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Careers in Finance

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Abstract

Employees in finance are known to earn higher wages and returns to talent than non-finance workers since the 1990s, suggesting that finance may have attracted talent at the expense of other industries. However, the allocation of talent is likely to respond to differences in career paths across industries, not in wages at a given date. We analyze the careers of 9,964 individuals from 1980 to 2017 based on their resumes, and find that they tend to remain in the same industry for most of their working lives, consistently with them choosing occupations based on comparisons of entire career paths. Comparing various aspects of careers - levels, slopes, PDV and risk of pay profiles - we document that finance as a whole offers a career premium compared to manufacturing and high tech, through higher and steeper pay profiles. This however masks significant diversity within finance: while asset managers enjoy a large career premium and no commensurate career risks, the opposite applies to banking and insurance employees. Furthermore, relative to manufacturing, the asset management career premium has risen for cohorts entering soon before and during the financial crisis, even after controlling for career risk, while the high-tech career premium has become commensurately large for the latest cohorts.

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

Keywords: careers, hedge funds, asset managers, market discipline, scarring effects.

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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 workers since the 1990s (Philippon and Reshef (2012) and Boustanifar et al. (2018)), and significantly higher returns to talent (Celerier and Vallee, 2019). These findings raise the question whether finance may have lured talent away from other sectors, especially via attractive performance-based pay (Bénabou 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. 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 manufacturing and high tech.

Using resume-based data on the careers of 9,964 randomly drawn individuals who work in finance, manufacturing and high tech at some point between 1980 and 2017, we start by documenting that workers tend to remain in that industry for most of their working life. More than 80% of the workers who initiate their career in either finance or non-finance remain in the same industry 10 years later, and over 75% of them are found in the same industry 30 years into their working life. Even within specific sectors of finance, there is persistence in career choices: between 30% and 40% of workers in asset management or commercial banking spend their entire career in that sector – a figure that rises above 45% in the case of insurance and real estate.

Such persistence in occupational choices squares with evidence that early-career shocks durably affect workers’ 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 ask whether careers in finance differ from those in manufacturing and in high tech. 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, 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 different sectors of the finance industry, i.e., asset management (AM), commercial banking (CB), insurance (IN) and real estate (RE).

We find that the typical career profile of workers in finance features a 9% higher entry-level wage than that of non-finance workers in our sample, as well as a steeper slope, the average wage in finance being about 18% larger after 25 years of on-the-job experience. When we consider total imputed compensation rather than wages, we find entry-level average compensation to be about the same in finance and non-finance, but as careers proceed a significant difference emerges: total compensation of finance workers rises to almost \$1.5 million towards the end of the career, and to less than \$1 million in non-finance. 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.

Careers also differ across the sectors of finance: the average career profiles of employees in asset management and real estate lie above those in manufacturing and high tech, while the opposite applies to employees in commercial banking and insurance (except at the end of their careers, for the latter). Hence, not all finance sectors offer career paths that are more remunerative than those in non-finance. Within the latter, careers in high tech feature higher and steeper career profiles than those in manufacturing. Importantly, these sector-level differences between career paths persist also upon controlling for workers' characteristics, in terms of educational attainment, quality of the educational institution, gender and cohorts, and therefore do not simply reflect sector heterogeneity in worker 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 the pay level within the relevant industry or 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 the same interval of time, e.g. the first 20 years 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, defined as the difference 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 workers in manufacturing and high-tech, but such premium is concentrated in asset management and real estate, while commercial banking and insurance feature discounts. Within the non-finance sector, careers in high tech pay a premium relative to manufacturing 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. We adopt several approaches to measure such risk. We start by investigating differences in the probability of demotion risk across sectors, demotion being defined as a drop in the imputed wage associated with a change in job, both unconditionally and conditioning on workers’ characteristics. We find that this metric of downside risk is not significantly higher in finance than in manufacturing, with the exception of real estate, and in fact it is significantly lower in asset management than in manufacturing. As such, it cannot account for the asset management career premium. The only case where this risk metric correlates with career premium is the high tech sector, where the probability of demotion is higher than in manufacturing,

The probability of demotion however only refers to infrequent and persistent drops in job level and compensation, and misses higher frequency wage fluctuations around the typical career path in a given sector. To this purpose, we also measure the variability of wages as the standard deviation of the residuals of worker-specific regressions of log wages on experience and its square. Based on this alternative metric, we find that most finance sectors (including asset management) and high tech feature significantly higher career risk than manufacturing, suggesting that risk

may indeed play a role in explaining career premia. However, this measure of career risk is based only on the time-series volatility of wages around worker-specific trends, and misses the risk stemming from the cross-sectional variability of careers within each sector: it would be appropriate only if workers knew the individual trend of wages over their working life. But before entering a sector workers may be uncertain about the very shape of career paths in that sector.

This leads us to a third metric that takes into account both the time-series and the cross-sectional variation in career paths, based on the idea that a workers' entry in a given sector is a draw of a specific career path from a distribution of possible paths in that sector. Specifically, we compute the career "certainty equivalent" (CE) 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 observed wage (or total compensation), 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 manufacturing, while the opposite applies to banking and insurance. Hence, differential risk cannot account either for the observed asset management career premium or for the banking and insurance career discounts relative to manufacturing. Only for high tech and real estate CE differentials have the same sign as career premia.

Finally, 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 all cohorts in our sample. 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 lifetime 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 intergenerational comparisons. Hence, we compute the CE of the wage over the first 10 years of experience for successive cohorts groups and sectors from 1980 to 2017. Interestingly, the asset management career premium, as well as its CE, turn out to be positive and significant for most cohorts, and to *rise* for the cohorts entering soon before or during the financial crisis, whose first decade of experience might have been scarred by the crisis and by the subsequent regulatory tightening. Moreover, careers in high tech feature an increasing premium

and CE differential relative to manufacturing. Their size for post-2005 cohorts is comparable to those of asset management. Hence, the evidence shows that careers in asset management and high tech currently dominate those in manufacturing, even after controlling for their greater risk.

Our paper makes three contributions to the literature. First, we introduce the notion of a career premium, which refers to the entire career profile, as opposed to that of the wage premium used so far in the literature. Using this measure to compare careers within finance and between finance and non-finance allows us to bring new evidence to the growing literature about careers in finance (Celerier and Vallee (2019), Ellul et al. (2019), Philippon and Reshef (2012) and Boustanifar et al. (2018)). We show that career premia differ significantly within finance, and not just between finance and non-finance, suggesting that we cannot speak generically about careers in finance, especially given the limited mobility across the sectors of finance.

Second, we contribute to the debate about whether and how careers of asset managers have changed after the financial crisis: we document that the career premium of asset management has risen for the cohorts entering soon before or during the crisis, and that such increase is unrelated to career risk. This is the same sector that was identified by the literature to have grown the most in the decade before the financial crisis (Greenwood and Scharfstein, 2013), and where relative pay rises was suggested to have been fuelled by pre-crisis deregulation (Philippon and Reshef, 2012). Increased regulatory burden and oversight after 2009 could have been conjectured to penalize careers in this sector. Our evidence instead shows that this has not happened, suggesting that the determinants of the career premium are still not fully understood.

Third, our evidence indicates that the high-tech sector has emerged as a potential competitor to asset management when it comes to attract talent. Both sectors offer a commensurate career premium relative to manufacturing, and competing for a common, highly numerate talent pool, as witnessed by the ebb and flow of young graduates between the two sectors in recent years: the 2000s finance boom 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 greatly reducing the availability of jobs in finance, prompted elite students (such as MIT bachelors' 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 finance and non-finance workers, as well as across various sectors in both industries. Section 4 presents evidence of how these differences have changed over time, by considering successive cohorts, and Section 5 concludes.

2 Data

Our analysis is based on manually collected data on the careers of a sample of 9,964 randomly drawn individuals. The resulting 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. Due to its source, 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 incentive to publicize their CVs, though for opposite reasons: the least successful because they have less to be proud of, 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.

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 four sectors: asset management, investment banking

and financial advice (AM); commercial banking (CB); insurance (IN); and real estate (RE).¹

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 real 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 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 statements 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

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

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 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).

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.

2.2 Persistence of occupational choices

The first question that can be addressed with our data is whether careers are segmented along industry or sector lines: do individuals spend most of their working life in a single industry, so that a career can be regarded as 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 30 years of experience.

