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 on graduates of elite French institutions. Using this measure, we show that wage returns to talent are three times higher in the finance industry than in the rest of the economy. This greater sensitivity to talent almost fully absorbs the level of the finance wage premium, as well as its increase since the 1980s. Finally, returns to talent correlate with the share of variable compensation.

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

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

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1 Introduction

Compensation in the finance industry has been both higher and more skewed than in other sectors since the beginning of the 1980s. Controlling for education and other individual characteristics, **?** find the finance wage premium to be 50%, on average, in 2006. The financial sector has therefore largely contributed to the gains at the top of the wage distribution since the 1980s (Kaplan and Rauh, 2013, Bell and Van Reenen, 2013) and has consequently often been criticized as a source of growing income inequalities. This public debate, associated with increased regulatory scrutiny, calls for a better understanding of the drivers of bankers' pay. A growing theoretical literature relies on talent as a key ingredient to model bankers pay (**?**, **?**, **?**, **?**). However, empirically assessing 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 on the basis of their national ranking in a competitive exam that covers a wide range of subject matters, in both written and oral formats. We exploit this rigorous, multi-dimensional selection process to build a measure of talent, which we use to address our research question: are wage returns to talent relatively high in finance compared to the rest of the economy? More broadly, does talent effects drive the cross-section of wages in finance?[1] Using our novel measure of talent, we show returns to talent to be three times higher in the finance industry than in the rest of the economy, and to absorb almost fully the finance wage premium once included in regression specifications. Returns to talent have also increased threefold since the 1980s, in line with the significant growth in bankers' pay over the period. We also show that talented workers in finance receive a relatively large share of variable compensation. These empirical facts are largely consistent with theories of competition for talent. We use the selectivity of French engineering schools to measure the talent of its alumni for the following reasons. 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 gauges such personality traits

[1] For the purpose of this analysis, we define talent as the aptitude to reach an objective in a competitive environment.

as endurance, commitment, and ambition.[2] Two years spent in the highly selective and competitive environment of preparatory schools prior to examination, as well as the high stakes of the exam outcome, ensures that candidates are highly motivated. Their talent is thus the binding constraint. In addition, with more than 35 hours of classes, one written and two oral exams per week, and heavy homework, the intense workload ensures that their performance is unbiased by personal coaches, exam preparation boot camps, or other support resources that are often used by applicants to U.S. universities. A further element of the suitability of our research set-up is its focus, by virtue of analyzing talent heterogeneity in a highly educated cohort, on the right tail of the population.[3] Finally, there are 225 small scale engineering schools in France, which provides a high level of data granularity. We complement this school-level measure of talent, and control for school treatment effects, by also considering how many years it took a candidate to get into a given "Grande Ecole".[4] A student accepted at a top school after only a year of exam training is likely more talented than a student who requires three years of training. We match these talent measures to a detailed compensation survey dataset that covers 7% of the total population of French graduate engineers. The survey, which gathers alumni data from 199 of the 225 French engineering schools, includes detailed information on education, occupation, family situation, industry, firm type and size, and compensation. Because engineering, business administration and medicine are the only fields that are selective in France, 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. Using this survey data, we show that French graduate engineers in the finance sector are better paid, earning a premium of 25% over our sample period. This premium has been multiplied threefold since the 1980s. This finding is consistent with **?**. In line with **?** and **?**, we also observe a relatively high and increasing skewness in wage distribution in the finance industry. The

[2] **?** exploit this specificity of the French educational system for business schools.

[3] The heterogeneity in talent for the right tail is typically overlooked in population-wide measures like SAT scores.

[4] Age at graduation maps with age at entry. While a large number of students repeat the last year of preparatory class to improve their ranking, virtually no students skip or repeat a year during engineering school.

central result of our paper is that returns to talent are significantly higher in the finance industry, and that they almost entirely absorb the finance wage premium when included in the econometric specification. The main equation in our empirical analysis regresses the log of yearly gross wage on our talent measure and its interaction with industry dummies. 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 interactions between our talent measure and sector fixed effects we observe that the premium for working in the finance industry decreases from 25% down to 2.4% and is no longer significant. The finance wage premium is thus disproportionately allocated to the most talented individuals of this industry. Within finance, returns to talent are even higher for front office jobs than 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 to be absorbed through school fixed effects. We again find wage returns to talent to be three times higher in the finance industry than in the rest of the economy, and to account for a significant part of the finance premium. This additional analysis rules out school differences in quality of training or intensity of focus on finance as explanations for our main result. Our result is robust as well to the introduction of individual fixed effects in a panel regression that estimates the effect on wages of switching to the finance industry from another sector. We track individuals across surveys via detailed socio-demographic variables, such as father's and mother's occupations and years of birth, and educational variables like name of engineering school and type of specialization. We find that the wage premium obtained at switching to the finance industry is fully absorbed when we control for heterogeneous returns to talent across industries. Therefore, our main result should not be driven by unobserved time-invariant characteristics at the individual level, such as social background or risk aversion. All these three results are robust to introducing finance-year fixed effects, which absorb any overall translation of wages in finance.

We also observe a trend towards increasing returns to talent. The most talented individuals in finance have thus received most of the increase in the wage premium over past decades. Estimating our main equation over sub-periods reveals wage returns to talent in finance to have increased nearly threefold over the period 1980-2011. Thus, our results shed new light on the wage growth in finance since the 1980s documented in the literature.

Finally, we show that the share of variable compensation is positively correlated with returns to talent.[5] Our findings thus point to an interaction between returns to talent and structure of compensation. We find alternative channels for higher returns to talent in finance difficult to reconcile with our empirical facts. A battery of specific tests rules out network effects, social background and compensating wage differential, as potential drivers for our results. For example, we find that returns to our talent measure are even higher for first-generation graduate, children of parents without any university degree. Favorable social background or personal relations are unlikely to play an important role for this sub-sample of graduates..

We then discuss the possible explanations for the finance wage premium in light of our results. The finance wage premium may result from labor market competition, firms competing for workers and paying them according to their marginal productivity, which is a function of their talent.[6]. Conversely, the pay gap with other sectors could result from market failures that lead to rent extraction by finance workers from their employers (for example incentive rents) (**?**, **?**). While both theories predict higher return to talents, our results appear more consistent with a labor market competition view. 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. **?**, **?**, and **?** - based on data from the Census Population Survey, a Stanford MBA survey, and Harvard alumni compensation survey, respectively - find that the finance premium varies from 40% (in **?**) to more than 100% (in **?** and **?**). **?** documents the post 1980s increase in compensation in finance relative to the rest of the private sector, after controlling for education, and **?** and **?** show that the financial sector share in top end brackets 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.

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

[6]This is one of the key assumption of a growing theoretical literature investigating the effects of competition for talent in the finance industry (**?**, **?**, **?**, **?** and **?**). Financial workers may be more talented at extracting rents from society rather than more socially productive as in **?** and **?**

Our paper also 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 (?), social norms (?; ?), incentives, and competition for talent or managerial skills (?, ?, ?, ?, ?). Our results are consistent with the evolution of wages reflecting a change in market returns to talent, magnified in recent decades by scale effects (?, ?, and ?) and skill-biased technological change (?; ?).

Our paper also provides new evidence on the interaction between competition for talent and the structure of compensation. ? show wages to be more closely related to worker production in performance-pay than in non-performance-pay jobs, and ? 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 (?), higher productivity of effort, or better outside options (?), but the causality can also be in the opposite direction; performance pay may be used as a sorting mechanism to attract talented workers (?).

Finally, the results reported in this paper raise questions concerning the externalities that might be generated by competition for 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 (? and ? argue that this may have a downward impact on economic growth) or from financial regulation (?, ?). ?, however, shows the financial industry's talent-capture effects to be limited, and ? find no evidence that the selection of talent into finance increased or improved. Competition for talent can also generate inefficient risk taking (?), lead to excessive overbids (?), increase the fragility of banks (?), or shift effort away from less contractible tasks, resulting in efficiency loss (?).

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, investigate the relation between returns to talent and the structure of pay in Section 5 Section 6 rules out alternative channels for our results on return to talents in finance. Section 7 discusses and interprets our results in the light of the predictions from related theories. Section 8 concludes.

2 Measuring Talent

We use a specificity of the French educational system to build a unique proxy for talent. To earn the official title "graduate engineer", students in France need to graduate from a master program in any field of engineering offered by one of 225 selective small scale institutions.[7] These so-called "Grandes Ecoles d'Ingénieurs" select students on the basis of their national ranking in a competitive exam. We use this selection process to build a measure of talent for the entire population of engineers.

2.1 French Engineering Schools' Selection Process

The national competitive exam on the basis of which French Grandes Ecoles d'Ingénieurs select students for admission includes both written and oral tests. Students' performance on this exam reflects strong cognitive and academic skills as well as ambition, motivation, commitment, endurance, and ability to work under pressure. Figure **??** summarizes the selection process of French engineering schools.

The exam assesses, through written tests covering a wide range of subjects, a large set of formal academic skills, with mathematics, physics, programming, French literature, and a foreign language being among the compulsory topics. Candidates also select an optional topic from among biology, chemistry, engineering, and computer science. More than 80 hours of testing are involved over a three-week period (see Figure 1 for coefficients and exam length for each topic).

A series of complementary 20-minute oral exams test, for an equally wide range of subject matter, presentation, communication, and interaction skills. Candidates solve problems provided to them and present their solutions to one or more professors in interviews.

The process concludes with the assignment of a final national ranking that assures applicants to engineering school a priority position. 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 for three years on campus before being awarded a graduate degree.

