



WORKING PAPER No. 561

Careers in Finance

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Abstract

The finance wage premium since the 1990s has arguably lured talent away from other industries. However, the allocation of talent is likely to respond to differences in career paths, not in wages at a given date. We use resume data to reconstruct the careers of 11,255 professionals in finance, high-tech and services from 1980 to 2017, and find that careers mostly develop within sectors. Careers in asset management feature higher and steeper pay profiles than those of employees in banking, insurance and non-finance, yet this career premium cannot be explained by higher risk. Labor market entry responds positively to career premia in asset management and high-tech, and these sectors are regarded as substitutes by potential entrants, consistently with high-tech competing with asset management in attracting talent.

JEL Classification: G20, G23, J24, J62, J63.

Keywords: careers, finance premium, asset management, labor market entry, high-tech.

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1 Introduction

Employees in finance, and especially in asset management, are known to earn significant higher wages than comparable non-finance professionals since the 1990s (Philippon and Reshef, 2012; Boustanifar et al., 2018), and significantly higher returns to talent (C  l  rier and Vall  e, 2019). These findings raise the question whether finance may have lured talent away from other sectors, especially via attractive performance-based pay (B  nabou and Tirole, 2016). However, the allocation of talent is likely to respond to differences in career paths across industries, rather than to wage differentials at a given point in time. This is because entering a certain industry requires costly industry-specific education and on-the-job training, which creates persistence in occupational choices. Indeed, educational choices are based on expectations about future earnings in the corresponding sectors (Kirkeboen et al., 2016; Wiswall and Zafar, 2021). Hence, the allocation of talent should be driven by the comparison between the lifetime profiles of earnings associated with careers in different industries, i.e. by the resulting value and riskiness of human capital. This is precisely the approach that we take in this paper to assess the attractiveness of finance relative to other sectors.

Using resume-based data on the careers of 11,281 randomly drawn professionals who work in finance, manufacturing and high-tech at some point between 1980 and 2017, we start by documenting that the choice of industry made by professionals at entry is quite persistent: 75% of those who initiate their career in either finance or non-finance remain in the same industry 20 years later. Even within specific sectors of finance, professionals are far more likely to stay in their entry sector (e.g., asset management) than to switch to other sectors. Such persistence in occupational choices squares with evidence that early-career shocks durably affect compensation and career advancement: a buoyant stock market encourages MBA students to go directly into investment banking upon graduation, with a large and lasting positive effect on their careers (Oyer, 2008), while people graduating during recessions suffer a decade-long earnings gap (Oreopoulos et al., 2012). Also CEOs' careers are permanently affected by macroeconomic conditions at the time of their labor market entry (Schoar and Zuo, 2017).

Given the persistence of industry choices in our sample, we assign careers to sectors on the basis of the sector of entry of a given individual: as such, a career in a given sector (say, banking and insurance) allows for possible subsequent switches

to other sectors (e.g., asset management), weighted by their respective frequencies observed in our data. Since our resume data provide information about job titles but not actual compensation levels, we measure the typical earnings potential associated with a specific job and sector by imputing the corresponding average annual compensation drawn from the Current Population Survey (CPS). For executive jobs, we also allow imputed compensation to include bonus payments, stocks and options, drawn from 10-K forms and proxy statements, besides the salary component. These dollar metrics of job titles enable us to compare career paths in finance and non-finance, as well as between subsectors of the former, i.e., asset management (AM) and commercial banking and insurance (CB&IN), or of the latter, i.e., high-tech (HT), manufacturing (MN) and services (S).

We find that the typical career profile of professionals in finance features a substantial wage differential relative to non-finance professionals in our sample, averaging 37% at the time of entry. When we consider total imputed compensation rather than wages, the differential with non-finance workers is not only large but increasing over the career, the average differential being 40% at entry and 67% after 30 years. This evidence partly reflects the fact that careers in finance are faster, as witnessed by finance professionals being significantly more likely to attain top executive positions.

Careers also differ across the sectors of finance: the average career profiles of professionals in asset management lie above those in banking and insurance, as well as those of non-finance employees. High-tech features the second highest career profile, sharply above that of employees in banking and insurance, services and manufacturing. Importantly, these sector-level differences between career paths persist also upon controlling for individual characteristics, in terms of educational attainment, quality of the educational institution, gender and cohorts, and therefore do not simply reflect sector differences in composition.

While the visual comparison of average wage and total compensation profiles enables us to effect a broad comparison of career paths across industries and sectors, it fails to provide a synthetic measure of the various different dimensions of career paths that may naturally affect the valuation by a (risk-averse) worker. Indeed, careers may differ in their intercept (i.e., entry-level pay level), slope (i.e., return to on-the-job experience), and risk (i.e., predictability of pay within the relevant sector).

To overcome these problems, we devise synthetic measures of career characteristics. The most basic one, which does not include risk, is the present discounted value (PDV) of the average wage (or total compensation) that workers earn in our

sample over time, i.e. the risk-neutral valuation of their human capital when invested in a given sector. Such valuation can also be conditioned on the worker’s characteristics in terms of education, gender and cohort, thus controlling for workers’ heterogeneity. Importantly, this metric enables us to compute the “career premium” (or “discount”) of one subsector (say, asset management) against a common benchmark (that we choose to be the service sector), defined as the ratio between the PDVs of the respective average wages (or total compensation).

We find that workers in the finance sector earn a “career premium” relative to similar non-finance workers, but such premium is concentrated in asset management only. Within the non-finance sector, careers in high-tech pay a premium relative to service firms, though not as large as the premium paid in asset management.

Our next step is to investigate to what extent such premia can be regarded as a compensation for differential career risk, stemming both from the time-series volatility of wages and the cross-sectional variability of careers within each sector: before entering a sector workers may be uncertain about the shape of career paths, so that entry in a given sector is a draw of a specific career path from a distribution of possible paths in that sector. To take this into account, we compute the “certainty equivalent” (CE) of careers in each sector, defined as the constant pay that would yield the same expected utility as that obtained by the typical worker entering a given sector, based on his/her observed pay, assuming a time-additive, constant relative risk aversion (CRRA) utility function. As the estimated CE depends on the assumed CRRA coefficient, we compute it for values of this coefficient ranging from 0 to 2, which according to Chetty (2006) is the CRRA upper bound consistent with existing estimates of labor supply elasticity. We find that for this parameter range the CE of asset management significantly exceeds that of other sectors, with that of high-tech being the second highest. Hence, differential risk alone cannot account either for the career premium observed in asset management and high-tech.

Next, we inquire whether the career premia documented for the sample as a whole have been persistent over time or not, by applying our approach to the first 10 years of the career paths of all cohorts entering our sample from 1990 until 2006. In this respect, it is worth noticing that our notion of career premium differs conceptually from the wage premium analyzed by Philippon and Reshef (2012), because it refers to the prospective income of a particular cohort, rather than the cross-sectional average of the incomes of all employees (belonging to different cohorts) in a given year; as such it enables comparisons across cohorts and even generations. Indeed we find

that careers in asset management, though featuring a higher CE than those in other sectors for all cohorts, have become comparatively less attractive over time: the asset management career premium has declined between 1990 and 2006, especially relative to the high-tech sector. This finding highlights the difference between our metric and that proposed by Philippon and Reshef (2012), who document a steadily increasing finance wage premium since the 1990s. The reason for this finding is that, although asset management careers became more attractive in the early 1990s and 2000s, in each case there was a reversal, possibly due to the labor market impact of financial crises. Instead, the CE of careers in other sectors displays a trend increase, especially in high-tech, except for a sharp setback after the burst of the 2001 dotcom bubble.

Finally, we explore whether changes in the attractiveness of careers over time have any explanatory power for the allocation of labor across sectors. The fraction of new entrants in finance – especially in asset management – declined markedly from 1990 to 2020, while it rose in high-tech, with a first wave in 1993-2000 and a second one after 2010, as well as in services in 2000-10. To establish whether entry choices are correlated with changes in the attractiveness of careers across sectors, we estimate a multinomial logit model where the entry choices of the individuals in our sample are regressed on the sector CE premia (relative to the service sector), controlling for worker characteristics. Our choice of measuring job market entrants’ beliefs based on ex-post realizations of career paths is consistent with Zafar2021, who analyze survey data regarding the careers of high-ability college students, and document that “the distribution of expected and realized own earnings are remarkably similar” (p. 1365).

We find that entry in asset management and high-tech responds positively and significantly to increases in their respective CE premia, while entry in high-tech and services responds negatively to increases in the asset management CE premium. This suggests that a career in high-tech or services is perceived by labor market entrants as substitute for a career in asset management, and that competition by these sectors may account to the decline in the fraction of entrants in asset management observed in our sample.

Hence, our paper makes two main contributions. First, we introduce the notion of career certainty equivalent (CE) pay, which refers to a worker’s pay profile over his/her entire career, and can also take into account the risk of the career profile. Comparing this metric across sectors provides a metric of their relative attractiveness for a labor market entrant. When applied to the comparison between finance and

non-finance workers, it yields a measure of the (risk-adjusted) finance career premium, as opposed to the wage premium used so far in the literature. As mentioned above, this brings a fresh perspective relative to the existing literature about the finance wage premium (Célérier and Vallée, 2019; Philippon and Reshef, 2012; Boustanifar et al., 2018). Indeed, we document that, not only wages, but also entire career paths differ greatly both between finance and non-finance, and within finance. Moreover, we show that career choices at the entry stage respond significantly to career premia, rather than to entry-level wage premia.

Second, we contribute to the debate about how careers in finance have changed over time: we document that, although careers in asset management became more attractive for the cohorts entering in the early 2000s, consistently with the growth of compensation in this sector before the financial crisis (Greenwood and Scharfstein, 2013; Philippon and Reshef, 2012), they have become less attractive for cohorts entering right before the crisis, especially compared to those in high-tech and services. Indeed, our evidence is consistent with high-tech being a potential competitor to asset management in the attraction of talent. Not only both sectors offer a significant career premium relative to others, but the fraction of entrants has been declining in asset management and rising in high-tech, and the probability of entry in high-tech is inversely correlated with the career premium in asset management. This squares with other evidence regarding the ebb and flow of young talent between these two sectors in the last two decades: the finance boom in the early 2000s led to a reallocation of engineers to the financial sector that made them less likely to subsequently become entrepreneurs (Gupta and Hacamo, 2019); conversely, the 2008-09 crisis, by reducing the availability of jobs in finance, prompted elite students (such as MIT graduates) to major in science and engineering instead of management or economics, and thus diverted them away from asset management into innovative jobs in science and engineering (Shu, 2018).