[Insert Figure 2]

Also within finance, a large fraction of workers tend to spend their whole career in a single sector: Figure 3 shows the distribution of the fraction of years spent in a given sector, conditional on that sector being prevalent in their career (in the sense of being the sector where the worker spends the longest time). All four histograms feature a spike at 1, whose height measures the fraction of people who spend their entire career in the corresponding sector: between 30% and 40% of the workers whose prevalent sector is asset management or commercial banking spend their entire career in that sector; this figure rises to 45% and 50% for workers whose prevalent sector is insurance or real estate, respectively.

[Insert Figure 3]

2.3 Workers' characteristics

Table 1 describes the characteristics of the individuals in our sample. Workers are classified on the basis of their prevalent industry of occupation (i.e. that where they spend most of their career). The sample breakdown by industry is roughly balanced across finance (3,924 workers), manufacturing (3,125) and high tech (2,915). Within finance, AM employees, i.e. those in asset management, investment banking and financial advice, are 44% more numerous than those in commercial banking (CB), insurance (IN) and real estate (RE).

[Insert Table 1]

On average, the imputed wages of employees in asset management and high tech exceed those in manufacturing, and the same holds for median imputed wages in

these sectors. But the opposite applies to average wages in commercial banking and insurance, which fall short of wages in manufacturing. Hence the data point to an asset management wage premium, and a banking and insurance wage discount – 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 the median total compensation coincides with the median wage, in all sectors.

In the whole sample, the fraction of person-year observations referring to employees in top executive positions is slightly less than half (43%, of which 16% in CEO status), but is larger in asset management (49 percent) and in real estate (64%), 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 several 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 40 percent of the sample, a Master’s for 41 percent, and a J.D. or a Ph.D. for 16 percent. Surprisingly, education in STEM subjects is not prevalent: only 24 percent of the individuals in the sample received their highest degree in economics or finance, and only 13 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 20 percent of employees are female, against 16 and 15 percent in manufacturing and high tech, respectively.

On the whole, these descriptive statistics indicate that employees in asset management and real estate have quite distinctive characteristics, most of which are in common with employees in the high-tech sector: higher imputed wages and total compensation, higher frequency of attainment of top executive positions, and greater likelihood of having received a Ph.D. and graduated from a top-15 university than employees in banking, insurance and manufacturing.

3 Are careers in finance different?

As career paths appear to be quite segmented by industry, it is worth asking whether these paths differ and, if so, how. The descriptive statistics of Table 1 already indicate considerable diversity in the level of average pay across industries and sectors. In this section we investigate how career paths differ across industries and sectors, not only in levels but also in slopes and risk. We shall see that such differences is not be 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 shows that the typical career profile of finance employees is not only higher but especially steeper than that of non-finance workers. The top panel plots the average real imputed wage (excluding bonus pay) in thousand dollars: finance features a rising premium, wages being about 9% higher for entry-level jobs, and 18% larger after 25 years of experience. 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. The entry-level average total compensation of finance employees is virtually identical to that of non-finance ones, and for both sub-samples it grows almost at the same rate over the first 8 years of experience,

rising from about \$350,000 to \$600,000 for both groups. But in the subsequent years of experience, the total compensation of finance employees grows significantly faster on average, rising to \$1,465,000, against \$971,000 for non-finance ones. Hence the finance premium seems associated mostly with careers being faster in finance than in other sectors: after the first decade of experience, finance employees are more likely than non-finance ones to achieve top executive jobs entailing high bonus pay.

3.2 Diversity within finance

The overall picture emerging from Figure 4 masks great diversity within finance, as well as some diversity between manufacturing and high tech. This is apparent from Figure 5, which shows average imputed real wages paid over workers' careers in various sectors within finance and non-finance. The top panel indicates that entry-level wages in asset management exceed significantly – by about 24% – those in manufacturing, and rise at a faster rate throughout workers' careers, becoming 39% larger towards the end of the career. The opposite applies to commercial banking and insurance, where career profiles lie below those in manufacturing except towards the end. The bottom panel shows that also careers in high tech dominate those in manufacturing: the high-tech premium is positive and rises steeply over the career, from about 7% for entry-level positions to 27% for workers with 30 years of experience.

[Insert Figure 5]

A qualitatively similar picture emerges also from data for total imputed compensation, shown in Figure 6. The inclusion of bonus pay considerably magnifies the scale of the typical premium paid by careers in asset management, real estate and high-tech relative to manufacturing, as well as the extent to which the asset management premium rises with experience. But it confirms the existence of sizeable negative premia in banking and insurance. 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 Figures 6 and 7]

The estimates confirm that, even controlling for these worker characteristics, careers feature significantly positive entry-level premia in asset management (amounting to about \$20,000), and negative ones in commercial banking and insurance (−\$20,000). Moreover, job experience commands a significantly larger premium in asset management and in high tech than in manufacturing: each extra year of experience adds almost \$3,000 to annual wages, against \$1,700 in manufacturing. The return to experience in other sectors of finance also exceeds that in manufacturing, but the difference is not statistically significant.

Careers in finance appear to benefit from education: graduate training increases annual pay by \$10,000 in commercial banking and \$12,000 in insurance, while a degree from a top-15 university is associated with a \$7,000 annual pay increase in asset management, \$55,000 in insurance, \$12,000 in high tech and \$8,000 in manufacturing.

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 insurance (where it is largest), high tech and manufacturing. Instead, it is barely significant in asset management, where it is especially low as a fraction of wages. However, this result may be partly due to selection: asset management features lower female participation (only 15%: see Table 1), so that average female asset managers 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 industry or sector). For instance, career paths may cross: for instance, in Figure 6 the average total compensation in the insurance sector falls short of that in manufacturing in the early career phase, but exceeds it towards the end. Moreover, the average pay profile in one sector (say, asset management) may lie entirely above its analogue in another sector (say, manufacturing), 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 time, e.g. the first 20 years 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, 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”) 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 manufacturing or in banking, irrespective of their education and gender, then individuals may require a higher expected labor income PDV to enter asset management. We investigate this point via three complementary approaches. The first one focuses on the likelihood of career setbacks, the second on the variability of wages over workers’ careers, while the third also takes into account the cross-sectional dispersion of career paths within each sector.

We start by assessing the extent to which workers in each sector are exposed to downside risk over their career, by estimating how often they experience a drop in imputed wage associated with a change in job. We consider such a wage drop as the result of a worker-specific “demotion”, rather than an economy-wide reduction in the wage paid for his/her job. Figure 8 shows that in asset management the yearly probability of demotion is not significantly higher than in other sectors, except for real estate, and is in fact significantly smaller than in commercial banking and high tech. Hence, the difference in the level of compensation across sectors does not appear

to be positively correlated with career downside risk.

[Insert Figure 8]

In principle, these differences in demotion risk may stem from systematic differences in the characteristics of employees across sectors: for instance, asset management may attract more educated employees than commercial banking, thus accounting for the different incidence of demotions in those two sectors. To address this concern, Table 2 presents panel regressions where the probability of demotion is regressed on sector dummy variables, experience and employee characteristics (Column 1) as well as on their previous imputed wage, to take into account that by construction demotion is less likely at lower levels of imputed wages (Column 2). Errors are clustered at the employee level, and the specification includes year fixed effects to control for aggregate factors such as market turbulence. Worker-level variables are indeed correlated with the frequency of demotions: workers with graduate training, greater work experience and higher past wages, as well as female workers, are more likely to face demotions, other things equal.

[Insert Table 2]

As manufacturing is the omitted sector in the regressions of Table 8, the estimate of the coefficient of each sector indicator can be interpreted as the difference between the probability of demotion in that sector and in manufacturing, all other factors being equal. The estimates confirm that, even controlling for workers' characteristics and a quadratic term in experience, demotion risk is not significantly different in asset management than in manufacturing, while it is higher in commercial banking and high tech. In real estate, demotion risk is conditionally lower than in manufacturing, and in insurance it is not significantly different.

When downside career risk is measured by the percentage drop in wage at the time of a demotion (Columns 3 and 4 of Table 2), the estimates indicate that downside risk is not significantly higher in finance than in manufacturing, with the exception of real estate. Hence, on the whole the evidence is not consistent with demotion risk being systematically higher in the sectors where careers are more remunerative and faster. The only case where such a claim is partially consistent with the evidence is the high tech sector, where the probability of demotion is higher than in manufacturing, even though the wage drop upon demotion is not significantly different.

