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# *Career Risk and Market Discipline in Asset Management*

**Andrew Ellul[*], Marco Pagano[**], and Annalisa Scognamiglio[***]**

**Abstract**

We establish that the labor market helps discipline asset managers via the impact of fund liquidations on their careers. Using hand-collected data on 1,948 professionals, we find that top managers working for funds liquidated after persistently poor relative performance suffer demotion coupled with a significant loss in imputed compensation. Scarring effects are absent when liquidations are preceded by normal relative performance or involve mid-level employees. Seen through the lens of a model with moral hazard and adverse selection, these results can be ascribed to reputation loss rather than bad luck. The findings suggest that performance-induced liquidations supplement compensation-based incentives.

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

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

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# 1 Introduction

The salaries of employees of financial firms are typically much higher than those of non-finance employees with similar education (Philippon and Reshef, 2012). This feature is more extreme in asset management, and particularly in the hedge fund industry. To some extent, these compensation differentials reflect agency rents: the discretion typical of asset management calls for high-powered incentive pay schemes, especially for professionals with the greatest decision-making power (see Murphy (1999) and Edmans et al. (2017)). Indeed, in this industry a substantial portion of compensation is performance-sensitive, with a fixed base salary supplemented by performance-related bonuses. But the performance-based component is typically much more sensitive to upside than to downside risk,[1] to the point that the resulting bonuses are often doubted to be a true reflection of managers' actual effort and talent. For instance, in 2012 *The Economist* wrote: "It is ... easy to think of people who have become billionaires by managing hedge funds; it is far harder to think of any of their clients who have got as rich".[2] Indeed recent evidence shows that "the risk-return trade-off for hedge fund investors is much worse than previously thought" (Dichev and Yu (2011), p. 249) to the point of raising "serious questions about the perceived superior skills of hedge fund managers" (Griffin and Xu (2009), p. 2531).

Therefore, it is worth asking whether asset managers are also exposed to the risk of permanent career setbacks when their fund is liquidated following underperformance. The question, that is, is whether the managerial labor market acts as a device for disciplining asset managers, over and above the incentives provided within the firm

[1] This applies particularly to hedge fund managers, whose performance-based incentive fee effectively amounts to a call option written on the hedge fund's asset value, with a strike price determined by the "high watermark" and "hurdle rate" provisions, together with the value at which investors underwrite the fund. The high watermark provision states that the manager receives the incentive fee only if the fund's net asset value exceeds its previous peak; the hurdle rate is the minimum return above which the manager gets the incentive fee.

[2] "Rich managers, poor clients", 22 December 2012.

(Agarwal et al., 2009). This is the research question we address here. In investigating it, we also consider the alternative hypothesis that fund liquidations induce career setbacks even in the absence of underperformance, as labor market frictions may prevent employees from finding an equally attractive job after the liquidation.

We focus on professionals working in hedge funds, as incentive concerns and their career implications can be expected to be particularly salient in this segment of asset management, for three complementary reasons. First, the hedge fund industry is the quintessential business of risk-taking, where a single bad decision may blow up an entire fund. Second, hedge fund managers have the greatest discretion in their investment choices, owing to the lightly regulated nature of the business: the difficulty of monitoring and reining in top talent creates severe moral hazard, typically addressed by up-or-out contracts with dynamic incentives (Axelson and Bond, 2015). Third, the performances of hedge funds are more closely determined by the strategies of individual fund managers than those of other institutional investors, which are typically larger and less nimble organizations. Hence, observing a hedge fund's performance can be quite informative about its managers' talent.

We manually collect data on the careers of 1,948 individuals who at some point worked in a hedge fund (according to the Lipper-TASS database) as low, middle or top manager in the investment company managing the fund. Thus not all our sample professionals eventually become CEOs (only 58% do): in this respect, our data differ from those used in most studies on managers' careers, which consider only CEOs. The resulting dataset covers employment histories from 1963 to 2016. For each individual, we observe gender, education, year of entry in the labor market, and all job changes within and across firms (not only hedge fund companies but also banks, insurance companies, mutual funds and non-financial companies). We classify jobs according to position within the corporate hierarchy and, to measure the earnings potential associated with a specific job and sector, we impute to each job title its average sector-specific compensation.