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 illustrates the differences in career paths between the finance and non-finance sectors, as well as across their subsectors. Section 4 analyzes how these differences have changed over time, by considering successive cohorts, and explores their correlation with individual labor market entry decisions. Section 5 concludes.

2 Data

Our analysis is based on manually collected data on the careers of a sample of 11,281 randomly drawn individuals. The data set covers employment histories from 1980 to 2018. For each individual, we observe gender, education, year of entry in the labor market, and all job changes within and across firms. To measure the earnings potential associated with a specific job and sector, we impute to each job title its average sector-specific compensation.

The data are drawn from the individual resumes available on a major professional networking website. We choose this data source because we focus on the allocation of talent and on its compensation. Indeed, our sample over-represents highly educated professionals relative to the U.S. population. It may also under-represent both the least and the most successful professionals, as individuals in both tails of the distribution may have less incentives to publicize their CVs, though for opposite reasons: the least successful because they have less to showcase, the most successful because they are less likely to search for new jobs. However, there is no reason to expect such selection to differ significantly across industries. In any event, our sample is less skewed towards top talent than those used by Célérier and Vallée (2019) and Shu (2018), which are drawn from populations of elite school graduates.

2.1 Data construction

To measure the time profile of compensation over the careers of the workers in our sample, we merge data from different sources, proceeding in the following steps, as illustrated by Figure 1.

[Insert Figure 1]

First, we assign each employer in our sample to finance, manufacturing or high-tech, and within finance to one of two sectors: asset management, investment banking and financial advice (AM) and commercial banking and insurance (CB&IN).¹

¹We identify the sectors of most employers in our sample based on information available in their websites, LinkedIn webpages and online financial press. To determine the sectors of the remaining employers, we use a machine learning algorithm that exploits the association between job titles and sectors: certain titles are found much more commonly in some sectors than in others. For instance, a loan officer is typically found in commercial banking, a trader in asset management and an insurance agent in insurance. The algorithm detects systematic associations between sectors

Next, we match the job titles reported in individuals' resumes with the Standard Occupational Classification (SOC) codes produced by the Bureau of Labor Statistics (BLS), and for each position held by workers, we estimate the corresponding yearly real wage as the average CPI-deflated salary reported in the CPS for the Census Occupation Code corresponding to the relevant SOC code, sector and year. Since the CPS database contains no information about the variable (i.e., performance-based) component of compensation, which can be very large for managerial positions, we impute bonus pay for these positions from data drawn from 10-K forms and proxy statements available through the Edgar system, which report both the fixed and variable components of top management pay. Specifically, we hand-collect data from the annual 10-K forms and proxy statements filed by firms with the SEC on total compensation and its components (salary, bonus, stock options and stock-based remuneration) awarded to the top five executives by the boards of the listed firms in the corresponding industry.² Then, to avoid over-representation of large firms in the estimate of total compensation for managerial positions, for each sub-sector and year, we first compute mean compensation within each decile of the firm size distribution (where size is measured by the stock market capitalization of each firm), and then we average and CPI-deflate the decile-specific mean compensations at the sector-year level.

The end result is an imputed value of real wage and of total real compensation (including bonus pay) for each job title, sector and year. For individuals employed by more than one company at a time, we keep track of all their positions, defining their compensation as that associated with their best paid job in the relevant year. Imputed compensation varies with the SOC code for the relevant job title and, within each SOC code, with the sector. For instance, over the 1980-2017 period the average yearly compensation of a sales manager ranges from \$96,277 in manufacturing and

and job titles on the basis of the manually matched sub-sample of employees and employers, and exploits them to sort the remaining observations (see Ellul et al. (2019) for a detailed description). We drop observations regarding individuals employed in real estate because they are too few to obtain reliable estimates of career profiles. The need to have a sufficient number of observations in each subsector also explains why we treat commercial banking and insurance as a single subsector.

²The titles of the top five executives vary. We collect compensation data for Chief Executive Officers (or Chairmen and Chief Executive Officers) and other executives such as the Chief Financial Officers, Chief Operating Officers, Vice President, Accounting and Corporate Controller, Principal Accounting Officer Vice President, Accounting and Corporate Controller, Principal Accounting Officer, Senior Vice President, Senior Vice President and General Manager, Senior Vice President, Corporate Development and General Counsel, etc.

\$101,283 in high tech to \$93,227 in commercial banking and insurance and \$107,455 in asset management.

2.2 Persistence of occupational choices

The first question that can be addressed with our data is to what extent the individual choice of a sector or subsector made at the time of labor market entry are persistent over time: do individuals spend most of their working life in a single industry, so that for most people a career is a lifetime choice? The answer is broadly positive: in our data, individuals' professional choices feature high persistence. Figure 2 shows the fraction of individuals who remain in finance or non-finance at different moments of their career, conditional on their respective initial choice. In both cases, the fraction stays above 75% even after 20 years of experience.

[Insert Figure 2]

Also within each sector, individuals tend to remain in their initially chosen subsector, as shown by the 10-year transition matrix across subsectors illustrated by Figure 3. The size of each circle in the figure measures the fraction of the entrants in subsector i on the vertical axis who are employed in subsector j on the horizontal axis. The fact that the largest circle in each column lies along the diagonal indicates that after 10 years of experience the largest group in each subsector is formed by employees who joined that subsector at the time of labor market entry. Interestingly, the largest off-diagonal circle in the finance sector is that formed by employees moving from banking and insurance into asset management, implying that it is not uncommon for banking and insurance careers to include stints in asset management. The reason why the circles in the last column are the largest reflects the sheer magnitude and heterogeneity of the service sector, which mechanically implies that other sectors' entrants may eventually end up in the services sector.

[Insert Figure 3]

2.3 Individual characteristics

Table 1 describes the characteristics of the individuals in our sample. Workers are classified on the basis of their entry industry of occupation (i.e. that where they start their career). The sample breakdown by industry is roughly balanced across finance

subsectors (1,654 workers in asset management and 1,521 in banking and insurance), while in non-finance the service subsector is prevalent (6,577 employees out of 8,080).

[Insert Table 1]

On average, the imputed wages of employees in asset management and high tech exceed those in manufacturing and services, and the same holds for median imputed wages in these subsectors. In contrast, the average wages in commercial banking and insurance are roughly in line with those in manufacturing. Hence the data point to the existence of an asset management wage premium, rather than to a finance wage premium. The same qualitative conclusion applies when one focuses on total compensation, which includes bonus pay, on top of wages. Naturally, the distribution of total compensation is much more variable and strongly right-skewed across workers in each sector, as bonus pay is concentrated at the top of the pay scale and greatly exceed wages. This is confirmed by the fact that in all subsectors the difference between median total compensation and median wage is much smaller than the difference between the corresponding means.

In the whole sample, the fraction of person-year observations referring to employees in top executive positions is slightly more than half (54 percent, half of which in CEO status), but is larger in asset management (60 percent) and high-tech (29 percent), which contributes to explain why in these sectors wages and total compensation are larger: careers are on average faster than in other sectors. Nevertheless, these figures underscore that the sample does not consist only of people who eventually become CEOs, as in other recent studies such as Benmelech and Frydman (2015), Graham et al. (2013), Kaplan et al. (2012), and Malmendier et al. (2011).

Almost all the employees in the sample have a university degree: the highest degree is a B.A. or B.S. for 42 percent of the sample, a Master's for 40 percent, and a J.D. or a Ph.D. for 15 percent. Surprisingly, education in STEM subjects is not prevalent: only 22 percent of the individuals in the sample received their highest degree in economics or finance, and only 14 percent in science or engineering. A sizable minority (15 percent) obtained their highest degree from a top-15 university, according to the QS Ranking.

Consistently with anecdotal evidence, gender imbalance is highest in finance, and especially in asset management, where only 15 percent of employees are female, against 28, 24 and 22 percent in manufacturing, services and high-tech, respectively.

On the whole, these descriptive statistics already indicate that careers in asset management have quite distinctive characteristics, most of which are in common with employees in the high-tech sector: higher imputed wages and total compensation, and higher frequency of attainment of top executive positions.

3 Are careers in finance different?

As career choices appear to be quite persistent, it is worth asking whether career paths differ and, if so, how. In this section we characterize career paths not only in terms of the level, but also of the slope and risk of the corresponding compensation. We shall see that such differences are not entirely accounted for by heterogeneity in employees' characteristics in terms of education and gender.

3.1 Finance vs. non-finance

To illustrate how career profiles differ across sectors over the whole sample, we purge compensation data from their aggregate yearly variation by regressing them on year effects and adding the estimated residuals to 2010 average wages: this eliminates possible spurious variation in relative wages across sectors due to differences in the composition of the sample over time.

Figure 4 compares the typical career profile of finance and non-finance workers in our sample. The top panel plots the average real imputed wage (excluding bonus pay) in thousand dollars: the average wage of finance workers exceeds that of non-finance workers by 37% at the time of entry, and the differential remains sizeable throughout the career. These estimates of the finance wage premium are considerably smaller than the 50% estimate reported by Philippon and Reshef (2012): the difference probably reflects the fact that our sample is more homogeneous than the U.S. population, being skewed towards educated professionals. Indeed the wage difference between financiers and engineers reported by Philippon and Reshef (2012) ranges between 0 and 40% over the 1980-2005 period, and therefore is closer to our estimate.

[Insert Figure 4]

The bottom panel of Figure 4 instead plots the average total imputed compensation of finance and non-finance employees: this includes also bonus pay, which is

so large as to raise total compensation by a factor of 4 to 10 relative to the wage compensation shown in the top panel. For total imputed compensation, the differential with non-finance workers is not only larger than for the wage, but increases over the career: the average differential is 40% at entry, as well as over the first 10 years, and then grows steadily, ending at 67% after 30 years. This evidence partly reflects the fact that careers in finance are faster, as witnessed by finance workers being significantly more likely to attain top executive positions.

3.2 Diversity within finance

The overall picture emerging from Figure 4 masks great diversity within finance, as well as some diversity between high-tech and other non-finance sectors. This is apparent from Figure 5, which shows average imputed real wages paid over workers' careers in various subsectors within finance and non-finance: in asset management entry-level wages significantly exceed both those in banking and insurance and those in non-finance sectors. High-tech careers offer the second highest wages over the first 20 years of experience, significantly larger than careers in manufacturing and services, as well as in banking and insurance. A qualitatively similar picture emerges from data for total imputed compensation, shown in Figure 6. The only significant difference relative to the previous figure is that the inclusion of bonus pay significantly magnifies the extent to which the asset management premium rises with experience.

