Returns to Talent and the Finance Wage Premium*

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Abstract

To study the role of talent in finance workers' pay, we exploit a special feature of the French higher education system. Wage returns to talent have been significantly higher and have risen faster since the 1980s in finance than in other sectors. Both wage returns to project size and the elasticity of project size to talent are also higher in this industry. Last, the share of performance pay varies more for talent in finance. These findings are supportive of finance wages reflecting the competitive assignment of talent in an industry that exhibits a high complementarity between talent and scale. (*JEL* G21, G24, J24, J31, J33, M52)

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Introduction

Compensation in the finance industry is higher and more skewed than in other sectors, and has been increasingly so since the beginning of the 1980s (Oyer 2008; Goldin and Katz 2008; Philippon and Reshef 2012). Controlling for education and other individual characteristics, Philippon and Reshef (2012) find that the finance wage premium reached, on average, 50% in 2006, and 250% for the top decile of the industry. The financial sector has therefore largely contributed to the observed gains at the top of the wage distribution since the 1980s (Kaplan and Rauh 2010; Bakija et al. 2012; Bell and Van Reenen 2013). However, the economic mechanism driving compensation in finance is actively debated. A growing theoretical literature has been exploring this question, relating the distribution of pay in finance to heterogeneous levels of talent (Acharya, Pagano, and Volpin 2016; Benabou and Tirole 2016; Glode and Lowery 2016; Thanassoulis 2012). Is talent an economically significant determinant of finance workers' pay? If so, what is the underlying mechanism? The objective of this paper is to address these questions in a novel empirical setting.

To structure our empirical analysis and flesh out the economic mechanism driving pay in finance, we first develop a simple theoretical framework derived from Murphy and Zábojník (2004). In this framework, firms compete for incumbent workers with heterogeneous talent and the marginal impact of a worker's talent increases with the size of the project under their control. The main prediction of this simple framework is that returns to talent are high in industries where output elasticity to scale is high, as it results in a higher complementarity between talent and scale. The dematerialized nature of capital flows, the widespread use of information technologies in financial firms, as well as the increase in scale allowed by globalization and financial deregulation, suggest that output elasticity to scale is high in finance. Our study therefore tests the empirical predictions of our framework applied to the finance industry.

Assessing returns to talent across industries requires accurately observing and measuring worker talent. We exploit a unique feature of the French higher education system to develop a measure of talent: *Grandes Ecoles*, the top academic institutions, select students solely based on their performance on a nationwide competitive exam.[1] This

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

selection process provides us with a unique setup to answer our research questions for the following reasons. First, the competitive exam discriminates between individuals in the right tail of the skill distribution, where most of the finance premium lies (Philippon and Reshef 2012; Bell and Van Reenen 2013).[2] Second, all individuals in our sample have completed a 5-year master's degree in engineering from an elite institution. Studying individuals with the same level and field of education allows us to disentangle returns to talent from returns to schooling, a major challenge of the empirical labor literature. Third, this selection process assesses not only academic, cognitive, and communication skills but also personality traits, such as endurance, commitment, ambition, and competitiveness. The literature shows that such personality traits are important determinants of wages (Heckman 1995; Bowles, Gintis, and Osborne 2001; Heckman and Kautz 2012; Deming 2017).[3] Finally, family or social background affects admission to the top schools only through students' performance on the competitive exam. The admission process is anonymous and does not rely on recommendations.

The central result of our paper is that the finance wage premium is associated with high returns to talent in this industry: returns to talent are 3 times higher in finance than in the rest of the economy. This result is robust to controlling for occupation fixed effects, as well as for individual fixed effects in a panel model. We also instrument worker self-selection into finance using stock market performance at graduation to further alleviate endogeneity concerns (Oyer 2008).

Our second result is that the high returns to talent in finance reflect a high complementarity between talent and scale. At the macro-level, we document that returns to talent have increased significantly faster in finance than in the rest of the economy since the 1980s. While returns to talent were 50% larger in finance than in other industries in the 1980s, they are almost 4 times larger in the 2000s. This trend is consistent with the increasing amount of capital per employee observed in the finance industry since

environment. Hence, talent encompasses the intersection of cognitive skills with noncognitive skills and personality traits, such as motivation, self-discipline, low cost of effort, and an ability to perform in a competitive environment. Deming (2017) documents the growing importance of social skills in the labor market.

[2]The selection process allows us to identify the top 0.01% of an age cohort, making our measure significantly more granular than those used in other studies. The heterogeneity in talent at the right tail is typically overlooked in discreet population-wide measures, such as military tests.

[3]Ors et al. (2013) exploit this specificity of the French higher education system to investigate the gender gap in individual performance in a competitive environment.

the 1980s (Kaplan and Rauh 2010). At the micro-level, we establish that more talented individuals are matched with larger projects, and that the elasticity of size to talent is higher in finance than in the rest of the economy. Wage returns to scale are also higher in finance than in the rest of the economy.

We also document three stylized facts that are consistent with firms competing for t alent mostly within industries, which would result, for instance, from the existence of industry-specific skills that are acquired on the job. First, the gap in returns to talent between finance and the rest of the economy increases with worker experience. Second, this gap is also larger for jobs requiring general skills than for jobs requiring technical skills, the former being more likely to provide workers with industry-specific skills rather than only job-specific ones. Third, as worker project size has increased since the 1980s, finance has attracted an increasing share of talented workers as forfeiting skills specific to other industries is increasingly offset by higher returns to talent in finance.

Finally, we provide evidence suggesting that firms use performance pay as a retention device, and that this phenomenon is more pronounced in finance. Consistent with Lemieux, MacLeod, and Parent (2009), the share of performance pay increases with talent and wage returns to talent are higher in performance-pay jobs than in non-performance-pay jobs. The relationship between the share of performance pay and talent—and its associated returns—is more pronounced in finance than in other industries.[4]

We then consider a comprehensive set of alternative explanations for our results: the existence of a compensating differential for working in finance or in certain finance occupations, the possible endogenous selection of workers into finance and into occupations within this industry, the possibility that our talent measure captures characteristics that are more valuable in finance than in other industries, including social network, and different treatment effects across schools. The data do not support these alternative explanations.

Our results shed light on the debate regarding the drivers of pay in finance. We show that high returns to talent are consistent with finance wages resulting from the competitive assignment of talents like in Acharya, Pagano, and Volpin (2016); Benabou

[4]This result also could be consistent with a version of a moral hazard model where the productivity of effort increases with talent and occupation scale. Therefore, such a channel is nested in the broader mechanism of a higher complementarity between talent and scale in finance.

and Tirole (2016); Glode and Lowery (2016); Thanassoulis (2012). Our results also complement recent works showing that mutual fund manager compensation is related with fund revenues (Ibert et al. 2017; Naim and Sokolinski 2017). High returns to talent also can be optimal because of moral hazard if it is more profitable for firms to incentivize talented workers (Axelson and Bond 2015; Biais, Rochet, and Woolley 2015). High returns to talent, however, are more difficult to reconcile with the managerial power view, where powerful managers set their own pay to extract rents from their employers (Bebchuk and Fried 2004).[5]

Second, our paper provides new empirical evidence on the interaction between competition for talent and the structure of compensation. Our results are consistent with performance pay being used as a mechanism to attract and retain talented workers (Lemieux, MacLeod, and Parent 2009; Lustig, Syverson, and Van Nieuwerburgh 2011; Benabou and Tirole 2016). Relying on performance pay also may be higher for talented workers in finance because of a higher benefit of effort for talented workers magnified by scale effects (Gayle and Miller 2009; Edmans and Gabaix 2016; Edmans, Gabaix, and Jenter 2017).

Third, our paper adds to the literature on the allocation of talent in the economy. By offering relatively high wages for the same level of talent, the finance sector may lure talented individuals away from other industries (Murphy, Shleifer, and Vishny 1991; Philippon 2010; Bolton, Santos, and Scheinkman 2016) or from financial regulation (Shive and Forster 2016; Bond and Glode 2014). We find evidence of a "brain-drain" towards finance, which is, however, of moderate magnitude relative to the significantly larger returns to talent in this sector.[6] This result is consistent with the literature on occupational choice that identifies earnings as only one of the drivers of worker allocation to an industry in general (Blau et al. 1956; Dolton, Makepeace, and Van Der Klaauw 1989), and to finance in particular (Shu 2016; Böhm, Metzger, and Strömberg 2018).[7]

Last, our results contribute to the understanding of the well-documented rise in income inequalities driven by finance workers' and top executives' pay (Piketty and Saez 2006;

[5]In this study, we do not address the question of whether or not the finance industry extracts rents from society, like in Bolton, Santos, and Scheinkman (2016) and Biais and Landier (2015). If high-skilled workers are more talented at extracting rents from society, higher wages still may be the result of optimal contracting with their employer.

[6]Using U.S. data, Nandini and Hacamo (2018) confirm our finding that finance increasingly attracts top engineering graduates.

[7]Other key determinants of occupational choices are individual psychological characteristics and social structure.

Kaplan and Rauh 2010). Our results are consistent with the evolution of wages reflecting a disproportionate increase in returns to talent for certain occupations, as their scale expand (Gabaix and Landier 2008; Greenwood and Scharfstein 2013; Mueller, Ouimet, and Simintzi 2017), due to technological change (Katz and Murphy 1992; Garicano and Rossi-Hansberg 2006), or globalization and deregulation (Boustanifar, Grant, and Reshef 2017).

1 Theoretical Framework

1.1 Basic framework

We follow Murphy and Zábojník (2004) to explore the labor market outcome when firms compete for talent and there is complementarity between talent and scale.

More specifically, we consider a one period economy in which firms produce output by combining exactly one worker with talent T with a project of size S that yields the following profit:

$$T \times S^{\alpha} - S - w(T),$$

where $w(T)$ denotes the market wage of a worker of talent T. The market has a finite supply of workers with heterogeneous levels of talent T.[8] The unitary cost of capital is one. α measures the output elasticity to size, with $\alpha < 1$ implying decreasing returns to scale.[9]

All firms can observe the talent T of every worker in the economy. Firms can start freely any new project of any size S. At the beginning of the period, all firms make simultaneous job offers and wage bids to all workers in the economy. Workers then decide which offer to accept.

The free entry of firms implies that a firm hires a worker of talent T to work on the project of size $S^*(T)$ that is the best match for their talent level to maximize their net impact on firm surplus:

$$S^*(T) = arg \max_{S} \left[T \times S^{\alpha} - S\right],$$

[8] We justify this assumption in Section 1.1.1 when considering the presence of market imperfections that fragment the labor market into industry-specific labor markets in which firms compete for a finite set of workers with heterogeneous talent.