Upon being hired by a managing company, the professionals in our sample experience a significant acceleration of their career. The acceleration is greatest for those with high talent, as measured by graduate degrees from top universities and previous job experience in asset management, and for men, consistent with other evidence on gender bias in the finance industry. Career progress is also faster for those who get jobs in funds that outperformed their benchmark in the previous three years, which suggests that the respective parent companies have more financial firepower to allocate to recruitment, possibly due to greater fund inflows from investors.[3]

While entry into the hedge fund industry typically propels professionals quickly to high-level positions, it also exposes them to the danger of permanent setbacks upon the liquidation of the funds they work for. Hedge funds are particularly well suited to investigating how careers are affected by liquidations, as these are not rare events, especially in the wake of unsatisfactory performance. We find that such setbacks are quite severe in both job level and imputed compensation, and are frequently accompanied by switches to other employers: the likelihood of switches to other employers rises by 20 percentage points in the two years after the liquidation, and that of leaving asset management is 5 percentage points greater in the five years after liquidation. The career slowdown is concentrated among high-ranking managers: following the liquidation of their funds, on average top executives (e.g. CEO, CFO, CIO etc.) suffer an imputed compensation loss of about \$500,000, if the estimation is performed without conditioning on previous fund performance.

In principle, such "scarring effects" may result either from a loss of reputation or from the accidental destruction of the professionals' human capital, owing, say, to

[3]This is consistent with the evidence provided by Brown and Matsa (2016), based on applicants' responses to job postings during the recent crisis, that high-quality job seekers shy away from distressed financial firms.

overall adverse market trends in the relevant fund class or the whole market. We refer to the scarring effects arising in these two cases as "reputational losses" and "accidental losses", respectively. To discriminate between these two cases, we investigate whether the scarring effects of liquidations depend upon the fund's previous relative performance: only liquidations that are preceded by poor relative performance should be associated with a drop in reputation. Furthermore, to affect a professional's subsequent career, the drop in reputation should be sufficiently large, which is typically associated with consistently poor relative performance. We find that scarring effects are present only in funds that consistently underperform *relative* to their benchmark before liquidation: high-ranking managers of funds liquidated after 2 years of average underperformance suffer job demotion and an imputed compensation loss over the subsequent 5 years, which is $752,000 larger than if their fund had performed normally before liquidation. Hence, rather than accidental career setbacks, the scarring effects of liquidations appear to be associated with a drop in managers' reputation.

Seen through the lens of a model of career concerns, these empirical results suggest that the managerial labor market can provide a discipline device, over and above the incentives stemming from managerial compensation: incentives will then come not only from the "carrot" of performance pay but also from the "stick" of career damage.[4] Performance-related liquidations should have a particularly strong incentive effect when professionals expect fund liquidations to occur almost exclusively in the wake of underperformance and to carry no penalty otherwise. In our sample, 79% of the liquidated hedge funds performed worse than their benchmark in the previous two years, and no career setbacks are associated with accidental liquidations.

Our findings nicely complement those of Chevalier and Ellison (1999), who show

[4]Besides penalizing low-performing managers via career setbacks, the managerial labor market can also reward high-performing ones with post-retirement board service, as documented by Brickley et al. (1999). Hence the indirect incentives provided by the labor market extend even beyond retirement.

that the labor market provides implicit incentives to mutual fund managers via their career concerns: they find that managerial turnover is sensitive to a fund's recent performance and, consistently with the hypothesis that fund companies learn about managers' abilities, turnover is more performance-sensitive for younger fund managers. Kaplan (1994) documents a similar relationship between performance and managerial turnover for companies in the US and Japan, while Cziraki and Groen-Xu (2018) document that the turnover of US CEOs is more sensitive to firm performance when their contracts are closer to expiration. However, the poor firm performance that triggers CEOs' turnover may be caused by factors beyond their control, such as bad industry and market performance, as documented by Jenter and Kanaan (2015). There is also evidence that forced turnover has persistent scarring effects on CEOs' subsequent careers: using Danish administrative data, Nielsen (2017) shows that the personal income of ousted CEOs drops by 35-45% in the five years following dismissal.