[Insert Figure 5 and Figure 6]

As one would expect, career profiles feature considerable heterogeneity depending on education and gender, not just experience. This is witnessed by the estimates shown in Figure 7, where the imputed wage of the individuals in our sample are regressed on sector indicators, experience, graduate education attainment (equal to 1 for individuals with a Master or a Ph.D. and 0 otherwise), education quality (equal to 1 for individuals who received their highest degree from a top-15 university, based on QS rankings, and 0 otherwise), gender (1 for females and 0 for males), and cohort effects (for the cohorts entering the labor market in 1980-86, 1987-90, 1994-97, 1998-2000, 2001-04, 2005-08, 2009-14, and 2015-17).

[Insert Figure 7]

The estimates confirm that, even controlling for these worker characteristics, careers feature significantly positive entry-level premia in asset management: the average entry-level wage in asset management is \$103,000, while in services it is \$61,000 in services, and in other sectors it is intermediate but still significantly lower than in asset management. Job experience commands a significantly larger premium in services and in commercial banking and insurance than in asset management, manufacturing and high-tech.

Careers in finance appear to benefit from education: graduate training increases annual pay by \$8,200 in commercial banking and insurance, while a degree from a top-15 university is associated with a \$12,230 annual pay increase in asset management, \$14,630 in banking and insurance, \$9,680 in manufacturing, and \$13,150 in services (while there is no significant effect in high-tech). On the whole, female workers earn significantly less than males, in line with findings on the gender gap reported by many studies (Bertrand et al. (2010), Bertrand and Hallock (2001), Mulligan and Rubinstein (2008) and, within finance, Adams and Kirchmaier (2016)). The gender gap does not differ significantly across sectors but is significantly different from zero only in manufacturing (where it is largest), high-tech and services. Instead, it is barely significant in finance. However, this result may be partly due to selection: finance features the lowest female participation (see Table 1), so that average female finance employees may be of higher unobserved ability relative to women working in other sectors.

3.3 Career premia

While the graphic comparison of average wage and total compensation profiles presented so far enables us to effect a broad comparison of career paths across industries and sectors, it fails to provide a synthetic measure of the various different dimensions of career paths that may naturally affect the valuation by a (risk-averse) worker. Indeed, careers may differ in their intercept (i.e., entry-level pay level), slope (i.e., return to on-the-job experience), and risk (i.e., predictability of the pay level within the relevant subsector). For instance, career paths may cross: for instance, in Figure 6 the average total compensation in high-tech exceeds that of services in the first part of the career, but not in the last. Moreover, the average pay profile in one sector may lie entirely above its analogue in another one, having both higher intercept and slope, yet it may feature greater risk: hence, a sufficiently risk-averse worker may

prefer the latter to the former.

To overcome these problems, we devise synthetic measures of career characteristics. The most basic one, which does not include risk, is the present discounted value (PDV) of the average wage (or total compensation) that workers earn in our sample over the same interval of on-the-job experience, i.e. the risk-neutral valuation of their human capital when invested in a given sector. Such valuation can also be conditioned on the worker’s characteristics in terms of education, gender and cohort, and therefore enables us to control for workers’ heterogeneity. Importantly, this metric enables us to compute the “career premium” (or “discount”) of one sector (say, asset management) against a common benchmark (say, services), defined as the percentage difference between the PDVs of the respective average wages (or total compensation).

However, the presence of such a “career premium” (or “discount”) as just defined may reflect the different risk characteristics of careers in different sectors. For instance, if asset managers face higher labor income risk for each level of experience than employees in banking, irrespective of their education and gender, then individuals may require a higher expected labor income PDV to enter asset management. The risk associated from entering a given sector stems not only from the sector-specific variability of pay over time, but also arise from cross-sectional variation across worker-specific trends in that sector. Both dimensions of risk can be taken into account by viewing entry in a given sector as a draw from a distribution of possible career paths in that sector.

Accordingly, we estimate the expected utility associated with entry in a given sector as the average utility obtained by the sub-sample of workers in that sector, using the wage (or total compensation) data over the observed careers. Specifically, we estimate the expected discounted utility that worker $i \in (1, \dots, N_j)$ obtains from a career in sector j as the sample mean of the discounted utility of the career paths observed in that sector, assuming constant relative risk aversion instantaneous utility:

$$E(U_j) = \sum_{i=1}^{N_j} \frac{1}{N_j} \sum_{t=0}^T \beta^t \frac{w_{ijt}^{1-\gamma}}{1-\gamma}, \quad (1)$$

where w_{ijt} is the observed wage of worker i in sector j and experience t , β is the discount factor, and N_j is the number of employees in sector j . We assume $\beta = 0.97$ and evaluate expression (2) for the six sectors in our data, using the first 20 years of imputed compensation data for each employee, i.e., setting $T = 20$. Then we compute

the constant certainty-equivalent yearly compensation ($\bar{w}$) under four alternative assumptions about the coefficient of relative risk aversion (RRA) γ , i.e., 0 (risk neutrality), 0.5, 1 (logarithmic utility) and 2, which is shown by Chetty (2006) to be the upper bound on γ consistent with existing estimates of labor supply elasticity:

$$E(U_j) = \sum_{t=0}^T \beta^t \frac{\bar{w}_j^{1-\gamma}}{1-\gamma}. \quad (2)$$

Figure 8 plots the certainty equivalent (CE) of the imputed annual wage in each sector and the respective confidence bounds, computed using the Delta method to approximate the asymptotic variance of the non-linear transformations of the estimated expected utilities. The figure shows that in asset management the CE annual wage is significantly larger than in services, irrespective of the assumed RRA coefficient. The magnitude of the CE is decreasing in the assumed risk aversion for all subsectors. But the ranking between the CE annual wage in the five subsectors stays unchanged irrespective of the assumed risk aversion: even for $\gamma = 2$, asset management yields a sizeable premium relative to all other sectors, and high-tech yields the second highest premium relative to the service sector: the CE annual wage is \$113,000 in asset management and \$87,800 in high-tech, and the respective career premia relative to the \$72,250 CE in services are both statistically significant.

[Insert Figure 8]

Figure 9 shows the CE of imputed total compensation in each sector. The results are qualitatively similar to those obtained in the previous figure using wage data. However, the CE of imputed total compensation is naturally higher than the CE of imputed salaries and more sensitive to the level of relative risk aversion: as γ increases, the CE of imputed total compensation gets closer to the CE of imputed salaries. Moreover, only the CE of total compensation in asset management significantly exceeds that of other subsectors only in asset management: for $\gamma = 2$, the CE of total compensation is \$197,000 in asset management, with a statistically significant premium over its analogue of \$117,200 in services. On the contrary, the CE of total compensation does not differ significantly across banking and insurance, high-tech, manufacturing and services.

[Insert Figure 9]

4 Evolution of careers in finance and non-finance

The methodology presented so far can be used not only to measure the relative attractiveness of careers in different sectors of the economy, but also to assess whether and how this has changed over time, and whether its changes are systematically correlated with the allocation of labor market inflows across sectors. In particular, it enables us to inquire whether the asset management career premium documented so far has been a stable feature of the economy, and whether the observed choices of labor market entrants are consistent with them considering careers in asset management and other sectors as substitutes, namely, competing for a common pool of talents.

In this section, we apply the methodology presented in the previous section to bear on these issues, by applying it to the estimation of the CE of the annual pay for the first 10 years of experience received by successive cohorts entering each subsector between 1990 and 2006. On the one hand, we discard the earliest cohorts, because those from the 1980s are not numerous enough to yield reliable estimates of their CE of annual pay. On the other hand, the last cohort for which we can perform the estimation is that entering in 2006, since for subsequent cohorts less than 10 years of pay data are available. Note that the CE of annual pay may vary across cohorts not only due to changes in the level and slope of their typical career paths, but also due to changes in career risk. We assume logarithmic utility, but the results are qualitatively unaffected assuming different values of relative risk aversion.

Figure 10 shows 3-year moving averages of the CE annual wages in each subsector, for each cohort entering the labor market between 1990 and 2006. The figure reveals that, although careers in asset management dominated careers in other sectors for all cohorts, their relative attractiveness, i.e., the asset management career premium, has gradually decreased over time: its CE annual wage in 2006 is almost the same as in 1990, i.e. about \$120,000, while in all other sectors it has grown over time. This is especially evident when they are compared to careers in high-tech: the percentage career premium of asset management relative to high-tech declined from about 50 percent in 1990 to about 20 percent in 2006. This evidence differs sharply from that about the steady rise in the finance wage premium documented by Philippon and Reshef (2012) since the 1990s, reflecting the fact that our metric has a forward-looking nature and refers to a whole cohort rather than to a cross-section of employees at a point in time.

[Insert Figure 10]

Beside the different time trends, Figure 10 also reveals interesting cycles: careers in asset management became more attractive in the early 1990s and 2000s, but in each case a reversal followed, possibly reflecting the setbacks of the asset management industry in the 2000-01 and 2008-09 financial crises. The contraction of the high-tech sector after the burst of the dotcom bubble in 2000-01 is also likely to account for the decline of the attractiveness of high-tech sector in the early 2000s. This is consistent with the evidence by Hombert and Matray (2018), who show that the cohort of skilled workers entering the high-tech sector during the high-tech boom of the late 1990s experienced a persistent drop in wages after the burst of the bubble, using matched employer-employee data from France: this cohort of high-tech skilled workers starts with 5 percent higher wages, but then faces lower wage growth and ends up with 6 percent lower wages fifteen years out, relative to similar workers who started outside the high-tech sector. Our evidence indicates that in the U.S. this effect materializes for high-tech employees entering soon before, concomitantly or soon after the 2001 dot-com crash. But our data also indicate that in 2006 the prospective attractiveness of the high-tech sector rose again, while that of asset management kept declining.

These findings are broadly confirmed by Figure 11, which repeats the exercise of the previous figure using data for the first 10 years of total compensation (including bonus pay) instead of wages. The only substantive differences with the previous figure are that, when bonus pay is taken into account, the CE of annual compensation features a positive trend in all sectors, including asset management, and much wider fluctuations over time, especially in asset management and high-tech, reflecting the much greater volatility of bonus pay relative to the base wage in these sectors. But perhaps the most remarkable finding is that the differential between the CE of total compensation in asset management and high-tech drops to zero both for cohorts entering the labor market in the late 1990s and for that entering in 2006.

