Are Bankers Worth Their Pay? Evidence from a Talent Measure*

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Abstract

This paper investigates empirically the source of the wage premium in the finance industry. We exploit the ranking in a competitive examination to build a precise measure of talent. By using a comprehensive compensation survey among an educational elite, we show that wage returns to talent are relatively high in the finance industry. This higher sensitivity to talent explains both the finance wage premium and its evolution.

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

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

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1 Introduction

Since the beginning of the 1980s, compensation in the finance industry has been relatively high compared to other sectors. Philippon and Reshef (2012), controlling for education and other characteristics, find that the finance wage premium amounts to 50% on average in 2006. In the aftermath of the financial crisis, this high level of pay has generated an intense debate among the public opinion and politicians. When examining this question, academic researchers offer three types of explanations for the finance wage premium: a more severe moral hazard problem in the finance industry combined with workers limited commitment (Biais et al. (2009), Axelson and Bond (2013)), a compensating differential for hours worked, unemployment risk and/or working conditions (Oyer (2008)), or an intense competition among financial firms for a scarce supply of talent (Glode and Lowery (2013), Acharya et al. (2013), Thanassoulis (2012) and Bijlsma et al. (2012)).

The empirical estimation of the impact of talent on wages across industries has so far received low academic attention, mainly due to the challenge of precisely observing talent. The research question we address in this paper is the following: Do talent effects explain the high level and skewed distribution of bankers' pay?

This paper provides empirical evidence that the wage premium observed in the finance industry is driven by a relatively high wage sensibility to talent. For this purpose, we build a unique measure of talent among equally highly educated workers and study how wages are sensitive to talent across industries. Our findings show that returns to talent are three times as high in the finance industry as in the rest of the economy.

We hypothesize that wage sensitivity to talent is higher in finance due to specificities of the finance sector on three dimensions: technology, labor market conditions and scale effects. First, the finance industry has relatively high information-technology intensity (Philippon and Reshef (2012)). Information technology increases returns to talent by substituting routine tasks and complementing non-routine tasks (Autor et al. (2003)). Second, talent in the finance industry is easily observable and portable across banks. In highly concentrated markets, this may result in financial firms bidding strategically for the services of workers who impose negative externalities on rival firms (Glode and Lowery (2013)). Finally, the dematerialized nature of fund flows, the integration of world capital markets, and their deregulation since the 1980s increase scale effects and hence talent leverage.

We exploit the results of a competitive examination among equally highly-educated and motivated candidates to provide a measure of talent. French engineering schools select students for admission based on their ranking in a nationwide competitive exam.[1] Consisting of both written and oral sections in a wide variety of subjects, this examination assesses academic, cognitive and communication skills, while also gauging specific personality traits such as endurance, volition, and ambition. The written part of the exam takes place over a three week period and totals more than 80 hours of testing. In the oral portion, students take a series of 20 minutes interviews in which they have to solve randomly picked problems. Prior to the exam, candidates spend two years in preparatory schools offering a highly selective and competitive environment that ensures that their talent constraint is binding. We use the national ranking to this competitive exam of the last admitted student of each engineering schools. We derive a classification of schools into nine categories, representing nine levels of talent. We then match this

[1]French engineering schools consist in 240 small scale institutions delivering 30,000 degrees per year

talent measure to a detailed survey dataset covering 8% of the total population of French engineers.

Our dataset comes from a comprehensive survey on wages implemented by the French Engineering alumni association.[2] The survey gathers data on alumni from 160 out of 222 French engineering schools and spans from 1983 to 2011. Each of the 15 annual samples covers an average of 30,800 individuals from France and abroad. The survey includes detailed information on education, occupation, family situation, industry, firm type, firm size, and compensation. From this survey, we confirm that finance is the sector in which French graduate engineers are better paid, with a premium of 30% on average over the period 2004-2011, and that the premium has been increasing since the 1980s. This finding is consistent with Philippon and Reshef (2012). In line with Bell and Van Reenen (2010) and Bell and Van Reenen (2013), we also observe a relatively high skewness in the wage distribution in the finance industry. The top 1% of the wage distribution in the finance industry captures 7.5% of the total wage bill, against 3.3% in the rest of the economy. This result is confirmed by a quantile regression: wage gains since the 1980s have been much higher at the 90$^{\text{th}}$ percentile than at the 10$^{\text{th}}$ and 50$^{\text{th}}$ percentiles of the wage distribution.

The central result of the paper is that wage sensitivity to talent is relatively high within the finance industry and almost entirely explains the wage premium of this sector. The trend towards an increasing sensitivity accounts also for the evolution in the wage premium over the past decades. The main equation of the paper regresses the log of the yearly gross wage on our talent measure and its interaction with industry dummies.

[2] Focusing on an educational elite is suited to our analysis: if talent is quasi-normally distributed, heterogeneity in talent should be higher in top jobs, and hence easier to identify.

Having graduated from a school one notch higher in terms of selectivity induces a 2.5% average wage premium, versus a 9% relative premium in the finance industry. We also find that when we include the $talent \times industry$ interaction term, the finance wage premium almost disappears. This result is robust when using an alternative measure of talent allowing us to control for school fixed effects. Since more talented students have an earlier graduation rate on average, we use the age at graduation as a second proxy for talent that allows the absorption of all school-level unobserved variables with fixed effects. Finally, by estimating this equation over sub-periods we show that wage elasticity to talent in the financial sector has been increasing almost threefold over the period 1980-2011. This increase in wage sensitivity to talent accounts for the evolution of finance wages since the 1980s that is documented in the literature.

Our analysis allows us to reject alternative explanations for the finance wage premium. First, to ensure that our results are not driven by a rigid allocation of alumni from specific schools to the highest paying jobs, we control for job title within the finance industry (e.g. trader, risk manager). We find that talent is still a statistically and economically significant driver of wage level. Second, we rule out network effects as a driver of our results. To do so, we first exclude from our sample the group of schools known for their strong economic and political connections, i.e. Ecole Polytechnique and its related schools. In a second estimation, we control for the size of the network of each school by using its annual number of graduates. As a final test, we estimate our main equation on the sample of engineers working outside France, where network effects should be weaker. Our main result still holds in these three specifications. Third, we rule out principal agent models of moral hazard as an alternative explanation for our main result. If variable wages are driven by incentives and not talent, our result should not hold for the variable share of the compensation package. When using variable wage as a left hand side variable in our main specification, however, we find that this part of the compensation package is equally affected by the level of talent.[3] Finally, we confirm that our results are not due to compensating differential for hard working conditions or unemployment risk in finance by controlling for these variables.

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, as well as a high skewness at the top of the wage distribution. Philippon and Reshef (2012), Oyer (2008), and Goldin and Katz (2008), based on data from respectively the Census Population Survey, a Stanford MBAs survey, and a Harvard alumni compensation survey, find that the finance premium amounts from 40% in Philippon and Reshef (2012) up to more than 100% in Oyer (2008) and Goldin and Katz (2008). Philippon and Reshef (2012) describe how compensation in finance has increased since the 1980s compared to the rest of the private sector, after controlling for education. Moreover, Kaplan and Rauh (2010) and Bell and Van Reenen (2010) show that the share of the financial sector in top end brackets of the income distribution has significantly increased. The main contribution of this paper is to show that these patterns of the wage distribution in the finance industry are attributable to a higher and increasing wage sensitivity to talent in finance.

This paper also contributes to the literature investigating the dramatic growth of top executives pay that has been observed since the 1980s. This literature includes theories of managerial power (Bebchuk and Fried (2004)), social norm (Piketty and Saez (2006);

[3] We calculate the variable wage from a specific question of the survey on the compensation structure.

Levy and Temin (2007)), incentives and competition for talent. Our results support the theory of competition for talent, which is intensified by scale effects (Gabaix and Landier (2008), Kaplan and Rauh (2013)) and skill-biased technological change (Katz and Murphy (1992); Garicano and Rossi-Hansberg (2006)). Gabaix and Landier (2008) argue that the increase in CEOs pay since the 1980s can be attributed to the increase in firm size that has induced higher returns to the hiring of the talented CEOs. Katz and Murphy (1992) explain how technological changes have raised the productivity of skilled workers. Both theories induce higher wage sensitivity to talent and superstar effects, which we observe in our data. Our results are also in line with Gao et al. (2013), who provide direct evidence that labor market competition drives the growth of executive pay.