Our evidence is also reminiscent of Gibbons and Murphy (1990), who provide empirical support for relative performance evaluation in CEO pay and retention policies. While our data do not allow us to test explicitly for the effects of labor market discipline on managerial effort, documenting the scarring effects of performance-related liquidations is important because it shows that performance shapes managers' careers not only within the firm but also in the managerial labor market.

In the banking sector, the evidence of labor market discipline is less clearcut. According to Griffin et al. (2018), senior executives of top banks who signed RMBS deals entailing large losses and misreporting rates or implicating the bank in lawsuits experienced no setbacks in their internal career or in their subsequent job opportunities. In contrast, Gao et al. (2017) document that, following negative credit events affecting their loan portfolios, managers working in banks underwriting syndicated loans were more likely to switch to a lower-ranked bank, and face demotion in their subsequent career.

Our evidence about the "scarring effects" of fund liquidations also relates to previous work on the effect of firm bankruptcies. Eckbo et al. (2016) report that only one third of CEOs maintain executive employment after a bankruptcy filing, especially when their firm's previous profitability was below the industry average, and departing CEOs suffer large income and equity losses. Graham et al. (2017) study how bankruptcies affect the careers of rank-and-file employees: they analyze matched employer-employee panel data from the US Census, documenting a persistent 15-percent drop in wages following bankruptcy.

Despite the superficial similarity, however, hedge fund liquidations are quite different from firm bankruptcies. As investment companies typically manage several funds, liquidating a fund rarely coincides with the closure of the firm and the forced reallocation of its employees to other employers. By the same token, the liquidation of a fund is a corporate decision that may convey information about the employees who worked for it. If it follows disappointing performance relative to other funds in the same class, the liquidation could reflect a negative judgment about their skills and potential; alternatively, it could result simply from overall market trends that induce the relevant investment company to redeploy its resources–including personnel–to other sectors. So it is important to condition the career effects of liquidations on previous fund performance, to infer whether they follow from a revision of beliefs about employees' skills or the fortuitous loss of valuable human capital.

Our paper also adds to a strand of work on careers that studies how macroeconomic or financial market conditions at the time of labor market entry affect employees' subsequent labor market outcomes: Oyer (2008) shows that a buoyant stock market encourages MBA students to go directly into investment banking upon graduation, with a large and lasting effect on their career. Schoar and Zuo (2017) find that CEOs' careers are durably affected by the macroeconomic conditions that prevail upon their original labor market entry. Similarly, Oreopoulos et al. (2012) and

Schwandt and von Wachter (2018) find that people who graduate during recessions suffer an earnings gap that lasts ten years. Our work differs from these studies in focusing on the role of the labor market in inflicting reputational losses (in case of low relative performance) rather than accidental ones (such as those arising from macroeconomic conditions).

The paper is organized as follows. Section 2 explains the construction of the data set, illustrates its structure, and describes the characteristics of the professionals in the sample and of their careers. Section 3 investigates how careers evolve upon entry into the hedge fund industry, depending in part on employee and fund characteristics. Section 4 documents that the professionals working in liquidated hedge funds suffer a large and significant slowdown in their careers compared to a control group, especially if they held a high-ranking position before the liquidation. In Section 5 we investigate the potential causes of these "scarring effects": to this purpose, we show that scarring effects are present only when fund liquidations are preceded by persistently poor relative performance, and as such they can be interpreted as reputational losses. Section 6 concludes.

## 2 The Data

We collect data on the characteristics and career paths of professionals who are listed as employees – traders, analysts, portfolio managers, top executives – in an investment company present in the 2007-2014 vintages of the Lipper Hedge Fund Database (TASS).[5] Most of the professionals in the sample also held positions in other companies in the course of their careers, at other asset management companies

[5]TASS contains quantitative and qualitative information about 21,000 hedge funds, such as monthly performance, addresses, inception date, investment focus, management and parent company, plus the names of employees, the investment company employing them, the hedge funds for which they worked and their job title.

(managing mutual funds, pension funds, private equity funds, etc.), banks, insurance companies, consultancies or even non-financial companies. Some worked for more than one employer at the same time. This occurs almost exclusively for high-ranking positions: for instance, the COO of a company may also be the managing director of another, possibly within the same group. When employed by an investment company that manages several funds, the same professional may operate in multiple funds.