[Insert Figure 11]

This evidence gains further interest when it is considered alongside with the data on the flow of labor market entrants in each subsector as a percent of total entrants in the same year: Figure 12 plots the 3-year moving averages of these fractional flows from 1991 to 2017, based on our data. The figure shows that the choices of labor market entrants have changed remarkably over time: finance, and especially asset management, features a trend decline of labor inflows, particularly since the 2008-09 financial crisis; conversely, the high-tech sector attracted two waves of entry, one in

1993-2000 (during the dotcom bubble) and a second one after 2010, and services attracted a strong wave of entrants in 2000-10. This is in line with the evidence by Shu (2018) that during the financial crisis elite science graduates opted for careers in science and engineering rather than in finance. Hence, the overall picture is one of a declining labor inflow into asset management, and an expanding one into high-tech and services, symmetrically with the shrinking career premium of asset management observed in Figures 10 and 11.

[Insert Figure 12]

The previous figures suggest that the reallocation of labor across industries may have been driven by changes in the relative attractiveness of careers over time. To investigate this hypothesis, we estimate a multinomial logit model relating the entry choices of individuals in our sample to the risk-adjusted career premia of each subsector, i.e., the ratios of the cohort-specific CE of each sector to that of the service sector (used as benchmark), controlling for individual entrants' characteristics: gender, quality of education (degree from a top-15 school), education level (dummy for Master or Ph.D.), and subject of the highest degree. The observations used in the estimation refer to individuals who entered the labor market between 1989 and 2007, but the career premia used to account for their choices are based on wage data up to 2017, being forward-looking.

Figure 13 shows the estimates of the marginal effects of career premia on the probability of entry in each sector. Where significant, the coefficient estimates indicate that labor entry in a given subsector is positively associated to increases in the career premium of that subsector, and negatively associated to increases in the career premium of other subsectors. Specifically, entry in asset management and in high-tech responds positively to a rise in their own career premium relative to services: a 1-standard-deviation increase in their own career premium is associated with a 2.8 percentage points increase in the probability of entry in asset management (about 11 percent of its mean) and a 1.8 percentage points increase in the probability of entry in high-tech (about 19 percent of the mean). Careers in finance and high-tech appear to be substitutes: the probability of entry in high-tech decreases by 1 percentage point (about 10 percent of its mean) for a 1-standard-deviation increase in the asset management career premium and 2.1 percentage point (about 22 percent of its mean) for a 1-standard-deviation increase in the banking and insurance career

premium. Following the same logic, careers in asset management and services also appear to be substitutes.

[Insert Figure 13]

Interestingly, when the same models are estimated replacing career premia with wage premia, defined as the average entry wage in the relevant sector divided by the entry wage in the service sector, the estimates of the marginal effects of wage premia on the probability of entry in each sector are never significantly different from zero. The corresponding estimates are not shown for brevity. Hence, career premia appear to have more explanatory power for career choices than the typical entry wage.

The results shown in Figure 13 are consistent with entry choices being affected by rationally anticipated shifts in labor demand, triggered by changes in the distribution of future labor earnings: for instance, an expected rise in labor productivity in high-tech relative to other sectors should lead to an expected rise in the demand for labor by high-tech firms and thus to an expected rise in the wage profile (and the CE annual wage) in that sector, which in turn prompts greater current entry in high-tech and lower entry in other sectors, especially in those that labor market entrants view as closest substitutes of high-tech.

Note that concurrent shifts in labor supply are likely to reduce the size of the estimated coefficients: for instance, a supply-driven increase in the entry into asset management can be expected to lead to a decrease in future realized labor earnings in that sector, hence to a negative relation between entry into asset management and the corresponding career premium.

Figure 14 shows the estimates of the marginal effects of workers' characteristics on their entry choices. It shows that obtaining one's highest degree in a top-15 school is associated with a greater probability of entry in asset management (by 10 percentage points) and a lower probability of entry in banking and insurance (by 5 percentage points) and in high-tech (by 4 percentage points). Conversely, holding a Master or a Ph.D. is associated with a lower probability of entry in asset management (by 9.4 percentage points) and banking and insurance (by 4.6 percentage points) and a higher probability of entry in high-tech (by 3 percentage points). This suggests that for a career in asset management a degree from a top school is more highly valued than a Master or Ph.D. *per se*, while the opposite applies to a career in high-tech. The estimates also imply that female labor market entrants are less likely to start a career

in asset management or high-tech (by 4.4 and 2,3 percentage points, respectively), while they are more likely to start it in services (by 6.8 percentage points).

[Insert Figure 14]

To dig deeper into the response of talent allocation to sectoral career premia, we re-estimate the multinomial logit model separately for individuals with and without graduate education. Consistently with the idea that asset management and high-tech compete for a common pool of talent, we find significant evidence of substitutability across these two sectors only for professionals holding a master or a Ph.D. (upper panel of Figure 15): the marginal effect of the asset management career premium on entry in high-tech is negative and significantly different from zero only in the upper panel of the figure. This indicates that the set of skills typically acquired with graduate education are to some extent fungible between asset management and high-tech jobs.

[Insert Figure 15]

As a robustness check, we repeat the estimation of the multinomial logit model measuring the career premia of each subsector based on the CE ratio of total compensation, including bonus pay, instead of the sole wages. The results are qualitatively unchanged relative to those illustrated by the previous two figures. Only the magnitude of the estimated marginal effects of career premia is smaller, because the magnitude of the premia is larger.

5 Conclusions

This paper investigates how careers differ along several dimensions between finance and non-finance sectors, as well as across their subsectors. To do so, we introduce a synthetic measure of the attractiveness of careers, i.e., the certainty equivalent of the annual compensation along the career paths of individuals who initially entered a given sector. This measure encompasses all the dimensions of the career paths of those individuals, i.e. the level, slope and risk of their compensation over time. By scaling these certainty equivalents against a benchmark sector, we define the notion of career premium, which measure the attractiveness of careers in the relevant sector relative to the benchmark. When applied to the comparison between careers

in finance and in other sectors, this metric defines the finance career premium, which differs conceptually from the wage premium used so far in the literature because it refers to the lifetime income of a cohort of workers, rather than the cross-sectional average of the incomes of all employees in a given period.

We apply this methodology to a manually collect data set on the careers of a sample of 11,281 randomly drawn individuals who work in the finance, manufacturing, services and technology sectors, for which we obtain detailed employment histories from 1980 to 2017. We find that those choosing a career in finance earn a career premium, reflecting higher and steeper compensation profiles, compared to non-finance employees, but this result masks significant differences within finance. While asset managers start with better paid jobs than workers in other sectors, featuring faster advances, greater returns to education and no offsettingly high career risk, this is not true for those choosing banking and insurance.

However, we also find that the attractiveness of careers changes considerably over time, especially in asset management, high-tech and services. The data for the cohorts entering between 1990 and 2006 reveal a trend decline of the relative attractiveness of careers in asset management relative to other sectors, especially those in high tech. Symmetrically, the flows of new entrants declined strongly in asset management, and increased in high-tech and services, a picture that appears consistent with these sectors competing with asset management in attracting talent.

We bring to bear the individual entry choices observed in our data on this issue, by estimating a multinomial logit model to test whether individual choices of entry sector are related to the relative attractiveness of careers, as measures by their respective career premia, controlling for worker characteristics. The estimates indicate that entry in asset management and high-tech responds positively to a rise in their own career premia relative to services, and that labor market entrants – especially those with graduate education – appear to consider careers in finance and high-tech as substitutes. These results are consistent with evidence by Gupta and Hacamo (2019) and Shu (2018) about the ebb and flow of young numerate entrants across these two sectors, as well as with the practitioners’ view that asset management firms and investment banks have faced increasingly tough competition for talent from high-tech firms, forcing them to raise the compensation offered to job market candidates:

“Year after year, investment banks were among those shelling out more as they vied with ascendant Silicon Valley giants for the best candidates

and tried to head off poaching by investment firms, such as buyout and hedge funds. College grads are particularly valuable to tech firms, because theyre trained on the fast-moving frontier of computer science.”³

³Eric Kebs, “Junior Bankers Raises Widen Record Pay Gap Among College Grads”, 13 August 2021, <https://www.bloomberg.com/news/articles/2021-08-13/junior-bankers-raises-widen-record-pay-gap-among-college-grads>

References

- Adams, R. B., and T. Kirchmaier. 2016. Women on Boards in Finance and STEM Industries. *American Economic Review* 106:277–81.
- Bénabou, R., and J. Tirole. 2016. Bonus Culture: Competitive Pay, Screening, and Multitasking. *Journal of Political Economy* 124:305–370.
- Benmelech, E., and C. Frydman. 2015. Military CEOs. *Journal of Financial Economics* 117:43–59.
- Bertrand, M., C. Goldin, and L. F. Katz. 2010. Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics* 2:228–255.
- Bertrand, M., and K. F. Hallock. 2001. The Gender Gap in Top Corporate Jobs. *Industrial and Labor Relations Review* 55:3–21.
- Boustanifar, H., E. Grant, and A. Reshef. 2018. Wages and Human Capital in Finance: International Evidence, 1970–2011. *Review of Finance* 22:699–745.
- Célérier, C., and B. Vallée. 2019. Returns to Talent and the Finance Wage Premium. *The Review of Financial Studies* 32:4005–4040.
- Chetty, R. 2006. A New Method of Estimating Risk Aversion. *American Economic Review* 96:1821–1834.
- Ellul, A., M. Pagano, and A. Scognamiglio. 2019. Career Risk and Market Discipline in Asset Management. *The Review of Financial Studies* 33:783–828.
- Graham, J. R., C. R. Harvey, and M. Puri. 2013. Managerial attitudes and corporate actions. *Journal of Financial Economics* 109:103–121.
- Greenwood, R., and D. Scharfstein. 2013. The Growth of Finance. *Journal of Economic Perspectives* 27:3–28.
- Gupta, N., and I. Hacamo. 2019. Early Career Choices of Superstar Entrepreneurs. SSRN Working paper No. 3136751.
- Hombert, J., and A. Matray. 2018. Technology Boom, Labor Reallocation, and Human Capital Depreciation. SSRN Working paper No. 3190030.

- Kaplan, S. N., M. M. Klebanov, and M. Sorensen. 2012. Which CEO Characteristics and Abilities Matter? *The Journal of Finance* 67:973–1007.
- Kirkeboen, L. J., E. Leuven, and M. Mogstad. 2016. Field of Study, Earnings, and Self-Selection. *The Quarterly Journal of Economics* 131:1057–1111.
- Malmendier, U., G. Tate, and J. Yan. 2011. Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies. *The Journal of Finance* 66:1687–1733.
- Mulligan, C. B., and Y. Rubinstein. 2008. Selection, Investment, and Women’s Relative Wages over Time. *The Quarterly Journal of Economics* 123:1061–1110.
- Oreopoulos, P., T. von Wachter, and A. Heisz. 2012. The Short- and Long-Term Career Effects of Graduating in a Recession. *American Economic Journal: Applied Economics* 4:1–29.
- Oyer, P. 2008. The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income. *The Journal of Finance* 63:2601–2628.
- Philippon, T., and A. Reshef. 2012. Wages and Human Capital in the U.S. Finance Industry: 1909–2006. *The Quarterly Journal of Economics* 127:1551–1609.
- Schoar, A., and L. Zuo. 2017. Shaped by Booms and Busts: How the Economy Impacts CEO Careers and Management Styles. *The Review of Financial Studies* 30:1425–1456.
- Shu, P. 2018. Innovating in Science and Engineering or ‘Cashing In’ on Wall Street? Evidence on Elite STEM Talent. SSRN Working paper No. 2697777.
- Wiswall, M., and B. Zafar. 2021. Human Capital Investments and Expectations about Career and Family. *Journal of Political Economy* 129:1361–1424.