[7] Thirty thousand diplomas are awarded annually at the national level.

Two years are spent preparing for the exam at highly selective institutions (*Classes Preparatoires*), which are comparable to boarding schools, and select students on the basis of superior academic performance in high school.[8] Top high-school students are highly encouraged to apply to (*Classes Preparatoires.* These two years of studies, as well as the three years of engineering school, are virtually free, which limits concerns over selection on family wealth. Studying in *Classes Preparatoires* requires a high motivation and ability to work under pressure. First, students are ranked quarterly and eliminated after the first year if their performance is too low (**?**). Second, students have the easier option to switch to the non-selective and much-less-competitive French university system at any time. Third, the workload is very heavy, with more than 35 hours of classes per week, one written and two oral exams every week, and a substantial amount of compulsory homework.

A group of lower rank schools recruit directly after high school based on the results to the French *Baccalauréat* and therefore offer a five year curriculum.

INSERT FIGURE **??**

2.2 School Ranking and Talent Measure

We arrive at a talent measure by classifying engineering schools into ten categories based on selectivity in the 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.[9]

We compute a school's selection rate by dividing the rank in 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 period 2002-2012.[10,11] For prominent schools, namely "Ecole Polytechnique", all "Ecole Centrales", "Mines", "Ponts et Chaussees", "Supelec", "Supaero"

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

[9]Our results still hold when we use directly the selection rate as a talent measure (See online appendix)

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

[11]We use information from the end of that sample period, as the level of school selectivity is strongly persistent. Our results are robust to using the average over the period.

and "Telecom Paris", we take the rank of the last admitted student as given. As an example, in 2012, the marginal student in the mathematics option in Ecole Polytechnique is ranked 124$^{\text{th}}$, and 8,343 students take the national exam. Hence, the selection rate of Ecole Polytechnique is 1.5%. Because some students self-select and do not apply to the lower ranked schools, the rank of the marginal student for the other schools is biased upward. We therefore adjust the rank of the last admitted students for these schools by adding to the marginal student rank the number of students that do not apply. This calculation therefore assumes that the students that do not apply would be admitted if they do. Back to our example, the rank of the last admitted student in Enac Toulouse in 2012 is 1,645$^{\text{th}}$ in the mathematics option. Given that only 7,094 students apply to this school out of a total of 8,343 enrolled students nationwide, the adjusted rank of the last admitted students is 2,894$^{\text{th}}$ = 1,645+ (8,343-7094) , which gives a selection rate of 34.7% (2894/8343).

A smaller group of schools admit students directly after the *Baccalauréat*, and not through the national competitive exam following preparatory school. For this subgroup, we measure the selectivity of the Engineering school by using the average *Baccalauréat* grade of their admitted students. We allocate these schools across groups 7 to 10, where the average *Baccalauréat* grade of admitted students from other schools is comparable. Schools allocated to group 7 have an average *Baccalauréat* grade around 16/20, whereas the ones allocated to group 10 are around 12/20.[12]

Selection rates for each category 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. Figure **??** plots the admission rate across the different groups of our talent measure. Table A3 in appendix lists the rank and the selection rate of all schools in our sample.

INSERT FIGURE **??**

Our measure of talent possesses several key advantages. First, it covers, with high

[12]N.B: our results hold when excluding these schools. (See online appendix for more details.)

comparability owing to consistent ranking, the total population of French engineers since 1980. Second, the measure maps such traits requisite to successful careers as cognitive ability, resistance to stress, and interpersonal skills. Moreover, in terms of prestige, and even pay-off (students from the top school are eligible for stipends), the stakes of the competitive exam are comparable to those associated with professional careers. Third, the homogeneity of the population we analyze enables us to disentangle education and motivation from talent, making our talent measure extremely sensitive. All students have the same level of education and years of schooling, and follow the same educational path (pursued a science major in high school and applied, successfully, to a selective preparatory school). Each student self selects, with respect to personal investment and despite guaranteed admission to a French university in any year following their high school graduation, to sit the toughest of exams. Fourth, our focus on a small fraction of the right tail of the talent distribution makes our talent measure extremely precise compared to population-wide measures such as SAT scores. Lastly, the admission process limits distortions due to networking, social background, reputation, and donations, the written exam being totally anonymous and letters of recommendation not being required.

2.3 Non School Specific Measure of Talent

Using age at graduation as an alternative measure enables us to differentiate graduates within each school. In the French educational system, highly performing students, on average, graduate at a relatively early age either because they skip a year or because less talented students often repeat years.[13] Hence, a student who enters the first-ranked engineering school, Ecole Polytechnique, at the age of 19 after two years of preparation will be more talented, on average, than a student who enters the school at age 21 after three years of preparation. Age at graduation, not being school specific, enables us to control for school unobserved variables by introducing school fixed effects.[14] Figure **??** plots the distribution of graduation age in our sample.

INSERT FIGURE **??**

[13] As many as 25% of students preparing for engineering schools repeat the second year of preparation to improve their results in the competitive exam.

[14] For instance, schools might offer different quality of training or a more specific focus on finance.

3 Data

3.1 Survey

We analyze, empirically, 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 wage of each graduate as well as detailed information on demographics, education, careers, job position, and employer.[15, 16]

We clean the survey data by retaining only respondents between the ages of 20 and 65 who are full time employees and possess a valid industry code and more than one year of experience.[17] We exclude respondents whose compensation is less than the legal minimum wage, and, for each sector and year, winsorize compensation at the top 1% of the distribution.[18] Finally, all nominal quantities are converted into constant 2005 Euros using the French National Price Index (IPCN) from INSEE.[19] These operations leave us with 198,886 observations.

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 measure of talent. Its access to unique wage data, including information on its variable share is key to our analysis. Finally, the substantial information the survey provides on demographics, job position, employers, and work location (including engineers working outside of France, in London, for example, or New York) enables our analysis to control for a broad set of variables.

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

[16] Source: French Education Ministry.

[17] Survey respondents must provide from their latest December pay sheet their yearly gross wage and employer's five digit industry code. Retaining only observations accompanied by a valid industry code ensures that respondents actually consulted their pay sheets, and thereby maximizes the accuracy of wage data and limits measurement errors.

[18] We do not winsorize at the total sample level so that highly paid sectors are not overrepresented in the affected subsample.

[19] Data is available at http://www.imf.org/external/datamapper/index.php.

3.2 Summary Statistics

INSERT TABLE **??**

Table 1 provides key variable summary statistics together with information on the scope of the survey. Frequency has increased from every five years from 1983 to 1986 to every year from 2004 onwards. The number of respondents per survey averaging 23,000, each survey represents, on average, 6.9% of the total population of French engineers. The response rate is 18.8%.[20,21]

Wage distribution among French graduate engineers has become increasingly scattered 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 due to composition effects, wages at the 99$^{\text{th}}$ percentile increased by more than 14% over the same period.[22] This result is in line with recent literature showing inequality to have increased in most OECD countries, mainly at the very top of the wage distribution (**?**; **?**).

We define 48 industries based on the official industry classification codes respondents provided for their employers. 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.[23]

Table 1 also includes summary statistics on demographics, jobs, careers, employer, work location, and compensation structure. The decrease in respondents' average age is likely driven by the change to an e-survey format. The increase in the share of women respondents is in line with how the composition of engineer population has evolved nationwide. The share of respondents working outside of France has dramatically increased, which is consistent with the improved mobility of highly qualified workers. (See the online appendix for a list of the questions asked in the 2008 survey.)

[20]Although response is voluntary and the survey sent only to alumni whose names and addresses are known to the association, selection effects are likely to be low. First, median gross wage including bonuses in the 2009 survey is similar to that computed for the same population in a 2009 survey of French companies conducted by Towers Perrin, a leading compensation consulting company. Second, respondent demographics are similar to those obtained by the French National Statistical Institute (INSEE) in the French Employment Survey, for which the sample is randomly selected.

[21]The IESF mailed the survey until 2000, and has e-mailed it since 2002.

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

[23]See the online appendix for a detailed list of, and the distribution of workers across, all industries.

3.3 The Talent Measure

Table 2 reports the selection rate, number of schools and students, and summary statistics for individual characteristics by talent category. By construction (of our talent measure), a larger number of respondents is associated with the lower level of talent. Columns (6) and (7) show wage level and share of top managers to increase with talent. From column (8), which reports, by talent category, the share of respondents that graduated at least one year earlier than the standard age, age at graduation appears to be highly correlated with talent category. Its focus on a highly educated population notwithstanding, our sample offers considerable heterogeneity with respect to talent and wages.

INSERT TABLE ??

3.4 Representativeness of the Sample

We compare the patterns of compensation in the finance industry observed in our data to the ones found in the literature.

Graphical evidence of the evolution of the wage distribution is provided by Figure ??, which 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. Skewness in wages appears to have increased significantly over past decades.[24]

INSERT FIGURE ??

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

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

where $w_{i,t}$ is the log yearly gross wage, $Talent$ is the talent measure, I_i represents the vector of industry dummies, D_t the vector of year dummies, X_i is a vector of individual characteristics, and ϵ represents the average returns to talent in the economy.[25] This

[24]See Figure 1 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, chemistry, and consulting industries.

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

estimation controls for our talent measure, as well as for demographic, occupation, job, and employer characteristics.[26,27]

Results are displayed in column (1) of Table **??**. 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 results reported by **?**, **?**, **?**. That our estimation of the finance wage premium is in the lower range of recent estimations in the literature is likely due to our rich set of controls, most importantly our talent measure, and the educational homogeneity of our sample.