[9] The model yields comparable results with a more general production $f(S)$, which is increasing, continuously differentiable, and concave with $f(0) = 0$, $f'(0) = \infty$ and $lim_{\infty} f'(S) = 0$.

which yields:

$$S^*(T) = \alpha^{\frac{1}{1-\alpha}} T^{\frac{1}{1-\alpha}}. \tag{1}$$

Higher talent workers are hence allocated to larger projects.

Competition among firms for workers with heterogeneous levels of talent ensures that the worker has full bargaining power and obtain all the surplus from production. The equilibrium wage of the worker is equal to

$$w(T) = T \times S_T^{*\alpha} - S_T^*. \tag{2}$$

Substituting (1) into (2), we obtain

$$w(T) = T^{\frac{1}{1-\alpha}} \alpha^{\frac{\alpha}{1-\alpha}} (1-\alpha). \tag{3}$$

This simple wage equation provides predictions on the effect of talent on wages in the spirit of *superstar* models (Rosen 1981; Gabaix and Landier 2008). In particular, we have

$$\frac{\partial w(T)}{\partial T} = T^{\frac{1}{1-\alpha}-1} \alpha^{\frac{\alpha}{1-\alpha}}. \tag{4}$$

and

$$\frac{\partial^2 w(T)}{\partial T^2} = \frac{\alpha}{1-\alpha} T^{\frac{1}{1-\alpha}-2} \alpha^{\frac{\alpha}{1-\alpha}} \tag{5}$$

Equations (4) and (5) imply that, when there is complementarity between talent and scale, and firms compete for talent, wages are an increasing and convex function of talent. Returns to talent, which we measure as the elasticity of wages to talent, are

$$\frac{\partial w(T)/w(T)}{\partial T/T} = \frac{\partial S(T)/S(T)}{\partial T/T} = \frac{1}{1-\alpha} > 0. \tag{6}$$

Returns to talent, as well as size elasticity to talent, are therefore increasing and convex in output elasticity to scale α.

1.1.1 Industry-specific labor markets.

We now assume that the labor market is split across industry-specific labor markets to derive the central equation of our paper. We provide one possible micro-foundation for this assumption in Appendix A: when workers acquire industry-specific skills that are a complement to their talent, firms mostly compete for the limited set of experienced workers within their industry.

We consider two workers with talent levels T_n and T_0, $T_n > T_0$, working in an industry i with output elasticity to size α_i. T_0 is the lowest level of talent in the economy. Firms competition for workers in industry i implies that the wage ratio across these two workers is given by

$$\frac{w_i(T_n)}{w_i(T_0)} = \frac{T_n^{\frac{1}{1-\alpha_i}}}{T_0^{\frac{1}{1-\alpha_i.}}}$$

Plugging the log, we have

$$\ln\big(w_i(T_n)\big) - \ln\big(w_i(T_0)\big) = \frac{1}{1-\alpha_i} \times \ln\left(\frac{T_n}{T_0}.\right) \tag{7}$$

Let us define the function $\gamma(x) = \frac{1}{1-x}$, with $\gamma_i = \gamma(\alpha_i)$. We have

$$\ln\big(w_i(T_n)\big) - \ln\big(w_i(T_0)\big) = \gamma_i \times \ln\left(\frac{T_n}{T_0}\right)$$

in industry i.

We now consider that the same two workers are working in the rest of the economy $-i$, where α_{-i} is the output elasticity to siz and $\gamma_{-i} = \gamma(\alpha_{-i})$. The wage ratio is

$$\ln\big(w_{-i}(T_n)\big) - \ln\big(w_{-i}(T_0)\big) = \gamma_{-i} \times \ln\left(\frac{T_n}{T_0}\right).$$

We define $\beta_i = \ln\big(w_i(T_0)/w_{-i}(T_0)\big)$ and obtain

$$\ln\big(w_i(T_n)\big) = \ln(w_{-i}(T_0)) + \gamma_{-i}\ln\left(\frac{T_n}{T_0}\right) + (\gamma_i - \gamma_{-i})\ln\left(\frac{T_n}{T_0}\right) + \beta_i. \tag{8}$$

Therefore, by including the indicator variable $\mathbb{1}_i$ for working in industry i, we obtain the central equation of the paper that defines the wage of any worker in the economy:

$$\begin{aligned}\ln(w(T_n)) = \ln(w(T_0)) + &\underbrace{\gamma_{-i}}_{\text{Returns to talent in the rest of the economy}} \times \ln(\frac{T_n}{T_0}) \\ + &\underbrace{(\gamma_i - \gamma_{-i})\mathbb{1}_i}_{\text{Incremental returns to talent in industry } i} \times \ln(\frac{T_n}{T_0}) \\ + &\underbrace{\beta_i \times \mathbb{1}_i}_{\text{Residual premium for working in industry } i}\end{aligned} \tag{9}$$

1.1.2 Model extensions: Talent allocation, experience, general skills, and performance pay.

The micro-foundation of a segmented labor market by industry, namely the worker accumulation of industry-specific skills complementary to talent, generates a set of additional predictions that we develop in Appendix A in the Online Appendix. First, talented individuals are more likely to join a high α industry. Second, the gap in returns to talent between an industry with a high α and the rest of the economy is increasing with experience as workers acquire industry-specific skills. Last, this gap is higher in jobs where workers acquire more industry-specific skills rather than job-specific skills.

While we do not formally model the role of performance pay, our framework suggests that, when performance pay is used as a retention mechanism, (1) the share of performance pay should increase with a worker talent and (2) the effect should be larger in industries with a high output elasticity to scale α. Reciprocally, returns to talent should be higher in jobs with a large share of performance pay. Oyer (2004) and Lustig, Syverson, and Van Nieuwerburgh (2011) show that when firms compete for talent and workers' outside options are correlated with the firm's performance, the optimal compensation scheme includes performance pay. Contingent compensation contracts ensure that firms retain their talented workers in all states of nature by allowing wages to adjust to workers' outside options.

1.2 Empirical implications

When assuming that α is higher in finance than in the rest of the economy, our framework yields the following predictions:[10]

1. The finance wage premium is associated with higher returns to talent.
2. The finance wage premium is associated with size effects:
   (a) In the time series, both the finance wage premium and returns to talent increase along with the average project size.
   (b) In the cross-section, size varies with talent and size elasticity to talent is larger in finance. This results in a higher wage elasticity to project size in finance.
3. Model Extensions:
   (a) Returns to talent increase with experience, and even more so in the finance industry.
   (b) Returns to talent are higher in tasks that require general skills rather than technical skills, and even more so in finance.[11]
   (c) In the time series, talented individuals are increasingly likely to join finance as output elasticity to scale increases, and so does the average project size in finance.
   (d) The share of performance pay varies more with respect to talent in finance than in the rest of the economy. Returns to talent are higher in performance-pay jobs, and even more so in finance.

[10] A high α in finance is consistent, first, with the dematerialized nature of financial transactions that largely annihilates physical constraints. This dematerialization has been made possible by the ubiquitous presence of information technology in the industry (Philippon and Reshef 2012). Second, the integration of world capital markets and their deregulation since the 1980s have increased the average size of projects in finance, hence increasing returns to scale. Third, the skewed wage distribution (Piketty and Saez 2006; Bakija et al. 2012; Bell and Van Reenen 2013) and the high and increasing ratio of capital per employee observed in finance (see Kaplan and Rauh (2010) and Greenwood and Scharfstein (2013) for micro and macro evidence, respectively) are consistent with the predictions a talent assignment model when α is high.

[11] We interpret jobs for which workers acquire more industry-specific skills, rather than job-specific skills, as jobs that require more general skills, rather than more technical skills.

2 Measuring Talent

The selection process of the French engineering schools provides a comprehensive talent measure within a highly and homogeneously educated population that is well fitted to test our empirical predictions.

2.1 French engineering schools' selection process

To earn the official title of "graduate engineer," students in France need to graduate from a master's program in any field of engineering offered by 1 of the 225 selective, small-scale institutions called "Grandes Ecoles d'Ingenieurs."[12] French graduate engineers are then employed in virtually all industries and in more than 240 occupations (Table A10 in the Online Appendix provides the list of industries). Engineering, which is considered a generalist education, has traditionally been the main pathway to obtaining management or leadership positions in France.

These "Grandes Ecoles d'Ingenieurs" select students based on their ranking on a national competitive exam that includes both written and oral tests. Written tests cover a wide range of subjects, including mathematics, physics, programming, French literature, and foreign language sections, over a 3-week period. Oral exams last between 20 and 50 minutes and consist in candidates solving problems in a limited time in the presence of a jury of professors. The 2 years that students spend preparing for the exam at highly selective institutions—the *Classes Preparatoires*—are also a fundamental part of the selection process. Figure 1 summarizes the selection process of French engineering schools, and Appendix C in the Online Appendix provides more detail on the process.

INSERT FIGURE 1

2.2 Main talent measure

The main talent measure in this study is *1 minus the selection rate* of the 225 small-scale engineering schools with heterogeneous levels of selectivity at the nationwide competitive exam. We compute a school's selection rate by dividing the rank on the national exam of the last admitted student by the total number of enrolled students nationwide.

[12]Thirty thousand students graduate each year in engineering in France.

Information on the rank of the marginal student and on the total number of enrolled students is public and available for the 2002–2012 period.[13] The precise methodology for this calculation is described in Appendix D of the Online Appendix.

The bottom part of Figure 1 displays the selection rate for the most selective schools, and Table A9 in the Online Appendix lists the selection rate of all schools in our sample. The most selective school is Ecole Polytechnique, which recruits the top 2% of students enrolled to the nationwide competitive exam, followed by Mines de Paris, Ecole Centrale Paris, and Ecole des Ponts et Chaussees. The least selective schools accept virtually any applicant.

The first advantage of our talent measure is its focus on the right tale of the distribution, which captures most of the talent premium (Philippon and Reshef 2012). The objective of this selection process is indeed to precisely discriminate among individuals in a highly educated and homogeneous population. All graduates have the same level of education and years of schooling—a 5-year master's degree in engineering—and follow the same educational path. Because of the small scale of French engineering schools and their stable selectivity, our talent measure is granular at the 0.01% level of an age cohort.

Second, our talent measure is comprehensive, and maps most of the requisite traits for successful careers. Beyond academic, cognitive, and communication skills, the national competitive exam gauges personality traits, such as endurance, commitment, ambition, and an ability to perform in a competitive environment. The literature shows that personality traits and their interactions are important determinants of wages (Heckman 1995; Bowles, Gintis, and Osborne 2001; Heckman and Kautz 2012; Deming 2017). The highly selective and competitive environment of preparatory schools prior to the examination, as well as the high stakes of the exam outcome, test candidate motivation and resistance to both effort and stress. A high level of talent according to our measure of talent should be interpreted as an intersection of unusually high performance on the previously mentioned dimensions.