Table 1: Summary statistics

The table reports the summary statistics of the variables used in the analysis for the entire sample (Total) and separately for each sub-sector: asset management (AM), commercial banking and insurance (CB-IN), high-tech (HT), manufacturing (MN), and other services (S).

	Total	AM	CB-IN	HT	MN	S
No. of CVs	11,255	1,654	1,521	1,157	346	6,577
<i>Imputed wage, USD thous</i>						
Mean	110	137	107	115	104	102
Median	92	130	90	97	90	82
Standard deviation	58	61	57	57	50	55
<i>Imputed total compensation, USD thous</i>						
Mean	987	1,559	831	1,030	775	863
Median	104	142	100	111	99	94
Standard Deviation	1,706	2,418	1,574	1,550	1,327	1,470
<i>Top executives</i>						
Top executive (non-CEO) status	0.27	0.30	0.23	0.29	0.25	0.26
CEO status	0.27	0.30	0.23	0.29	0.25	0.26
<i>Education Level</i>						
High school	0.03	0.01	0.02	0.03	0.04	0.03
College	0.42	0.53	0.50	0.37	0.35	0.38
Master	0.40	0.39	0.36	0.44	0.43	0.40
JD or PhD	0.15	0.07	0.13	0.16	0.18	0.18
<i>Subject of highest degree</i>						
Econ or Finance	0.22	0.08	0.10	0.36	0.30	0.26
Science or Engineering	0.14	0.17	0.16	0.08	0.10	0.14
Other	0.56	0.72	0.68	0.44	0.48	0.52
Unknown	0.08	0.03	0.06	0.12	0.12	0.08
<i>Education quality</i>						
Top-15 university	0.15	0.20	0.10	0.12	0.14	0.15
<i>Gender</i>						
Female	0.22	0.15	0.20	0.22	0.28	0.24
<i>Cohort</i>						
1980-1998	0.40	0.40	0.37	0.26	0.27	0.29
1999-2008	0.41	0.41	0.42	0.39	0.39	0.40
2009-2018	0.19	0.19	0.21	0.35	0.34	0.31

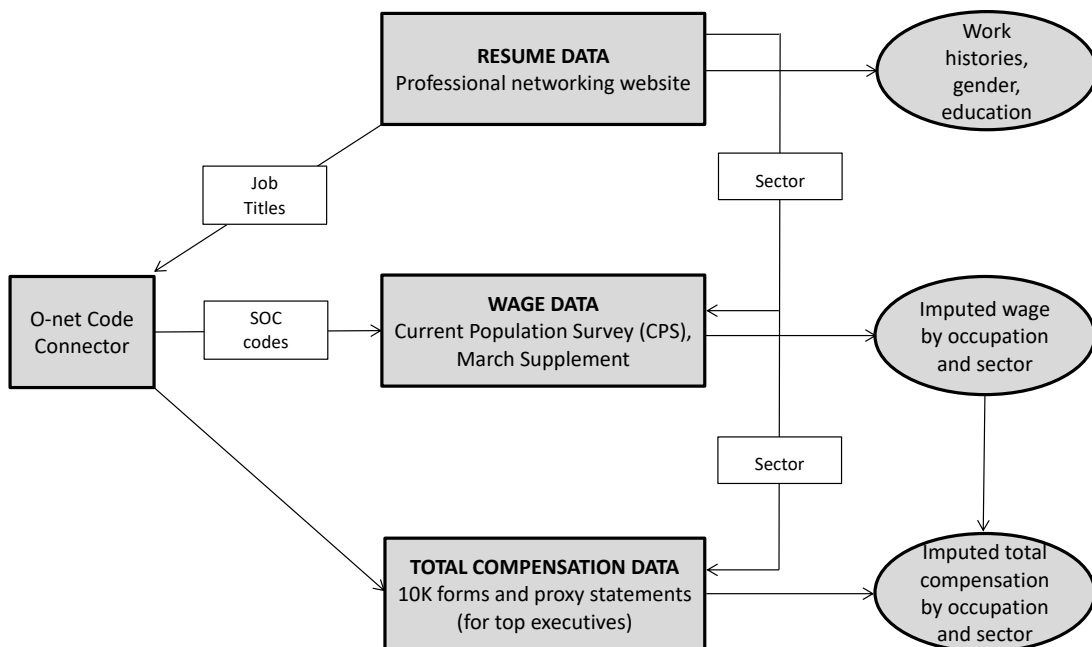


Figure 1. Data construction

Information about work histories (start dates, end dates, employers, and job titles), gender and education is drawn from individual resumes available on a major professional networking website. Job titles are matched with the Standard Occupational Classification (SOC) codes produced by the Bureau of Labor Statistics (BLS), via the O*Net code connector platform. SOC codes and employment sectors are mapped to the average annual wages using data from the March Supplement of the Current Population Survey (CPS), and to annual compensation (including bonus pay, for top executives) using data drawn from 10-K forms and proxy statements.

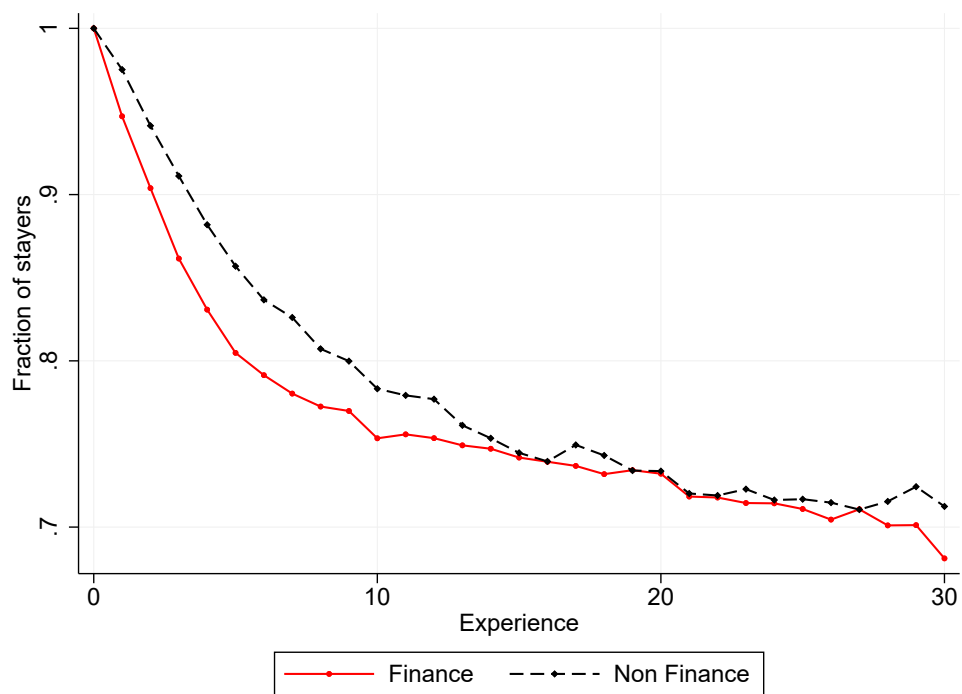


Figure 2. Persistence of initial industry choice

Fraction of employees remaining in the industry chosen at entry in the labor market, by experience.

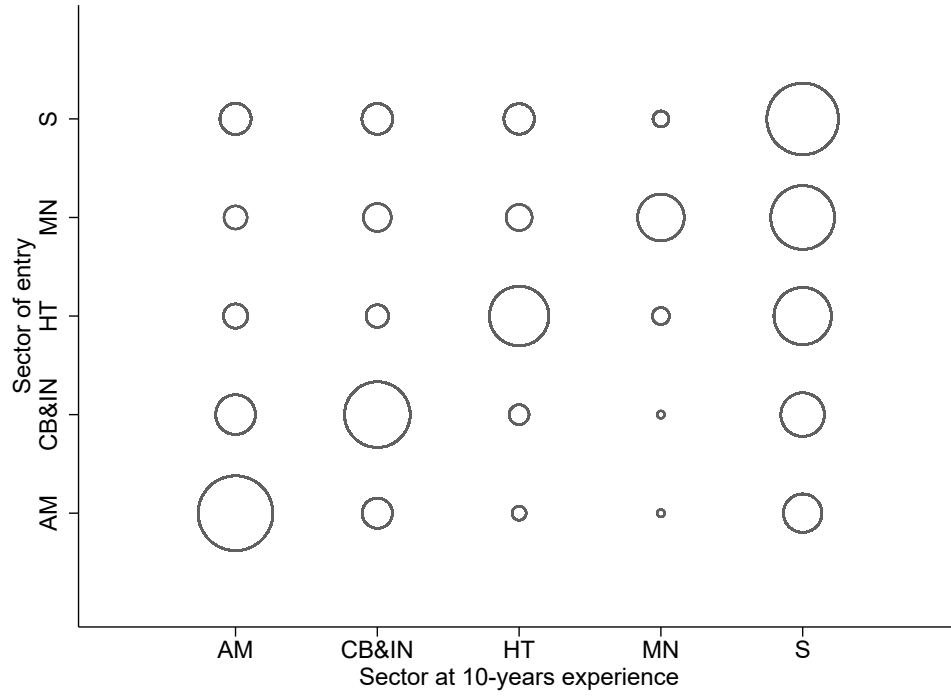


Figure 3. 10-year transition matrix across subsectors

The figure illustrates the 10-year transition matrix across subsectors. The size of each circle measures the fraction of the entrants in subsector i on the vertical axis who are employed in subsector j on the horizontal axis.