An alternative approach to measuring career risk is to estimate the variability of annual pay around a worker-specific time trend. Using data referring to workers observed for at least 5 years in our sample, we estimate worker-level regressions of log wages on experience and its square. The standard deviation of the residuals of each of these regressions yields an individual measure of labor income variability over the respective workers' careers. Column 5 of Table 2 shows how this measure differs across sectors, conditioning on workers' characteristics and using manufacturing as the omitted sector. This measure of career risk is higher in asset management, insurance and real estate than in manufacturing, and the same applies to high tech. Hence, using this metric career risk appears to be greater in most of finance and in high tech than in manufacturing. It is not surprising that these results differ from those obtained in columns 1-4, as the variability of imputed wages captures shocks due to economy-wide, sector-wide and even job-specific wage fluctuations along a worker's career, rather than wage drops resulting from worker-specific job demotions.

A limitation of the risk metric used in Column 5 of Table 2, however, is that it considers the variability of wages over careers around worker-specific trends, hence allowing for a worker-specific entry-level wage and career path slope. As such, it can be considered as an appropriate measure of labor income risk only insofar as each worker is assumed to know the individual trend of wages over her future career in a given sector. But before entering that sector, the worker may be uncertain about the level and slope of her future career path, not just about the future fluctuations of her wage around that path. In other words, this measure of risk fails to take into account that labor income risk may also arise from cross-sectional variation across worker-specific trends. This dimension 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 careers observed in our data. 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 9 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 manufacturing, irrespective of the assumed RRA coefficient. The magnitude of the premium is decreasing in the assumed risk aversion, confirming that in asset management wages are more volatile than in manufacturing, consistently with the estimates in column 5 of Table 2. But the premium is positive even for $\gamma = 2$: the CE annual wage is \$112,550 in asset management, and \$87,980 in manufacturing, the difference between the two being statistically significant. Similarly, commercial banking and insurance feature a significantly negative career premium relative to manufacturing, irrespective of the assumed risk aversion: for $\gamma = 2$, the CE annual wage is \$70,510 in banking and 69,820 in insurance, both statistically lower than in manufacturing. In contrast, the CE annual wage in the high tech sector, while significantly higher than in manufacturing for low risk aversion, drops to \$88,980 and is no longer significantly different from its manufacturing analogue for $\gamma = 2$, reflecting the greater volatility of wages in high tech. The same applies to the CE wage in the real estate sector. Hence, differential wage risk can account for the high tech and real estate career premia, but neither the asset management career premium nor the banking and insurance career discounts.

[Insert Figure 9]

Figure 10 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. Focusing on the case where $\gamma = 2$, the CE of total compensation is \$188,922 in asset management and \$137,381 in manufacturing, the difference between the two being statistically significant. Similarly, the CE of total compensation is \$97,648 in banking and \$88,012 in insurance, both significantly lower than in manufacturing.

[Insert Figure 10]

4 Evolution of careers in finance and non-finance

Even though the finance wage premium is known to be positive and to have risen steeply since the early 1980s (Philippon and Reshef (2012); Bell and Van Reenen (2013); Celerier and Vallee (2019)), during the 2008-09 financial crisis the compensation of finance employees dropped, especially in asset management, as shown by Figure 11, which plots the average real annual salaries for workers in asset management and manufacturing from 2004 to 2017. The top panel of the figure shows average imputed salaries in our sample, whereas the bottom panel is based on the CPS March supplement data. Both panels show that during the financial crisis the average annual salaries of asset management dropped significantly, while no such fall is visible in the salaries of manufacturing employees. The figure also indicates that the drop in the relative salary of asset management employees was mainly concentrated in the crisis years, but that their relative salary tends to be lower after the crisis than before it. Hence, based on such evidence one might infer that the asset management premium disappeared since the financial crisis.³

[Insert Figure 11]

The question is whether the behavior of relative wages triggered by the financial crisis has reduced the relative attractiveness of careers in finance, and particularly in asset management, compared to manufacturing and high tech. In this section, we

³The figure also shows that in our sample average annual salaries exceed those in the CPS March supplement, especially for manufacturing workers, because our sample over-represents highly educated professionals, as discussed in Section 2.

bring the methodology presented in the previous section to bear on this question, by applying it to successive cohorts entering the labor market from 1980 to 2008. The methodology allows us to investigate whether there have been structural changes in careers over time, especially since the financial crisis, taking into account not only changes in the level and slope of career paths, but also in career risk, by computing the CE of yearly compensation in different sectors for sets of different cohorts. We assume logarithmic utility and use imputed compensation data for the first 10 years of experience of each cohort.

Figure 12 shows the percentage difference between CE annual wages in each sector and in manufacturing – i.e., percentage career premia – for each set of cohorts entering the labor market in 1980-89, 1990-93, 1994-97, 1998-2000, 2001-04 and 2005-08. Three main findings stand out from the figure.

[Insert Figure 12]

First, the asset management career premium is around 20% for most cohorts until those entering in or after 2000, and rises for the last two sets of cohorts, namely those whose first decade of experience might have been affected by the financial crisis and by the subsequent regulatory tightening. Hence, in contrast with the evidence by Oyer (2008), we find that entering the labor market at a time of crisis has not generated persistent scarring effects for the careers of cohorts that chose to enter the asset management sector – at least, not more than it has affected the careers of workers in the manufacturing sector.

Second, the figure shows that for the cohorts entering between 1994 and 2004 careers in banking and insurance offered an approximately 20% lower CE wage than careers in manufacturing, this difference being statistically significant. This discount, however, disappears for banking and becomes at best marginally significant for insurance when one focuses on the latest cohorts of our sample, those entering in 2005-08. So also for these sectors there is no evidence of a scarring effect of the financial crisis.

Third, the figure documents that careers in high tech were almost as attractive as those in asset management for cohorts entering in 1998-2000 and in 2005-08, while this was not the case for the cohorts entering between 2001 and 2004, i.e., immediately after the bursting of the 1995-2000 high-tech bubble. This is partly 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% higher wages, but then faces lower wage growth and ends up with 6% 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 concomitantly or soon after the 2001 dot-com crash, rather than soon before it. But our data also indicate that since 2005 the high-tech sector has become again attractive – indeed as attractive as asset management for prospective employees, in line with the evidence by Shu (2018) that during the financial crisis elite, highly numerate graduates have opted for careers in science and engineering rather than in finance.

These three findings are confirmed by Figure 13, which repeats the exercise of the previous figure using data for the first 10 years of total compensation (including bonus pay) instead of wages. Due to data availability issues, CE of total compensation can be computed only for the cohorts entering since 1994. The only substantive differences with the previous figure are the considerably larger magnitudes of the percentage career premia and discounts in the various sectors, relative to manufacturing. The career premium in asset management is about 50% for the cohorts entering in 1994-97 and 2005-08, and is slightly above 100% in high tech for the cohorts entering in 2005-08. Symmetrically, the career discounts in commercial banking and insurance are in the order of magnitude of -50% for most cohorts. This reflects the fact that differences in the magnitude and variability of bonus pay tend to amplify sectoral differences between careers, compared with those in wages alone.

[Insert Figure 13]

One may wonder whether these sectoral differences in the CE of pay and their changes over time reflect to some extent a different composition of employees across sectors, and changes in this composition across cohorts. For instance, we know from Table 1 that employees in commercial banking and insurance feature on average lower educational attainment than employees in other sectors, which could account for the career discount observed in this sector. Figure 14 investigates this point by repeating the exercise performed in Figure 12 separately for more and less educated employees within each cohort and sector: for each set of cohorts, the dark bars refer to employees who hold a Master degree, Ph.D or D.Jur., and the light bars to those that do not. While most of the results found so far apply to both education groups and cohorts, there is indeed a sizeable difference between the career premia of more

and less educated employees entering the banking, insurance and real estate sectors between 1990 and 1993: the more educated ones feature a career premium (although imprecisely estimated), while the less educated ones faced a discount.

[Insert Figure 14]

5 Conclusions

This paper investigates how careers differ along several dimensions between finance and non-finance industries, as well as across different sectors within each industry. To do so, we introduce a synthetic measure of the career premium, that encompasses all the dimensions of the compensation profile of a career, i.e. the level, slope and volatility of compensation over the career.

Such career premium differs conceptually from the wage premium analyzed so far in the literature because it refers to the lifetime income of a particular cohort, rather than the cross-sectional average of the incomes of all employees in a given period. For our empirical analysis, we manually collect data on the careers of a sample of 9,964 randomly drawn individuals who work in the finance, manufacturing and technology sectors. We use the employment histories of these employees from 1980 to 2017, giving us precise information about all career stages of the workers in our sample.