Third, the French administration has designed the selection process to insulate it from any direct influence coming from networking, social background, reputation, and donations beyond talent.[14] The written exam is completely anonymous, and letters of

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

[14] Unsurprisingly, social background has predictive power over student performance on the competitive

recommendation are not used. The heavy workload imposed on all students during the 2 years of preparation limits the potential benefits of additional resources, such as tutors or exam preparation boot camps. A typical week in a preparatory class includes 35 hours of class, two or three 1-hour oral examinations, one 4-hour written examination, and several at home assignments.

Fourth, the high stakes of the competitive exam ensure that talent is binding. In terms of social prestige, and even payoffs (as students from the top school are eligible for stipends), the stakes of the competitive exam are very high and comparable to those associated with a professional career. Each competitor self-selects, with respect to personal investment, to sit for the toughest of exams, despite guaranteed admission to a French university in any year following their high school graduation.

Fifth, and finally, this selection process, which was designed in the early 20th century, is almost unchanged and has almost never varied with specific industry needs. Our measure hence covers the total population of French engineers since 1980 with a high comparability across years owing to stable selection rates.

The unique characteristics of our talent measure thus warrant a relatively large explanatory power when accounting for wage differences, 4 times higher than the one of the standard measures of the literature (Bowles, Gintis, and Osborne 2001).

2.3 Within-school talent measure

To complement our main talent measure, we develop a within-school measure of talent that relies on the student's age at entry. In the French educational system, high-performing students may enter *Grandes Ecoles* at a younger age than their cohort either because they skipped a year at school, or because less talented students often repeat years to improve their ranking at the national exam. Hence, a student who enters a top school at the age of 19 will be more talented, on average, than a student who enters the same school at an age of 20 or older. Early admission, which is not school specific, enables us to introduce school fixed effects in our analysis. We, therefore, build a dummy variable *Early admission* that takes the value of 1 for alumni that get admitted to an engineering

exam, but the selection process ensures that the social background affects the probability of success only through measured individual performance.

school at age 18 or 19. Figure A4 in the Online Appendix shows the distribution of the age at graduation in our sample.

3 Data Overview and Stylized Facts

3.1 Survey data

Our study uses a detailed wage survey of engineering school graduates from 1983 to 2011, conducted by the French Engineering and Scientist Council (IESF), a network of alumni organizations. The IESF represents 199 of the 240 French engineering schools, or 85% of the total population of French graduate engineers in 2010. The survey frequency progressively increased from every 5 years until 1986 to annually beginning in 2004. The filtered number of respondents per survey averages 17,885, and each survey represents, on average, 6.9% of the total population of French engineers (see Table 1), and a response rate of 18.8%, as the survey is sent only to alumni whose names and addresses are known to the organization.

The survey explicitly asks for the yearly gross wages available on the latest December pay sheet, as well as the employer's five-digit industry code. Yearly gross wages include cash bonuses but exclude compensation as stocks or options. Incentives to misreport due to tax concerns are low as, in France, firms directly declare wages to the tax authority and the survey is anonymous. In addition, we retain only observations accompanied by a valid five-digit industry code to ensure that respondents actually consulted their pay sheets when answering the survey. Table A10 in the Online Appendix provides a detailed list of the 48 industries represented, and the distribution of workers across these industries. Finance accounts for approximately 2.9% of the total sample.

The survey also collects detailed information on demographics, education, career, exact occupation title, hours worked, and employer characteristics. We provide more detail on the construction of the final sample and on how we convert our repeated cross-section data into panel data to include individual fixed effects, as well as tests on potential selection bias in the survey respondents in Appendix E of the Online Appendix.

We merge the survey data with information on the skill content of each occupation from the Occupational Information Network (O*NET) using the occupation title of each participant. Our sample includes 34,000 observations with occupation titles covering 245 distinct occupations from 2006 to 2010. We closely follow Autor, Levy, and Murnane (2003) and Deming (2017) to define the intensity of each occupation in each skill. The occupation intensity in *general skills* averages the occupation intensity in social skills, management skills, stress and competition tolerance, while the occupation intensity in *technical skills* averages math, coding and data processing skills. The Online Appendix provides more details on the methodology.

3.2 Summary statistics

Table 1 displays summary statistics on respondent demographics, jobs, careers, employers, work locations, and compensation. The wage distribution among French graduate engineers has become increasingly skewed over the past three decades. Whereas the average wage, in constant euros, decreased slightly in our sample, from 62,000 euros in the 1980s to 58,000 euros in the 2000s due to composition effects, the wages at the 99th percentile increased by more than 27% over the same period.[15] This result is in line with recent research showing that inequality has increased in most OECD countries, mainly at the very top of the wage distribution (Piketty and Saez 2003; Piketty and Saez 2006). The increase in the share of female respondents, as well as in the share of respondents working outside of France, is in line with the evolution of the composition of the engineering graduate population.

INSERT TABLE 1

Table 2 reports statistics on our talent measures. Column 1 displays the selection rate, and Columns 2 to 4 display the number of schools and students by buckets of selection level. Our talent measure is available for 226,846 observations. Less selective schools are, by definition, more numerous than highly selective ones. Column 5 reports the share of respondents that got admitted at least 1 year earlier than the standard age by talent category, which appears to be correlated with the school selection rate. Its focus on a highly educated population notwithstanding, our sample offers considerable heterogeneity with respect to talent.

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

We confirm that our talent measure is correlated with individual productivity by focusing on a specific field with available proxies for productivity: academic research. We proxy output using citation counts from Google Scholar. We collect the information for all alumni from the top-16 French engineering schools who work as academics at U.S. universities, which correspond to the top-four levels of our talent measure. We use *LinkedIn* and searches across top university departments to identify these alumni. Column 6 of Table 2 provides the predicted citation count for the top buckets of our talent measure. The predicted values result from an ordinary least squares (OLS) regression that controls for the research field, gender, experience, experience squared and experience cubed. We observe that the number of citations increases significantly with our talent measure.

INSERT TABLE 2

3.3 Level and distribution of pay in the finance industry: Stylized facts

We first estimate the finance wage premium via the following equation:

$$\ln(w_{n,t}) = \overline{\eta} Talent_n + \beta \mathbb{1}_{Finance_{n,t}} + \lambda X_n + \mu D_t + \epsilon_{n,t}, \tag{10}$$

where $w_{n,t}$ is the yearly gross wage of an individual n in year t, $\mathbb{1}_{Finance_{n,t}}$ represents the indicator variable for working in the finance industry, $Talent_n$ is our talent measure, which is a bijective transformation of a worker talent, D_t is the vector of year dummies, X_n is a vector of individual characteristics, and $\overline{\eta}$ is a function of $\overline{gamma}$, the average elasticity to talent in the economy. This estimation controls for demographic, occupation, job, and employer characteristics.[16]

[16] Demographic controls include years of experience, experience squared, experience cubed, gender, marital status, and gender×marital status. We control for occupation categories using nine dummies (production, logistics, development, IT, commercialization, administration, executive, and education) as Acemoglu, Daron and Autor,D.H (2011) provide evidence of the strong explanatory power of occupational categories in wage regressions, for employer type using five dummies (self-employment, private sector, state-owned company, public administration, and other [e.g., nongovernmental organizations]), and for firm size with four dummies (fewer than 20, from 20 to 500, from 500 to 2,000, and more than 2,000, employees). Job characteristics are represented by an "Ile de France" dummy (Paris area), a working abroad dummy (as well as country dummies for the United States, the United Kingdom, Germany, Switzerland, Luxembourg, China, and Belgium from 2004), and four hierarchical responsibility dummies

Column 1 of Table 3 displays the results. The average wage premium in finance over the 1983–2011 period in our sample is 24%, compared to 15%, 14%, and 8.4% in the next best paying industries, consulting, oil, and chemistry, respectively (see Table A3 in the Online Appendix). Figure A2 in the Online Appendix shows that the finance wage premium has been increasing over the 1983–2011 period.

Our findings that finance industry workers are the best paid and that this has been increasingly the case are consistent with Philippon and Reshef (2012), Oyer (2008), and Goldin and Katz (2008). Our estimation of the finance wage premium is in the lower range of these estimations, however, likely due to our rich set of controls, among which, most importantly, our talent measure, and to the educational homogeneity of our sample.

INSERT TABLE 3

Consistent with Bell and Van Reenen (2014) and Philippon and Reshef (2012), we also document an increasing skewness in the distribution of wages in the finance industry. Figure 2 plots the evolution of the coefficient of the finance sector dummy in quantile regressions estimated at the 10th, 50th, and 90th percentiles in the 1980s, 1990s, and 2000s samples.[17]

INSERT FIGURE 2

4 Empirical Results

This section provides tests of the predictions of the framework outlined in Section 2 and finds supportive empirical evidence for them.

4.1 Higher returns to talent in the finance industry

We first estimate the central equation of our theoretical framework. Consistent with Prediction 1, we find that returns to talent are significantly higher in finance than in the rest of the economy.

from no hierarchical responsibility to chief executive. Table A1 in the Online Appendix displays the coefficient of these control variables.

[17]See Figure A3 in the Online Appendix for a description of the evolution of wages at the 10th, 50th, and 90th percentiles of the earnings distribution in the finance, oil, chemical, and consulting industries and Table A2 in the Online Appendix, which replicates table 6 from Bell and Van Reenen (2014).

4.1.1 Main specification.

We implement the following specification to empirically estimate the ratio $\frac{\gamma_f}{\gamma_{-f}}$ in (9) that measures the relative returns to talent in finance:

$$\ln(w_{n,t}) = \eta_{-f} Talent_n + (\eta_f - \eta_{-f}) Talent_n \times \mathbb{1}_{Finance_{n,t}} + \beta \mathbb{1}_{Finance_{n,t}} + \lambda X_n + \mu D_t + \lambda_{j,t}.^{18}$$

The variables are the same as those used in Equation (10).

Column 2 of Table 3 reports the results. The coefficients of the variable $Talent$ and of the interaction $Talent \times \mathbb{1}_{Finance}$ indicate that returns to talent are 3 times higher in the finance industry than in the rest of the economy.[19] Graduating from a school that has a 10 percentage points lower selection rate is associated with a 5.3% higher wage for a finance worker, whereas this gap is only 1.7% for a worker from the rest of the economy.[20] Including the interaction term $Talent \times \mathbb{1}_{Finance}$ results in the finance premium dropping from 24.2% to 2.2% and being no longer significant. The finance wage premium is therefore allocated across workers mostly according to their talent level, which is consistent with higher returns to talent in this industry.

This finding is robust to interacting each individual control with the finance indicator variable (Column 3) and to including finance-year fixed effects (Column 4). Finally, the coefficient of the triple interaction term between the talent measure, an indicator variable for working in finance, and an indicator variable for working outside of France in Column 5 of Table 3 suggests that returns to talent are 58% higher for engineers who work in finance outside of France, that is, mostly in London or in New York.