The results of this paper raise the question of the externalities that competition for talent in the finance industry may generate. First, finance, offering relatively high wages for the same level of talent, may drive talented individuals away from other industries. Baumol (1990) and Murphy et al. (1991) argue that this may have a downward impact on economic growth. Competition for talent can also generate inefficient risk taking (Acharya et al. (2013)). If firms compete aggressively for talent, managers can take tail risks while moving rapidly between firms, and so raise their short-term performance and pay, while reducing their accountability for failures. Finally, in highly concentrated markets, competition for talent may result in financial firms biding excessively for the services of workers who impose negative externalities on rival firms (Glode and Lowery (2013)).

The paper proceeds as follows. Section 2 develops the theoretical framework of our analysis. Section 3 describes how we measure talent. Section 4 provides summary statistics of our dataset and assesses the representativeness of the sample. Section 5 presents our results. Section 6 discusses alternative explanations, and Section 7 concludes.

2 Theoretical Framework

The role of talent in compensation contracting is largely documented in the literature (e.g. Rosen (1981)). We build on these theoretical insights to develop our research hypothesis: the heterogeneity in the wage distribution observed across sectors comes from differences in terms of wage sensitivity to talent.

In a competitive labor market, firms want to retain talented workers who exhibit a high productivity. There are three reasons why firm competition for talent may result in heterogeneous wage returns to talent across industries. Technology first varies across industries, being more skill biased in some of them, which increases the relative productivity of skilled workers (Katz and Murphy (1992), Autor et al. (1998) and Autor et al. (2003)). Some industries are indeed 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. Second, labor market competition varies across industries. The matching of talent 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. Finally, 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.[4]

The finance industry ranks high in these three dimensions. 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. Philippon and Reshef (2012) find that the finance industry has relatively high information-technology intensity. 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. Kaplan and Rauh (2010) estimate that capital per employee in the top U.S. security firms has increased substantially from $124,000 (in 2004 dollars) in 1972 up to $1,789,000 in 2004. They also observe a twenty-three-fold increase in capital per managing director since the 1970s. Other sectors, such as law, consulting or computer technology, exhibit comparable characteristics, although in a lesser extent than the finance industry.

The empirical prediction we derive from our hypothesis is that wage elasticity to talent should be relatively high in the finance sector. The main contribution of this paper is to be the first to test this prediction, therefore identifying the driver of the finance premium.

[4] 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

This prediction builds on evidence from Bell and Van Reenen (2010) that the distribution of wages is more skewed in the finance industry.

Measuring talent accurately is therefore key for testing the role of output elasticity to talent in explaining the finance premium. The next section details how we exploit a specificity of the French education to do so.

3 Measuring Talent

We use a specificity of the French educational system to build a unique proxy for talent. In France, students who graduate from a master program in any field of engineering obtain the official title of "graduate engineer".[5] This title can only be delivered by one of the 240 selective small scale institutions called "Grandes Ecoles d'Ingénieurs" that select students based on their national ranking in a competitive exam. We use this selection process to build a measure of talent for the entire population of engineers.

3.1 The Selection Process of French Engineering Schools

French "Grandes Ecoles d'Ingénieurs" select students for admission based on their national ranking in a competitive exam including both written and oral tests. This recruitment process requires strong cognitive and academic skills, as well as high motivation, volition, ability to work under pressure, endurance, and ambition.

The competitive exam first assesses a very large set of formal academic skills through written tests covering a wide variety of subjects. Compulsory topics are Mathematics, Physics, Programming, French Literature and a Foreign Language. The candidate also

[5] 30,000 diplomas are delivered each year

selects an optional topic among Biology, Chemistry, Engineering and Computer Science. The written part of the national exam takes place over a three week period and totals more than 80 hours of testing.

In a second stage, students take a series of 20 minute oral exams that also test presentation, communication and interaction skills. The subjects covered are as wide as in the written tests. In each interview, candidates are given problems to solve and present their solution to one or several professors. At the end of the process, each candidate receives a final national ranking that gives the priority position when applying for each engineering school. When selecting a school, students favor reputation over field expertise or location, and deviations are very rare, especially for top schools. Once admitted, students spend three to four years studying on a campus and eventually obtain a graduate degree.

The two years spent preparing for this exam are also an important part of the selection process. Student training takes place in specific classes that are comparable to Boarding Schools. These institutions select students after high school based on their academic performance, and are themselves highly selective.[6] They offer a highly competitive environment for two years requiring a high motivation and ability to work under pressure, with school professors typically posting student monthly rankings in classrooms and excluding the ones with insufficient performance after the first year Ors et al. (2013).

A group of lower rank schools are also accessible directly after high school and include the curriculum covered during the two-year preparatory class in their program.

[6]In the Science and Engineering fields, the selection rate is around 15% after a Scientific *Baccalauréat*. *Source :www.data.gouv.fr*

3.2 School Ranking and Talent Measure

We construct a talent measure by classifying engineering schools into nine ordered categories by selectivity in the competitive exam. Group 1 corresponds to the most selective schools that possess the most talented students on average, while Group 9 includes the least selective schools.

We use the ranking of the last admitted student of each engineering school to measure how selective a school is.[7] We compute the admission rate by dividing the rank of the last admitted student to the number of applicants.[8] Columns (1) and (2) of Table 2 gives the selection rate of each category. The highest category includes the Ecole Polytechnique, which recruits top 3% students. The second one includes Ecole Centrale Paris, Mines de Paris and Ecole des Ponts et Chaussées. The last one includes the schools admitting students directly after high school. We observe that, consistent with a quasi-normal distribution of talent, the number of schools within each categories is increasing.

This measure of talent has several key advantages. First, it covers the total population of French engineers, even since 1980, with a high comparability since ranking is highly persistent. Second, this measure maps skills necessary to successful careers: cognitive ability, resistance to stress, and interpersonal skills. The stakes of the competitive exam are also comparable to the ones during a professional career in terms of prestige and even pay-off, as top school students are eligible to stipends. Third, the population we analyze is homogenous enough so that we can disentangle education and motivation from talent.

[7] Information on the rank of the marginal student is public and available for the period 2002-2012 on: http://www.scei-concours.fr/. The strong persistence of the ranking allows us to extend it over the whole period

[8] For example, the marginal student in the main option in Ecole Polytechnique was ranked 124th in 2010, whereas 5,312 students took the competitive exam. Hence, Ecole Polytechnique selects the top 2% students (124/5312).

This educational and personal investment homogeneity of candidates should make our talent measure very sensitive. Indeed (i) they all have the same level of education and years of schooling, (ii) they all have the same educational path since they all have a science major in high school and have chosen to apply to and have been admitted to the selective preparatory schools, (iii) they self-select themselves in terms of personal investment to sit the toughest of such exams despite the fact that they are guaranteed admission to a French university in any year following their high school graduation. Finally, the admission process excludes any kind of distortions due to networking, reputation or donations since the written exam is totally anonymous and letters of recommendation are not required.

3.3 Alternative Measures

Since we rank school into nine categories, distance between schools is arbitrarily set. To overcome this limit, we build a second measure of talent by taking the distribution of talent across schools. For each school, we use the share of applicants who are not selected by the school, which amounts to 98% for Ecole Polytechnique for instance. Figure 2 draws the distribution of talent across schools. This proxy for talent is continuous since each school are individually ranked, but excludes engineering schools recruiting directly after high school (43%).

Our third measure of talent is the age at graduation. In the French educational system, it is common among high performing students to skip a year at primary school. Moreover, up to 25% of students preparing engineering schools repeat the second year of preparation to improve their results in the competitive exam. On the other hand, it is extremely rare to skip or redo a year during engineering school. Graduation age is therefore a good proxy of admission age, which in turns captures talent. For instance, some students can enter the first-ranked engineering school, Ecole Polytechnique, after 3 years of preparation, which require less talent than doing so in 2 years. This measure is not school specific, and therefore allows us to control for school unobserved variables in our empirical analysis by putting school fixed effects.[9]

4 Data

4.1 The Survey

Our empirical analysis uses the results of a detailed survey on wages covering a total number of 324,761 observations of engineering school graduates from 1983 to 2011. The survey is conducted by the French Engineering and Scientist Council (IESF, http://www.cnisf.org), a network of alumni organizations gathering 144 out of 240 French engineering schools, or 85% of the total population of French graduate engineers in 2010.[10] Each respondent provides their latest yearly gross wage, as well as detailed information on demographics, education, careers, job position and their employer.

