in Table 2. In columns (1) to (4) the sample is restricted to the 13,366 individuals that are uniquely identified and tracked two years or more over the 2000-2010 period (see Section 4.3 for the methodology to build the panel). In columns (5) to (7) the sample is restricted only to the 3,275 individuals that switch sector. Columns (1) to (6) include year fixed effects, and column (4) also includes finance-year fixed effects. Standard errors are clustered at the individual level and reported in brackets, * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Returns to Talent across Jobs within Finance

	Log(Wage)		
	(1)	(2)	(3)
Talent	0.073***	**0.048*** **	0.043***
	(0.007)	(0.006)	(0.005)
Front Office			0.411***
			(0.061)
Talent **× Front Office**			**0.024** **
			(0.010)
Job Fixed Effects		**Yes**	-
Individual Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,753	1,753	1,753
R^2	0.496	0.617	0.589

This table reports the coefficient of OLS regressions, where the dependent variable is the log of the yearly gross wage. Yearly gross wage includes both fixed and variable compensation. The sample is restricted to the 1,753 workers in the finance industry who provide their exact job title over the 2006-2010 sample. Self described job titles of individuals from the 2006-2010 surveys have been manually sorted into job categories, including IT, Auditing, Middle Office, Corporate Finance, Asset Manager, Sales, Trader and Quant. Column (2) includes job category fixed effects. Columns (3) includes a indicator variable for *Front Office* jobs, which include Traders, Quants, Sales, Investment bankers, and Asset managers, and its interaction with our talent measure. All equations include year dummies, a female dummy, a married dummy, a female × married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, and four firm size dummies. Standard errors are clustered at the school level and reported in brackets, * p<0.10, ** p<0.05, *** p<0.01.

Table 6. Increasing Wage Returns to Talent in the Finance Industry

	Log(Wage)					
	1980s		1990s		2000s	
	(1)	(2)	(3)	(4)	(5)	(6)
Finance	0.075***	0.033*	0.162***	0.062**	0.324***	0.103***
	(0.011)	(0.018)	(0.019)	(0.025)	(0.043)	(0.021)
Talent	0.018***	0.018***	0.019***	0.018***	0.023***	0.020***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Talent **× Finance**		**0.010****		**0.022*****		**0.055*****
		(0.004)		(0.004)		(0.004)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,731	41,731	52,932	52,932	104,223	104,223
R^2	0.713	0.713	0.715	0.716	0.689	0.694

This table reports the coefficient of an OLS regression over three samples: 1980s = 1986 and 1989 surveys (Columns (1) and (2)); 1990s = 1992, 1995, 1998, and 2000 surveys (Columns (3) and (4)); and 2000s = 2004, 2005, 2006, 2007, 2008, 2010, and 2011 surveys (Columns (5) and (6)). The dependent variable is the log of the yearly gross wage. Yearly gross wage includes both fixed and variable compensation. *Talent* (which takes a value from 1 to 10) is equal to *10 minus School Rank*, with *School Rank* based on the ranking of the marginal student in the national competitive exam, as defined in Table 2. All equations include year dummies, a female dummy, a married dummy, a female × married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, nine occupation dummies, four firm size dummies, and four firm type dummies. Standard errors are clustered at the school level and reported in brackets, * p<0.10, ** p<0.05, *** p<0.01.

Table 7. Returns to Talent and Compensation Structure

	Fixed Compensation Log (Fixed Wage)		Variable Share Log(1 + Share)	
	(1)	(2)	(3)	(4)
Finance	0.045***	0.007	0.863***	0.368***
	(0.012)	(0.017)	(0.093)	(0.095)
Talent	0.024***	0.023***	0.053***	0.045***
	(0.002)	(0.002)	(0.009)	(0.009)
***Talent* × Finance**		**0.009*** **		**0.118*** **
		(0.003)		(0.013)
Individual Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	52,777	52,777	52,777	52,777
R^2	0.413	0.413	0.134	0.136

This table reports the coefficient of OLS regressions, where the dependent variable is the log of the yearly fixed wage in columns (1) and (2), and of the share of variable wage in columns (3) and (4). The sample is restricted to the period 2000 to 2011 for which our data includes information on the structure of pay. All equations include year dummies, a female dummy, a married dummy, a female × married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, nine occupation dummies, four firm size dummies, and four firm type dummies. Standard errors are clustered at the school level and reported in brackets, * p<0.10, ** p<0.05, *** p<0.01.

Table 8. Controlling for Network and Social Background Effects

	Log(Wage)				
Sample	Excluding *X* Related Schools	*First Generation*		Foreigners	
	(1)	(2)	(3)	(4)	(5)
Finance	0.083***	0.094*	0.113***	0.223**	0.122***
	(0.023)	(0.050)	(0.026)	(0.087)	(0.026)
Talent	0.016***	0.018***	0.022***	0.020***	0.022***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
***Talent* × Finance**	**0.037*** **	**0.074*** **	0.057***	**0.047*** **	0.058***
	(0.010)	(0.013)	(0.005)	(0.012)	(0.005)
Individual Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	178,377	14,488	114,781	1,399	104,097
R^2	0.689	0.665	0.650	0.566	0.649

This table reports the coefficient of OLS regressions, where the dependent variable is the log of the yearly gross wage. In column (1) the sample is restricted to schools that are not related to Ecole Polytechnique, the leading French Engineering school (The 14 excluded schools are Ecole Polytechnique, Mines de Paris, Ecole des Ponts, Supelec, AgroParis-Tech Grignon, Arts et Metiers Paris-Tech, Supaero, INP-ENSEEIHT, Ensta, Supoptic Orsay, ESPCI Paris, Chimie Paris, and Telecom Paris). In columns (2) and (3) the sample is restricted to *First Generation* students, whose parents do not have college education (the information is available from 2000 to 2010). In columns (4) and (5), the sample is restricted to individuals born outside France (the information is available from 2000 to 2010). All equations include year dummies, a female dummy, a married dummy, a female × married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, nine occupation dummies, four firm size dummies, and four firm type dummies. Standard errors are clustered at the school level and reported in brackets, * p<0.10, ** p<0.05, *** p<0.01.