Figure 3 further illustrates that returns to talent are higher in finance. We use a nonparametric estimation of Equation (10) and regress the logarithm of wages on fixed effects for selection rate buckets, separately for the finance industry and the rest of the economy. While wages appear to be an increasing function of talent in the whole economy,

[18] We show in Appendix B in the Online Appendix that $\frac{\eta_f}{\eta_{-f}}$ is equivalent to $\frac{\gamma_f}{\gamma_{-f}}$, because our talent measure $Talent_n$ is a bijective transformation of $\ln \frac{T_n}{T_0}$ in (9)

[19] We sum the coefficients of $Talent$ and of the interaction $Talent \times \mathbb{1}_{Finance}$ and divide them by the coefficient of $Talent$.

[20] Table A3 in the Online Appendix runs the same analysis for the 10 highest-paid industries including finance. Returns to talent are twice as high as in the rest of the economy in the consulting industry. However, returns to talent are not higher in the oil and chemical industries than in the rest of the economy, potentially because of physical constraints that limit the output elasticity to scale in these sectors.

the slope is significantly steeper in finance and relatively more convex.

INSERT FIGURE 3

Finally, to identify the part of the finance wage premium that is due to composition effects on worker characteristics, including talent, and the part that is due to differences in returns to these characteristics, we implement a Blinder-Oaxaca decomposition. Figure 4 displays both endowment (i.e., composition) and coefficient (i.e., returns) effects for the following determinants of wages in finance: social background, gender, experience, and talent. Differences in returns to talent appear to explain by far the largest share of the finance wage premium, whereas differences in returns to other characteristics, as well as composition effects are limited.

INSERT FIGURE 4

4.1.2 Occupation fixed effects: Controlling for the endogenous matching of worker to occupation.

Column 6 of Table 3 includes occupation fixed effects to address the concern of an endogenous matching to occupations within finance. This endogenous matching to occupations would result in an upward bias in measuring returns to talent if the more talented workers self-select into the best paying occupations of this industry. Some finance occupations, such as traders, pay much more, on average, than others, and wage dispersion is significantly higher in finance than in other industries. By including occupation fixed effects, we can identify returns to talent among graduates of heterogeneous talent within the same occupation. The statistical significance and the economic magnitudes of our coefficients of interests are left unchanged.

4.1.3 Panel analysis: Controlling for time-invariant individual characteristics.

Columns 7 and 8 of Table 3 estimate respectively equations (10) and (4.1.1) with individual fixed effects to control for selection into finance based on any time-invariant unobserved individual characteristics.

The coefficient of $\mathbb{1}_{Finance_{j,t}}$ in Column 7 of Table 3 indicates a 22% wage increase/decrease for a worker switching in/away from finance, which is close to the level of the finance wage premium estimated using the cross-section. This result is consistent with the result of Gibbons and Katz (1992) that the wage change experienced by a typical industry switcher closely resembles the difference in the industry wage differentials estimated in the cross-section.

The coefficient of the interaction $Talent \times \mathbb{1}_{Finance}$ in Column 8 confirms that returns to talent are significantly higher in finance than in other sectors even when controlling for individual fixed effects.

4.1.4 IV analysis: Exogenous variation in allocation to finance.

To further mitigate concerns over endogenous selection into finance, we instrument worker's finance career choice using stock market performance upon graduation as a plausibly exogenous shock to career decision (Oyer 2008).

The null hypothesis we want to test is whether finance workers are more talented than workers in other industries in a way we cannot observe but that is correlated with our talent measure. If this hypothesis holds, a high stock market performance would expand participation to workers with (unobserved) lower talent, hence decreasing the returns to talent in finance as we measure them. We hence use stock market performance upon graduation to measure the returns to talent for the marginal students that enter finance due to high stock market performance upon their graduation. A graduate's talent is unlikely to be correlated with the stock market performance upon his graduation, which supports the validity of the exclusion restriction.

We first replicate Oyer's (2008) findings that stock market performance in the 24 months preceding graduation has a large effect on graduates' probability to work in finance later in their career by regressing $\mathbb{1}_{Finance}$ on *2-year Stock Market Return* while including the same set of individual controls used in Equation (10). The coefficient of the variable *2-year Stock Market Return* in Column 9 in Table 3 is of comparable magnitude as the point estimate in table II of Oyer (2008). As our specification includes survey year fixed effect, the identification of this first stage is coming from graduates of different cohorts surveyed in the same year. In addition, the F-statistics for the null that $\beta = 0$

is 10.54, which exceeds the “rule of thumb” for strong instruments proposed by Staiger and Stock (1997) and reduces the concern of a weak instrument.

We next instrument $\mathbb{1}_{Finance}$ with the variable *2-year Stock Market Return* in Equation (4.1.1). Column 10 in Table 3 displays the results of this IV analysis. The coefficient of the interaction $Talent \times \widehat{\mathbb{1}_{Finance}}$ shows that returns to talent are actually slightly stronger under this specification. This larger coefficient is inconsistent with selection into finance based on - either time-varying or differently valued in finance - unobserved talent driving our result. The larger coefficient, however, is consistent with the local treatment effect on returns to talent being higher than the average treatment effect, which suggests that workers with higher (unobserved) talent participate more when they have more monetary incentives to do so, and therefore that returns to talent play a role in talent allocation as rationalized in our framework.

4.2 Scale effects

4.2.1 Macro-evidence: Increasing returns to talent in finance.

Prediction 2.a in our model states that both the finance wage premium and returns to talent in finance should increase along with the increase in worker project size that Greenwood and Scharfstein (2013) and Philippon (2015) document for this industry.

Table 4 shows that the returns to talent in finance have increased almost threefold between the 1980s and the 2000s. Columns 2, 4, and 6 report the OLS coefficients of Equation (4.1.1) over three subperiods: the 1980s, the 1990s, and the 2000s. In the 1980s, wage elasticity to talent in finance was 50% higher than in the rest of the economy (Column 2), whereas in the 2000s, returns to talent in finance were more than 4 times larger than in the rest of the economy (Column 6). This result sheds new light on the increased skewness of finance pay since the 1980s documented by Philippon and Reshef (2012).

INSERT TABLE 4

4.2.2 Micro-evidence : Matching between talent and project size.

We test Prediction 2.b from our framework that more talented individuals get matched with larger projects and that size elasticity to talent is larger in finance, which results in a higher wage elasticity to project size.

For this purpose, we first regress for each worker the total size of the projects the workers are responsible for on their level of talent.[21] Column 1 in Table 5 provides the regression coefficients. The coefficient of $Talent$ indicates that more talented workers work on projects of a larger size, while the coefficient of the $\mathbb{1}_{Finance}$ indicates that individuals from our sample are in charge of projects that are on average larger in finance than in the rest of the economy.

In Column 2, we introduce $Talent \times \mathbb{1}_{Finance}$ as an additional explanatory variable. The positive and significant coefficient of this interaction shows that the elasticity of a worker project size to the worker talent is higher in finance than in the rest of the economy. This result is consistent with a higher output elasticity to scale in finance.

We then explore the relationship between wages and project size. We first regress wages on both project size and a finance indicator variable. We observe in Column 3 that wages are positively correlated with the project size. In Column 5, we introduce the interaction $size \times \mathbb{1}_{Finance}$. The significant positive coefficient of this interaction in Column 5 is consistent with a higher wage elasticity to size in finance.

INSERT TABLE 5

4.3 Extensions

4.3.1 Returns to talent and experience.

We test Prediction 3a and find that the difference in returns to talent between finance and the rest of the economy increases with experience.

We start from our mainline specification from Equation (4.1.1), and introduce interaction terms between talent and indicator variables for levels of experience.[22] Column 1 of Table 6 displays the results. In the whole economy, we find that both wages and

[21] We have collected this information by contributing to the design of the 2010 and 2011 surveys.

[22] These levels of experience map to analyst, associate, vice president, and director and over in investment banks. Results are robust to using other cutoffs.

returns to talent increase with experience. We then restrict the sample to the finance sector.[23] While the direct effect of experience is similar in finance than in the rest of the economy, returns to talent, which are higher on average, also increase significantly faster with experience in finance. This empirical fact is consistent with a complementarity between talent and industry specific skills in finance, which might lead to a segmentation of the labor market, with firms competing for workers within their industry.

INSERT TABLE 6

4.3.2 General versus technical skills intensity.

We test Prediction 3b and find that returns to talent are higher in positions that require general skills versus technical skills, and that this pattern is more pronounced in finance relative to the rest of the economy.

We introduce in our general specification the proxies for the occupation intensity in general skills and in technical skills described in section 4, which we interact with the talent measure.

Column 3 of Table 6 displays the results. We first observe that the labor market better rewards occupations requiring general skills than occupation requiring technical skills, even after controlling for talent. This result is consistent with the literature documenting a large return to social and leadership skills (Kuhn and Weinberger 2005; Heckman, Stixrud, and Urzua 2006; Lindqvist and Vestman 2011; Kautz et al. 2014). We then introduce interaction terms between the proxies for skill intensity and the talent measure in Column 4. We observe a complementarity between talent and occupations that require general skills, as both the main effect and the interaction term bear a positive coefficient. On the other hand, for technical skills, the coefficient of the interaction term is positive, but the main effect is not as strong, which indicates that returns to talent are only modest in the most technical jobs.

We then restrict the sample to the finance industry in Column 5 and observe an even higher complementarity between talent and the need for general skills in this industry, as both the main effect coefficient and the interaction term coefficient are larger in magnitude

[23] Alternatively, we could keep the sample unchanged and interact all variables with a finance indicator. We restrict the sample for clarity purpose.

than for the whole economy. This result is consistent with financial firms rewarding mostly general skills, and even more so than in other industries.

4.3.3 Talent allocation.

We test Prediction 3c and find evidence of talented individuals increasingly selecting into finance as forfeiting skills specific to other industries is increasingly offset by higher returns to talent in finance.

Figure 5 plots the evolution of the share of graduate engineers from our sample working in finance for the whole sample and for the most selective schools of our sample, with a selection rate below 10%.[24] We observe that French graduate engineers have been increasingly working in finance and that this pattern is significantly more pronounced for the most talented individuals. While 3% of this group worked in finance in 1986, finance workers represent more than 8% of this subsample in 2011.[25]

INSERT FIGURE 5

4.3.4 Returns to talent and performance pay.

Last, we test Prediction 3d and find that the share of performance pay increases with talent, that returns to talent are higher in performance pay jobs, and that this is even more the case in finance.

Table 7 provides the results. Columns 1 and 2 first report estimates for a specification where the dependent variable is the share of performance pay over total pay. The coefficient of $\mathbb{1}_{Finance}$ in Column 1 indicates that the share of performance pay is higher in finance than in other sectors, and the coefficient on the talent measure that the share of performance pay is increasing with talent. In Column 2, the coefficient of $Talent \times \mathbb{1}_{Finance}$ indicates that the relation between talent and performance pay is even stronger in finance than in the rest of the economy.