Figure 1 shows how we combine data sets drawn from different sources in order to construct our sample. We draw the names of 13,056 hedge fund professionals from the TASS database, the investment companies that employ them, and the funds managed by the company. Crucially, this database can link a professional employed by a given investment company with the hedge funds managed. This information allows us to identify the professionals that are potentially affected by fund-level events such as liquidations. For each fund, TASS typically lists the names of two employees, whose job titles vary from analyst to President/CEO. Each job title refers to the position held by the employee within the hierarchy of the investment company that manages the fund, not within the fund itself. In building our sample of professionals, we rely on information reported both in the "live funds" and the "graveyard" TASS databases, so as to avoid the potential survivorship bias that would arise if one were to consider only professionals working for live funds in 2007-2014 and then backfill their careers.

**[Insert Figure 1]**

To complement the information provided by TASS with previous and subsequent work histories, we hand-collected data on education (degrees and dates, subject and school for each degree), year of the first job, and start dates, end dates, employers and levels of all the employment positions held throughout the career. The data are drawn from the individual resumes available on a major professional networking website, and from Bloomberg, Businessweek and company websites. A good many employment histories were excluded as missing or too incomplete, resulting in a final sample of 1,948 professionals. Our sample may under-represent both the least and the most successful professionals, as professionals 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 are less likely to search for new jobs.[6]

Both of these types of sample selection go in the direction of attenuating our estimates of the scarring effects of liquidations. On the one hand, insofar as successful managers like George Soros are less likely to have experienced a fund liquidation, the omission of their CVs from our sample lowers the estimated career path of non-liquidated fund managers, attenuating the difference between the career paths of liquidated and non-liquidated fund managers, i.e. our estimate of scarring effects. On the other hand, if individuals who experience fund liquidation are more likely to have unsuccessful careers, omitting their data from our sample raises the estimated career path of liquidated fund managers, again attenuating our estimate of scarring effects.

## 2.1 Job Levels

As shown in Figure 1, we classify the jobs in our sample along two dimensions: their position within the corporate hierarchy, and the typical compensation associated with each job title and sector. We first match the job titles reported in the resumes with the Standard Occupational Classification (SOC) produced by the Bureau of Labor Statistics (BLS). Then, in order to create a measure of the position of an employee in

[6]For example, George Soros makes only minimal biographical information available on LinkedIn, as he does not need to advertise it. Similarly, upon searching for the LinkedIn profiles of the 25 highest-earning hedge fund managers and traders listed by Forbes, one finds that only 5 provide information that is sufficiently complete as to qualify for inclusion in our sample. Similarly, a very unsuccessful employee may not post (or even remove) his/her CV from the web, in order not to publicize embarrassing information.

the company's job ladder, we group the SOC codes into six bins, designed to capture different degrees of decision-making power:[7]

1. Craft Workers, Operatives, Labors and Helpers, and Service Workers;
2. Technicians, Sales Workers, and Administrative Support Workers;
3. Professionals;
4. First/Mid Officers and Managers;
5. Top Executives (except for CEOs and similar positions);
6. CEOs, or other positions at the head of the corporate hierarchy.

## 2.2 Employment Sectors

Since the same hierarchical position may have different compensation in different sectors (e.g., a Chief Operating Officer typically earns more in asset management than in commercial banking), we assign the employers of the 1,948 individuals present in our sample to one of six sectors: (i) asset management (AM), (ii) commercial banking and other lending institutions (CB); (iii) financial conglomerates, defined as institutions encompassing lending, insurance and/or asset management (CO); (iv) insurance (IN); (v) other finance, which includes mainly financial consultancy and portfolio advisors (OF); and (vi) non-financial firms, government entities, supranational institutions and stock exchanges (NF). The total number of companies that employ the 1,948 professionals in our sample is 6,771. Of these, we identify the sectors of 2,129 companies based on information available in their websites, LinkedIn webpages and online financial press. To determine the sectors of the remaining 4,642

[7] These job bins are based on the EEO-1 Job Classification system, except for top executives, grouped in a separate bin.

companies, we use a machine learning algorithm that exploits the association between job titles and sectors: certain titles are found exclusively, or at least 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. For the sub-sample of 2,129 employers sorted manually into our six sectors, we know the employee job titles. The algorithm detects systematic associations between sectors and job titles on the basis of this manually matched sub-sample and exploits them to sort the remaining 4,642 employers. A detailed description of the algorithm is provided in the Appendix A.