INSERT TABLE **??**

The external validity of our sample is further supported by Table **??** in the appendix, which replicates Table 6 from **?**. The first column of Table **??** of the appendix shows the premium to have increased from 7% to more than 30%, on average, since 2004, and to have been 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 is concentrated among top earners, is again consistent with **?** and **?**.

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

[27] Demographic controls include years of experience, experience squared, experience cubed, gender, marital status, and gender × marital status. We control for occupation with nine dummies (for production, logistics, development, IT, commercialization, administration, executive, education, and for employer type with five dummies (self-employment, private sector, state-owned company, public administration, and others (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, United Kingdom, Germany, Switzerland, Luxembourg, China, and Belgium from 2004), and four hierarchical responsibility dummies from no hierarchical responsibility to chief executive.

4 Results

4.1 Heterogeneous Returns to Talent across Industries

We report here our central result, that returns to talent are much higher in the finance industry and absorb almost entirely the sector's wage premium.

Graphical evidence of this result is provided in Figure **??**, which plots respondents' predicted wage by industry over the ten categories of our talent measure. We calculate the predicted wages by regressing wages over talent category fixed effects, controlling for demographic and occupational characteristics (equation (**??**)). We observe wages to be an increasing function of talent, and the magnitude of this relationship to be significantly higher in the finance industry than in other sectors. For example, wages increase from the bottom to the top of the talent distribution in the finance industry by more than 64% and in the oil industry by only 35%. The relationship between our talent measure and wages in finance appear to be convex.

INSERT FIGURE **??**

We specifically test whether and to which extent wage elasticity to talent is high in finance by including interactions between talent and each industry dummies in equation (1),

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

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

Column (2) of Table **??** 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 wages for a finance worker, vs. 1.9% for a worker in the rest of the economy. The consulting industry, consistent with its high talent scalability, 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 chemistry industries than in the rest of the economy likely because of strong physical constraints that limit the scalability of talent in those sectors.

High returns to talent in the finance industry almost entirely absorb the finance wage premium. When we include the interaction term $I_i \times Talent_{i,t}$ in our specification, the finance premium almost disappears, at 2.4%, and is no longer significant (column 2). This result is strongly supportive of talent effects driving the finance wage premium, and is robust to including industry time year fixed effects (Column (3)), using (1 - school selectivity rate) as the talent measure, or the most granular school ranking possible.[28]

4.2 Controlling for School Fixed Effects

Our result is robust to including school fixed effects, which is possible when using graduation age as a measure of talent. Column (4) of Table **??** reports the regression coefficients when we interact age at graduation as a talent measure with our industry dummies. We find among alumni from the same school that those who graduate earlier in life are paid relatively more, and that this effect is significantly stronger in finance. Consistent with our previous result, we also find the coefficient on the finance sector dummy to decrease, albeit less than in our main specification, likely due to this talent measure being less granular. When we include year-industry fixed effects, to control for changes in industry job market characteristics, we find again that returns to talent are from three to four times higher than in the rest of the economy (Column (5)). This result suggests that treatment effects during school cannot explain our previous findings, and is consistent with the view widely held in France that most of the training occurs during the two years of hard work leading to the selection exam, rather than what is taught at the schools themselves.

4.3 Controlling for Individual Fixed Effects

We confirm our result by running regressions that include individual fixed effects. Returns to talent almost fully absorb the wage increase when a worker switches to the financial sector.

To include individual fixed effects, we convert our repeated cross-section data to a panel. We identify unique individuals across time using six socio-demographic variables:

[28]See Table 1 in the online appendix for these robustness checks.

year of birth, sex, name of the engineering school, type of specialization and, most important, father's and mother's occupations. The pseudo-panel covers the 2000-2010 period and contains 15,256 uniquely identified individuals.

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

$$w_{i,t} = \alpha_i + \beta \times I_{i,t} + \mu \times D_t + \lambda_{i,t} \tag{3}$$

where α_i represents the vector of individual fixed effects, $I_{i,t}$ is a dummy equal to 1 when a worker joins a given sector in year t, and D_t is the vector of year dummies. Results are reported in column (6) of Table **??**. The 25% wage increase enjoyed by a worker who joins the finance industry is close to the finance premium estimated in the cross section, and is significantly larger than that realized by workers who enter other sectors.[29]

To test whether an individual obtains higher returns to its talent in the finance industry, we include the interaction of the industry dummy with talent:

$$w_{i,t} = \alpha_i + \beta \times I_{i,t} + \bar{\epsilon} \times I_{i,t} \times Talent_i + \mu \times D_t + \lambda_{i,t} \tag{4}$$

Column (5) of Table **??** displays the result for this specification. We find talent to fully absorb the wage increase realized by a worker who joins the finance industry, the coefficient of the finance industry dummy decreasing down to 0. Elasticity to talent is significantly higher in finance than in other sectors. Conversely, talent is a poor predictor of the pay increase realized by workers who join other well-paying industries. This result is further evidence that returns to talent are higher in finance, even when all unobservable individual characteristics are absorbed.

4.4 Controlling for Job Fixed Effects

We exploit the granularity of our data to ensure that a potential selection of graduates from top schools to relatively high paying jobs in the industry does not drive our result. Some occupations in the finance industry, such as trader, pay indeed much more, on

[29]This result is consistent with **?**, 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.

average, than other jobs.

We reject this endogenous matching explanation by introducing exact job title fixed effects in equation (??), 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 of top and lower ranked schools.[30]

Our main result is robust to this constrained specification. Columns (1) in Table ?? reports the returns to talent for the subsample of individuals for which we possess the job title, without the job titles fixed effects. Moving one notch up our talent scale yields a 7.2% increase in wages for a finance worker, which is close to the level found in our main specification (column (2) of Table ??). When we include job title fixed effects in column (2), we still find returns to talent to be more than twice as high in the finance industry as in the rest of the economy: moving one notch up our talent scale yields a 4.9% increase in wages after controlling for job fixed effects. This means that a talented trader, everything else equal, earns significantly more than a less talented one.

INSERT TABLE ??

We complement this analysis by exploring whether returns to talent are higher for certain job categories. Columns (3) and (4) in Table ?? show that returns to talent are significantly higher in front office jobs (which includes Trader, Quant, Structurer, Sales, Asset manager, and Investment banker), when compared to other jobs in finance (IT, Audit, Middle and Back-office, other support functions). Finally, Figure ?? 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 ??

4.5 Increasing Returns to Talent in the Finance Industry

That returns to talent have increased over the years sheds new light on the increase in the finance premium since the 1980s, as documented by ?.

[30]Respondents are asked on the 2006-2010 surveys to give their job titles. 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.

Columns (1), (2), and (3) of Table **??** report the OLS coefficients of equation (1) over three periods: the 1980s, the 1990s, and the 2000s. We find the coefficient on the interaction term between talent and the finance industry dummy to have increased more than twofold. In the 1980s, one notch in our talent scale translated to an average 1.7% increase in wages, compared to a 2.8% increase in the finance industry (column (1)). In the 2000s, the same difference in talent generates a 7.5% increase in wages in finance, compared to a stable 2% increase in the economy at large (column (3)). The residual of the finance premium, measured by the finance sector dummy, remains stable over the different periods (columns (1) to (3)). Returns to talent thus increase in line with the finance wage premium.

INSERT TABLE **??**

A possible explanation for this increase in returns to talent in finance would be a long-term rigid supply effect. Thus, the pool of workers identified as talented may not have adjusted enough to the increase in the demand for skills in the finance industry over the last 30 years, due to the limited number of students graduating from top schools. This explanation may not fully explain the increasing trend we observe for two main reasons: first, top schools have been increasing their number of students over the sample period. Hence, the number of graduated engineers from state engineering schools has increased from 25,000 in 1990 up to 40,000 in 2008.[31]. Second, several papers in the literature show that the adjustment costs of supply to demand on the labor market are rather small in the long run, mainly because shifts in demands are matched by the entry of new workers (**?**, **?**, **?**). An increasing mismatch between the supply and demand of talent could therefore not fully explain the largely increasing premium we observe in the finance industry.

5 Returns to Talent and the Structure of Compensation

We next investigate the relationship between returns to talent and the structure of pay. Compensation contracts that include a large share of variable pay may be associated

[31] $http://media.enseignementsup-recherche.gouv.fr/file/2009/19/4/RERS2009_119194.pdf$

with high returns to talent for several reasons. First, intense competition for talent may amplify the need for variable pay by increasing the cost of incentivizing talented workers, either because of their better outside options (?), or because the productivity of their effort is higher. Second, high returns to talent may increase the need for retention mechanisms. Firms may use variable pay as a sorting mechanism for attracting and retaining talented workers (?, ?). Third, the high returns to talent we observe in finance may result from a better performance observability than in other industries, which translates into a higher share of variable pay as the firm can contract on performance with the worker. 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 the case in sectors such as finance, and in occupations such as trader, in which returns to talent are especially high.

5.1 Across Industries

Our analysis of variable compensation utilizes a specific question of the IESF survey. From the year 2000 survey onwards, respondents report the percentage of total compensation that is variable. Bonuses and firm specific incentive schemes are included, stock-options excluded. Variable compensation is confirmed to be a key component of wages in the finance industry, present in 65% of the compensation packages in finance, versus 41% in the rest of the economy.

We test whether our talent measure relates to the share of variable compensation in the finance industry. Column (3) in Table ?? documents 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 talent and the finance sector dummy. The coefficient of the interaction indicates that the effect of talent on the share of variable compensation is much larger in finance than in the rest of the economy, and the decrease in the coefficient on the finance dummy, which is divided by three, indicates that this talent effect largely explains the large share of variable pay in finance. These results are consistent with the high returns to talent affects not only the level, but also the structure, of pay.