We clean the survey data by only keeping respondents who are full time employees, who are between the ages of 20 and 65, provide a valid industry code and have more than one year of experience.[11] We also exclude respondents who have lower compensation than the legal minimum wage. For each sector and year, we winsorize compensation at the top

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

[10] Source: French Education Ministry

[11] Survey respondents have to provide their yearly gross wage coupled with the five digit industry code of their employer from their latest December pay sheet. In order to maximize the accuracy of wage data and to limit measurement errors, we only keep observations with a valid industry code that ensures that the respondent actually consulted their pay sheet.

1% of the distribution.[12] Finally, all nominal quantities are converted into constant 2005 Euros, using the French National Price Index (IPCN) from INSEE.[13] These operations leave us with 190,593 observations.

INSERT TABLE 1

Table 1 provides information on the survey scope and key variable summary statistics. The frequency between surveys has increased from every five years from 1983 to 1986, to every year from 2004 onwards. The average number of respondents per survey is around 23,000. The sample of each survey stands on average for 6.9% of the total population of French engineers and the answer rate amounts to 18.8%.[14]

The wage distribution has become increasingly scattered over the last three decades among French graduate engineers. While the average wage in constant euros has remained stable from 63,000 euros in the 1980s down to 58,000 euros in the 2000s, wages at the 99th percentile have increased by more than 14%.[15] This result is in line with the recent literature showing that inequalities have increased in most OECD countries and mainly at the very top of the wage distribution (Piketty and Saez (2003); Piketty and Saez (2006)).

We define 48 industries based on the official industry classification code of their employer respondents provide, as described in the online appendix. Table 1 details the percentage share of respondents in the highest-paying industries. Finance stands for around 2% of the total sample.

Table 1 also includes summary statistics on demographics, jobs, careers, employer,

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

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

[14] While until 2000 the IESF mailed the survey, the association is emailing it since 2002.

[15] The slight decrease is mainly due to a sample composition effect, as the age of the average respondent has decreased.

work location and compensation structure. Whereas the average age of respondents has decreased, the share of women has increased. The share of respondents working outside France has dramatically increased, which is consistent with the increasing mobility of highly qualified workers. The comprehensive list of questions asked in the 2000 survey is provided in the online appendix.

The IESF survey has key features of interest for our analysis. First, the survey provides the name of the engineering school each respondent has graduated, which is required for implementing our measure of talent. Second, the survey gives access to unique wage data on an educated elite. Since talent is fat-tailed, heterogeneity in talent for the same level of education should be higher at the top, and hence easier to identify. Third, the survey includes engineers working outside France, such as in The City of London or Manhattan's Financial District: from 2000 on, they account for more than 12% of the respondents. This characteristic strengthens the external validity of our results. Fourth, the large amount of information on demographics, job position, employers and work location allows us to control for a wide set of variables in our identification strategy.

4.2 The Talent Measure

The survey includes graduates from 144 engineering schools that are spread over the nine categories of our talent measure. The name of each engineering school and its corresponding talent category is given in the online appendix. The survey data allows us to precisely map the location of each graduate on our talent scale.

INSERT TABLE 2

Table 2 gives summary statistics of individual characteristics by talent category. We observe in columns (4) and (5) that the number of respondents is larger for lower level of talent. This is driven by fact that the number of schools is decreasing with talent, which is consistent with a quasi-normal distribution of talent. Column (6) shows that the level of wages and the share of top manager is increasing with talent. Finally, column (8) gives the share of respondents who have graduated at least one year earlier than the standard age, per talent category. Age of graduation appears to be highly correlated with the talent category.

4.3 Representativeness of the Sample

We first compare the patterns of compensation in the finance industry we observe in our data to the ones found in the literature. Table 3 replicates Table 6 from Bell and Van Reenen (2010).

We estimate the annual wage premia in the finance industry at the mean and at the 10^{th}, 50^{th} and 90^{th} percentiles with the following equation

$$w_{i,t} = \beta_i \times I_{i,t} + \gamma \times X_{i,t} + \mu_t \times D_t + \lambda_{i,t} \tag{1}$$

where $w_{i,t}$ is the log yearly gross wage, $X_{i,t}$ is a vector of individual characteristics, $I_{i,t}$ stands for the vector of industry dummies, and D_t for the vector of year dummies. $\epsilon_{i,t}$ is the error term. Each industry has a dummy variable and we impose that the sum of all the industry dummy coefficients is zero. This estimation controls for demographic, occupation, job and employer characteristics.[16] [17]

INSERT TABLE 3

Results are displayed in Table 3.[18] We find consistent results with Philippon and Reshef (2012), Oyer (2008), Goldin and Katz (2008): finance is the industry in which workers are best paid. The first row of Table 3 shows that the average premium over the 1983-2011 period amounts to 24%, against respectively 14%, 9% and 8% in the oil, consulting and chemistry industries, the following best paid industries. In terms of magnitude, our estimation of the finance wage premium is in the lower range of the recent estimations in the literature. This lower magnitude is likely to come from our rich set of controls and the educational homogeneity of our sample.

Second, we find that the finance wage premium has dramatically increased since the 1980s and is concentrated within top earners, which is again consistent with Philippon and Reshef (2012) and Bell and Van Reenen (2010). The first column of Table 3 shows that it has increased from 7% up to more than 30% on average after 2004. These relative wage gains have been much higher at the 90th percentile than at the 10^{th} and 50^{th} percentiles of the wage distribution. The last row of the Table displays the average annualized increase

[16] Acemoglu and Autor give evidence on the strong explanatory power of occupational categories in wage regression.

[17] Demographic controls include years of experience, experience squared, experience cubed, gender, marital status and gender × marital status. We control for occupation with nine dummies standing for production, logistics, development, IT, commercialization, administration, executive, education and else. There are five different dummies for employer type: self-employment, private sector, state-owned company, public administration and others (non-governmental organization), and four dummies for firm size: less than 20 employees, from 20 to 500, from 500 to 2000, more than 2000. Job characteristics are represented by a working in "Ile de France" dummy (Paris area), a working abroad dummy (together with seven country dummies for the US, UK, Germany, Switzerland, Luxembourg, China and Belgium from 2004 on) and four hierarchical responsibility dummies, from no hierarchical responsibility to chief executive.

[18] Each industry has a dummy variable, but for convenience we only show the coefficient of the finance industry dummy.

in the premia. It amounts to more than 2.8% at the 90$^{\text{th}}$ percentile of the distribution against less than 0.7% at the 50$^{\text{th}}$ percentile, and 0.3% at the 10$^{\text{th}}$ percentile.

Figure 1 gives additional graphical evidence of these distribution effects. As in Bell and Van Reenen (2010), we draw the Lorenz curve for wages in finance, and compare it to the oil, chemistry, and consulting industry ones. More precisely, we sort employees of each industry in the 2004-2011 surveys by wages and then split them up into 100 groups of equal size. The figure draws the share of the total wage bill by industry that each group captures. The figure shows that the distribution of wages is positively skewed in finance, much more than in the rest of economy. The top 1% of the wage distribution in finance captures 7% of the total wage bill, against 3.1% in the rest of the economy.

INSERT FIGURE 1

For more description of the evolution of wages at the 10$^{\text{th}}$, 50$^{\text{th}}$ and 90$^{\text{th}}$ percentiles of the earnings distribution in the finance, oil, chemistry and consulting industries, see the online appendix.

5 Results

5.1 Heterogeneous Returns to Talent across Industries

This subsection describes our central result: a higher wage elasticity to talent in the finance industry almost completely explains the wage premium of this sector, as well as the skewness of the wage distribution.

Figure 3 provides graphical evidence for a higher sensitivity of wages to talent in the finance industry. We plot the predicted wage of respondents over the nine categories of our talent measure by sectors. The predicted wages are calculated by regressing wages over talent category fixed effects, controlling for demographic and occupation characteristics. This methodology allows us to address composition effect compared to a raw two-way scatter. We observe that wages are an increasing function of talent. The coefficient of this quasi-linear relationship appears higher in the finance industry than in the others. For example, wages in the finance industry are almost the same as in the oil industry for low talent workers, but they are almost 40% higher for top talent levels. While wages increase by more than 64% from the bottom category of talent to the top of the talent distribution in the finance industry, the rise amounts to only 35% in the oil industry.

INSERT FIGURE 3

To first identify the effect of talent on wages, we conduct the following OLS regression

$$w_{i,t} = \epsilon \times Talent_{i,t} + \beta \times I_{i,t} + \gamma \times X_{i,t} + \mu_t \times D_t + \lambda_{i,t} \tag{2}$$

where $w_{i,t}$ is the log yearly gross wage, $Talent$ is the talent measure, $I_{i,t}$ stands for the vector of industry dummies, $X_{i,t}$ for a vector of individual characteristics, and D_t for the vector of year dummies. ϵ represents the average wage elasticity to talent in the economy.[19] This specification allows us to identify whether talent is an important driver of the wage distribution.