[24] The pattern is similar if we use a 5% cutoff.

[25] As with any survey data, a potential concern is that the allocation of respondents across industries may not be perfectly representative of the whole population. That we consider the relative evolution across talent levels and industries partly mitigates this concern. If anything, we should expect that the incentives of the most talented workers to answer the survey would have decreased with years, and even more so in finance, as the opportunity cost of answering the survey increases.

Second, Column 3 reports estimates of our wage equation where we interact $Talent$ with an indicator variable for performance-pay occupations, further interacted with $\mathbb{1}_{Finance}$ in Column 4. The coefficient of the double interaction *Talent* $\times$ *Performance-pay Occupation* in Column 3 indicates that returns to talent are higher in performance-pay occupations (consistent with Lemieux, MacLeod, and Parent (2009)), and the coefficient of the triple interaction *Talent* $\times$ *Performance-pay Occupation* $\times \mathbb{1}_{Finance}$ in Column 4 shows the effect is even larger in finance. Hence, returns to talent are higher in performance-pay than in non-performance-pay jobs, and the gap is larger in finance than in the rest of the economy.

INSERT TABLE 7

This result is consistent with finance employers relying more on performance pay to attract and retain talent than other firms (Lazear 2000; Gabaix and Landier 2008; Lemieux, MacLeod, and Parent 2009; Benabou and Tirole 2016), and/or in line with models of moral hazard where the marginal benefit of effort is larger for talented workers in finance than in other industries. Both channels point towards a high observed productivity of talent in finance.

5 Competing Explanations

5.1 Compensating wage differential.

An alternative explanation for higher returns to talent in finance would be that firms compensate more talented workers in finance for specific job attributes affecting disproportionately this group. These attributes may include a higher level of income risk, lower nonpecuniary benefits, a poorer fit with workers' preferences or a higher level of required effort, all resulting in a disutility from working in finance that is higher for talented workers.

However, both the existing literature and our findings suggest that the compensating wage differential cannot explain the finance wage premium and the higher returns to talent in finance we document.

First, Philippon and Reshef (2012) and Oyer's (2008) estimates of the lifetime pay premium in finance explicitly control for hours worked, wage risk, career length, and the risks of exiting the finance sector.

Second, our central result is robust to controlling for hours worked and elicitations of stress levels, job insecurity, and income risk. We exploit data from our survey to build four indicator variables for high perceived stress, job insecurity, and long hours (i.e., either more than 5 extra hours per week or more than 10 extra hours per week) . We also interact each of these variables with the finance indicator variable and find no impact on the measured returns to talent.[26] Table A5 in the Online Appendix displays the regression coefficients of our central specification when including such controls.

Third, our results are robust to including occupation fixed effect in our main specification (see Column 6 of Table 3). For the compensating differential to hold as an alternative explanation for our result, the intensity of the compensated condition needs therefore to be positively correlated with the worker level of talent, keeping the occupation identical. In a given finance occupation, talented workers would work longer hours, face higher income or redundancy risk, or particularly dislike finance, which is difficult to square with their higher abilities, their decision to join finance, and the firm decision to hire them.

5.2 Selection effects.

A previously mentioned challenge of our analysis is to control for the endogenous selection of workers into finance (Roy 1951). Endogenous selection might drive our results if it relies on characteristics that are correlated with our talent measure.

We complement the panel and IV analyses in Section 4.1 with a Heckman's selection model. We investigate whether returns to talent might appear to vary across industries because workers self-select into an industry only when their expected income exceeds some industry-specific threshold. These heterogeneous thresholds, which might result

[26]We do not control for stress or excessive workloads in our main results, because this information is not available for the entire sample. Self-reported level of stress and job security might be biased. Indeed, if talented individuals who work in finance are those who choose risky, high-pressure environments, they might not report different levels of stress or perceived job security even if a neutral observer would see a large difference. However, in equilibrium, these individuals should not receive such a large compensating premium if they do not suffer from their working conditions. Therefore, controlling for workers' perceptions is adequate in our setup.

from industry specific nonpecuniary benefits, would induce individuals with low and high talent to heterogeneously self-select into industries.[27]

However, we find moderately higher returns to talent after running a Heckman selection model. Columns 1 and 2 of Table 9 display the regression coefficients.

5.3 Measurement errors of returns to talent in finance

One important empirical challenge we face is that the higher returns to talent we observe in finance might result from our talent measure capturing worker characteristics uniquely suited to working in finance.

5.3.1 Observable individual characteristics.

Our talent measure might be correlated with individual characteristics that are more compensated in finance, potentially biasing upwards the returns to talent in finance relative to other industries. For example, graduates from the most selective schools are more likely to live in Paris than in the rest of France, and working in Paris might have a higher impact on wages in finance than in other industries.

To address this concern, we run our mainline specification including interaction terms between working in finance and the vector of individual characteristics provided in our data: location, social background, family status and gender.

Column 4 of Table 3 shows that our result is robust when we control for the interaction of each of these individual characteristics with the finance dummy. The Blinder Oaxaca decomposition displayed in Figure 4 confirms that returns to talent largely dominate returns to any other individual characteristics when describing the finance wage premium.

The instrumental variable analysis from the previous section also addresses this concern as selection into finance induced by high stock market performance is orthogonal to these individual characteristics.

[27]In industries with a high wage threshold, this selection would lead to underestimating returns to talent, as among low-talent workers, the econometrician only observes those with unusually high earning potential. Conversely, the difference in returns to talent between finance and the rest of the economy might be biased upward if the wage threshold to work in finance is lower than in other industries. This lower threshold could be rationalized by, for instance, the prestige associated with working in finance.

5.3.2 Social background and individual network.

Another concern is that our measure of talent is correlated with social background and individual network, and that this may drive our result if these attributes are more valued in finance. While social background affects the accumulation of human capital (Becker 1994), we want to ensure that social background and network do not affect wages *beyond* an individual's talent.

In Table 8, we conduct three different tests to rule out individual networks as a potential driver of our result. First, we run our main specification, while including parental occupation fixed effects (Column 2) and the interaction of parental occupation fixed effects with $\mathbb{1}_{Finance}$ (Column 3). These specifications allow us to control for potential composition effects on social background, as well as for social background being differentially valued in finance. The coefficient on $Talent \times \mathbb{1}_{Finance}$ is unaffected by these controls. This is consistent with the results from Heckman selection model in Table 9 that includes parental occupation dummies in the selection equation.

Second, in Column 4, we restrict our sample to *First Generation* students whose parents do not possess any university degrees and are therefore less likely to benefit from a powerful professional network. We find that our results are robust to restricting our analysis to this subsample; in fact, they are actually strengthened, as the coefficient on the interaction between talent and finance is significantly higher than for the benchmark sample (Column 5).[28]

Finally, in Column 6, we restrict our sample to graduates of non-French nationality working in France, following the rationale that their parents are likely to be less integrated into French social networks. We find that our main result remains robust to this specification.

INSERT TABLE 8

5.4 Treatment effects at the school level

One additional concern about our empirical strategy would be that our results are driven by an unobserved variable at the school level that is both correlated with the school

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

selection rate and has heterogeneous effects on wages across industries. For example, the school alumni network might be stronger in top schools, and more valuable in finance. Alternatively, top schools might teach skills more relevant to finance than other schools. We develop a set of complementary empirical strategies to tackle this concern.

5.4.1 Absorbing school characteristics with a school fixed effect.

To absorb school-level unobserved characteristics, we use our within-school measure of talent, age at entry, and include school fixed effects in our main specification. Column 4 of Table 9 reports the regression coefficients when we interact the *Early Admission* talent measure with the finance indicator variable. We find that, among alumni from the same school, those who get admitted early are paid relatively more and that this effect is significantly stronger in finance. The effect is amplified when we control for industry-year fixed effects (Column 5).[29]

INSERT TABLE 9

5.4.2 A quasi-natural experiment: A shock to average talent at Supélec.

We then exploit a shock to the average level of talent within one specific school. In 1985, the École Superieur d'Electricite (Supélec) opened a third campus and thereby increased by 25% its number of students. This increase in the size of each cohort led to a drop in selectivity, which translated to a decrease in the average talent of Supélec cohorts. At the same time, other school-level characteristics, such as alumni network or curriculum remains unchanged, as all Supélec students receive the same degree and can move between campuses during the curriculum.

We therefore implement a difference-in-differences specification, to test whether returns to being a graduate from SupÉlec are differentially reduced in finance and in the rest of the economy after the drop in selectivity. We restrict the sample to graduates that entered an engineering school less than 3 years before the reform and less than 3 years after. The model also includes year fixed effects to control for the year of the survey. Results are reported in Columns 6 and 7 of Table 9. We observe in Column 6 that

[29] This measure of talent has a lower coefficient, which can be explained by the lower variance in talent within schools, as compared to the variance in talent across schools.

returns to graduating from Supélec drop following the drop in selectivity of this school. Column 7, however, shows that this drop is significantly more pronounced for Supélec graduates working in finance. This result is difficult to reconcile with unobserved variable characteristics at the school level being the driver of our central result.

5.4.3 Robustness to excluding top schools.

To further rule out alumni networks as the driver of our main result, we exclude schools related to Ecole Polytechnique, the leading French engineering school, from our sample. The rationale is that elite alumni networks would be the most effective in the most selective and prestigious schools. Column 1 in Table 8 displays the regression coefficients for this restricted sample: our central result—the significantly higher returns to talent in finance—still holds for this restricted sample.

5.4.4 Controlling for finance training.

Finally, to control for differences in what students learn in engineering schools, we exploit information from our survey about the educational track of each respondent within their school. Higher returns to talent could be driven by a larger share of students opting for economics or finance training in top schools. Lemieux (2014) documents that workers earn more when they are matched to a job that is related to their field of study. Therefore, we include a dummy that indicates whether the engineering graduate followed a specialization in economics or finance in our main specification, as well as its interaction with our finance sector dummy.[30] Column 5 in Table A4 in the Online Appendix shows that our main result is unaffected: returns to talent are still 3 times higher in the finance industry.

6 Conclusion

In this paper, we show that returns to talent are high and have been increasing over the years in the finance industry. To estimate returns to talent calls for an appropriate

[30] In our sample, 1.6% of engineers opted for an economics or finance major. Among the engineers who opted for an economics or finance major, 34% work in the finance industry. Overall, only 13.5% of the engineers working in finance opted for an economics or finance major.

measure of talent. We exploit, for this purpose, the results of a competitive examination among highly educated candidates that captures not only cognitive skills but also personality traits, such as motivation, self-discipline, and low cost of effort. Our set of empirical findings are consistent with finance workers' pay being a competitive outcome driven by a high complementarity between talent and scale in finance. The higher returns to talent in finance raise potential questions over its effects on talent allocation and income inequalities.