INSERT TABLE ??

5.2 Across Jobs

Using the detailed information we have on the exact job title of respondents from 2006 to 2009, we explore whether returns to talent and the structure of compensation are correlated across jobs within finance. Figure ?? plots returns to talent over the share of variable compensation for the main occupation categories in finance. We observe a strong positive correlation: occupation with the highest returns to talent also pay with the largest share of variable compensation. This fact is consistent with a higher scalability of these tasks coupled with talent being more easily observable for these jobs.

INSERT FIGURE ??

6 Alternative Channels

This section discusses alternative explanations for our result that are not based on talent effects.

6.1 School Network Effects

Our results could be driven by school network effects, rather than talent. More precisely, the high returns to school ranking we observe in finance might come from alumni networks being more influential in finance than in the rest of the economy. In the US, students in high ranking schools are likely to benefit from strong alumni networks and social connections, independent of their talent. A recent literature on networks insists on their importance in such labor market processes as hiring, promotion, and setting compensation (?, ? and ?). We conduct two distinct tests to rule out this alternative explanation.

We first exclude from our sample individuals from the most connected schools, i.e. France's Ecole Polytechnique and related schools, as graduates of these schools are over-represented among top executives and CEOs (?,?.[32] Column (1) in Table ?? shows that

[32]The excluded schools are Ecole Polytechnique, Mines de Paris, Ecole des Ponts, Supelec, AgroParis-Tech Grignon, Supaero, INP-ENSEEIHT, Supoptic Orsay, ESPCI Paris, and Chimie Paris et Telecom Paris. Centrale Paris is excluded as well, its level of recruitment being equivalent.

returns to talent are still three times higher in the finance industry than in the rest of the economy in this sample. Therefore, our results are not driven only by the powerful networks associated with top schools.

INSERT TABLE ??

As a second test, we restrict our sample to graduates working outside of France in columns (2) and (3), the rationale being that networks of French engineering schools are likely to have significantly weaker effects abroad. The size of the coefficient of the interaction in column (3), shows that returns to talent are even higher for graduates who work outside of France. This result is supportive of networks effect not playing an important role in returns to talent. Given that the United States and United Kingdom capture more than 50% of graduates outside of France, the likely more competitive labor market in these countries may explain the larger size of the coefficient.

6.2 Social Background

Our results could be driven by the social background 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 (4) and (5) of Table ??, we restrict our sample to *First Generation* students, meaning that their parents do not possess university level education. We find that our results are robust to this sub-sample, and are actually strengthened as the coefficient on the interaction between talent and finance is significantly higher than in the full sample. Second, in columns (5) and (6), we restrict our sample to graduates that do not possess the French nationality, following the rationale that their parents are likely to be less integrated in French social networks. We find again that our main result is robust to this specification, making our data hard to reconcile with a social background explanation.

6.3 Compensating Wage Differential

A final alternative explanation would be that higher compensation in finance aims at offsetting tougher working conditions, or higher income risks. More talented workers would deserve a higher compensating differential because they work relatively harder, or because their health, income or employment are more at risk. However, **?** and **?**'s estimate of the lifetime pay premium in finance explicitly control for hours worked, wage risk and the risks of exiting the finance sector.

We nevertheless conduct additional tests to rule further out this possibility.

Using data on job satisfaction and hours worked, and controlling for both stress and excessive workload in equation (**??**), we conduct a battery of additional tests.[33] 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. We find no significant downward impact of these variables on talent returns in the finance industry. Results are reported in Table 2 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 per sector as a measure of unemployment risk.[34] We find a negative correlation between wages and industry unemployment risk, that unemployment risk has been constant in the financial sector since 1999 (layoff rate = 1.7%), and that the finance sector has one of the lowest layoff rates (whole economy average = 2.9%). Second, we use as an additional control a survey question that asks if interviewees experience low job security, which leaves our main result unchanged (Table 2 in online appendix).

In addition, to ensure that our result does not come from a correlation between income risk and talent due to a large share of variable pay, we restrict our analysis to the fixed part of workers compensation package. Columns (1) and (2) in Table **??** show the coefficients for equations (**??**) and (**??**) where the dependent variable is the level of fixed compensation. We find that finance workers earn also a premium on the fixed part of their pay, which presents low, if any, income risk. In addition, the level of talent also explains the level of fixed compensation in the financial sector.

[33] We do not control for stress and excessive workload in our main results, this information not being available for the entire sample.

[34] 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.html

Overall, our results are hard to reconcile with alternative stories where talent effects are not driving the finance wage premium.

7 Discussion

7.1 Labor market competition for talent

In a competitive labor market, firms want to retain talented workers who exhibit a high productivity. There are three main reasons why firm competition for talent may result in heterogeneous wage returns to talent across industries.

First, technology varies across industries, being more skill biased in some of them, which increases the relative productivity of skilled workers (**?**, **?** and **?**). For example, some industries are more information-technology intensive. Information technology substitutes to routine tasks but complements non routine ones, hence increasing returns to skills and the demand for high skilled worker. In some cases, technology may also allow talented workers to extract more rents from the economy, if for example technology can be used to increase opacity.

Second, labor market competition varies across industries. The matching of talents to tasks is more efficient when labor markets are more competitive. Competition for talent is higher when talent is observable and portable across firms and industry-general rather than firm specific.

Third, scalability of operations plays an important role in talent productivity: when talent can be easily leveraged, a small difference in talent leads to a high difference in productivity, and consequently wages. Scale effects are high in jobs such as novel writer or software programmer, and low in physically bounded industries in which the level of physical capital is high such as restaurant owner.[35]

We develop a simple model in the online appendix based on **?** and **?** in which competition for workers and scalability are associated and result in high returns to talent.

[35] A recent example of talent scalability and its potential impact on wages is given by evening class high school teachers in South Korea. Talent has always been key in teaching. However the implementation of online technologies has led to a shock in teaching scalability, multiplying the productivity of talented teachers. This scalability effect has led top teachers wages to skyrocket, with some of them earning seven figures pay checks. Source: http://online.wsj.com/article/SB10001424127887324635904578639780253571520.html

In this model, very little adjustment costs can predict large differences in returns to talent across industries.

The finance industry ranks high in the three dimensions previously mentioned. First, the use of information technology is ubiquitous in the finance industry, and ranges from real time database to powerful in-house risk management and asset pricing softwares. **?** find that the finance industry has relatively high information-technology intensity. In addition, finance faces much less hard-wired technological constraints than manufacturing, which increases plasticity and flexibility in financial activities, opening up the scope for creative financial innovations. These innovative financial activities are often complex and difficult to understand for outsiders, which may increase the possibility for talented workers to extract rents from their counterparties (**?**,**?**). Second, talent is easily observable and portable across banks. The productivity of a given finance worker can be quantified by its P&L and can be observed inside and outside the firm at a low cost. This facilitates efficient job assignments and capital allocation. Finally, the dematerialized nature of financial transactions induces low physical constraints and hence a large flexibility of capital that can easily fly to talents. Additionally, the integration of world capital markets and their deregulation since the 1980s has reinforced this scalability effect. Hence, **?** find that deregulation has been associated with skill intensity, job complexity and high wages for finance employers. **?** 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. Other sectors, such as law, consulting or computer technology, exhibit comparable characteristics, although in a lesser extent than the finance industry.

Therefore, our main result of higher returns to talent in the finance industry, combined with the high skewness of the wage distribution, are strongly consistent with the predictions from the labor market competition theory. In the time series, this theory also predicts that returns to talent should have increased over the years, because of deregulation and financial innovations that have increased scalability and hence the marginal (but not necessarly social) productivity of one unit of talent from a finance worker.

Moreover, the labor market competition theory also predicts that returns to talent should be higher in more scalable tasks, or in markets where labor market competition is more intense. This is consistent with our results on higher returns to talent in more scalable jobs, such as front office jobs, and on higher returns to talent in more competitive labor markets such as in the United Kingdom or the United States. Finally, in the labor market competition view, variable compensation may be used to attract talented workers (**?**), which is consistent with our empirical correlation between returns to talent and structure of pay.

7.2 Rent Extraction from Financial Employers

Another stream of theoretical literature explores how the finance wage premium may come from a rent extraction by finance workers *from* their employers. This rent extraction is defined within the firm, as opposed to the view where finance workers extract rents *for* their employer. [36]

There are two main reasons why workers may be able to extract larger rents from their employers in finance than in other industries. First, the moral hazard problem may be more severe in the finance industry. The exact effort of an employee may be hard to monitor in innovative financial activites. On the other hand, each employee may manage a large amount of capital, making it important that each employee exerts sufficient effort and be sufficiently attentive. **?** develop a dynamic model of financial contracting taking into account this severe moral hazard problem in the finance industry. They predict that employees in the finance industry earn larger rents relative to other equally talented individuals in other industries. Second, finance workers may have captured a large share of the pay setting process within banks, for example through managerial power (**?**).

Managerial power or incentive problems would result in higher returns to talent if more talented workers use their skills to extract rents from their employers, or are more costly to monitor or incentivize. It is not clear why banks would consistently hire talented workers who use their skills to extract rents from them, and in an increasingly manner over time. Incentive problems are more likely to be related to job characteristics than to individual characteristics. Therefore, the fact that our result is robust to job title fixed effects suggests that moral hazard is not the main driver of high returns to talent in the

[36]In this latter settup, banks will adequately pay workers as a function of their talent in extracting rent for the bank, which is consistent with the labor market competition theory.

finance industry.