Our comprehensive dataset allows us to include a wide set of controls, significantly larger than in other papers in the literature on the finance premium (e.g., Bell and Van Reenen (2013)) and thus making us able to disentangle talent effects from other

[19]For clarity, $Talent$ is defined as 10 minus the rank of the school the respondent graduated, so that $Talent$ is increasing with workers' skills.

characteristics. This regression includes controls for demographics, careers, occupation, job and employer characteristics.[20,21] Column 1 in Table 4 reports OLS regression coefficients for this specification. Consistent with our prediction from Section 2, talent has a positive impact on wages. The coefficient is both economically and statistically significant. One notch up our talent measure corresponds to a 2.7% increase in wages. When conditioning on talent, we observe a finance wage premium of 24% over the period 1983-2011.[22]

In a second stage, we test whether sector-specific wage elasticity to talent can explain the cross-section of wages, by including an interaction between talent and the industry dummies from the previous specification. The equation to estimate becomes

$$w_{i,t} = \epsilon \times Talent_{i,t} + \beta \times I_i + \bar{\epsilon} \times I_i \times Talent_{i,t} + \gamma \times X_{i,t} + \mu_t \times D_t + \lambda_{i,t} \qquad (3)$$

where $\bar{\epsilon}$ is the industry specific component of wage elasticity to talent and other variables are the same as in the previous equation.

Column 2 reports the results. The positive and significant coefficient of the interaction term between the finance dummy and the talent measure shows that wage elasticity to talent is significantly higher in the finance industry than in the rest of the economy. We

[20] Acemoglu and Autor (2011) give evidence on the strong explanatory power of occupational categories in wage regression.

[21] Demographic controls include years of experience, experience squared, experience cubed, gender, marital status and gender × marital status. We control for occupation with nine dummies standing for production, logistics, development, IT, commercialization, administration, executive, education and other. There are five different dummies for employer type, and four dummies for firm size. Dummies for employer type include: self-employment, private sector, state-owned company, public administration and others (non-governmental organization). The dummies for firm size are categorized by: less than 20 employees, from 20 to 500, from 500 to 2000, more than 2000. Job characteristics are represented by a working in "Ile de France" dummy (Paris area), a working outside France dummy (together with seven country dummies for the US, UK, Germany, Switzerland, Luxembourg, China and Belgium from 2004 on) and four hierarchical responsibility dummies, from no hierarchical responsibility to chief executive.

[22] Unconditionally, the finance wage premium amounts to 27%.

find that elasticity to talent is three times as high in the finance industry as in the rest of the economy: one notch up on our talent scale leads to a 7.7% increase in wages for a finance worker. The consulting industry also displays a high wage elasticity to talent, which is twice as high as in the rest of the economy and is consistent with the high talent scalability of this industry. In contrast, wage elasticity to talent is significantly lower in the oil and chemistry industries than in the rest of the economy. We believe that this result is consistent with the strong physical constraints in the oil and chemistry sectors that limit talent scalability.

Our analysis also shows that the high wage elasticity to talent in the finance industry can almost entirely explain the finance wage premium. After including the interaction term $I_i \times Talent_{i,t}$ in our specification, we find that the finance premium almost disappears, standing at 2.3% (column 2).

Our results are robust to the measure of talent we use. Columns 3 and 4 show consistent results when using school rank or graduation age as a measure of talent. For each talent measure, we find that elasticity to talent is close to three times higher in the finance industry than in the rest of the economy. Including interaction terms of talent with sector dummies drives the finance wage premium downwards again. This downward revision is lower when using early graduation as a measure of talent, which is likely to come from the lower heterogeneity of this explanatory variable.

INSERT TABLE 4

5.2 Increasing Wage Sensitivity to Talent in the Finance Industry

We show that the wage elasticity to talent has been increasing over the years, which explains the contemporary increase of the finance premium since the 1980s documented by Philippon and Reshef (2012).

Columns 1, 2 and 3 of Table 5 display the OLS coefficients of equation (3) over three sub-periods: the 1980s, the 1990s and the 2000s. We find that the coefficient on the interaction term between talent and the finance industry dummy has increased more than twofold. In the 1980s, one notch in our talent scale translates into an average increase in wages of 2.3%, against a 3.4% increase the finance industry (column 1). In the 2000s, the same difference in talent induces a 9% increase in wages in finance, against a stable 2.6% increase in the whole economy (column 3). On the other hand, the residual of the finance premium, measured by the finance sector dummy, remains stable over the different periods (columns 1 to 3). The sector specific wage elasticity to talent explains therefore both the cross-section and the time-series of the finance wage premium.

INSERT TABLE 5

6 Alternative Hypotheses

This section discusses alternative explanations for the wage premium in the finance industry.

6.1 Talent Allocation

The high returns to talent we observe in the finance industry may not be driven by an actual compensation for talent, but by a selection of talented people into the highest paying jobs within the industry. Indeed, some job titles in the finance industry, such as trader, pay much higher on average than other jobs. Our results could be driven by certain schools preempting these highest paying roles, independently of individual talent. This allocation pattern may come from school field specialized training.

To rule out this possibility, a solution is to introduce exact job title fixed effects in the main wage equation. This allows us to compare between traders only, examining the alumni of top schools with those of lower ranked schools. To do so this we use a specific question of the 2006-2010 surveys: respondents are asked to give their job title.[23] Our main result resists to this robustness check: when controlling for job titles, we find that returns to talent only decrease by 14%, and are still more than twice as high as in the rest of the economy (columns 1 and 2 in Table 6).

INSERT TABLE 6

6.2 Network Effects

Our measure of talent may be a proxy for network strength rather than talent. Indeed, students in high ranking schools are likely to benefit from strong alumni networks and social connections, independently of their talent. A recent literature on networks insists on its importance in labor market processes, such as hiring, promoting or setting compensation (Butler and Gurun (2012), Engelberg et al. (2013) and Shue (2013)). Thus, it

[23] Table 8 in Appendix gives the frequencies of answers for workers in the Finance industry.

becomes necessary to investigate whether the quality, size or reach of an alumni network can account for the returns to school ranking that we observe.

France's Ecole Polytechnique and its related schools offer the perfect opportunity to test whether the quality of a school network can account for the returns to school rankings we observe. Graduates of these schools are over-represented among top executives and CEOs (Kramarz and Thesmar (2013); Ravanel (2013)). To rule out network as the dominant mechanism at play, we exclude these schools from our sample.[24] Columns (x) in Table 6 shows that returns to talent in the finance industry remain significantly positive. Our results are therefore not only driven by schools offering the most powerful networks, but remain valid for the entire school universe. In addition, we also observe that if 19.3% of the CAC40 firms are managed by a CEO who graduated from Ecole Polytechnique, the rate is only 17% when we focus on the finance industry.

We then account for the size of alumni networks. If this dimension matters, including network size should absorb most of the talent effect in our regressions. We use the yearly number of graduated students to control for the network size of each engineering school in our standard specification. Results are displayed in column (6) in Table 6. We find that returns to networks are higher in the finance industry than in the rest of the economy. However, wage returns to talent are still three time as high as in the rest of the economy, and dominates the size of network effects.

As a final test, we restrict our sample to alumni working outside France. Networks of French engineering schools are likely to have significantly weaker effects abroad. Restricting our analysis to this subsample allows the exclusion of network effects. If competition

[24]It consists in the following set of schools: Ecole Polytechnique, Mines de Paris, Ecole des Ponts, Supelec, AgroParisTech Grignon, Supaero, INP-ENSEEIHT, Supoptic Orsay, ESPCI Paris, Chimie Paris et Telecom Paris. We exclude also Centrale Paris since the level of recruitment is equivalent.

for talent is indeed driving our results, returns to talent should be equivalent or even higher for this subsample. The United States and the United Kingdom, which exhibit less rigid labor markets than France, are indeed a frequent destination for graduates outside France. The significant and positive coefficient on the triple interaction term between finance, talent and working outside France in column (7) shows that returns to talent are higher for graduates working outside France. This result is consistent with the competition for talent hypothesis.