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7 Figures

Figure 1. Selection process of French engineering schools

High school: science major

⇓

Preparatory school: 2 years, *selection rate: 15%*

Subject	**# hours (per week)**	**# exams (per month)**
Mathematics	12	4
Physics and chemistry	8	2
Industrial science	2	0
Literature	2	1
Foreign language	2 to 4	2
Programming	2	0

⇓

National competitive exam

Written competitive exam		**Oral competitive exam**	
Subject	**Coefficient**	**Subject**	**Coefficient**
Mathematics 1	8	Mathematics 1	16
Mathematics 2	7	Mathematics 2	16
Physics	6	Physics	20
Industrial science	6	Industrial science	15
Literature	6	Literature	8
Foreign language	6	Foreign language	8
Computer science	4	Chemistry	9
		Sports	5

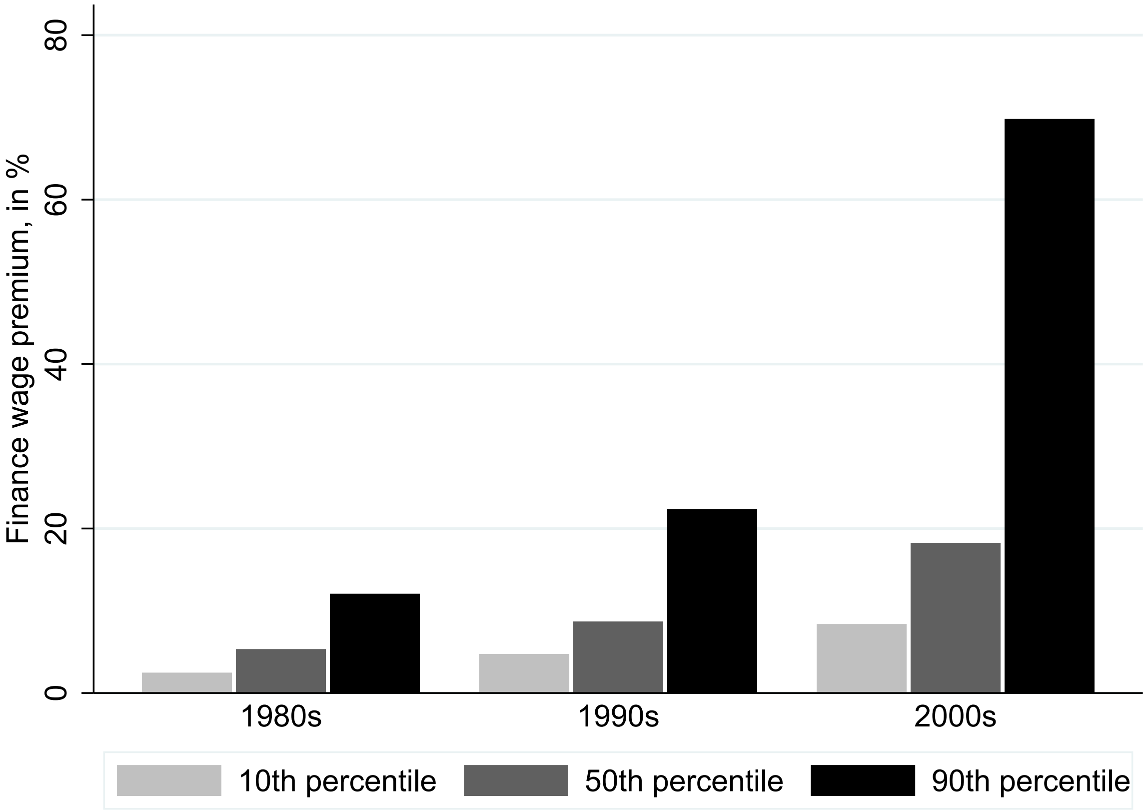
⇓

Final ranking: Allocation to a school

Rank	**School**	**Selection rate (%)**
1	Ecole Polytechnique	1.5
2	Mines Paritech	2.5
3	Centrale Paris	4.6
4	Ponts Paristech	4.9
5	ESPci Paristech	6.8
..	....	...
215	Esme Sudria Ivry Sur Seine	95
216	Esigetel Fontainebleau	97.6
217	Ei-Ispa Alencon	98.2
218	3II Limoges	98.5

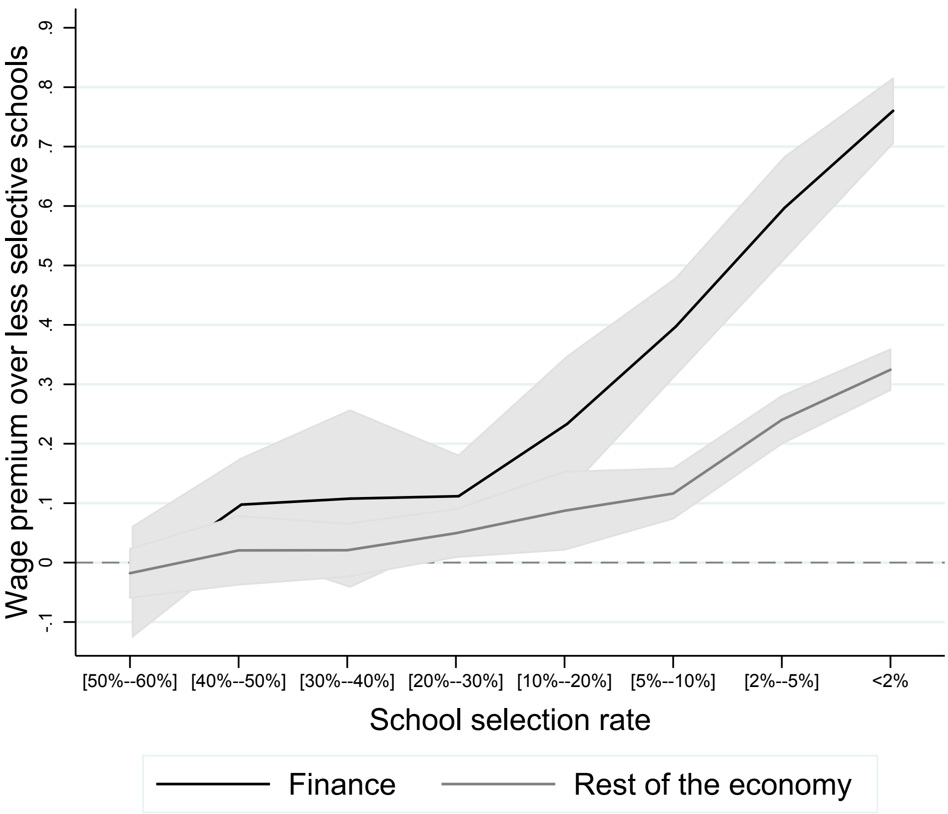
This figure summarizes the selection process for French Engineering Schools and illustrates the resultant school selection rate. French engineering schools, or "Grandes Ecoles," admit student based on their national ranking in a competitive written and oral exam. The school selection rate, measured as the ratio of the marginal student's rank in the national competitive exam to the total number of competing students, is the measure of talent used throughout the paper.

Figure 2. Evolution of the finance wage premium by percentile of the wage distribution



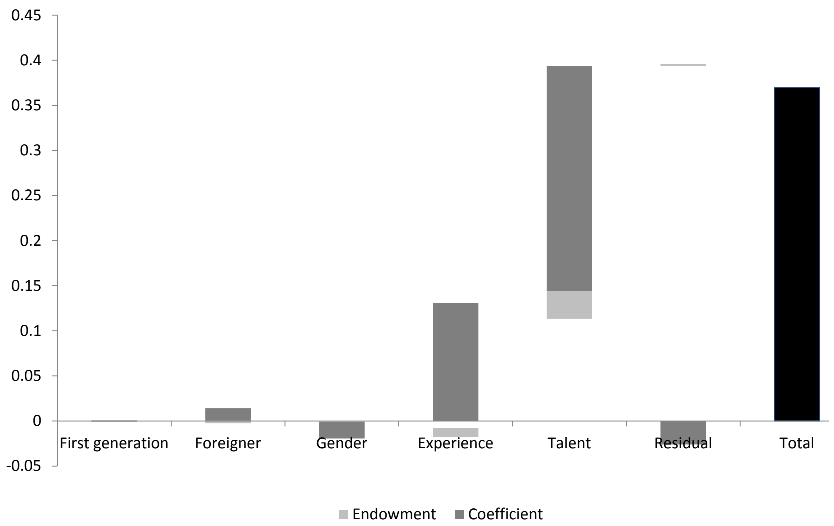
This figure plots the evolution of the coefficient of the financial sector dummy in quantile regressions estimated at the 10th, 50th, and 90th percentiles of the wage distribution, in which the dependent variable is the log of the yearly gross wage. We use 48 industry dummies, with the sum of all industry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

Figure 3. Returns to talent: Finance versus other industries



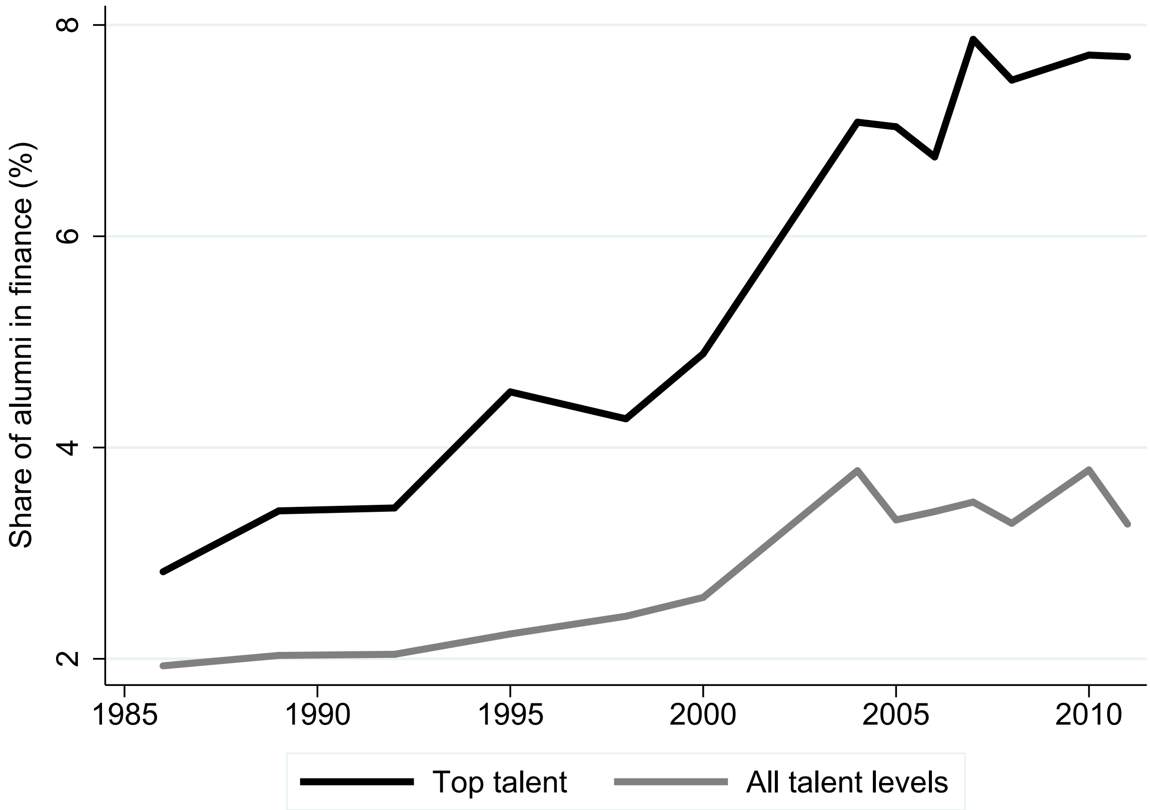
This figure compares returns to talent in finance with returns to talent in the rest of the economy. Talent is measured as the school selection rate, as per the engineering *Grandes Ecoles* selection process, which is described in Section 3. The figure plots regression coefficients from Equation (10), where $Talent$ is replaced with a set of dummies for ranges of school selection rate. The dependent variable is the log of the yearly gross wage, and the regression is estimated over the sample of finance workers (black line) and the other workers (gray line). The lines indicate point estimates, and the gray areas indicate 90% confidence bounds based on standard errors clustered at the school level. The model includes year fixed effects and experience level, squared and cubed.