However, an alternative explanation, which is robust to the inclusion of job title fixed effects, would be that more talented workers have better outside options and hence are more costly to monitor (?). In this model, as well as in ?, incentive problems interact with competition for talent.

8 Conclusion

The main contribution of this paper is to show that high and increasing returns to talent in finance explain both the distribution and evolution of bankers' pay. To estimate returns to talent calls for an appropriate measure of talent. We exploit for this purpose the results of a competitive examination among equally highly educated and motivated candidates.

We apply our talent measure to a unique dataset derived from a compensation survey of the population of French graduate engineers that includes detailed information on wages, exam performance, career, and demographics. In line with the existing literature investigating wages in the finance industry, we find that the level of wages in finance is high and positively skewed, and that these patterns have increased since the 1980s.

Our results raise questions concerning the possible negative externalities that competition for talent in the finance industry might generate. High returns to talent may lure talented individuals away from other industries or from regulation (?), fuel excessively high levels of pay (?), exacerbate bank fragility (?), or induce inefficient risk-taking (?). An additional question is whether banks correctly internalize the productivity of workers, for instance by taking into account long-term risks.

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A Figures

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
		Sport	5

⇓

Final Ranking

Figure 1. Selection Process in French Engineering Schools

Note: This figure summarizes the selection process to enter in French Engineering Schools.

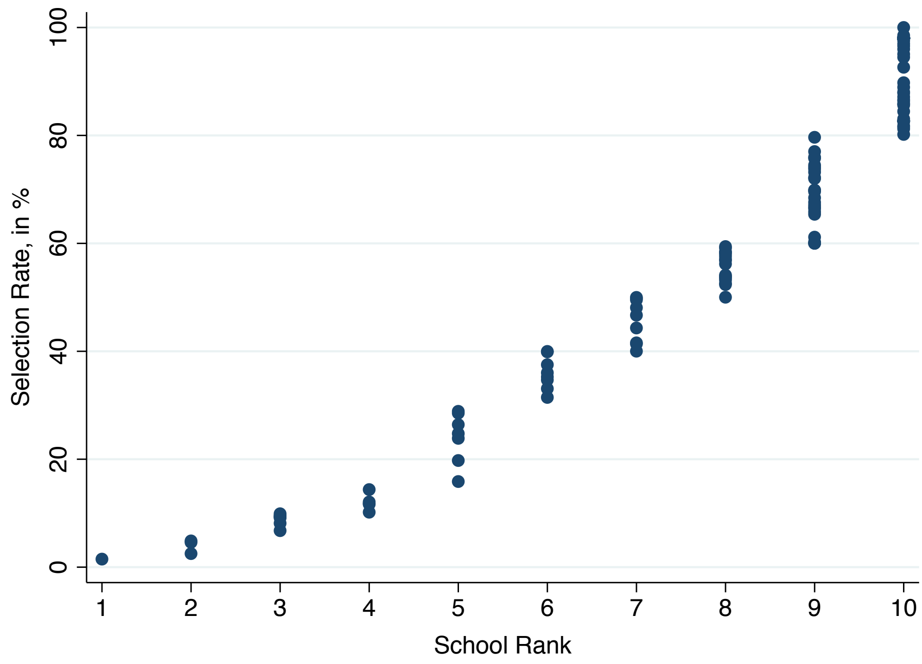

Figure 2. Distribution of Engineering Schools by Admission Rate

Note: This figure displays the selectivity of Engineering schools fby level of the talent scale. French engineering schools, or "Grandes Ecoles", select students for admission based on student 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.

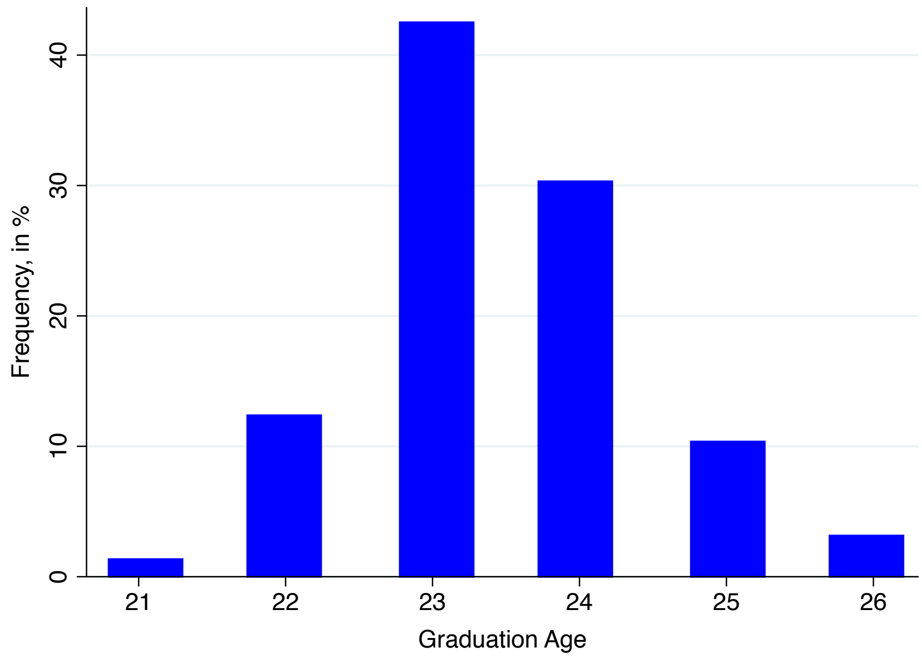

Figure 3. Distribution of Age at Graduation

Note: This figure plots the distribution of graduation age across the survey sample, which maps into age at entry. Heterogeneity results mainly from some students skipping years before high school, while others repeat a year, typically the second year of preparatory class to improve their performance to the national competitive exam.

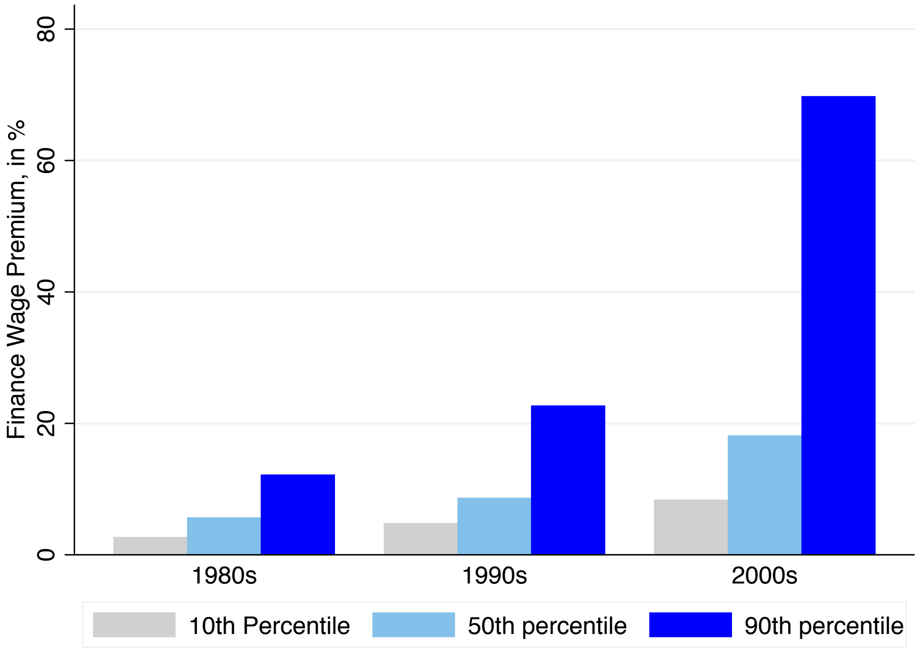

Figure 4. Evolution of the Finance Wage Premium by Percentiles of the Wage Distribution

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.

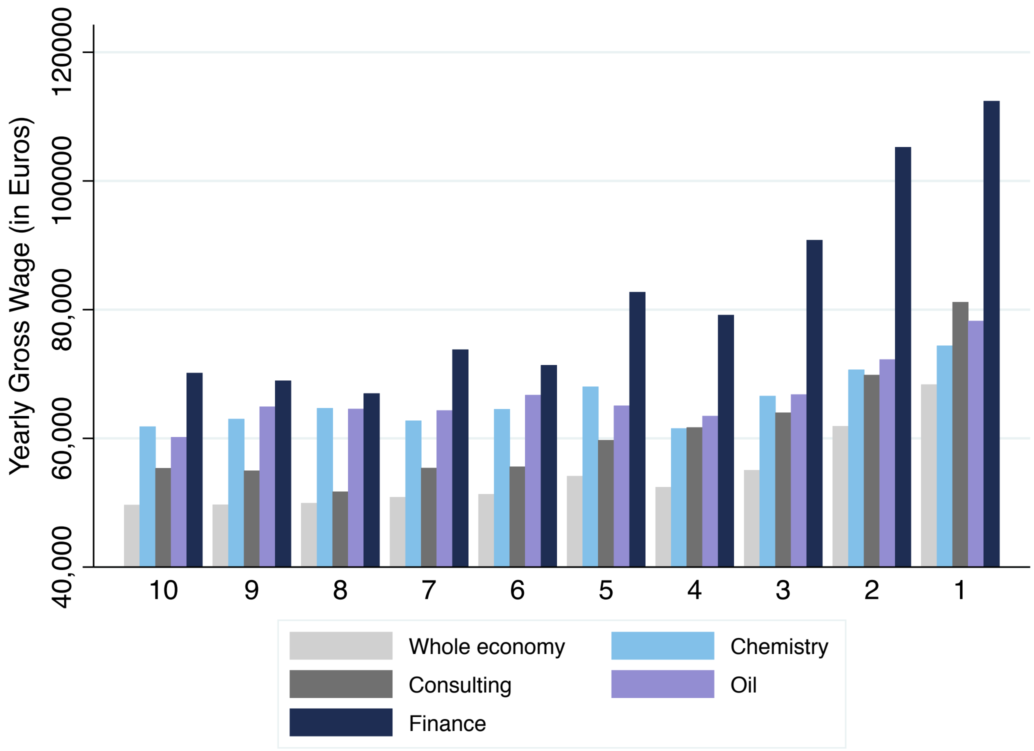

Figure 5. Predicted Wage over School Rank and Sectors

Note: This figure displays the predicted yearly gross wage calculated from the estimation of an OLS regression at the different levels of our talent scale, with average values for all other variables. The dependent variable in the estimation is the log of the yearly gross wage, and is estimated over the 2004-2011 period for five different samples: the whole economy (124,433 observations), and the chemistry (2,752 observations), oil (717 observations), consulting (3,773 observations), and finance (3,431 observations) industries. 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.