6.3 Moral Hazard

We also consider principal agent models of asymmetric information and moral hazard as an alternative explanation for our main result. These models explain industry rents by either a high cost of failure or of monitoring (Axelson and Bond (2013), Biais et al. (2009)). The variable share of compensation is used to incentivize workers, and because of limited liability, the total amount of compensation in equilibrium is high, which leads to incentive rents.

If variable wages are driven by incentives, our main result should not hold when restricting our analysis to this part of the compensation package. If our result is still valid, it means that variable wages follow the same talent retention rationale of fixed compensation.[25] In addition, variable compensation in standard moral hazard models should vary along with the idiosyncratic individual performance, or if it is not observable, with the overall firm performance, but not with the performance of the whole industry. Relative performance measures should be favored (Holmström (1982)).

[25] A variation would be to state that talented employees are more costly to incentivize. This additional cost has to be offset by additional productivity or banks would switch to less talented people.

We use a specific question of the IESF survey to conduct our analysis on variable compensation. From the year 2000 survey onwards, respondents may report the percentage of total compensation that is variable. This information includes only bonuses and firm specific incentive schemes, excluding stock-options. We drop outliers where variable compensation exceeds four times the fixed compensation of the total annual compensation and lower than 0. Variable compensation is indeed a key component of wages in the finance industry: whereas 41% of individuals declare variable compensation in the total economy, they are 65% in the financial sector.

In order to disentangle the two hypotheses, we first test whether our talent measure can also explain variable compensation in the finance industry. Columns (1) and (2) in Table 7 assess the validity of our main result for the subsample of respondents who provided an answer to the question on the variable share. The talent measure explains the finance premium well, as in the main sample. We then divide Total Compensation into its two components: the variable and the fixed parts. We observe that our talent measure explains the finance premium for both the fixed and variable share of compensation, which is consistent with the competition hypothesis. Second, Figure 7 shows that the share of variable compensation is highly correlated with the overall finance sector profits, which is inconsistent with the incentive hypothesis according to which a relative performance measure should be favored.

6.4 Compensating Wage Differential

A last hypothesis for our results is that talented people work relatively more or have their health or employment more at risk, and therefore deserve a higher compensating differential

Using data on job satisfaction and hours worked, we control for both stress and workload in our main wage equation.[26] We use two dummy variables that are equal to one if the respondent declares suffering from stress and workload, and zero if not. In addition, we introduce a variable indicating whether the respondent works overtime occasionally, 5 to 10 hours or more than 10 hours. We do not find any significant downward impact of these variables on the talent return in the finance industry premium. Results are displayed in appendix.

We also control for unemployment risk using two different strategies. First, we observe the fraction of layoffs in the total population of employees per sector as a measure of unemployment risk.[27] We find that there is a negative correlation between wages and industry unemployment risk, that the unemployment risk has been constant in the financial sector from 1999 onwards (layoff rate of 1.7%), and that the financial sector is one of the sectors with the lowest layoff rate (average: 2.9%). Finally, we use a specific question of the survey that asks interviewees whether they suffer from job insecurity. Again, this additional control leaves our main result unchanged.

7 Conclusion

This paper shows that talent effects are an important determinant of wages in the finance industry. Estimating talent effects requires to observe and appropriately measure talent. We exploit the results of a competitive examination among equally highly educated and

[26]We do not control for both stress and workload in our main results since this information is not available for the whole sample

[27]Source: 2009 labor turnover data from the French Ministry of Labor, Employment and Health

motivated candidates to develop a unique measure of talent.

We use a new dataset from a compensation survey among the population of French graduate engineers, which includes detailed information on wages, performance in the competitive examination, career and demographics. In line with the existing literature investigating wages in the finance industry (Philippon and Reshef (2012) and Bell and Van Reenen (2013)), we find that the level of wages in finance is high, positively skewed, and that these patterns have been increasing since the 1980s.

The contribution of this paper is to show that talent effects explain both the level and skewed distribution of bankers' pay. We find that wage returns to talent are relatively high in finance, and have been increasing since the 1980s.

Our result raises the question of the possible negative externalities that competition for talent in the finance industry may generate. High returns to talent in the finance industry may drive talented individuals away from other industries, lead to excessively high level of pay (Glode and Lowery (2013) or induce inefficient risk-taking (Acharya et al. (2013)).

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A Figures

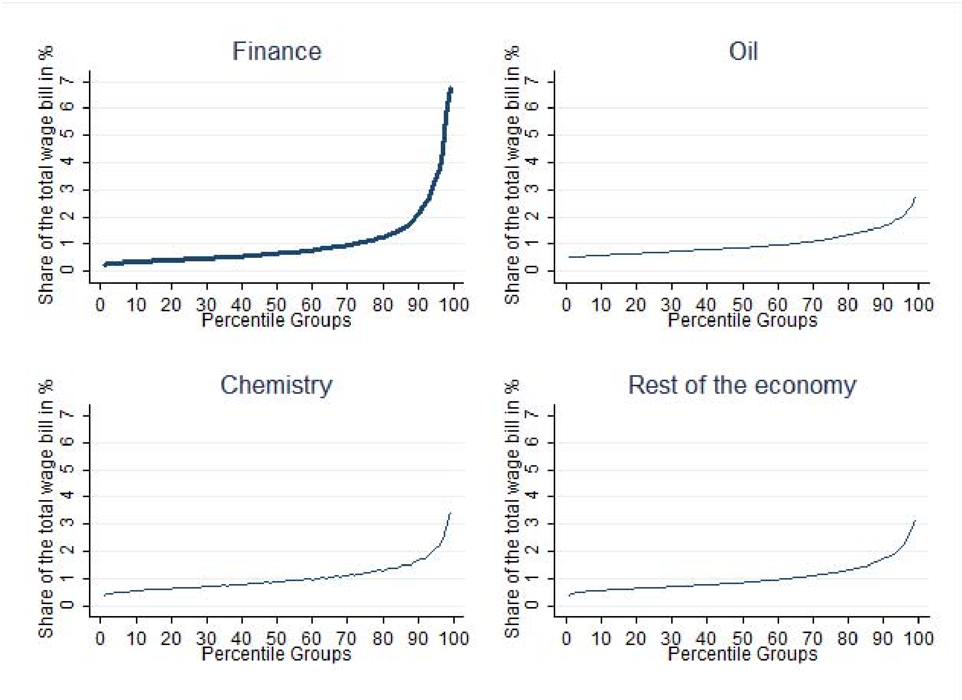

Figure 1. Share of the Total Wage Bill by Percentiles of the Wage Distribution

Note: Data are from the 2004-2011 surveys. In each sectors, observations are sorted by wages and divided into 100 groups of equal size. The total wage bill is the sum of compensation within the sector. The share of the total wage bill is the sum of all wages within each group divided by the total wage bill.

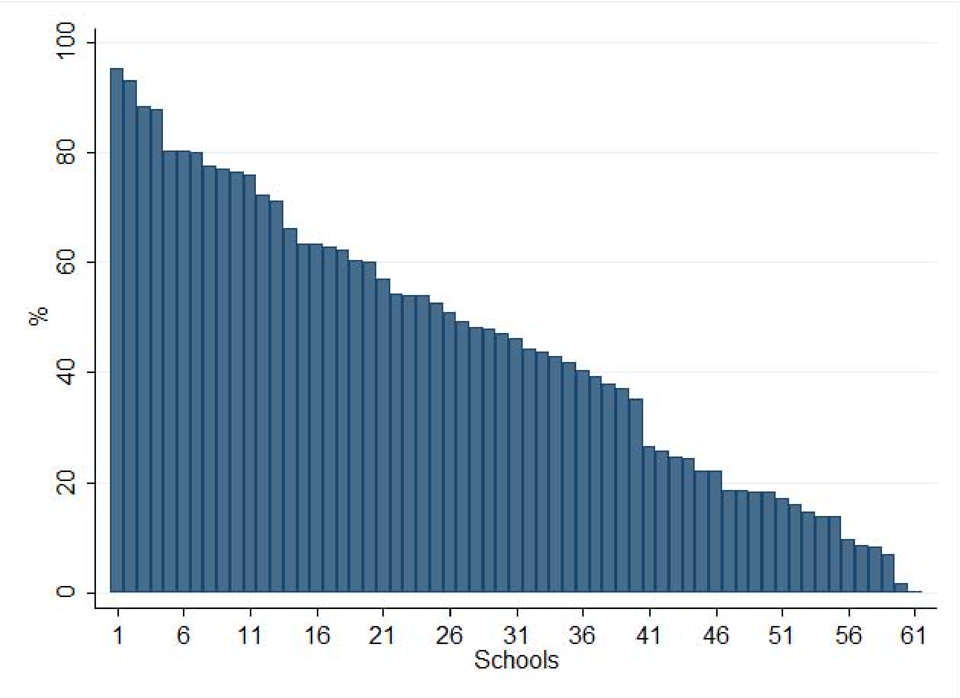

Figure 2. Distribution Function of Student's Performance at the Entry Examination over Schools

Note: This graph displays the share of students that performed less at the entry examination compared to the marginal student in each school in 2011. French engineering schools, namely "Grandes Ecoles", select students for admission based chiefly on national ranking in a competitive written and oral exam. Schools are sorted on their level of recruitment, measured as the ratio of the rank at the national competitive exam of the marginal student of the school to the total number of competing students. The selection rate distribution function is then calibrated to the school sample of the survey.