## 2.3 Imputed Compensation

Once all the individuals in our sample are sorted into sectors, we can impute their annual compensation. For job levels 1 to 4, the imputed compensation is the average salary corresponding to each SOC code and sector, based on the 2016 Occupational Employment Statistics (OES).[8] Since the OES database does not contain information about the variable component of compensation, which is very large for job levels 5 and 6, we impute compensation for these job levels 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 in 2015 to the top five executives by the boards of the listed firms in the financial industry.[9] We collect data for firms in each of the 6 above-listed

[8]Since sufficiently disaggregated OES salary data are available only since 2000, we ignore time-series variation in salaries for the same SOC code and sector, so as to include pre-2000 data in the sample. However, our results are robust to the use of time-varying imputed compensation.

[9]The titles of the top five executives vary across firms. We collect compensation data for Chief Executive Officers (or Chairmen and Chief Executive Officers) and other executives. Chairmen and

sectors, with the following breakdown: (i) 114 firms in asset management, (ii) 388 in commercial banking and other lending institutions, (iii) 22 financial conglomerates, (iv) 109 insurance firms, and (v) 244 firms defined as "other finance". To impute the executive compensation awarded by non-financial firms we randomly choose 400 firms in the service sector.

The end result is an imputed compensation for each job title and sector. This imputed compensation gauges the typical earning capacity associated with an employee's position: it is not meant to capture the employee's actual pay, but rather to provide a measure of the earnings potential associated to a specific job in a specific sector, namely, a dollar-equivalent measure of the success attained by being in a given position and sector. This dollar-equivalent measure conveys additional information beside that contained in job levels alone: a regression of imputed compensation on job levels in our sample yields an $R^2$ of 0.76, so that a linear relationship with job levels leaves 24% of the variation in imputed compensation unexplained. There are three reasons for this. First, compensation is a convex function of job levels: promotions (demotions) at the top of the corporate hierarchy translate into much larger pay rises (drops) than at its bottom. Second, the mapping from job levels to compensation differs across sectors: imputed compensation provides a common monetary metric that makes careers comparable across sectors. Third, imputed compensation varies not only across the six job levels listed above, but also, within each level, with the SOC code for the relevant job title. For instance, the compensation of professionals (level-3 employees) ranges between \$30,000 and \$205,000, and that of mid-level managers (level-4 employees) between \$65,000 and \$221,000.

For individuals employed by more than one company at a time, we keep track of all their positions, defining their job level as the highest one held at any moment and

CEOs are classified as job level 6, all the others as level 5.

their imputed compensation as that associated with the corresponding SOC code and sector. Table 1 reports the average imputed compensation of professionals for each level, where the average is computed for our entire sample. The table also lists examples of job titles associated with each level: for obvious reasons of space, the table cannot report the thousands of job titles present in our data. The ranking of job levels in the table is broadly consistent also with the pay scale reported for hedge fund professionals in the specialized press, by which CEOs and executives are paid substantially more than CIOs and other top managers, these are better paid than portfolio managers, which in turn earn more than analysts.[10]

**[Insert Table 1]**

The table shows that the steepest increases in imputed compensation come in the step from middle management (level 4) to top management (level 5), which brings more than a nine-fold pay rise, and from the latter to positions such as CEO or executive director (level 6), where imputed compensation more than doubles. These two jumps arise mostly from the variable component (bonuses, stock and options), which is included only for level 5 and 6. On average, the variable component of imputed compensation amounts to $1,247,797 for level-5 and $3,214,088 for level-6 jobs, i.e. 79% and 87% of total compensation, respectively.

## 2.4 Characteristics of Professionals and Careers

Table 2 reports the characteristics of the 1,948 individuals in our sample. The observed career of the average individual spans about 22 years, so that the total number of person-year observations is 42,339. All those who report educational attainment

[10]See for instance the median total compensation reported for different job titles in hedge funds with more than $250 million of assets under management in the SumZero Fund Compensation Report, 2017 Edition, `https://sumzero.com/headlines/business_services/342-the-sumzero-2017-fund-compensation-report`, p. 14.