Figure 4. Blinder-Oaxaca decomposition of the finance wage premium



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

Figure 5. Engineer allocation to finance by level of talent and over time



This figure plots the evolution of the share of graduate engineers from our sample working in finance, for the total sample and for top-talented graduates, that is, graduates from schools with a selection rate lower than 10%, as per the engineering *Grandes Ecoles* selection process described in Section 3.

8 Tables

Table 1. Summary statistics

	1980s	1990s	2000s
Sample size			
Average number of observations per survey	21,752	14,769	17,753
Number of surveys	2	4	7
Total number of observations	43,503	59,074	124,269
Response rate (%)	20.5	17.5	Nd
Coverage of total population of French engineers (%)	9.2	7.1	6.1
Compensation (in 2005 constant euros)			
Mean yearly gross wage	61,594	62,631	57,992
90th percentile	98,662	102,114	95,600
99th percentile	145,645	170,011	186,439
SD	26,665	31,898	39,098
Engineers per sector (%)			
Finance	2.0	2.3	3.5
Consulting	0.0	1.6	3.6
Oil	3.0	1.8	0.7
Chemical	3.7	3.7	2.6
Demographics			
Mean age	38.1	38.0	35.0
% female	6.6	11.9	15.3
% married	76.5	73.3	77.2
Foreigners	–	–	8.6
First generation	–	–	11.8
Job location			
% working outside of France	2.4	4.1	12.1
% working in the Paris area	45.9	42.6	39.3
Job characteristics			
% Performance-pay jobs	–	–	42.2
Project size, median (million euros)	-	-	2.0
Project size, p10 (million euros)	-	-	0.10
Project size, p90 (million euros)	-	-	45.0
Career			
Mean experience (years)	14.4	13.5	11.9
% team manager	31.7	25.2	21.4
% department head	15.9	19.2	17.7
% top executive	7.0	11.3	7.1

This table reports summary statistics for the main compensation and demographic variables in our data set. 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 selection rates

Selection rate	#*schools*	Graduates		% early acceptance	# citations (academics)	Round wage
		Number	% share			% share
(1)	(2)	(3)	(4)	(5)	(6)	(7)
< 2%	1	6,173	2.7	35.8	3,174***	24.5
[2%–5%]	3	12,868	5.7	21.1	1,897***	22.3
[5%–10%]	7	20,119	8.9	14.1	1,623**	20.3
[10%–20%]	7	15,414	6.8	13.9	1,147**	20.5
[20%–30%]	5	9,004	4.0	16.3	–	15.0
[30%–40%]	8	11,468	5.1	11.3	–	19.6
[40%–50%]	14	46,676	20.6	12.8	-	20.2
[50%–60%]	21	20,747	9.1	8.7	—	27.7
[60%–70%]	35	30,057	13.2	11.6	–	28.3
[70%–80%]	10	6,558	2.9	7.6	–	25.8
[80%–100%]	88	47,762	21.1	9.9	–	29.4
Total	199	226,846	100.0	–	–	24.1

This table reports summary statistics by school selection rates. French engineering schools, or "Grandes Ecoles," admit students based on students' national ranking in a competitive written and oral exam. Selection rate (Column 1) is measured as the ratio of the marginal student's rank in the national competitive exam to the total number of competing students. Columns 2, 3, and 4 report, respectively, the number of schools, the number of students, and the share of students in our data for each bracket of selection rate. Column 5 reports the share of respondents that are admitted in an engineering school at least 1 year ahead of the regular curriculum. Column 6 gives the predicted number of citations (at mean experience) of academics that graduated from a school of the corresponding level of selection. The predicted values result from an OLS regression where the dependent variable is the 1% winsorized number of citations in Google Scholars. The model includes field fixed effects, experience, experience square, experience cubed and gender dummies. The sample comprises 98 graduates from top engineering schools working at U.S. universities. Column 7 reports the share of respondents that declare a multiple of 100 as wage for each level of talent .

Table 3. Returns to talent in the finance industry

	OLS						Panel		IV	
	log(wage)								$\mathbb{1}_{Finance}$	log(wage)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}_{Finance}$	0.242***	0.022			-0.013	0.039	0.224***	0.074		
	(0.034)	(0.032)			(0.027)	(0.038)	(0.042)	(0.058)		
Talent	0.179***	0.166***	0.166***	0.165***	0.168***	0.172***			1.287***	0.199***
	(0.029)	(0.026)	(0.026)	(0.026)	(0.027)	(0.030)			(0.357)	(0.039)
Talent $\times\mathbb{1}_{Finance}$		0.369***	0.368***	0.394***	0.290***	0.327***		0.274**		
		(0.071)	(0.068)	(0.062)	(0.059)	(0.064)		(0.126)		
Talent $\times\mathbb{1}_{Finance}\times$ *Abroad*					0.238***					
					(0.065)					
2-year stock market return									0.126***	
									(0.039)	
$\widehat{\mathbb{1}_{Finance}}$										0.135***
										(0.015)
Talent $\times$ $\widehat{\mathbb{1}_{Finance}}$										0.486***
										(0.025)
Controls										
Individual fixed effects	–	–	–	–	–	–	Yes	Yes	–	–
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $\times\mathbb{1}_{Finance}$	–	–	Yes	–	–	–	–	–	–	–
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbb{1}_{Finance}\times$ year FEs	–	–	–	Yes	–		–	–	–	–
Occupation fixed effects	–	–	–	–	–	Yes	–	–	–	–
Observations	198,886	198,886	198,886	198,886	198,886	37,271	22,582	22,582	151,517	150,650
R^2	.691	.694	.696	.696	.697	.703	.939	.940		
F statistic									10.75	

This table reports the coefficient of OLS regressions and instrumental variable analyses, where the dependent variable is the log of yearly gross wage. Returns to talent in the finance industry amount to the coefficient of *Talent* plus the coefficient of the interaction *Talent* $\times\mathbb{1}_{Finance}$. *Talent* is equal to *1 minus selection rate*, where *Selection rate* is the selection rate of each school. Column 5 shows the coefficient of the interaction $Talent\times\mathbb{1}_{Finance}\times Abroad$, where $Abroad$ is an indicator variable for working outside of France. The model also includes the corresponding double interactions $\mathbb{1}_{Finance}$ $\times$ *Abroad* and *Talent* $\times$ *Abroad*. Columns 6 is restricted to the 37,000 observations with occupations over the 2006–2010 period and includes occupation fixed effects. Columns 7 and 8 include individual fixed effects in a panel analysis. Columns 9 and 10 display the regression coefficients from the two stages of an instrumental variable analysis where working in finance is instrumented with stock market performance upon graduation. Column 9 shows the first-stage regression, where the dependent variable is an indicator variable for working in finance, whereas *2-year market return* indicates the 2-year average market return upon graduation. Column 10 shows the coefficients from the second stage of the IV analysis, where $\mathbb{1}_{Finance}$ is instrumented by *2-year market return*. All equations include year dummies, a female dummy, a married dummy, a Paris area dummy, a working abroad dummy, experience level, squared and cubed, four hierarchic responsibility dummies, nine occupation category dummies, four firm size dummies, and four firm-type dummies. Column 3 also includes interactions of each of our individual controls with the finance indicator variable, and Column 4 includes $\mathbb{1}_{Finance}\times Year$ fixed effects. Standard errors are clustered at the school level and reported in brackets. * p<.10; ** p<.05; *** p<.01.

Table 4. Increasing wage returns to talent in the finance industry

	log(wage)					
	1980s		1990s		2000s	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{Finance}$	0.072***	0.017	0.142***	0.013	0.304***	0.015
	(0.012)	(0.024)	(0.020)	(0.030)	(0.044)	(0.035)
Talent	0.164***	0.162***	0.164***	0.158***	0.180***	0.159***
	(0.023)	(0.023)	(0.028)	(0.027)	(0.033)	(0.030)
Talent $\times \mathbb{1}_{Finance}$		0.087**		0.208***		0.501***
		(0.041)		(0.045)		(0.071)
Controls						
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,731	41,731	52,932	52,932	104,223	104,223
R^2	.713	.713	.713	.714	.685	.690

This table reports the coefficient of an OLS regression over three samples: 1980s = 1986 and 1989 surveys (Columns 1 and 2); 1990s = 1992, 1995, 1998, and 2000 surveys (Columns 3 and 4); and 2000s = 2004, 2005, 2006, 2007, 2008, 2010, and 2011 surveys (Columns 5 and 6). The dependent variable is the log of the yearly gross wage. *Talent* is equal to *1 minus selection rate*, as described in Section 2. All equations include year fixed effects, a female dummy, a married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, nine occupation category dummies, four firm size dummies, and four firm-type dummies. Standard errors are clustered at the school level and reported in brackets. * p<.10; ** p<.05; *** p<.01.