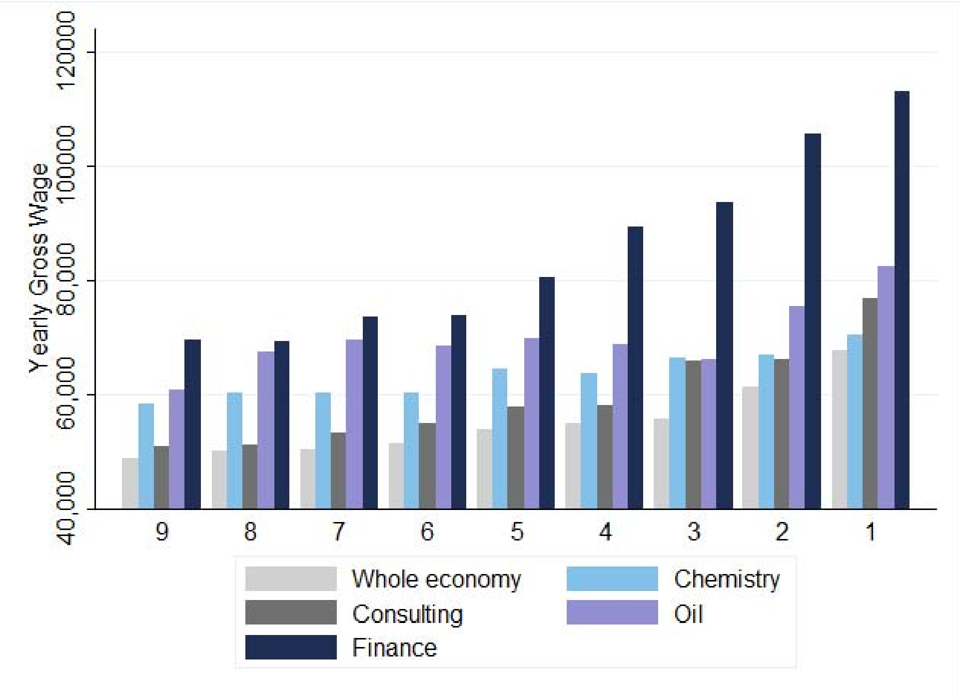

Figure 3. Predicted Wage over School Rank and Sectors

Note: This graph displays the predicted yearly gross wage calculated from the estimation of an OLS regression at fixed value of School Rank and averaging over all other variables. The dependant variable is the log of the yearly gross wage. The estimation period is 2004-2011. The regression is estimated over 5 samples: the whole economy (139,884 observations), 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, 8 education dummies, a working abroad dummy, 6 country dummies, experience level, squared and cubed, 4 hierarchic responsibility dummies, 9 occupation dummies, 4 firm size dummies, 4 firm type dummies.

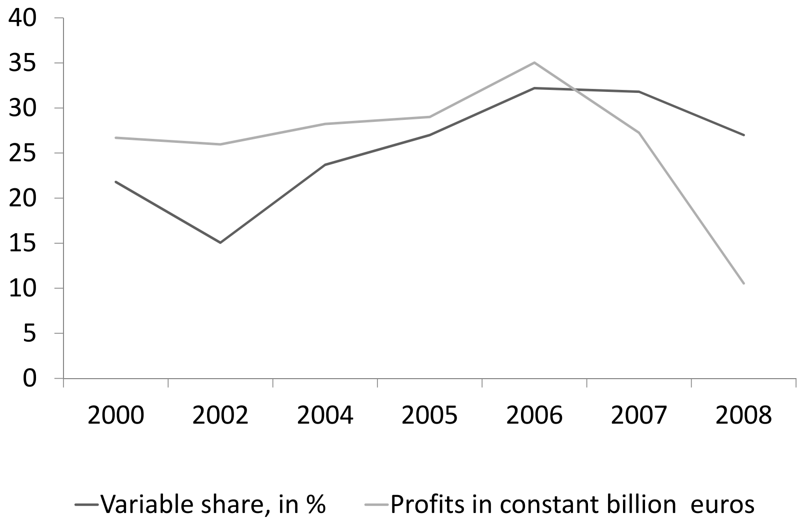

Figure 4. Variable Compensation and Bank Profits

Note: The evolution of the variable share (in %) and profits in the financial sector (in billion of constant euros) - 2000-2008 - Data are from the French Commission Bancaire.

B Tables

Table 1. Summary Statistics

	1980s	1990s	2000s
Sample Size			
Average number of observations per survey	21,648	20,585	25,353
Number of Surveys	3	4	7
Total Number of Observations	64,694	82,640	177,477
Response rate (%)	21	18	Nd
Coverage of total population of French engineers (%)	9	7.4	6.1
Compensation (in 2005 constant euros)			
Mean yearly gross wage	62,858	63,585	56,839
90th centile	101,376	103,698	96,903
99th centile	157,527	170,779	179,742
Standard Deviation	27,223	32,221	37,155
Engineers by Sectors (in %)			
Finance	1.8	1.8	2.3
Consulting	0.0	3.0	2.5
Oil	3.1	1.8	0.5
Chemistry	3.5	3.5	1.8
Demographics			
Mean Age	38.4	38.7	34.8
Percent Female	6.4	11	15.7
Percent Married	77.6	74.2	75.6
Work Location			
Percent Working Outside France	2.8	4.7	12.1
Percent Working in Paris Area	46.6	42.4	39.4
Career			
Mean Experience (in years)	14.6	14.3	11.6
Percent Team Manager	32.3	26.9	20.6
Percent Department Head	15.4	19.2	17.3
Percent Top Executive	6.5	9.9	7.4

This table reports summary statistics of key wage and demographic variables of the sample. 1980s = Graduates from the 1983, 1986 and 1989 surveys; 1990s = 1992, 1995, 1998 and 2000 surveys; 2000s = 2004, 2005, 2006, 2007, 2008, 2010, 2011 surveys. Source: IESF Compensation Survey

Table 2. Measuring Talent

School	Recruitment	N	Graduates		2011	% Top	% Early
Level	Level	Schools	Number	% Share	Wage	Manager	Graduation
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	Top 3%	1	9,165	3.2	95,149	32.9	36.3
2	Top 10%	3	16,363	5.6	81,125	21.8	20.9
3	Top 15%	4	8,563	2.9	69,211	13.8	14.2
4	Top 20%	6	18,864	6.5	67,967	14.5	15.8
5	Top 25%	5	12,413	4.3	67,196	17	16.4
6	Top 30%	3	30,635	10.5	66,111	17.2	11.4
7	Top 40%	19	34,534	11.9	53,624	9.5	10.4
8	Top 50%	36	66,836	23.0	55,261	11.9	11.9
9	Undergraduate	67	93,555	32.2	52,390	10.0	9.4
Total		*144*	*290,928*	*100.0*	*58,818*		

This table reports summary statistics over our talent measure "School Level". This talent measure takes value 1 to 9 and sorts school based on their level of recruitment. French engineering schools, namely "Grandes Ecoles", select students for admission based chiefly on national ranking in a competitive written and oral exam. The recruitment level (column 2) is the level of the marginal student in each school. Columns 3 and 4 give the number of and the share of students for each level of talent. Columns 5 is the average yearly gross wage in 2011 in 2005 constant Euros. Column 7 is the share of interviewees who is leading at least a department after 20 years of experience. Column 8 gives the share of interviewees that graduate early (at least one year ahead).

Table 3. 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 replicates Table 6 in Bell and Van Reenen (2010). It 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, 4 hierarchic responsibility dummies, 9 occupation dummies, 4 firm size dummies, 4 firm type dummies. Standard errors are in parentheses. Trend estimates are multiplied by 100 and adjusted by the number of years and so are interpretable as % relative annual wage increase for finance workers.