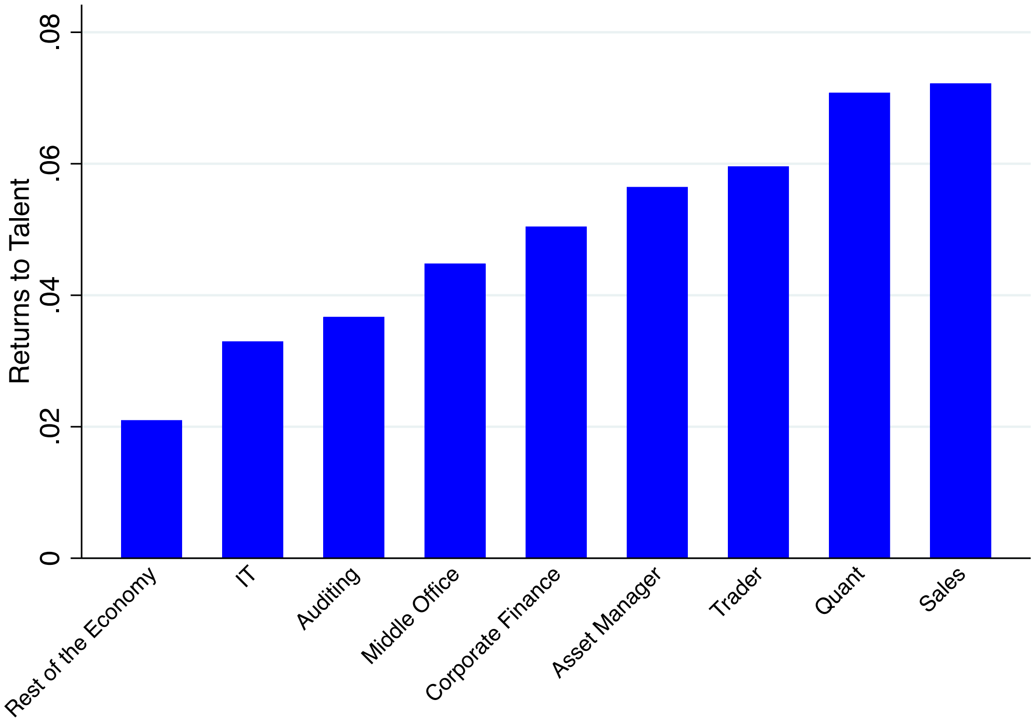

Figure 6. Returns to Talent across Jobs in Finance

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.

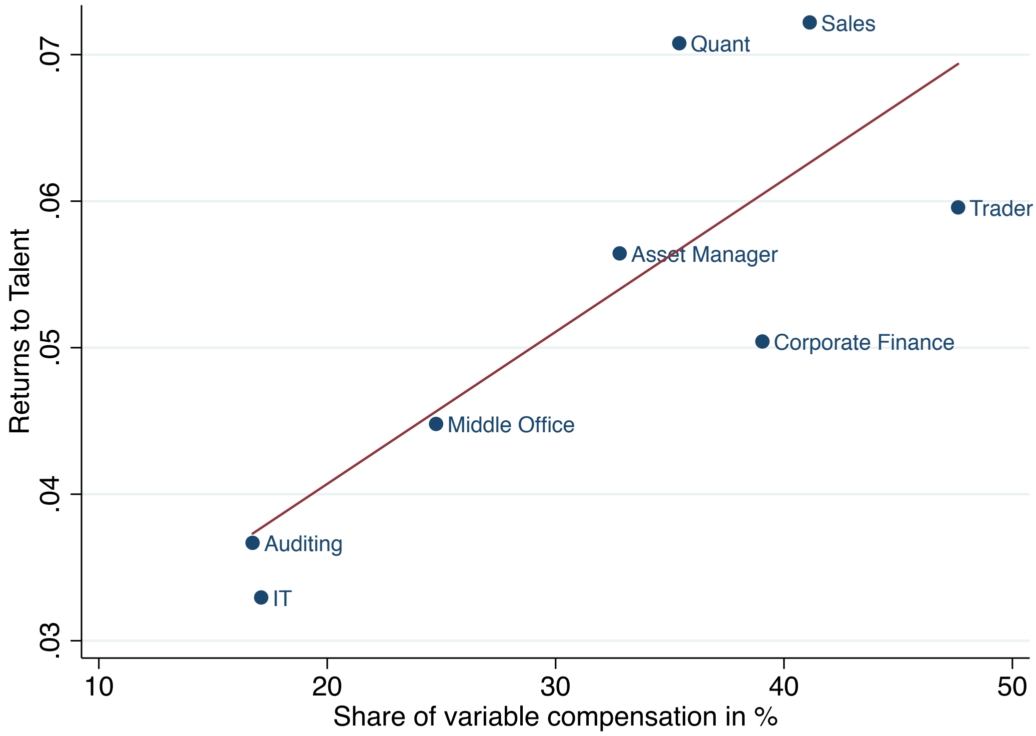

Figure 7. Returns to Talent and the Structure of Pay

Note: This figure displays the estimated returns to talent over the average share of variable compensation for each job category. 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 × married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, and four firm size dummies.

B 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} centile	99,718	101,964	95,598
99^{th} centile	146,253	169,870	186,438
Standard deviation	27,073	31,827	39,086
Engineers per sector (in %)			
Finance	1.9	2.3	3.5
Consulting	0.0	1.5	3.6
Oil	3.1	1.8	0.7
Chemistry	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 France	2.6	4.1	12.1
Percent working in Paris area	46.9	42.4	39.3
Career			
Mean experience (in 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		2011 Wage	% Top Manager	% Early Acceptance
			Number	% Share			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	Top 2%	1	6,173	2.7	97,740	32.2	36.0
2	Top 5%	3	12,868	5.7	83,128	17.6	21.2
3	Top 10%	5	16,983	7.5	67,811	10.5	14.8
4	Top 15%	5	12,236	5.4	64,718	10.8	12.8
5	Top 30%	7	12,182	5.4	66,576	15.5	17.1
6	Top 40%	8	11,468	5.1	55,018	10.3	11.4
7	Top 50%	14	46,676	20.6	59,279	9.7	13.0
8	Top 60%	21	20,747	9.1	53,421	8.8	8.9
9	Top 80%	45	36,615	16.1	51,698	9.7	11.2
10	100%	87	50,898	22.4	54,477	5.4	10.3
Total	-	196	226,846	100.0	59,934	-	-

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) is the average yearly gross wage in 2011 for each level of talent in 2005 constant euros. Column (7) is the share of respondents leading a department or more, after 20 years of experience. Column (8) reports the share of respondents that are admitted in an engineering school early (at least one year ahead).

Table 3. Heterogenous Wage Returns to Talent across Industries

	Log(Wage)							
	OLS					Panel		
Talent Measure	11-School Rank			Graduation Age (# Years Ahead)		11-School Rank		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Finance	0.248***	0.024		0.175***		0.254***	-0.021	
	(0.033)	(0.026)		(0.039)		(0.075)	(0.117)	
Talent × Finance		0.044***	0.046***	0.039*	0.057***		0.058**	0.058**
		(0.006)	(0.005)	(0.021)	(0.022)		(0.024)	(0.024)
Consulting	0.139***	0.049***		0.041		0.074	0.078	
	(0.012)	(0.017)		(0.029)		(0.055)	(0.081)	
Talent × Consulting		0.020***	0.020***	0.019	0.020		-0.001	-0.003
		(0.003)	(0.003)	(0.015)	(0.016)		(0.020)	(0.020)
Oil	0.128***	0.155***		0.137**		0.146*	0.099	
	(0.010)	(0.019)		(0.061)		(0.081)	(0.158)	
Talent × Oil		-0.005	-0.005	0.003	0.001		0.009	0.003
		(0.003)	(0.003)	(0.017)	(0.017)		(0.023)	(0.025)
Chemistry	0.072***	0.089***		0.050		0.094*	0.059	
	(0.007)	(0.011)		(0.032)		(0.051)	(0.100)	
Talent × Chemistry		-0.004**	-0.004**	0.003	0.002		0.009	0.007
		(0.002)	(0.002)	(0.013)	(0.013)		(0.025)	(0.025)
Talent	0.021***	0.019***	0.019***	0.025***	0.024***			
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)			
Individual FE	-	-	-	-	-	Yes	Yes	Yes
School FE	-	-	-	Yes	Yes	-	-	-
Individual Controls	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	52,332	52,332	62,718	62,718	62,718
R^2	0.698	0.701	0.703	0.548	0.551	0.949	0.949	0.950