Table 5. Evidence of high talent scalability in the finance industry

	log(project size)		log(wage)		
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}_{Finance}$	0.436***	0.029	0.391***	0.065	-0.278
	(0.164)	(0.251)	(0.067)	(0.056)	(0.279)
Talent	0.526***	0.503***		0.210***	
	(0.189)	(0.187)		(0.037)	
Talent $\times \mathbb{1}_{Finance}$		0.735*		0.585***	
		(0.396)		(0.104)	
Project size (log)			0.051***	0.049***	0.050***
			(0.002)	(0.002)	(0.002)
$\mathbb{1}_{Finance} \times$ *Project size (log)*					0.044**
					(0.020)
Controls					
Individual controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	10,462	10,462	10,235	10,235	10,235
R^2	.128	.129	.551	.576	.552

This table reports the coefficient of OLS regressions, where the dependent variable is the total size of the projects the workers are responsible for in Columns 1 and 2 and the log of the yearly gross wage in Columns 3 to 5. *Talent* is equal to *1 minus selection rate.* The total size of the projects each worker is responsible for are self-reported in the 2010 and 2011 surveys. Column 1 illustrates that project size is larger in finance, and that talents are allocated to larger projects. The coefficient on the interaction term $Talent \times \mathbb{1}_{Finance}$ in Column 2 is consistent with the talent-scale matching effect being more pronounced in finance. In Column 5, the coefficient on the interaction term $\mathbb{1}_{Finance} \times Projectsize$ is consistent with the effect of scale on wages being larger in finance. All equations include year fixed effects, a female dummy, a married dummy, and a Paris area dummy. Standard errors are clustered at the school level and reported in brackets. * p<.10; ** p<.05; *** p<.01.

Table 6. Talent, experience, and general skills: Evidence for complementarity

	Experience		Skills		
	log wage				
Sample	Finance (1)	All (2)	All (3)	All (4)	Finance (5)
Talent	0.313***	0.158***	0.236***	-0.557***	-0.259
	(0.056)	(0.023)	(0.044)	(0.118)	(0.751)
Experience, 3 to 6 years	0.137***	0.129***			
	(0.041)	(0.006)			
Experience, 6 to 9 years	0.286***	0.280***			
	(0.050)	(0.009)			
Experience, more than 9 years	0.640***	0.623***			
	(0.048)	(0.018)			
Talent × *Experience, 3 to 6 years*	0.203***	0.008			
	(0.065)	(0.011)			
Talent × *Experience, 6 to 9 years*	0.322***	0.034*			
	(0.065)	(0.018)			
Talent × *Experience, more than 9 years*	0.280***	0.098***			
	(0.076)	(0.033)			
General skills			0.256***	0.161***	0.387***
			(0.011)	(0.020)	(0.127)
Talent × *General skills*				0.197***	0.321*
				(0.043)	(0.181)
Technical skills			-0.105***	-0.143***	0.058
			(0.008)	(0.013)	(0.085)
Talent × *Technical skills*				0.077***	0.030
				(0.022)	(0.116)
Finance			0.523***	0.516***	
			(0.050)	(0.048)	
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	5,793	206,637	39,000	39,000	1,321
R^2	.452	.506	.595	.596	.309

This table reports the coefficient of OLS regressions, where the dependent variable is the log of the yearly gross wage. $Experience, 3to6years$, $Experience, 6to9years$, and $Experience, morethan9years$ are dummy variables indicating, respectively, whether the individual has between 3 and 6 years, 6 and 9 years, and more than 9 years of experience. The variable $Generalskills$ measures the intensity of each occupation in the following skills: social skills, management skills, stress , and competition tolerance . The variable $Technicalskills$ measures the intensity of each occupation in the following skills : mathematical, coding, and data processing. The interaction $Talent \times Skills$ measures how returns to talent vary with the skill intensity of a worker's occupation. The skill intensity of each occupation comes from O*NET. See the text and the Online Appendix for details on the construction of each O*NET occupation measure. All equations include year dummies, a female dummy, a married dummy, a Paris area dummy, a working abroad dummy, and experience level squared and cubed. Standard errors are clustered at the school level and reported in brackets. * p<.10; ** p<.05; *** p<.01.

Table 7. Performance pay and talent

	Performance-pay share (% of total pay)		Total pay log (total wages)	
	(1)	(2)	(3)	(4)
$\mathbb{1}_{Finance}$	10.432***	1.741	0.206***	-0.018
	(1.300)	(1.235)	(0.029)	(0.024)
Talent	1.867***	1.021**	0.139***	0.137***
	(0.548)	(0.449)	(0.024)	(0.024)
Talent $\times \mathbb{1}_{Finance}$		14.417***		0.050
		(2.184)		(0.039)
Performance-pay job dummy			0.128***	0.135***
			(0.011)	(0.009)
Talent $\times$ *Performance-pay job*			0.094***	0.054***
			(0.022)	(0.017)
$\mathbb{1}_{Finance} \times$ *Performance-pay job*				0.104***
				(0.035)
Talent $\times \mathbb{1}_{Finance} \times$ *Performance-pay job*				0.290***
				(0.056)
Controls				
Individual controls	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	52,195	52,195	51,122	51,122
R^2	.202	.211	.702	.709

This table illustrates how the use of performance pay relates to talent and returns to talent. The table reports the coefficient of OLS regressions, where the dependent variable is the share of performance pay in Columns 1 and 2 and the log of the yearly gross wage in Columns 3 and 4. The sample is restricted to the period 2000 to 2011, for which these data include information on the structure of pay. The performance-pay indicator variable is equal to 1 for jobs where the performance-pay share is strictly higher than 10% of total pay (the median value in our sample). All equations include year fixed effects, 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<.10; ** p<.05; *** p<.01.

Table 8. Controlling for network and social background effects

	log(wage)						
Sample	*Excluding X*	*With parent occupations*		*First generation*		*Foreigners*	
	Related schools			*Only*	*Control group*	*Only*	*Control group*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}_{Finance}$	0.055	0.011		-0.030	0.010	0.087	0.016
	(0.039)	(0.035)		(0.067)	(0.035)	(0.102)	(0.035)
Talent	0.129***	0.155***	0.155***	0.132***	0.158***	0.160***	0.158***
	(0.027)	(0.028)	(0.028)	(0.020)	(0.029)	(0.041)	(0.030)
Talent $\times \mathbb{1}_{Finance}$	0.277**	0.484***	0.479***	0.598***	0.489***	0.494***	0.499***
	(0.112)	(0.068)	(0.068)	(0.135)	(0.068)	(0.130)	(0.071)
Controls							
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent Occ. FEs	–	Yes	Yes	–	–	–	
Parent Occ. $\times \mathbb{1}_{Finance}$ FE	–	–	Yes	–	–	–	
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,713	114,116	114,116	14,100	114,781	1,399	104,097
R^2	.690	.690	.690	.701	.689	.579	.690

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 excludes schools 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, Telecom Paris, and Centrale Paris. In Columns 2 and 3, the sample is restricted to the 2000–2010 period where information on parent occupation is available. The specification includes parent occupation fixed effects in Column 2 and parent occupation fixed effects $\times \mathbb{1}_{Finance}$ in Column 3. Parent occupations are grouped into the following categories: manager, intermediate occupation, employee, worker, independent profession and other. In Column 4 the sample is restricted to *First generation* graduates, whose parents do not have college education, and in Column 5 the sample is restricted to the corresponding control group, as the information on parents' occupation is only observable on the 2000–2010 period. In Column 6, the sample is restricted to individuals born outside France, and in Column 7 to the corresponding control group. Information on parents' country of origin is also only available from 2000 to 2010. All equations include year fixed effects, a female dummy, a married dummy, a Paris area dummy, a working abroad dummy, and an experience level squared and cubed. Standard errors are clustered at the school level and reported in brackets. * p<.10; ** p<.05; *** p<.01.

Table 9. Controlling for endogenous matching to finance: Heckman selection model, within-school talent measure, natural experiment

LHS variable	log(wage)						
	Heckman model		OLS: Within-school talent measure			Natural experiment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}_{Finance}$	0.336***	0.024	0.233***	0.225***		0.186***	0.169***
	(0.049)	(0.033)	(0.014)	(0.013)		(0.038)	(0.030)
Talent	0.180***	0.158***					
	(0.032)	(0.029)					
Talent $\times \mathbb{1}_{Finance}$		0.507***					
		(0.067)					
Early admission			0.008***	0.006***	0.006***		
			(0.002)	(0.002)	(0.002)		
$\mathbb{1}_{Finance} \times$ *Early admission*				0.046*	0.069***		
				(0.024)	(0.022)		
Supelec						0.092***	0.088***
						(0.009)	(0.009)
Supelec $\times$ *After*						-0.051***	-0.047***
						(0.005)	(0.005)
$\mathbb{1}_{Finance} \times$ *After*							0.030
							(0.040)
$\mathbb{1}_{Finance} \times$ *Supelec*							0.137***
							(0.037)
$\mathbb{1}_{Finance} \times$ *Supelec* $\times$ *After*							-0.156***
							(0.041)
Controls							
Parental occupation FEs	Yes	Yes	–	–	–	–	–
School FE	–	–	–	Yes	Yes	–	–
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbb{1}_{Finance} \times$ Year FEs	–	–	–	–	Yes	–	-
Observations	114,116	114,116	193,818	193,818	193,818	23,573	23,573
R^2			.710	.710	.712	.661	.661

This table reports regression coefficients from a Heckman selection model to control for selection effects into finance (Columns 1 and 2), from a model using a within-school measure of talent (Columns 3 to 5) and from a natural experiment to control for school treatment effects (Columns 6 and 7). Columns 1 and 2 report the results of a Heckman selection model where the explanatory variables of the underlying selection model include our talent measure, experience, year, gender and dummies for each parent occupation category: manager, intermediate occupation, worker, employee, independent, or other. In Columns 3 to 5, *Early Admission* is an indicator variable on whether the individual is admitted at a younger age than the regular curriculum would predict, that is, at 19 or before. Highly performing students get admitted earlier on average because they often skipped 1 or 2 years of education. 12.9% of the individuals in our sample get admitted early. Columns 4 and 5 include school fixed effects, and Column 5 also includes finance-year fixed effects. In Columns 6 and 7, we measure the effect of a decrease in the level of selectivity of one specific school, Supelec, on wages of its graduates. The shock took place in 1985 and the sample is restricted to Engineer graduates entering school between 1982 and 1988. The coefficient of the interaction $Supelec \times After$ measures the decrease in the relative wages for graduates from Supelec after the reform, and the coefficient of the interaction $Supelec \times \mathbb{1}_{Finance} \times After$ measures the relative size of the wage effect in finance compared to other industries. All equations include year fixed effects, a female dummy, a married dummy, a Paris area dummy, a working abroad dummy, experience level squared and cubed, four hierarchic responsibility dummies, nine occupation dummies, four firm size dummies, and four firm-type dummies. Standard errors are clustered at the school level in Columns 1 to 2 and at the school-year levels in Columns 3 to 5 and reported in brackets. * p<.10; ** p<.05; *** p<.01.