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 manufacturing and technology, featuring faster advances, greater returns to education and no higher career risk, the opposite is true for those choosing banking and insurance.

Furthermore, the asset management career premium relative to manufacturing has risen since the financial crisis, in spite of the substantial increase in the burden financial regulation. This increase cannot be accounted for by an increase in asset managers' career risk. The high-tech career premium has become commensurate to that in asset management for the cohorts entering in 2005-08, suggesting that since the financial crisis high tech has emerged as a serious contender of talent from asset management.

References

- Adams, R. B., and T. Kirchmaier. 2016. Women on Boards in Finance and STEM Industries. *American Economic Review* 106:277–81.
- Bell, B. D., and J. Van Reenen. 2013. Extreme Wage Inequality: Pay at the Very Top. *American Economic Review* 103:153–57.
- 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.
- Celerier, C., and B. Vallee. 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. URL <http://www.aeaweb.org/articles?id=10.1257/jep.27.2.3>.

- Gupta, N., and I. Hacamo. 2019. Early Career Choices of Superstar Entrepreneurs. Working paper, SSRN.
- Hombert, J., and A. Matray. 2018. Technology Boom, Labor Reallocation, and Human Capital Depreciation. Working paper 3190030, SSRN.
- Kaplan, S. N., M. M. Klebanov, and M. Sorensen. 2012. Which CEO Characteristics and Abilities Matter? *The Journal of Finance* 67:973–1007.
- 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. Working paper 2697777, SSRN.

Table 1: Summary statistics

	Total	AM	CB	IN	RE	HT	MN
No. of CVs	9,964	2,698	653	358	215	3,125	2,915
<i>Imputed wage, USD thous</i>							
Mean	121	142	93	93	118	125	107
Median	110	133	83	80	92	112	95
Standard deviation	59	64	44	56	64	58	47
<i>Imputed total compensation, USD thous</i>							
Mean	711	904	352	402	959	763	563
Median	118	141	89	85	110	119	106
Standard Deviation	1,046	1,244	676	926	1,215	1,042	799
<i>Top executives</i>							
Top executive (non-CEO) status	0.28	0.31	0.17	0.12	0.41	0.28	0.27
CEO status	0.16	0.18	0.08	0.07	0.23	0.17	0.16
<i>Education Level</i>							
High school	0.03	0.01	0.01	0.00	0.08	0.02	0.06
College	0.40	0.44	0.58	0.76	0.48	0.34	0.34
Master	0.41	0.41	0.37	0.21	0.39	0.45	0.41
JD or PhD	0.16	0.13	0.05	0.03	0.06	0.19	0.19
<i>Subject of highest degree</i>							
Econ or Finance	0.24	0.07	0.10	0.10	0.06	0.38	0.33
Science or Engineering	0.13	0.14	0.18	0.34	0.15	0.10	0.11
Other	0.54	0.74	0.69	0.54	0.66	0.42	0.45
Unknown	0.14	0.08	0.05	0.02	0.31	0.17	0.20
<i>Education quality</i>							
Top-15 university	0.15	0.20	0.07	0.03	0.07	0.15	0.16
<i>Gender</i>							
Female	0.23	0.16	0.18	0.16	0.31	0.24	0.29
<i>Cohort</i>							
1980-1998	0.42	0.42	0.33	0.41	0.27	0.26	0.26
1999-2008	0.39	0.39	0.44	0.40	0.41	0.40	0.39
2009-2018	0.19	0.19	0.23	0.20	0.31	0.34	0.34

Table 2: Career Risk by Sector

The table shows the estimates of regressions of individual career risk measures on sector indicators, education, gender, experience, experience squared, and lagged log wage. In columns 1 and 2 the dependent variable equals 1 for a demotion, and 0 otherwise, a demotion being defined as a drop in the imputed wage relative to the previous year. In columns 3 and 4 the dependent variable is the absolute value of the percentage change in the imputed wage conditional on a demotion, and 0 otherwise. In Column 5 the dependent variable is the variability in imputed wages, measured as the standard deviation of the residuals of worker-level regressions of wage levels on linear and quadratic experience variables. The sectors are asset management (AM), commercial banking (CB), insurance (IN), other finance (OF), and high tech (HT); in columns 1-4 these indicators refer to the sectors to which workers belong in the demotion year, while in column 5 they refer to their prevalent sector.

	Demotion indicator		Wage drop		Imputed wage variability
	(1)	(2)	(3)	(4)	(5)
AM	0.000 (0.002)	-0.004* (0.002)	0.000 (0.001)	-0.005*** (0.002)	0.026*** (0.005)
CB	0.009*** (0.003)	0.011*** (0.003)	0.001 (0.002)	0.004* (0.002)	0.012 (0.009)
IN	0.002 (0.003)	0.004 (0.004)	0.003 (0.003)	0.007** (0.003)	0.031*** (0.010)
RE	-0.013*** (0.003)	-0.012*** (0.003)	0.015*** (0.003)	0.017*** (0.004)	0.098*** (0.009)
HT	0.008*** (0.002)	0.006*** (0.002)	-0.001 (0.001)	-0.002 (0.002)	0.021*** (0.005)
Education quality	-0.003 (0.002)	-0.004* (0.002)	0.004** (0.002)	0.002 (0.002)	0.011* (0.006)
Graduate education	0.008*** (0.002)	0.007*** (0.002)	0.002** (0.001)	0.002* (0.001)	0.015*** (0.004)
Female	0.004* (0.002)	0.005** (0.002)	0.004*** (0.002)	0.006*** (0.002)	0.019*** (0.005)
Experience	0.001*** (0.000)	0.001** (0.000)	0.001*** (0.000)	0.000* (0.000)	
Experience ²	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	
Lagged imputed wage		0.014*** (0.001)		0.018*** (0.001)	
Year effects	Yes	Yes	Yes	Yes	No
Cohort effects	No	No	No	No	Yes
Observations	102659	102659	107935	103704	7638

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

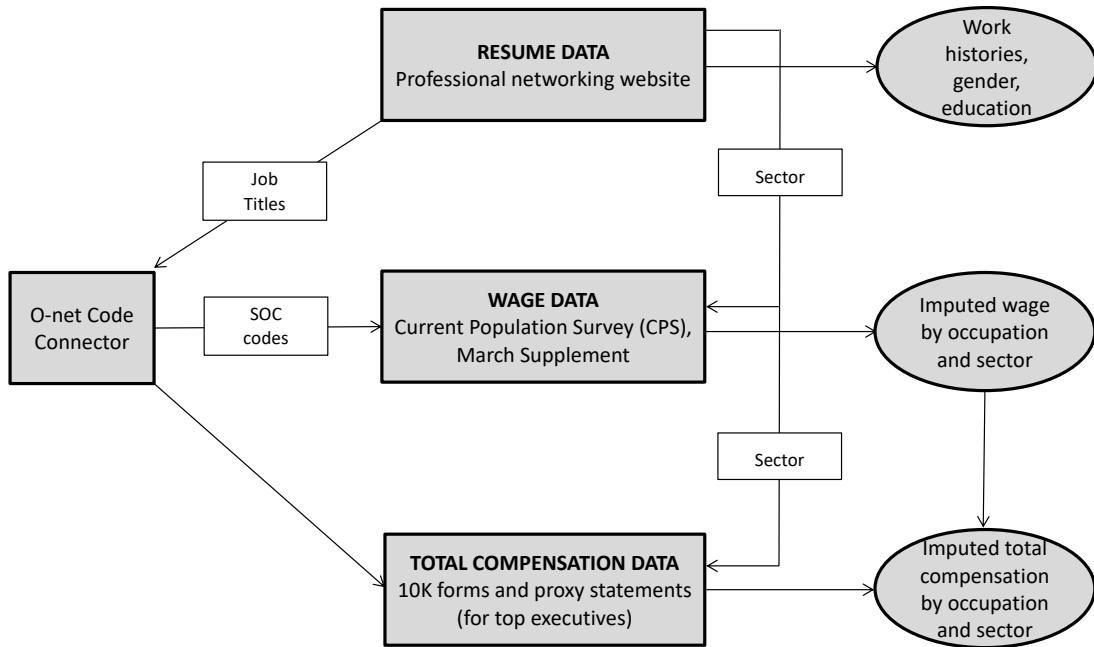


Figure 1. Data construction Information about work histories (start dates, end dates, employers, and job titles), gender and education is drawn from individual resumes available on a major professional networking website. Job titles are matched with the Standard Occupational Classification (SOC) codes 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 and proxy statements.