This table reports the coefficient of OLS regressions, where the dependent variable is the log of yearly gross wage. All specifications include dummies for working in the oil, finance, chemistry, and consulting industries. In columns (1), (2), (4) and (5), *Talent* is equal to 11-*School Rank*, with *School Rank* based on the ranking of the marginal student in the national competitive exam, as defined in table **??**. In column (3), *Talent* is equal to 26 - *Age at Graduation*. The average age at graduation is 23 years old. Highly performing students graduate earlier on average because they often skipped a year during primary school, whereas less talented students often repeat years during prep school to improve their result at the national competitive exam. Columns (1) and (2) cover the total sample, whereas in column (3) male students born before 1978 are excluded from the sample (as some of these individuals postponed graduation due to military service). In columns (4) and (5), the sample is restricted to the 15,256 individuals that are uniquely identified and tracked over the 2000-2010 period through their demographic characteristics. Column (3) includes school fixed effects, and columns (4) and (5) include individual 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 and reported in brackets, * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Returns to Talent and Jobs in Finance

	Log(Wage)			
Sample	Finance Workers			
	(1)	(2)	(3)	(4)
Talent	0.073*** (0.007)	0.049*** (0.005)	0.057*** (0.005)	0.044*** (0.004)
Front Office			0.409*** (0.043)	0.233*** (0.060)
Talent × Front Office				0.033*** (0.008)
Job Fixed Effects	-	Yes	-	-
Individual Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,399	2,399	2,399	2,399
R^2	0.512	0.622	0.576	0.581

This table reports the coefficient of OLS regressions, where the dependent variable is the log of the yearly gross wage. The sample is restricted to the 2,399 workers in the finance industry who provide their exact job title. Columns (2) includes job category fixed effects. Self described job titles of individuals from the 2000-2010 surveys have been manually sorted into job categories, including IT, Auditing, Middle Office, Corporate Finance, Asset Manager, Sales, Trader and Quant. Columns (3) and (4) include a indicator variable for *front office* jobs, which include traders, quants, sales, investment bankers, and asset managers, and in column (4) this indicator variable is interacted 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 5. Increasing Wage Returns to Talent in the Finance Industry

	Log(Wage)		
	S1980 (1)	S1990 (2)	S2000 (3)
Finance	0.016	0.011	0.020
	(0.021)	(0.026)	(0.026)
Talent × Finance	0.010**	0.024***	0.056***
	(0.004)	(0.004)	(0.005)
Talent	0.018***	0.018***	0.020***
	(0.002)	(0.003)	(0.003)
Individual Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	41,731	52,932	104,223
R^2	0.713	0.715	0.694

This table reports the coefficient of an OLS regression over three samples: S1980 = 1986 and 1989 surveys (Column (1)); S1990 = 1992, 1995, 1998, and 2000 surveys (Column (2)); and S2000 = 2004, 2005, 2006, 2007, 2008, 2010, and 2011 surveys (Column (3)). The dependent variable is the log of the yearly gross wage. *Talent* (which takes a value from 1 to 10) is equal to 11-*School Rank*, with *School Rank* based on the ranking of the marginal student in the national competitive exam, as defined in table **??**. 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 6. Returns to Talent and the Structure of Compensation

	Fixed Compensation Log (Fixed Wage)		Variable Share Log(1 + Share)	
	(1)	(2)	(3)	(4)
Finance	0.045***	-0.002	0.863***	0.250***
	(0.012)	(0.019)	(0.041)	(0.075)
Talent × Finance		0.009***		0.118***
		(0.003)		(0.012)
Talent	0.024***	0.023***	0.053***	0.045***
	(0.002)	(0.002)	(0.003)	(0.003)
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 7. Controlling for Network and Social Background Effects

	Log(Wage)						
Sample	No-X Schools	First Generation		Foreigners		Working Abroad	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Finance	0.047	0.515***	0.204***	0.340***	0.020	0.471***	0.175*
	(0.032)	(0.050)	(0.040)	(0.053)	(0.059)	(0.057)	(0.097)
Talent × Finance	0.037***		0.058***		0.074***		0.047***
	(0.010)		(0.007)		(0.013)		(0.012)
Talent	0.016***	0.023***	0.017***	0.020***	0.018***	0.023***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	178,377	14,934	14,934	14,488	14,488	1,399	1,399
R^2	0.689	0.535	0.544	0.660	0.665	0.561	0.566

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) to (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 (3) to (4), the sample is restricted to individuals born outside France (the information is available from 2000 to 2010). Finally, in columns (6) and (7), the sample is restricted to individuals working outside France. 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.

Appendix A - List of Main Variables

Selection rate: the ratio of the rank of the last admitted candidate to the total number of applicants. See online appendix for more details on this coding.

Graduation age: the age at which a student obtains the "Engineer" degree; in France, a student who has neither skipped nor repeated a year of schooling usually graduates at 23 years of age.

Predicted wage: the wage obtained when predicting wages using the coefficients of the main equation.

Early graduation: an indicator variable for graduating earlier than the standard age (23 years old).

Top manager: an indicator variable for holding a top management position, defined in the survey by being on the executive committee.

Finance: an indicator variable for working in the financial sector, which includes banks, investment funds, and insurance companies.

Wage: the gross annual salary of a given engineer, as disclosed in the alumni survey.

Variable compensation: the annual amount of variable compensation, disclosed in a specific question on the survey.

Job title: the exact occupation within finance (e.g., trader, risk manager, investment banker).

School rank: the level of selectivity of a given engineering school within ten categories (see table **??** in the appendix for the list of schools by level of selectivity).

X-schools: schools affiliated with the top French engineering school, Ecole Polytechnique.

Appendix B - Figures

Figure 1. The Finance Wage Premium Evolution

Note: The figure displays the evolution of the coefficient of the financial sector dummy in OLS regressions estimated over the 1983-2011 period, in which the dependent variable is the log of the yearly gross wage. 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.

Appendix C - Tables

Table A1. Standard Determinants of Wages (Controls)

	Log(Wage) **(1)**
Female	-0.073***
	(0.002)
Age	0.009***
	(0.000)
Married	0.035***
	(0.001)
Experience (years)	0.054***
	(0.001)
Experience^2	-0.002***
	(0.000)
Experience^3	0.000***
	(0.000)
Paris Area	0.115***
	(0.001)
Outside France	0.323***
	(0.002)
Talent	0.023***
	(0.000)
Hierarchical Responsabilities: Team Manager	0.076***
	(0.001)
Hierarchical Responsabilities: Department Head	0.204***
	(0.002)
Hierarchical Responsabilities: Top Executive	0.322***
	(0.003)
Occupation: Production	0.002
	(0.002)
Occupation: IT	-0.008***
	(0.002)
Occupation: Sales	0.064***
	(0.002)
Occupation: Office Work	0.112***
	(0.003)
Occupation: Head Office	0.156***
	(0.004)
Firm Size: 20 to 500 employees	0.081***
	(0.002)
Firm Size: 500 to 2000 employees	0.127***
	(0.002)
Firm Size: >2000 employees	0.159***
	(0.002)
Firm Type: Private Sector	0.065***
	(0.004)
Firm Type: State Firm	0.020***
	(0.004)
Firm Type: Administration	-0.178***
	(0.004)
Firm Type: Other	-0.090***
	(0.008)
Year Fixed Effects	Yes
Observations	198,886
R^2	0.687

This table reports coefficients of OLS regressions over the total sample. The dependent variable is the log of the yearly gross wage. The explanatory variables include all the controls used in the paper.

Table A2. The Finance Premia

	MEAN (1)	10^{TH} (2)	50^{TH} (3)	90^{TH} (4)
1983 Premia	0.080	0.022	0.057	0.091
	(0.014)	(0.022)	(0.013)	(0.022)
1986 Premia	0.032	-0.002	0.029	0.029
	(0.011)	(0.019)	(0.012)	(0.019)
1989 Premia	0.090	0.034	0.072	0.141
	(0.011)	(0.017)	(0.012)	(0.016)
1992 Premia	0.086	0.045	0.058	0.081
	(0.012)	(0.021)	(0.010)	(0.012)
1995 Premia	0.120	0.050	0.090	0.177
	(0.017)	(0.033)	(0.015)	(0.025)
1998 Premia	0.131	0.035	0.074	0.169
	(0.013)	(0.018)	(0.013)	(0.022)
2000 Premia	0.163	0.021	0.076	0.344
	(0.014)	(0.019)	(0.012)	(0.026)
2004 Premia	0.250	0.071	0.126	0.579
	(0.015)	(0.020)	(0.016)	(0.022)
2005 Premia	0.272	0.053	0.173	0.589
	(0.013)	(0.018)	(0.012)	(0.019)
2006 Premia	0.320	0.082	0.163	0.740
	(0.011)	(0.015)	(0.009)	(0.017)
2007 Premia	0.320	0.080	0.192	0.740
	(0.010)	(0.015)	(0.009)	(0.014)
2008 Premia	0.231	0.068	0.125	0.479
	(0.011)	(0.015)	(0.010)	(0.018)
2010 Premia	0.287	0.109	0.190	0.622
	(0.012)	(0.016)	(0.012)	(0.020)
2011 Premia	0.301	0.096	0.219	0.655
	(0.014)	(0.017)	(0.011)	(0.019)
Trend Estimate	1.109	0.329	0.659	2.837

This table, which replicates Table 6 in Bell and Van Reenen (2010), reports coefficients of annual OLS (column (1)) and quantile regressions for q = 0.1 (column (2)), q = 0.5 (column (3)), and q = 0.9 (column (4)). The dependent variable is the log of the yearly gross wage. All equations include a female dummy, a married dummy, a female × married dummy, a Paris area dummy, school fixed effects, 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 parentheses. Trend estimates are multiplied by 100 and adjusted by the number of years so as to be interpretable as the % relative annual wage increase for finance workers.