Table 4. Heterogenous Wage Returns to Talent across Industries

	Log(Wage)			
Talent Measure	School Level		School Rank	Graduation Age
	(1)	(2)	(3)	(4)
Talent	0.027***	0.025***	0.218***	0.025***
	(0.000)	(0.000)	(0.003)	(0.001)
Talent *Finance		0.052***	0.606***	0.038***
		(0.001)	(0.018)	(0.007)
Talent *Consulting		0.025***	0.320***	0.019**
		(0.001)	(0.019)	(0.007)
Talent *Oil		-0.005***	-0.121***	-0.001
		(0.002)	(0.020)	(0.015)
Talent *Chemistry		-0.004***	-0.098***	0.004
		(0.001)	(0.014)	(0.008)
Finance	0.243***	0.023***	-0.098***	0.177***
	(0.003)	(0.006)	(0.013)	(0.020)
Consulting	0.133***	0.040***	-0.034***	0.041*
	(0.004)	(0.006)	(0.013)	(0.021)
Oil	0.116***	0.141***	0.197***	0.152***
	(0.005)	(0.009)	(0.012)	(0.045)
Chemistry	0.068***	0.082***	0.120***	0.047**
	(0.003)	(0.006)	(0.007)	(0.023)
Household Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
School FE	No	No	No	Yes
Observations	194,593	194,593	110,134	52,766
R^2	0.704	0.708	0.709	0.548

This table reports coefficient of standard OLS regressions. The dependent variable is the log of the yearly gross wage - The oil, finance, chemistry and consulting industries have a dummy variable. *Talent* (taking value 1 to 9) sorts school based on their level of recruitment, measured as the ranking of the marginal student at the national competitive exam. 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, 4 hierarchic responsibility dummies, 9 occupation dummies, 4 firm size dummies, 4 firm type dummies. Standard errors are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Increasing Wage Returns to Talent in the Finance Industry

	Log(Wage)		
	S1980	S1990	S2000
	(1)	(2)	(3)
Talent	0.023***	0.024***	0.027***
	(0.001)	(0.000)	(0.000)
*Talent*Finance*	0.011***	0.028***	0.065***
	(0.003)	(0.002)	(0.002)
Finance	0.018	0.007	0.021***
	(0.015)	(0.013)	(0.008)
Household Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	40,844	51,510	102,239
R^2	0.721	0.724	0.700

This table reports coefficient of standard OLS regression over three samples: S1980 = the 1986 and 1989 surveys (Column 3), S1990 = 1992, 1995, 1998 and 2000 surveys (Column 4) and S2000 = 2004, 2005, 2006, 2007, 2008, 2010, 2011 surveys (Column 5). The dependent variable is the log of the yearly gross wage - The oil, finance, chemistry and consulting industries have a dummy variable. *Talent* (taking value 1 to 9) sorts school based on their level of recruitment, measured as the ranking of the marginal student at the national competitive exam. 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, 4 hierarchic responsibility dummies, 9 occupation dummies, 4 firm size dummies, 4 firm type dummies.

Table 6. Robustness Checks

	Log(Wage)						
Sample	Finance Industry		Bottom Schools	Middle Schools	Top Schools	All	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Talent	0.069***	0.059***	0.019***	0.028***	0.065***	0.074***	0.079***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
*Talent**Finance			0.038***	0.063***	0.080***	0.131***	0.099***
			(0.006)	(0.008)	(0.011)	(0.003)	(0.004)
*Talent**Finance *Abroad							0.058***
							(0.008)
Finance			0.073***	0.092***	0.285***	0.158***	0.103***
			(0.011)	(0.018)	(0.025)	(0.006)	(0.004)
Network Size						0.040***	0.037***
						(0.002)	(0.002)
Finance*Network Size						0.055***	
						(0.013)	
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jobs Title FE	No	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,385	2,385	132,001	48,143	23,116	180,605	180,605
R^2	0.561	0.617	0.684	0.693	0.674	0.697	0.696

The dependent variable is the log of the yearly gross wage. Engineering schools are ranked from 1 to 9 and grouped into 3 categories: the top group gathers the top 10 schools, the middle group the 70 following schools and the bottom group the 80 bottom schools - 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, 4 hierarchic responsibility dummies, 9 occupation dummies, 4 firm size dummies, 4 firm type dummies.

Table 7. Variable Compensation

	Total Compensation		Fixed Compensation		Variable Compensation	
	(1)	(2)	(3)	(4)	(5)	(6)
Finance	0.201***	0.023*	0.042***	0.005	0.854***	0.225***
	(0.007)	(0.013)	(0.007)	(0.012)	(0.041)	(0.073)
Talent	0.033***	0.030***	0.029***	0.029***	0.062***	0.052***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
*Talent**Financ		0.041***		0.008***		0.145***
		(0.002)		(0.002)		(0.014)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,843	51,843	51,843	51,843	51,843	51,843
R^2	0.453	0.456	0.417	0.417	0.134	0.136

The dependent variable is the log of the yearly gross wage in columns (1) and (2), of the yearly fixed wage in columns (3) and (4) and of the yearly variable wage in columns (5) and (6) - 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, 4 hierarchic responsibility dummies, 9 occupation dummies, 4 firm size dummies, 4 firm type dummies.

Appendix A - Model

This section develops a simple partial equilibrium model of the labor market in which firms compete for talent. As in standard superstar models (Rosen (1981)), workers are heterogeneous in talent, and returns to talent are increasing. This model differs in the assumption that the economy is composed of several industries with heterogeneous output returns to talent. It develops predictions on the wage distribution and wage elsaticity to talent across industries.

Consider a one period economy composed of $i = 1, ..., S$ industries. In each industry, firms produce output by combining exactly one worker with talent T and capital. Specifically, the profit of a firm of size k from hiring a worker of talent T in industry i is

$$\pi(k, T, i) = T^{\epsilon_i} k^{\alpha_i} - k - w(T, i)$$

where $\epsilon_i \geq 1$, $\alpha_i < 1$. $w(T, i)$ denotes the market wage of a worker of talent T in industry i. The unitary cost of capital is one.

The key parameters in this model are ϵ_i and α_i. These values are determined by technology, and vary across industries. α_i represents *talent scalability.* If α_i is high, an increase in one worker's talent will be matched by a large increase in the size of the firm he is working at. *Talent scalability* is higher in industries with low physical constraints/replication costs. ϵ_i represents the *output elasticity of talent.* In industries in which the organizational structure is flatter, the impact of talent is higher and ϵ_i is higher. The assumption that $\epsilon_i \geq 1$ is meant to capture increasing returns to talent, whereas $\alpha_i < 1$ implies decreasing returns to scale.

All firms can observe the talent T of every worker in their industry. In each industry, at the beginning of the period, firms enter freely at any firm size k. Next, all firms make simultaneous job offers and wage bids to all workers in their industry. After that, workers decide which offer to accept.

The free entry of firms implies that a worker of talent T is hired by the firm of size $k^*(T)$ that is the best match for his level of talent.

$$k^*(T,i) = arg\max_k \left[T^{\epsilon_i} k^{\alpha_i} - k - w(T)\right]$$

which induces

$$k^*(T,i) = \alpha_i^{\frac{1}{1-\alpha_i}} T^{\frac{\epsilon_i}{1-\alpha_i}} \tag{4}$$

Within each industry, competition among firms for workers' talent ensures that firms earn zero profits. The market wage of a worker of talent T in industry i is

$$w(T,i) = T^{\epsilon_i} k_T^{*\alpha_i} - k_T^*$$

Introducing (4)

$$w(T,i) = T^{\frac{\epsilon_i}{1-\alpha_i}} \alpha_i^{\frac{\alpha_i}{1-\alpha_i}} (1-\alpha_i) \tag{5}$$

Consistent with Rosen (1981), wages are increasing and convex in talent T.