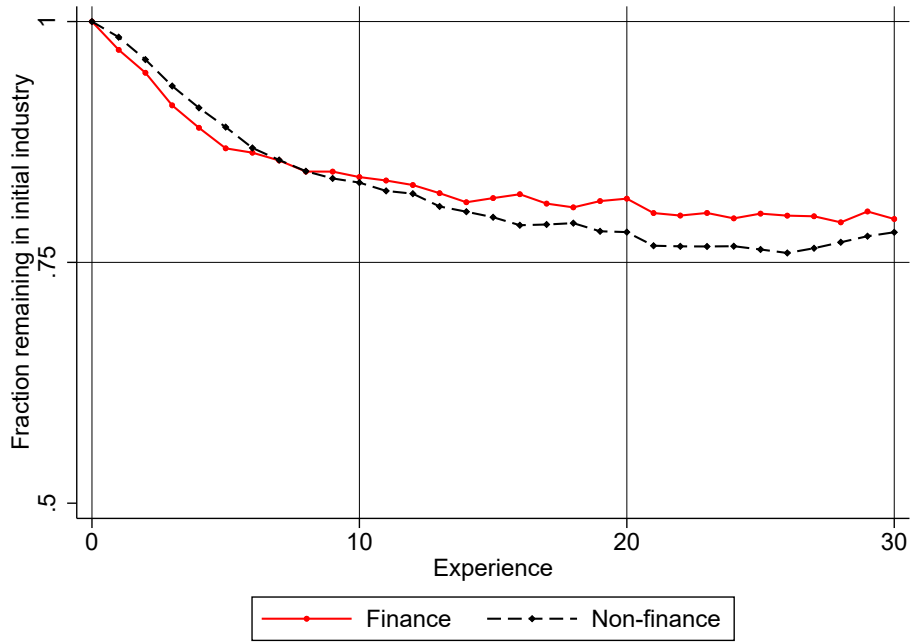


Figure 2. Persistence of initial industry choice Fraction of employees remaining in the industry chosen at entry in the labor market, by experience.

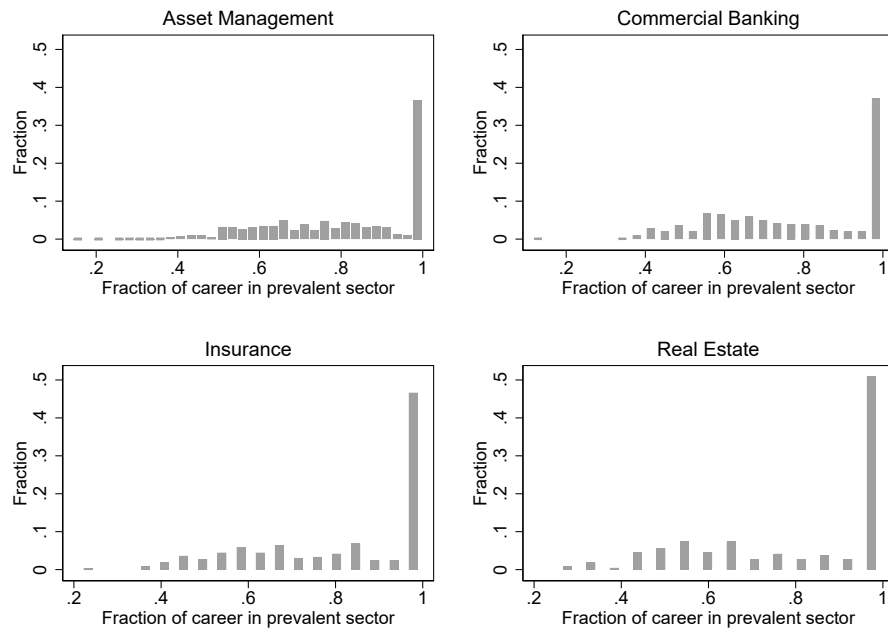


Figure 3. Sectoral specialization of careers Each panel shows the distribution of the fractional time spent in a given sector of the finance industry, conditional on that sector being the prevalent one in the worker's career (defined as the sector where the worker spends the longest time in his/her career).

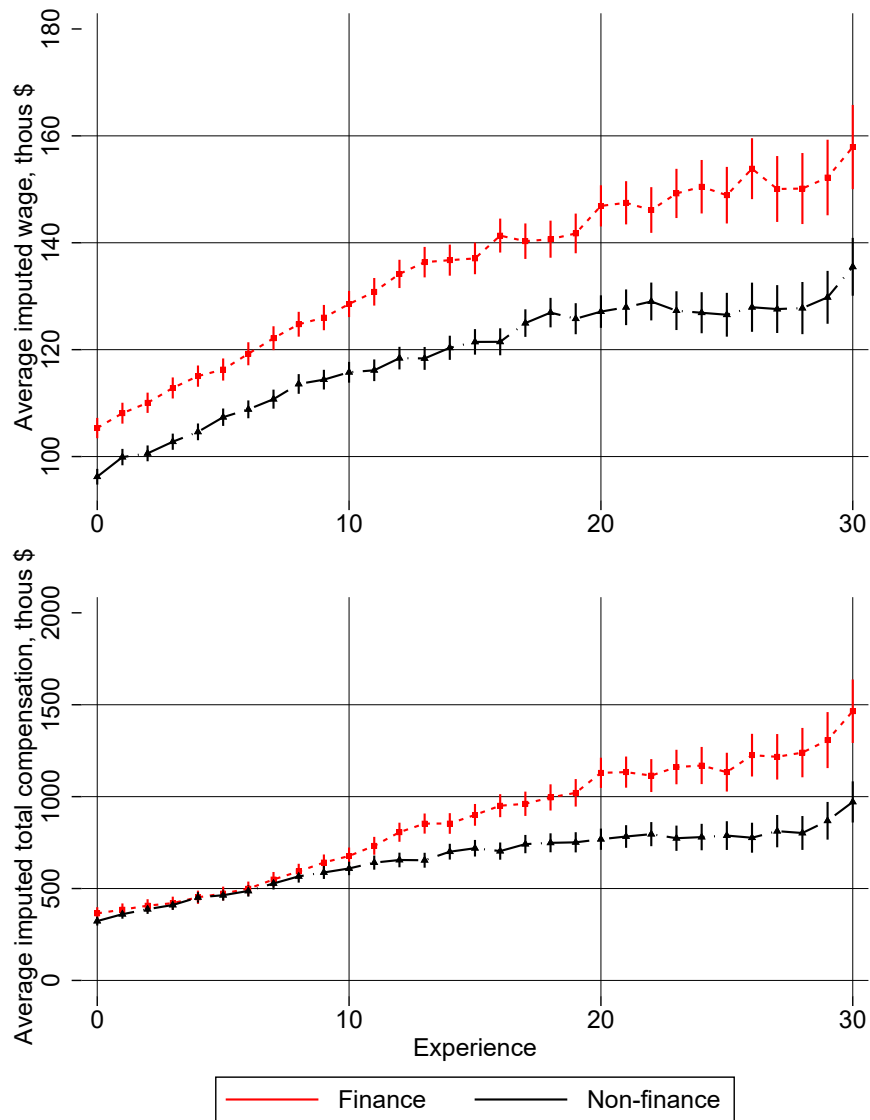


Figure 4. Average imputed wage by experience: finance vs. non-finance

Top panel: imputed wage of finance and non-finance employees for each experience level. Bottom panel: total imputed compensation of finance and non-finance employees, including wage and bonuses for each experience level.