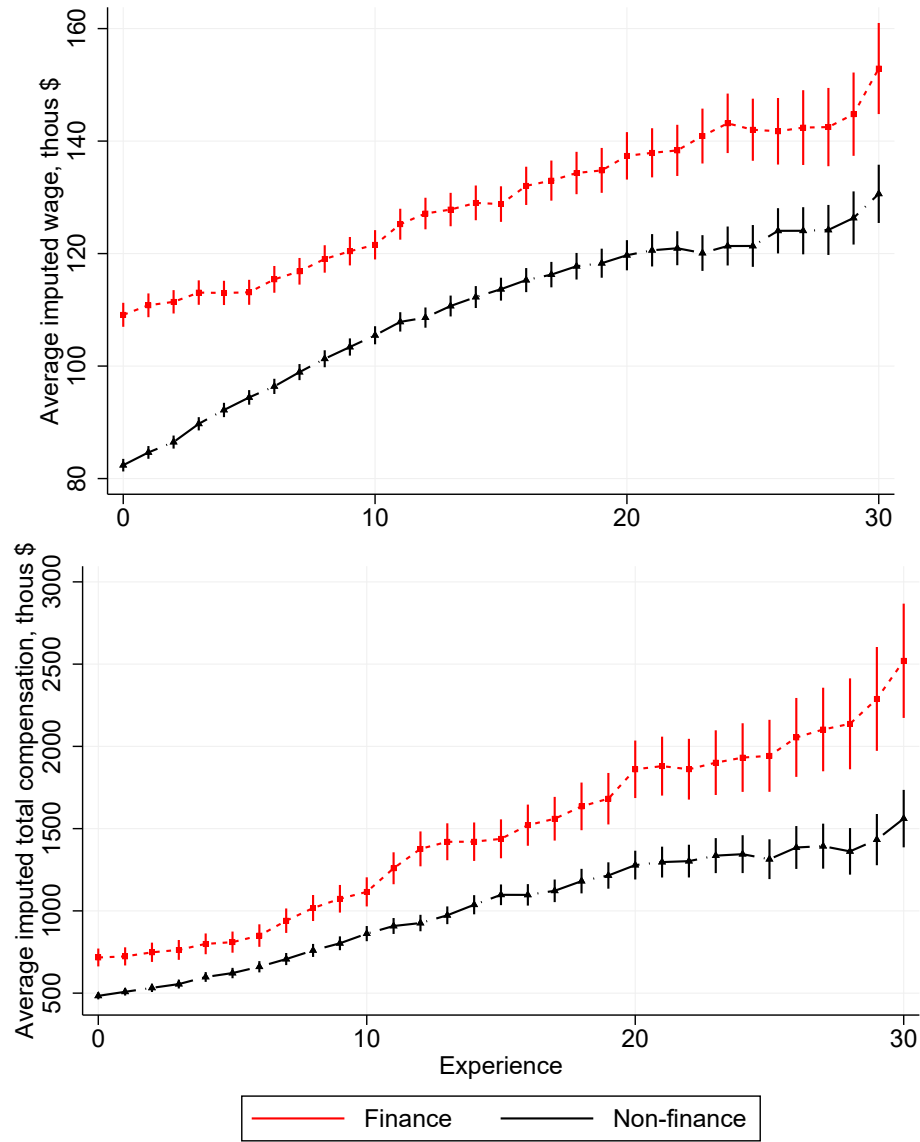


Figure 4. Average imputed pay by experience: finance vs. non-finance
 Top panel: imputed wage of finance and non-finance employees by each experience level. Bottom panel: total imputed compensation of finance and non-finance employees, including wage and bonuses by each experience level.

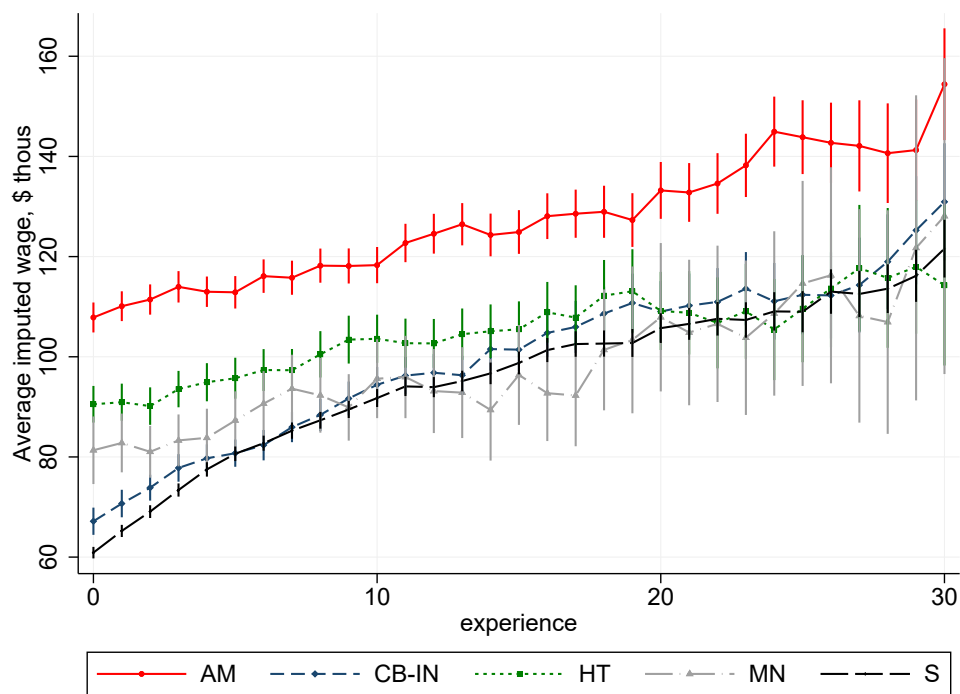


Figure 5. Average imputed wage over careers, by subsector

Average imputed wage of employees in each subsector by experience level. Subsectors: asset management (AM), commercial banking and insurance (CB%IN), manufacturing (MN), high-tech (HT) and services (S).

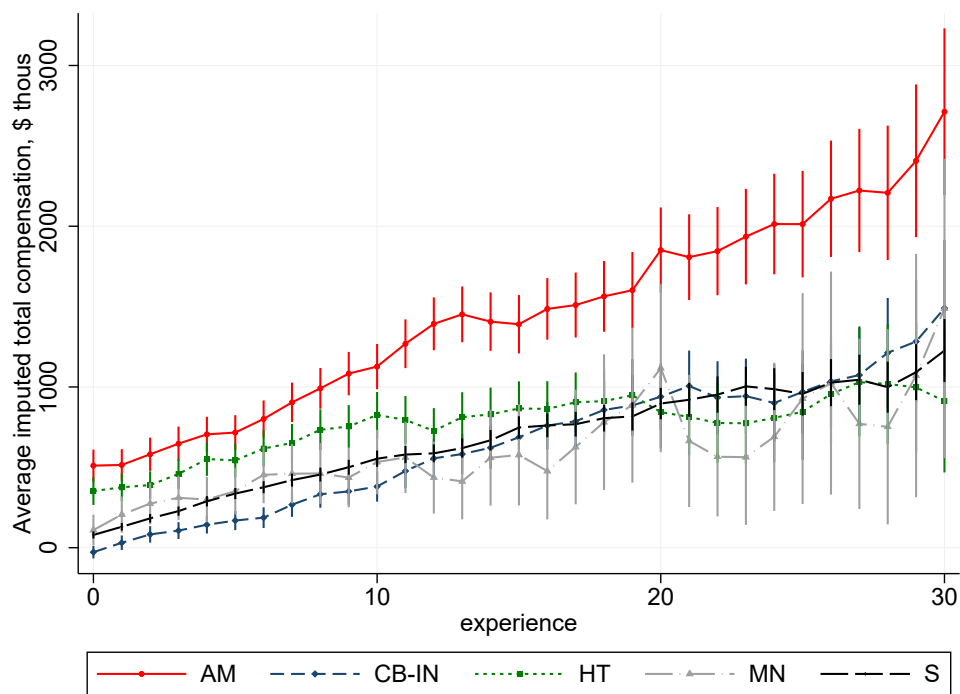


Figure 6. Total imputed compensation over careers, by subsector

Total imputed compensation of employees, including wage and bonuses, in each subsector by experience level. Subsectors: asset management (AM), commercial banking and insurance (CB&IN), manufacturing (MN), high-tech (HT) and services (S).

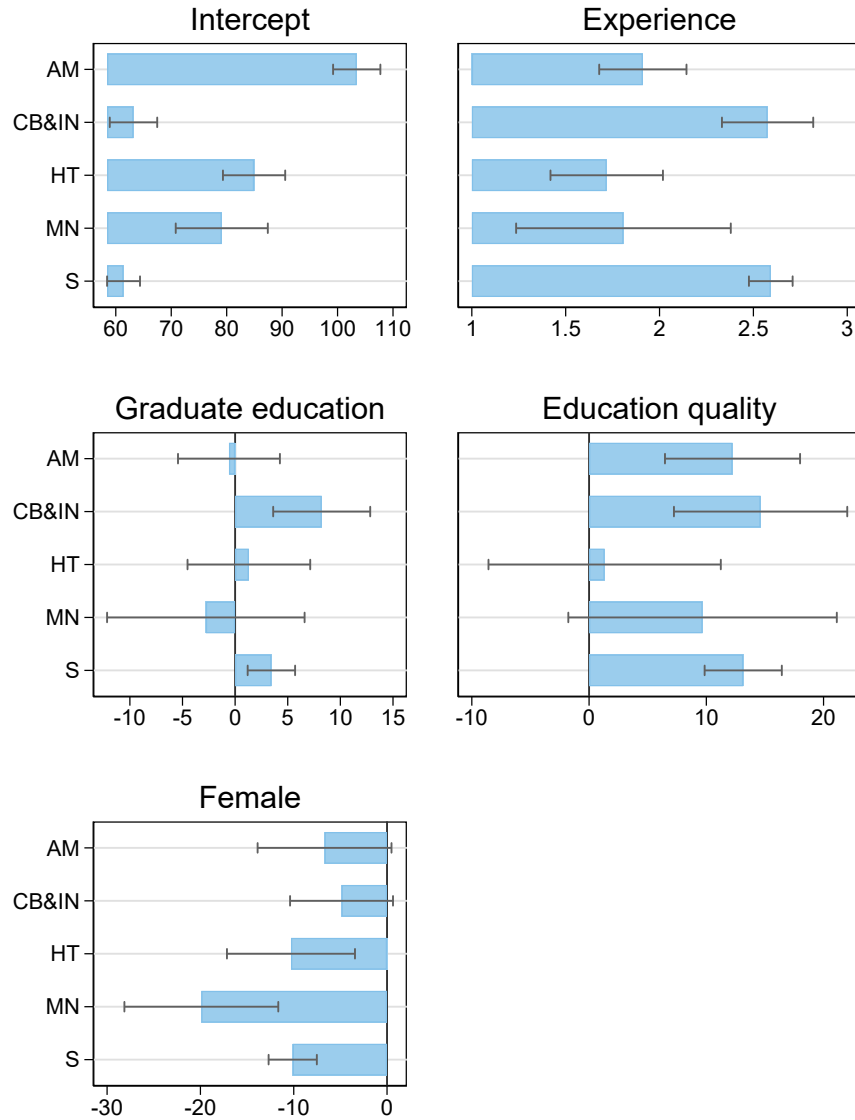


Figure 7. Career sensitivity to worker characteristics, by sector

Coefficient estimates and 95% confidence intervals obtained from a regression whose dependent variable is the imputed wage of each worker and date in the sample and the independent variables are sector indicators, experience, education (indicator equal to 1 for individuals with a Master or a Ph.D. and 0 otherwise), gender (indicator equal to 1 for females and 0 for males), and cohort indicators. Sectors: asset management (AM), commercial banking and insurance (CB&IN), high-tech (HT) and services (S).