Table A3: **Engineering School List**

School Name	**Rank**	**Admission Rate (%)**	***Baccalaureate* Grade** (Post-Bac Schools)
Ecole Polytechnique	1	1.5	
Mines Paristech	2	2.5	
Centrale Paris	2	4.6	
Ponts Paristech	2	4.9	
Espci Paristech	3	6.8	
Telecom Paristech	3	8.1	
Supelec	3	9.1	
Supaero (Isae) Toulouse	3	9.3	
Institut D'Optique Graduate School	3	9.3	
Ensta Paristech	3	9.5	
Centrale Lyon	3	9.9	
Centrale Lille	4	10.2	
Ensae Paristech	4	11.7	
Centrale Nantes	4	11.8	
Centrale Marseille	4	12.1	
Mines De Nancy	4	14.4	
Mines De Saint-Etienne	5	15.9	
Telecom Bretagne	5	19.8	
Chimie Paristech	5	23.9	
Ensica (Isae) Toulouse	5	24.8	
Grenoble Inp - Ensimag	5	26.4	
Agroparistech Grignon	5	28.5	
Montpellier Sup Agro	5	28.9	
Ensc Montpellier	6	31.4	
Grenoble Inp - Phelma	6	33.1	
Enac Toulouse	6	34.7	
Grenoble Inp - Ense3	6	35.2	
Grenoble Inp - PhelmaElectronique	6	37.5	
Ensma Poitiers	6	39.9	
Agrocampus Ouest	6	40.0	
Enseeiht Toulouse Genie Electrique	7	40.0	
Enseeiht Toulouse Electronique	7	41.4	
Arts Et Metiers Paristech	7	41.6	
Ensat Toulouse	7	44.3	
Ensc Lille	7	46.7	
Enscbp Bordeaux - Chimie-Physique	7	48.1	
Ensea Cergy	7	49.5	
Ensci Limoges	7	49.8	
Ensi Poitiers Eau Et Genie	7	50.0	
Insa Rennes	7		16
Insa Toulouse	7		16
Insa Strasbourg	7		16
Insa Lyon	7		16
Insa Rouen	7		16
Supmeca Paris	8	50.0	
Ensc Rennes	8	52.4	
Ensta Bretagne (Ex Ensieta)	8	52.6	
Ensaia Nancy	8	53.2	
Engees Strasbourg (Apprenti)	8	53.5	
Ensiacet Toulouse Genie Industriel	8	53.8	
Ensicaen Informatique	8	53.9	
Enseirb-Matmeca Bordeaux Electronique	8	54.1	
Ensic Nancy	8	56.2	
Ensmm Besancon	8	56.8	

Table A3 – continued from previous page

School Name	Rank	Admission Rate (%)	*Baccalaureat* **Grade** (Post-Bac Schools)
Ensem Nancy	8	57.6	
Enitab Bordeaux (Civil)	8	58.0	
Eost Strasbourg	8	58.3	
Cpe Lyon Electronique	8	58.4	
Ensp Strasbourg	8	59.1	
Ensil Limoges Ee	8	59.4	
Union Des Insa (2000)	8		15
Utc Compiegne	8		15
Inp Toulouse	8		15
Enesad Dijon	8		15
Isima Clermont-Ferrand	9	60.0	
Ensiame Valenciennes Meca Energ.	9	60.0	
Ensg Nancy	9	60.0	
Ecpm Strasbourg	9	60.2	
Ensc Mulhouse	9	61.1	
Entpe Vaulx En Velin	9	65.4	
Eivp Paris	9	65.9	
Esial Nancy	9	66.4	
Telecom St Etienne	9	66.7	
Enssat Lannion	9	67.1	
Telecom Sudparis - Cursus Evry	9	67.6	
Vetagro Sup Clermont-Ferrand (Civil)	9	68.4	
Agrosup Dijon	9	69.6	
Ecole Des Mines Nantes	9	69.8	
Estp Paris Topographie	9	69.9	
Polytech Lille	9	72.0	
Ecole Des Mines Douai	9	72.2	
Ecole Des Mines D'Ales	9	73.2	
Polytech Nantes	9	73.8	
Ecole Des Mines D'Albi	9	74.1	
Enstib Epinal	9	74.5	
Polytech Paris-Upmc	9	75.8	
Polytech Nice	9	76.0	
Isat Nevers	9	77.0	
Esil Marseille Biomedical	9	79.6	
Epf Sceaux	9		14
Utt Troyes	9		14
Ensgsi Nancy	9		14
Estaca Levallois-Perret	9		14
Insa Val De Loire	9		14
Polytech'Montpellier	9		14
Ifma Clermont-Ferrand	9		14
Inpl Nancy	9		14
Ist Bretagne	9		14
Groupe	9		14
Polytech Marseille	9		14
Polytech Grenoble	9		14
Ensg Marne La Vallee	9		14
Eivl Blois	9		14
Enitiaa Nantes	9		14
Enise Saint-Etienne	9		14
Telecom Lille1	9		14
Ensccf Clermont-Ferrand	9		14
Eisti Cergy-Pontoise	9		14

Table A3 – continued from previous page

School Name	**Rank**	**Admission Rate (%)**	***Baccalaureat* Grade** (Post-Bac Schools)
Grenoble Inp	9		14
Polytech Orleans	10	80.2	
Esstin Nancy	10	81.2	
Esmisab Brest	10	81.5	
Polytech Tours	10	81.8	
Isty Versailles	10	82.7	
Istil Epu Lyon 1	10	82.7	
Polytech Clermont-Ferrand	10	82.7	
Ensc Bordeaux	10	82.7	
Esirem Dijon Info-Elec.	10	82.7	
Ensim Le Mans	10	82.7	
Sup Galilee Villetaneuse	10	82.7	
Lasalle Beauvais	10	83.1	
Isen Brest	10	84.4	
Isep Paris	10	85.6	
Escom Compiegne	10	85.8	
Hei	10	85.9	
Ensisa Mulhouse Informatique Et Reseaux	10	86.4	
Ensisa Mulhouse Textile Et Fibres	10	86.6	
Eseo Angers	10	87.1	
Ece Paris	10	87.9	
Ensiie Evry	10	88.0	
Eigsi	10	88.9	
Ecam Lyon	10	89.8	
Ensait Roubaix	10	92.6	
Esigelec Rouen	10	94.5	
Esme Sudria Ivry Sur Seine	10	95.0	
Esb Nantes	10	96.0	
Efrei Paris	10	96.6	
Esiee Amiens	10	97.0	
Esigetel Fontainebleau	10	97.6	
Ei-Ispa Alencon	10	98.2	
3Il Limoges	10	98.5	
Grenoble Inp - Genie Industriel	10	100.0	
Enit Tarbes	10		13
Polytech Paris Sud	10		13
Ecam Rennes	10		13
Enim Metz	10		13
Esilv La Defense	10		13
Ebi Cergy	10		13
Ensgti Pau	10		13
Esiea Paris	10		13
Itech Lyon	10		12
Itii Bass-Normandie Mecanique Ensicaen	10		12
Itii Picardie Mecanique Cnam	10		12
Itii Alsace Mecanique Insa Strasbourg	10		12
Itii Pays De Loire Inform. Ind. Eseo	10		12
Itii Pays De Loire	10		12
Enspm Rueil-Malmaison	10		12
Isa Lille	10		12
Polytech Savoie	10		12
Itii Alsace Informatique Loire	10		12
Isara Lyon	10		12
Ingenieurs 2000	10		12

Table A3 – continued from previous page

School Name	**Rank**	**Admission Rate (%)**	***Baccalaureat* Grade** (Post-Bac Schools)
Cefipa		10	12
Ifitep		10	12
Fiti2A Quimper		10	12
Itii Pays De Loire Btp		10	12
Cesi		10	12
Isupfere		10	12
Itii Aquitaine Prod. Maintenance		10	12
Isa Angers		10	12
Esgt Le Mans		10	12
Utbm Belfort-Montbelliard		10	12
Ist Vendee Mecanique Et Automatique		10	12
Esitapa Val De Reuil		10	12
Istp Ensme St Etienne		10	12
Esite Epinal		10	12
Ist Toulouse		10	12
Cnam		10	12
Itii Champagne-Ardenne Mecanique Ensam		10	12
Itii Aquitaine Materiaux Enscpb		10	12
Itii Deux Savoies		10	12
Isel Le Havre		10	12
Itam		10	12
Isiv		10	12
Fip		10	12
Itii Bourgogne Genie Industriel		10	12
Dpe		10	12
Itiape Lille		10	12
Istimm		10	12
Ist Nord		10	12
Itii Lyon Informatique		10	12
Itii Aquitaine Mecanique		10	12
Itii Hte-Normandie Mecanique		10	12
Eia-Cesi		10	12
Igii Lens		10	12
Eme Ker Lann		10	12
Itii Centre Production Polytech'Orleans		10	12