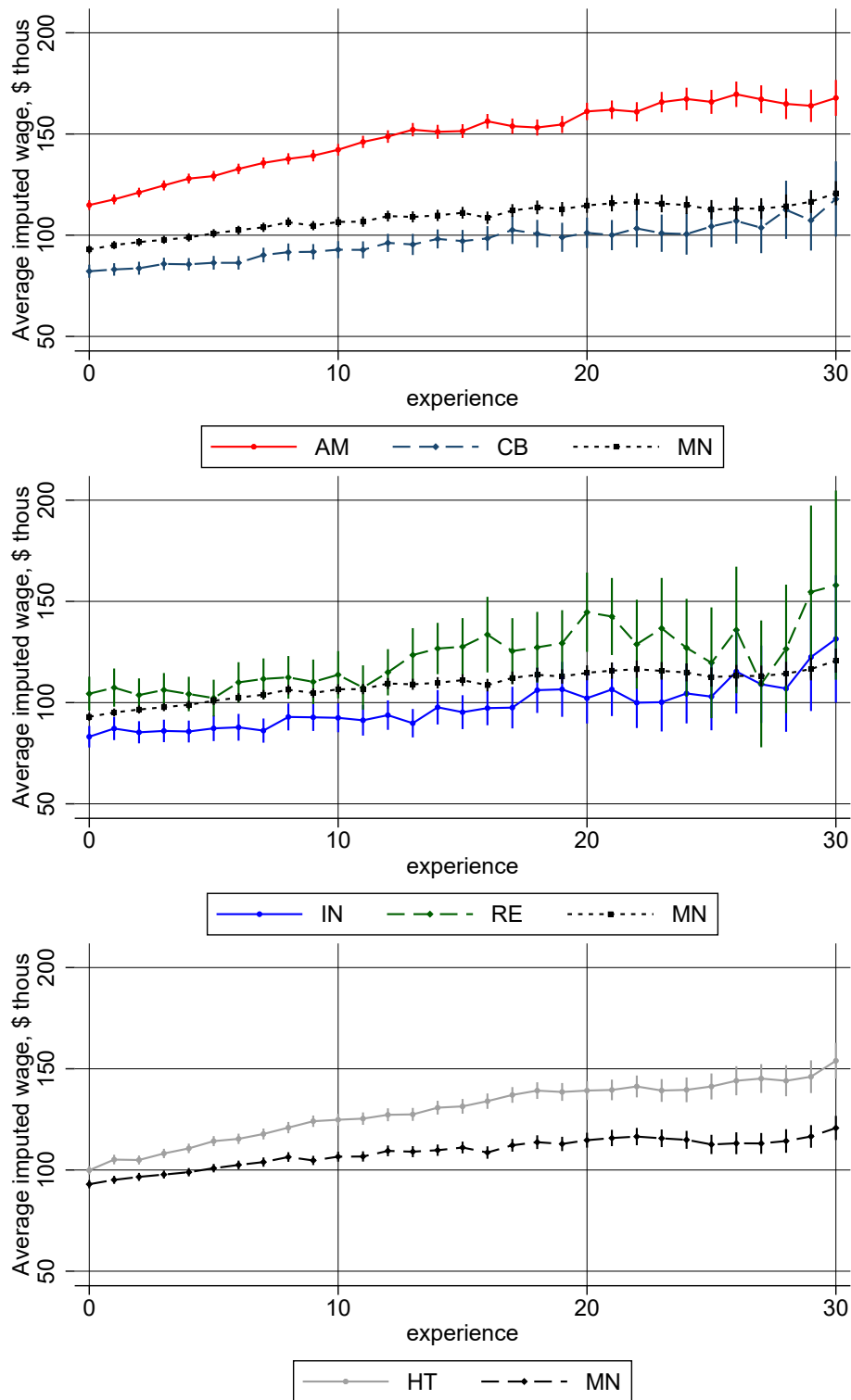


Figure 5. Average imputed wage over careers: finance vs. non-finance sectors Average imputed wage does not include bonus payments. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), manufacturing (MN) and high tech (HT).

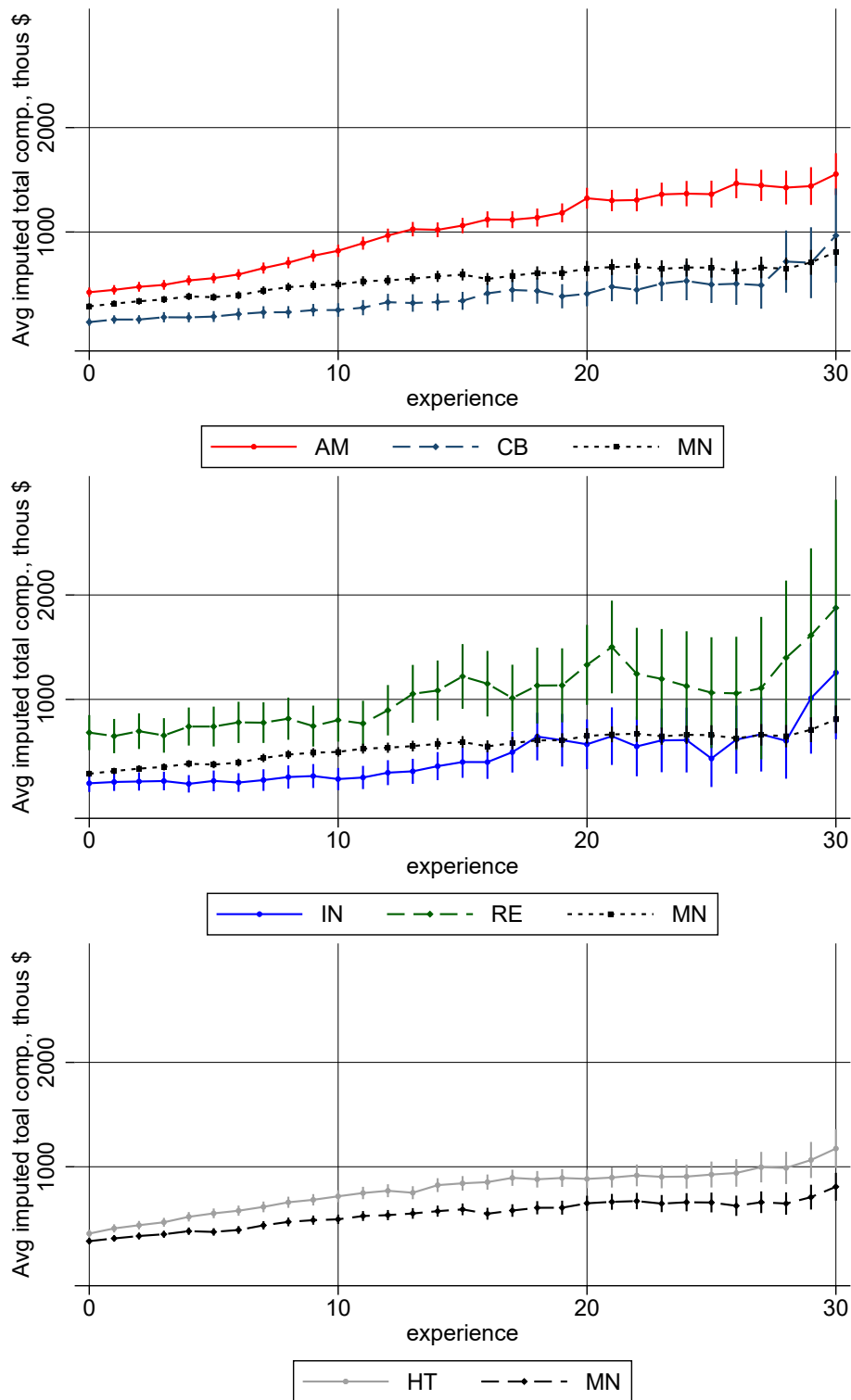


Figure 6. Total imputed compensation over careers, by sector Total imputed compensation is the sum of wages and bonuses for each experience level. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), manufacturing (MN) and high tech (HT).