What does this process imply concerning the distribution of wages within each industries? One measure of inequality is return to talent, which is given by

$$\frac{w'(T,i)}{w(T,i)} = \frac{\epsilon_i \alpha_i^{\frac{\alpha_i}{1-\alpha_i}} T^{\frac{\epsilon_i}{1-\alpha_i}-1}}{T^{\frac{\epsilon_i}{1-\alpha_i}} \alpha_i^{\frac{\alpha_i}{1-\alpha_i}} (1-\alpha_i)}$$

$$\frac{w'(T,i)}{w(T,i)} = \frac{\epsilon_i}{T(1-\alpha_i)}$$

We can see that the greater *talent scalability* α_i and *output elasticity of talent* ϵ_i are, the higher wage returns to talent are. If *talent scalability* α_i is high, an increase in worker's talent will be matched by a large increase in the firm's capital, which will increase the worker's rent substantially. Similarly, as the *output elasticity of talent* ϵ_i increases, the higher the impact of talent on output. We also have

$$\frac{\partial^2 w}{\partial T^2} = \epsilon_i \alpha_i^{\frac{\alpha_i}{1-\alpha_i}} (\frac{\epsilon_i}{1-\alpha_i} - 1) T^{\frac{\epsilon_i}{1-\alpha_i}-2}$$

Prediction 1 *As talent scalability α_i or output elasticity of talent ϵ_i increase, the more convex the wage schedule is.*

This prediction implies that when, in a specific industry, wage returns to talent are high, one should observe more convexity in the distribution of wages.

The model also makes predictions in terms of inter-industry wage differentials. Let us consider two workers with the same level of talent T working in two different industries, i and j, with $i \neq j$. The wage ratio is given by

$$\frac{w(T,i)}{w(T,j)} = T^{\frac{\epsilon_i}{1-\alpha_i} - \frac{\epsilon_j}{1-\alpha_j}}$$

The wage ratio increases with the level of talent. Plugging the log, we obtain the central equation of the paper:

$$ln(w(T,i)) - ln(w(T,j)) = (\frac{\epsilon_i}{1-\alpha_i} - \frac{\epsilon_j}{1-\alpha_j})ln(T)$$

Prediction 2 *For two workers of the same level of talent T working in industries i and j, with $i \neq j$, the wage ratio $\frac{w(T,i)}{w(T,j)}$ can be explained by the difference in wage elasticity to talent $\frac{\epsilon_i}{1-\alpha_i} - \frac{\epsilon_j}{1-\alpha_j}$.*

Predictions 1 and 2 have empirical implications concerning the distribution of wages within and across industries. Let consider an industry in which wage elasticity to talent is relatively high (the ratio $\frac{\epsilon_i}{1-\alpha_i}$ is high) . Prediction 1 implies that the distribution of wages should be more skewed than in other industries, Prediction 2 that the wage differentials should be higher at the top of the wage distribution and that the wage premium can be explained by higher returns to talent.

Appendix B - Figures

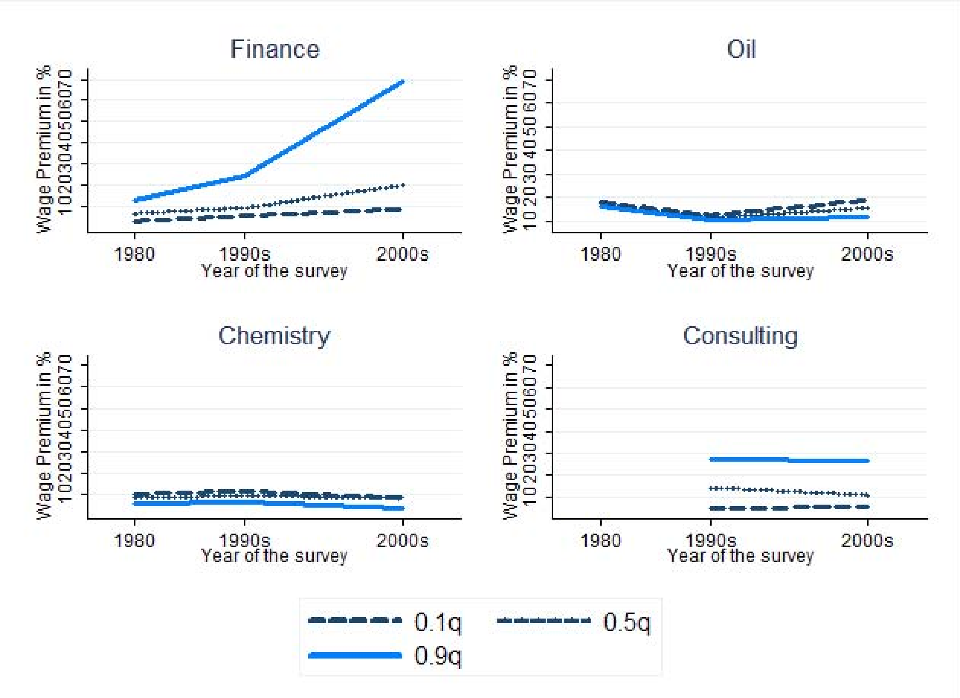

Figure 5. Premium Evolution over Deciles

Note: Each graph displays the evolution of industry dummy coefficients in quantile regressions estimated over three periods: the 1980s (1983, 1986 and 1989 surveys), the 1990s (1992, 1995, 1998 and 2000 surveys, 53,680 observations) and the 2000s (2005, 2006, 2007, 2009 and 2011 surveys, 96,611 observations) for q=0.1, q=0.5 and q=0.9. The four considered industries are the Finance, the Oil, the Chemical and the Consulting industries, which are the four highest-paying industries over the period. Each regression also controls for education, gender, marital status, occupation, firm type, firm size, hierarchical responsibilities, working abroad, working in Paris area, experience, experience squared and experience cubed.

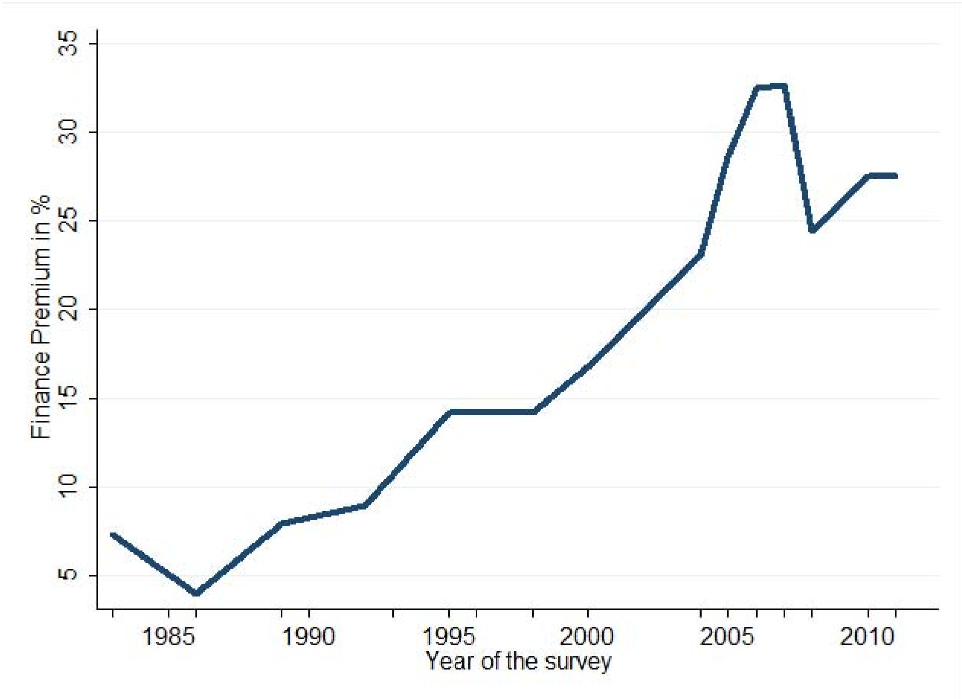

Figure 6. The Finance Wage Premium Evolution

Note: The graph displays the evolution of the coefficient of the financial sector dummy in OLS regressions estimated over the period 1983-2011 (251,071 observations), in which the dependant variable is the log of the yearly gross wage. There are 48 industry dummies, and the estimation is constrained such that the sum of all the industry dummy coefficients is zero. Each regression also controls for education, gender, marital status, occupation, firm type, firm size, hierarchical responsibilities, working abroad, working in Paris area, experience, experience squared and experience cubed.

Appendix C - Tables

Table 8
Finance Jobs

Jobs	Number	%
Analyst	169	6.2
Asset Management	91	3.3
Back Office	20	0.7
Controller	60	2.2
Executive	152	5.6
IT	454	16.7
Merger and Acq.	40	1.5
Other	924	33.9
Project Finance	84	3.1
Quant	92	3.4
Retail	127	4.7
Risk Management	104	3.8
Structurer	147	5.4
Trading and Sales	259	9.5
Total	2723	100.0

This table reports summary statistics on jobs in the financial industry in the survey sample (2006-2010).