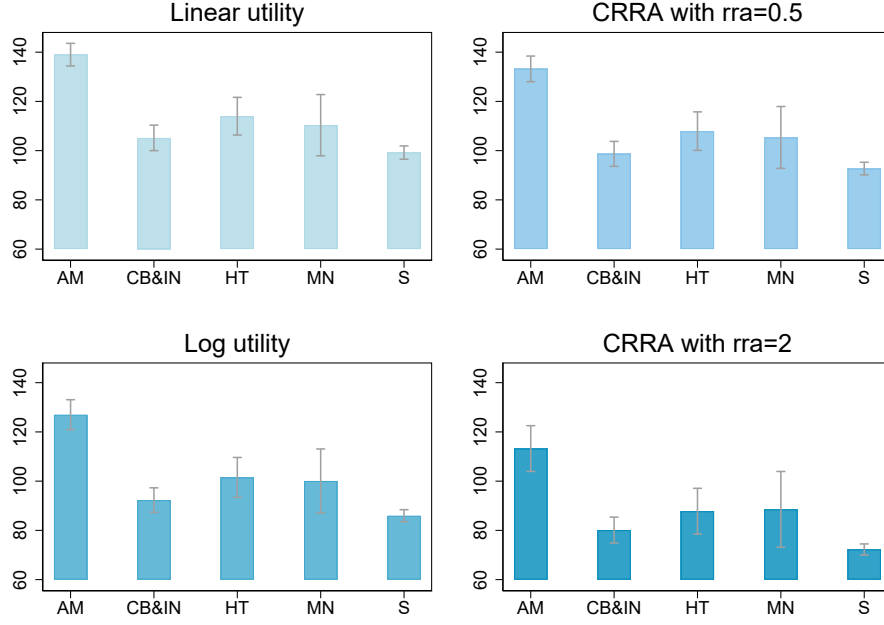


Figure 8. Certainty equivalent of yearly real wage, by sector

Certainty equivalent of the annual real imputed wage in each sector over a 20-year experience horizon, assuming a constant relative risk aversion (CRRA) utility function, for CRRA coefficient alternatively equal to 0 (linear utility) to 0.5 (square root utility), 1 (log utility) or 2. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), high-tech (HT) and manufacturing (MN).

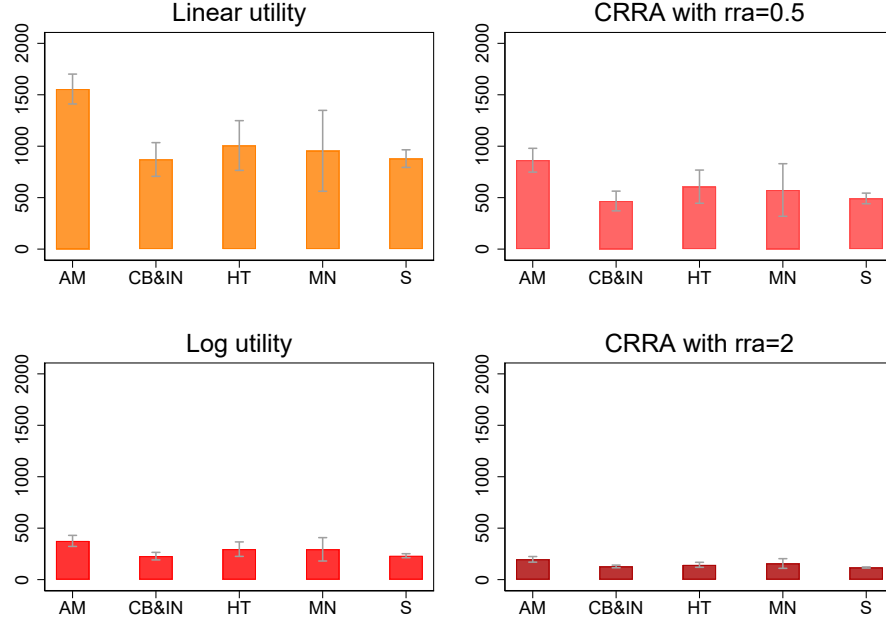


Figure 9. Certainty equivalent of yearly real total compensation, by sector

Certainty equivalent of the annual total imputed compensation (inclusive of bonus pay) in each sector over a 20-year experience horizon, assuming a constant relative risk aversion (CRRA) utility function, for CRRA coefficient alternatively equal to 0 (linear utility) to 0.5 (square root utility), 1 (log utility) or 2. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), high-tech (HT) and manufacturing (MN).

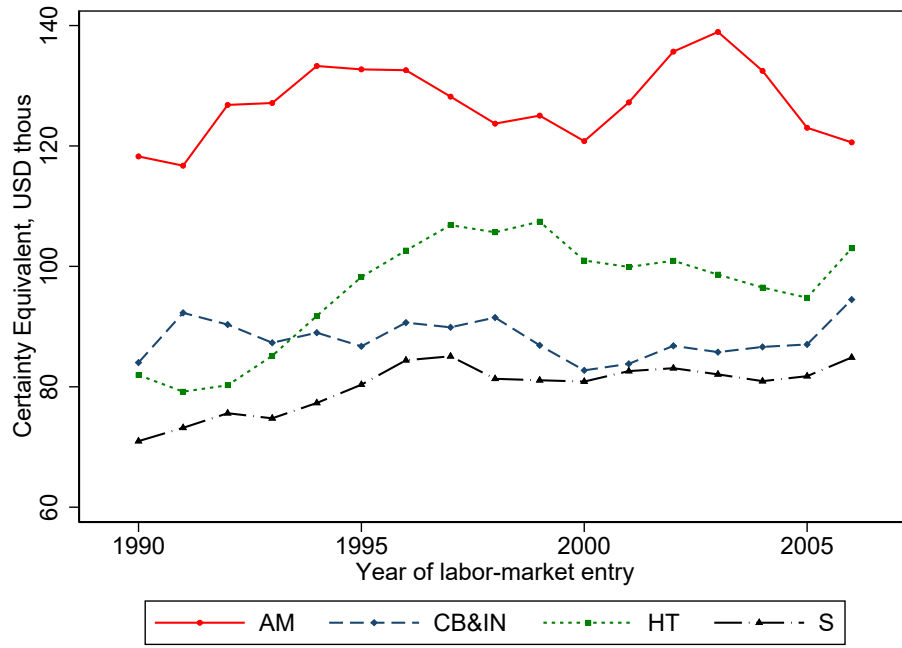


Figure 10. Certainty-equivalent wages by cohort and sector

3-year moving average of certainty-equivalent (CE) annual imputed wage in each subsector, computed over a 10-year experience horizon, assuming logarithmic utility. Subsectors: asset management (AM), commercial banking and insurance (CB&IN), high-tech (HT) and services (S).

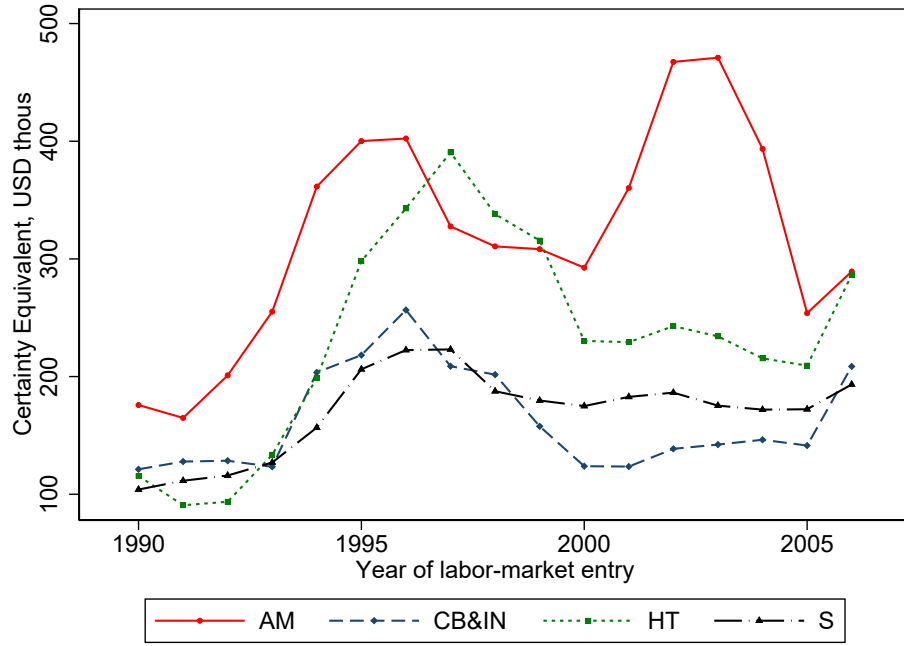


Figure 11. Certainty-equivalent total compensation by cohort and sector
 3-year moving average of certainty-equivalent (CE) annual imputed total compensation (inclusive of bonus pay) in each subsector, computed over a 10-year experience horizon, assuming logarithmic utility. Subsectors: asset management (AM), commercial banking and insurance (CB&IN), high-tech (HT) and services (S).