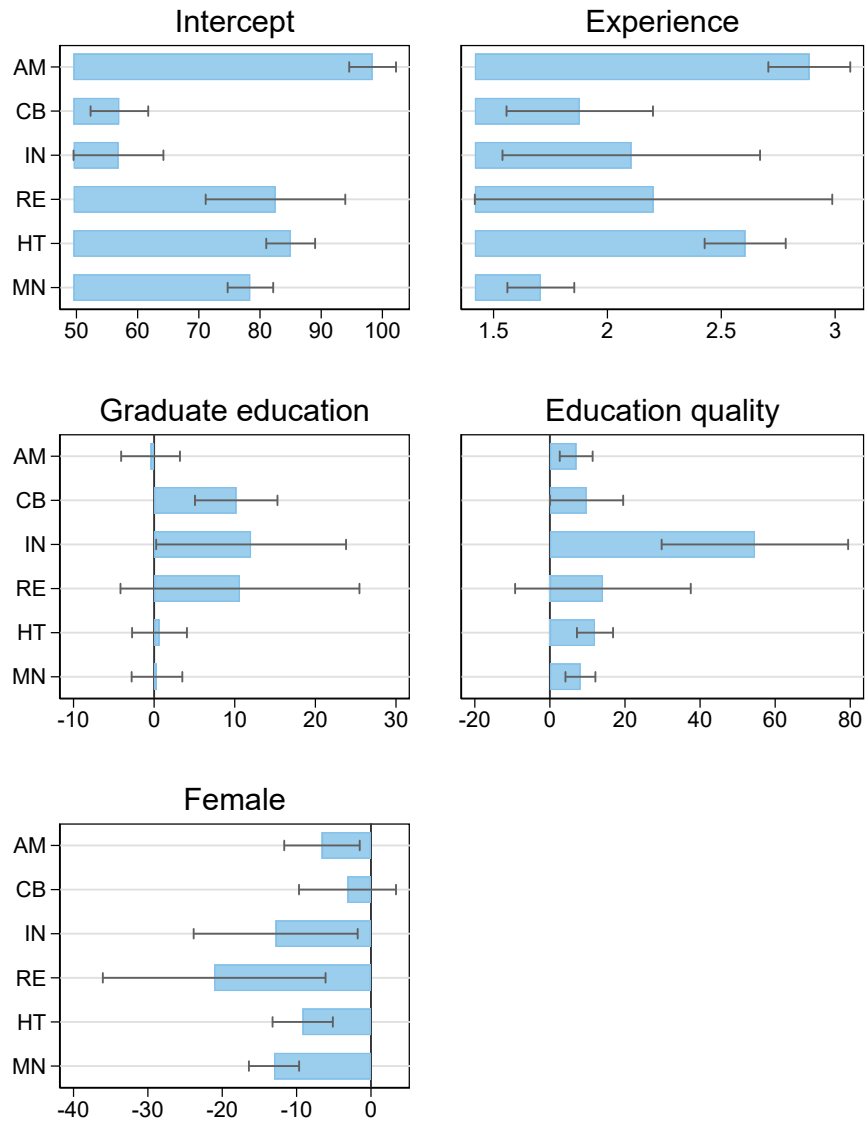


Figure 7. Career sensitivity to worker characteristics, by sector Coefficient estimates and 95% confidence intervals obtained from a regression whose dependent variable is the imputed wage of each worker and date in the sample and the independent variables are sector indicators, experience, education (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 (CB), insurance (IN), real estate (RE), and high tech (HT).

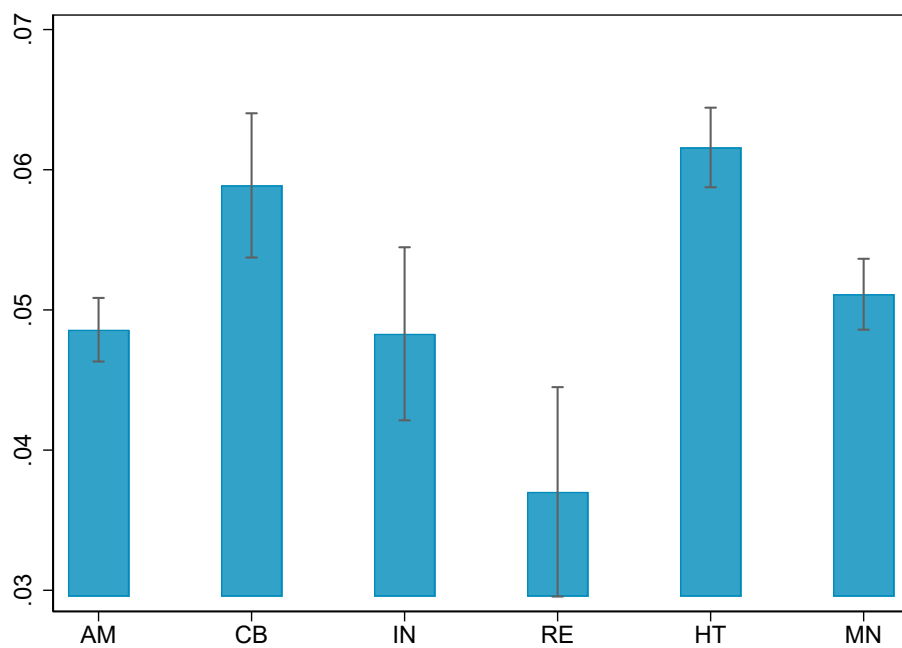


Figure 8. Frequency of job demotions by sector Fraction of person-year observations for which the imputed wage of workers employed in a given sector drops relative to the previous year, with the corresponding 95% confidence intervals. Since a drop in the imputed wage is associated with the reassignment to a lesser paid job, the figure refers to its occurrence as a demotion. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), high tech (HT) and manufacturing (MN).

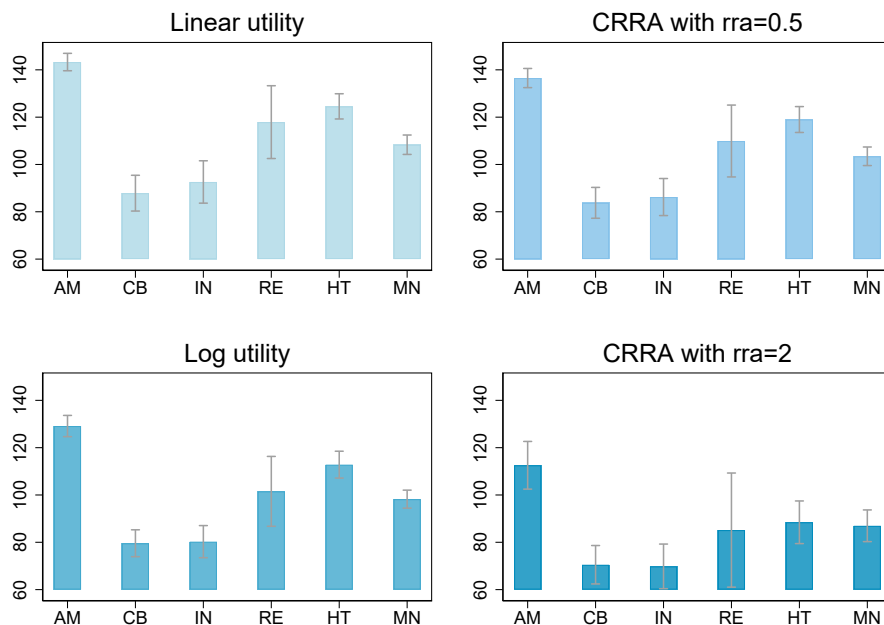


Figure 9. Certainty equivalent of yearly real wage, by sector

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).

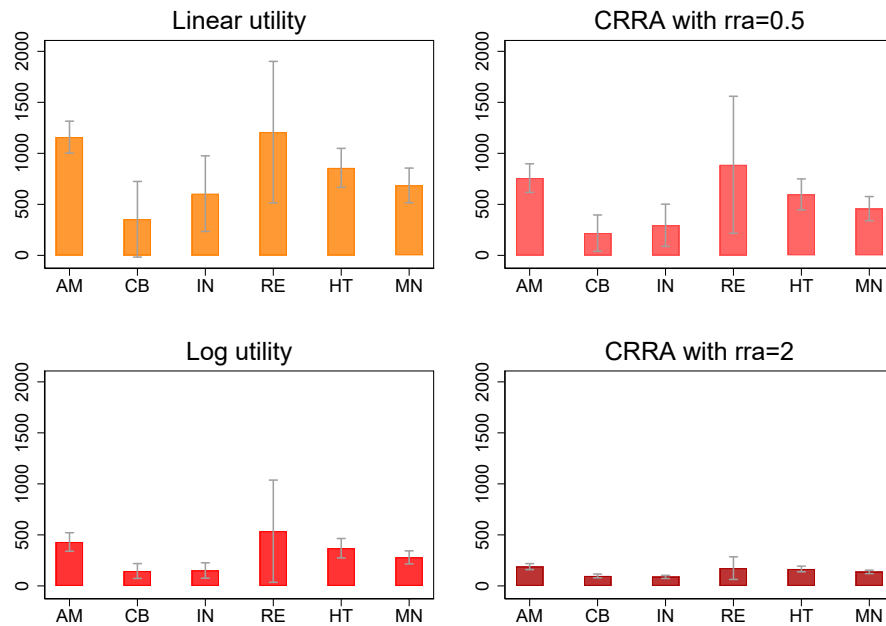


Figure 10.

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).

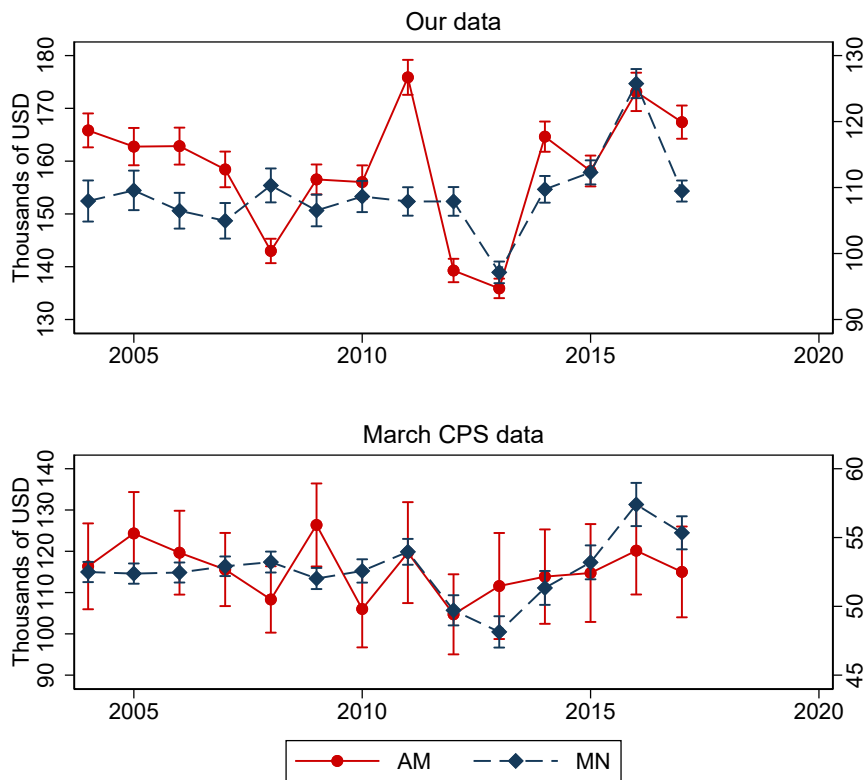


Figure 11. Average salaries and the financial crisis

The figure shows the evolution of average annual salaries (in thousands of dollars) around the financial crisis in our working data-set (top panel) and the March CPS supplement (bottom panel).

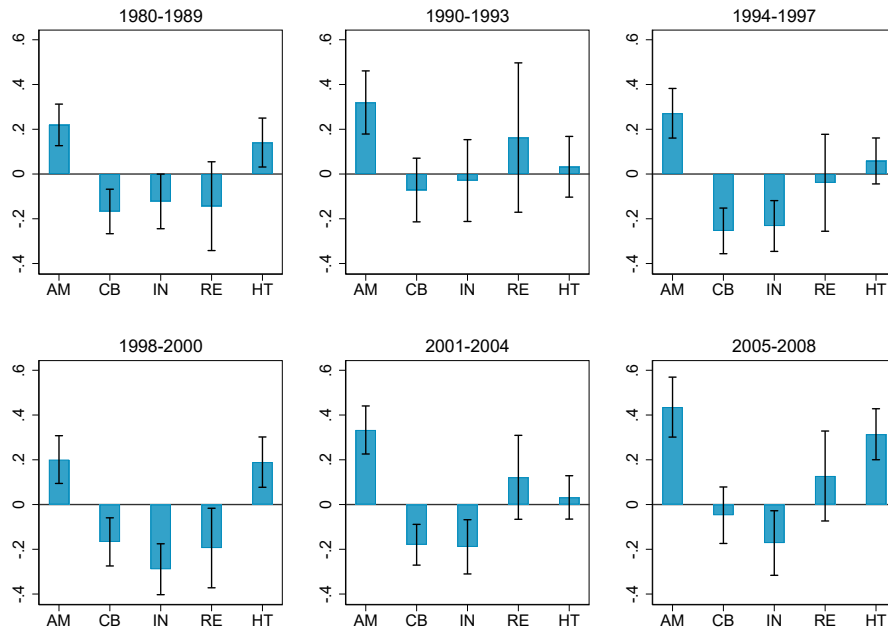


Figure 12. Certainty-equivalent wages by cohort and sector

Percentage difference between the certainty equivalent (CE) of the annual imputed wage in each sector and that in manufacturing. CE are computed over a 10-year experience horizon, assuming logarithmic utility. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), and high tech (HT).

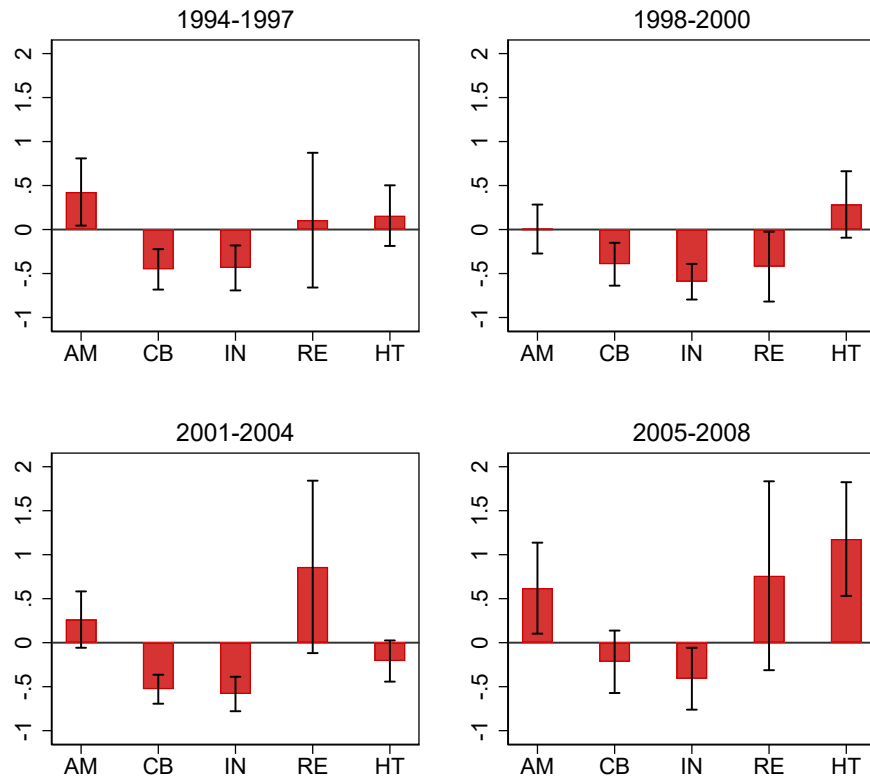


Figure 13. Certainty-equivalent total compensation by cohort and sector
 Percentage difference between the certainty equivalent (CE) of the annual imputed total compensation (inclusive of bonus pay) in each sector and that in manufacturing. CE are computed over a 10-year experience horizon, assuming logarithmic utility. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), and high tech (HT).

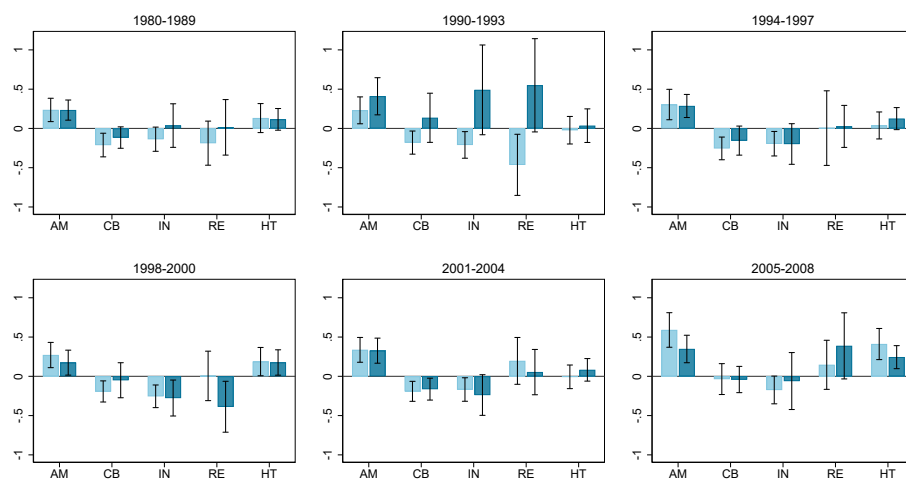


Figure 14. Certainty-equivalent wages by education, cohort, and sector

Percentage difference between the certainty equivalent (CE) of the annual imputed wage in each sector and that in manufacturing, separately for employees who hold at least a Master degree (dark bars) and those who do not (light bars). CE are computed over a 10-year experience horizon, assuming logarithmic utility. Sectors: asset management (AM), commercial banking (CB), insurance (IN), real estate (RE), and high tech (HT).