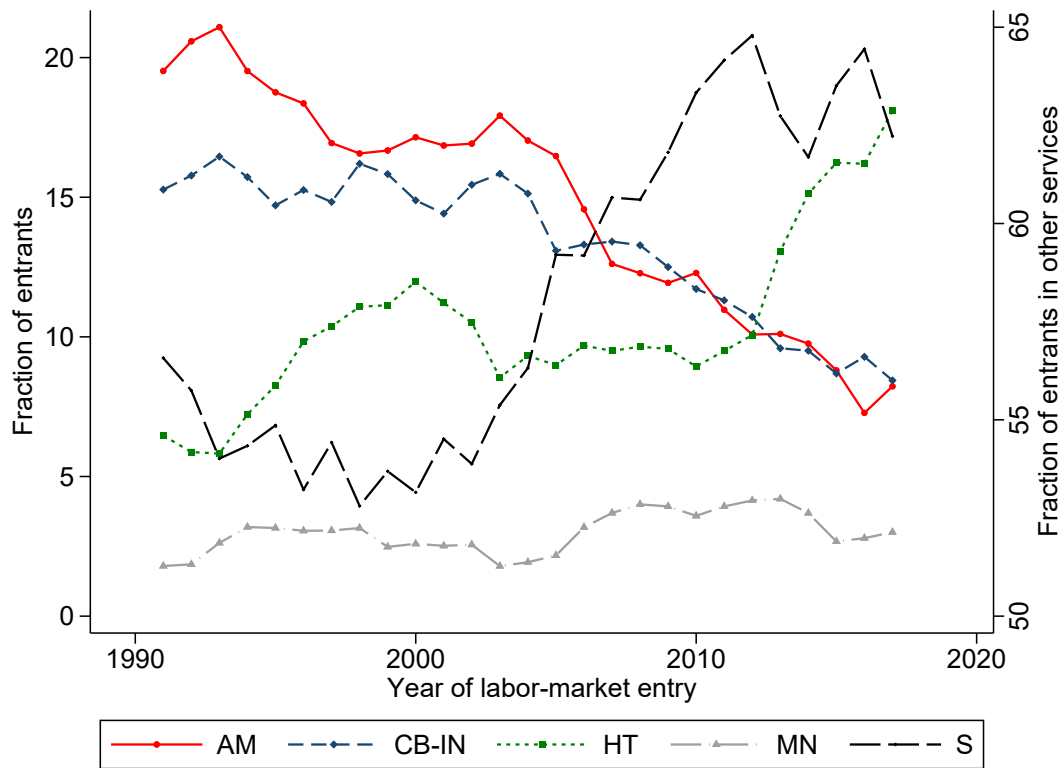


Figure 12. Flows of entrants by cohort and sector

3-year moving average of fractional flows of entrants, by subsectors: asset management (AM), commercial banking and insurance (CB&IN), high-tech (HT) and services (S).

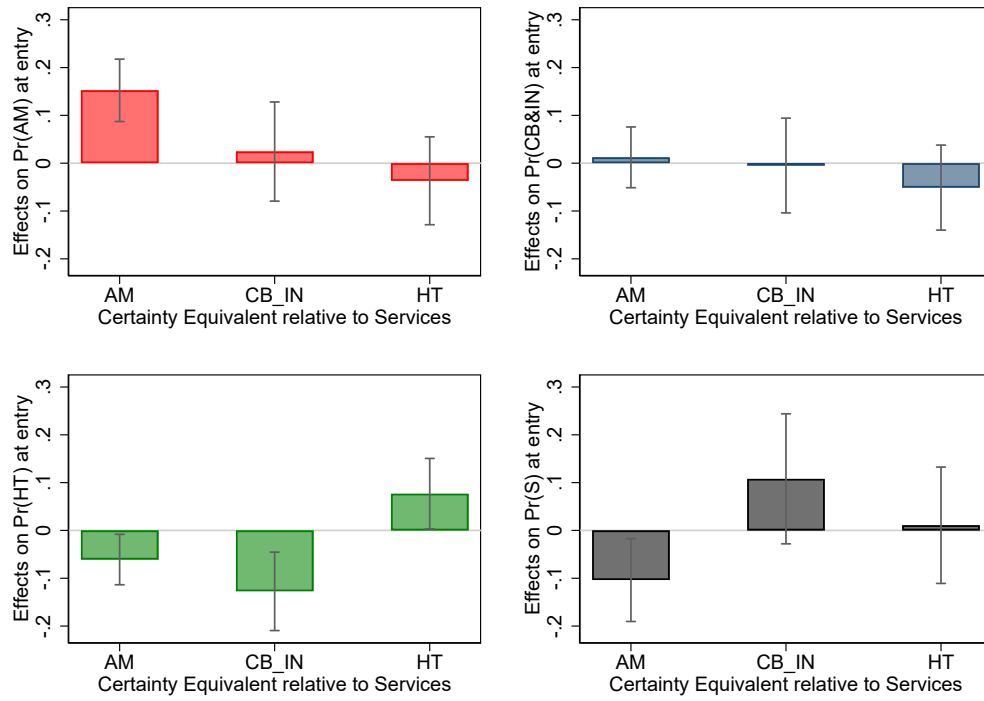


Figure 13. Career premia and entry choices

Marginal effects of career premia, measured by ratios of salaries' certainty equivalents relative to services, in a multinomial logit model of entry choices in the following subsectors: asset management (AM), commercial banking and insurance (CB&IN), high-tech (HT) and services (S).

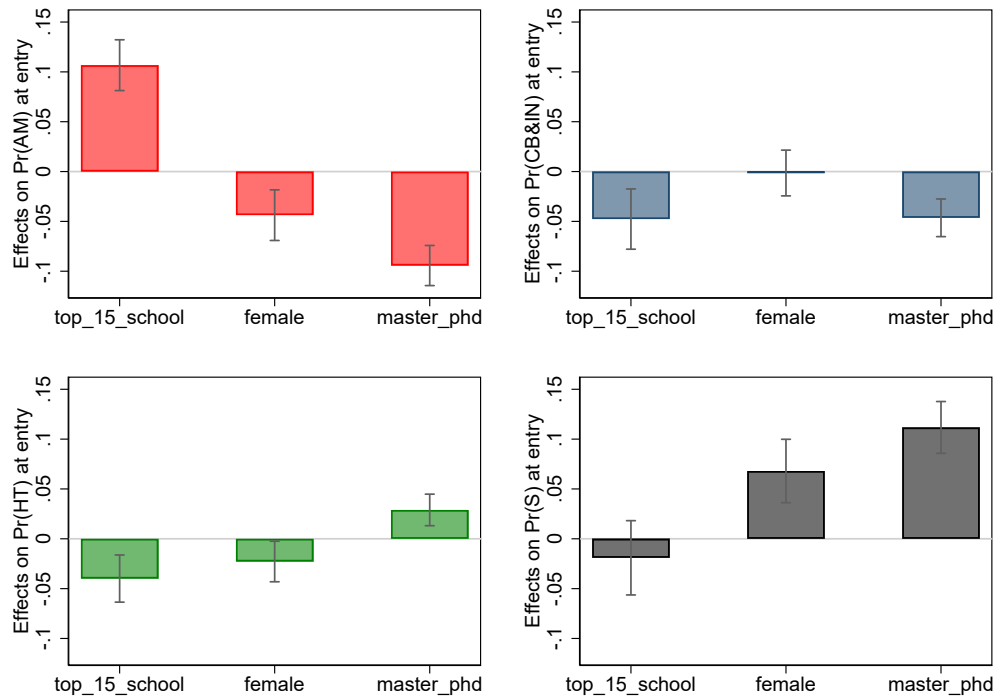


Figure 14. Individual characteristics and entry choices

Marginal effects of workers' characteristics in a multinomial logit model of entry choices in the following subsectors: asset management (AM), commercial banking and insurance (CB&IN), high-tech (HT) and services (S).

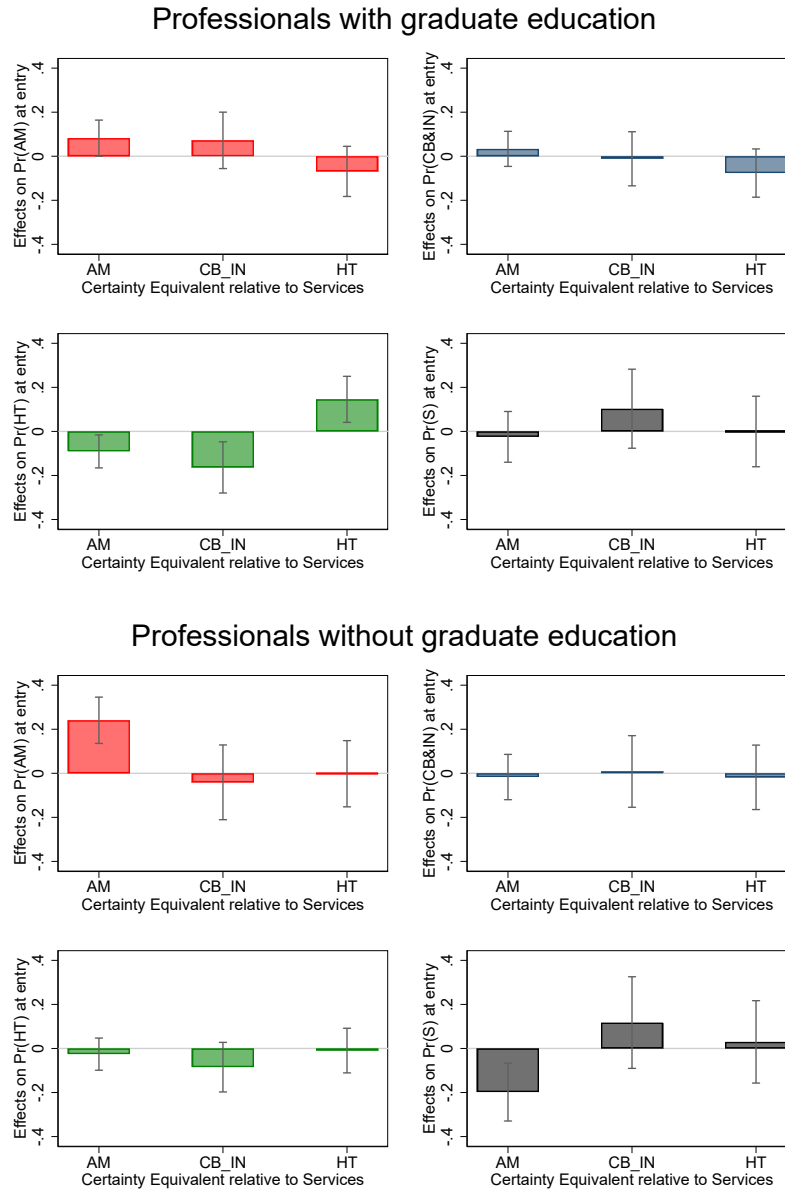


Figure 15. Career premia and entry choices, by education level

Marginal effects of career premia, measured by ratios of salaries' certainty equivalents relative to services, in a multinomial logit model of entry choices of professionals with graduate education (top panel) and without graduate education (bottom panel) in the following subsectors: asset management (AM), commercial banking and insurance (CB&IN), high-tech (HT) and services (S).