(83 percent) have at least one university degree: B.A. or B.S. for 39 percent of the sample, Master's for 41 percent, and Ph.D. or J.D. for 3 percent. As one would expect, education in economics or finance is dominant: 59 percent of the individuals in the sample received their highest degree in these subjects. A sizable minority (16 percent) obtained their highest degree from a top-15 university, according to QS Ranking, and a smaller group (6 percent) received it from a mid-level university (ranked 16th to 40th). By age, the cohort that started working in the 1990s is overweighted (almost half the sample), those that started in the 1980s and 2000s are 22 and 28 percent respectively, and only 4 percent started before 1980. Consistently with anecdotal evidence about gender imbalance in finance, the sample is male-dominated (83 percent).

**[Insert Table 2]**

By construction, our sample careers are dominated by the asset management industry, with 75 percent of all our person-year observations. However, some of the professionals in the sample spend part of their careers in commercial banking (6 percent of person-year observations) or outside finance (15 percent). The median job level in the sample is middle management (level 4 in our classification), with a median compensation of $221,000. The average compensation is much higher ($1,582,000), reflecting the extremely skewed income distribution of the financial industry. Individuals do not change only job levels but also companies in the course of their careers: 13 percent of person-year observations feature switches of employer.

A considerable number of individuals in our sample attain top positions: 33 percent of person-year observations refer to individuals holding level-6 jobs (Table 2). Mid-management positions are the next most common in the sample. The prevalence of managerial positions reflects the fact that the sample consists entirely of professionals who at some point in their career held jobs in the hedge fund industry, which typically attracts highly talented individuals. That is, our data set presumably over-represents talented workers, like those used in studies of careers of graduates from prestigious universities, such as Oyer (2008). However, our sample does not consist only of people who eventually become CEOs, as in Benmelech and Frydman (2015), Graham et al. (2013), Kaplan et al. (2012), and Malmendier et al. (2011). Unlike these studies, ours also includes individuals who rise only to low- or mid-level managerial positions, or even drop from a top position to a lower one.

Figure 2 illustrates the career paths of the 1,948 individuals in our sample by plotting their average imputed compensation against work experience, showing total compensation and its fixed component separately. On average, the fixed component starts off at $150,000 and levels off at $200,000 after 15 years. In contrast, total imputed compensation starts at about $1,000,000 and keeps rising throughout the career to triple after 45 years, although most of the increase comes in the first 25 years. This underscores the enormous importance of the variable pay component for asset management professionals.

[**Insert Figure 2**]

Where Figure 2 illustrates the career path in terms of imputed compensation, Figure 3 describes it in terms of position on the corporate ladder, i.e. job level. The progression is shown separately for three cohorts, namely those who entered the labor market in the 1980s, 1990s and 2000s. Those entering in the 1980s and 1990s feature the same typical career path, but that of the cohort entering in the 2000s differs significantly. These younger managers progress more slowly in the first 15 years of the career, and then experience a setback. This can probably be attributed to the fact that managers who started in the 2000s did not benefit from the earlier boom of the hedge fund industry and instead were hit by the crisis while still in the early phase of their careers, while their seniors had already reached top positions that sheltered them from the effects of the crisis.

**[Insert Figure 3]**

## 2.5 Hedge Fund Returns

The data on hedge fund returns come from TASS. Hedge funds are classified by their strategy as described by TASS and are grouped into six classes by Agarwal, Daniel and Naik (2009, pp. 2252-3): relative value, security selection, multiprocess, directional trading, funds of funds, and "other". Panel A of Table 3 gives descriptive statistics for the 19,367 hedge funds in the TASS database; Panel B compares the statistics for our sample of 4,944 funds with those for the TASS data.

The first two rows of Panel A display the mean and the standard deviation of the benchmarks' monthly percentage returns, defined as the average monthly return of the funds in the class for the 1978-2014 period. As expected, in light of hedge funds' high-risk strategies, mean benchmark returns are high, ranging from 0.73% per month for relative value funds to 1.32% for security selection funds; and their volatility is correspondingly high. The third row shows the standard deviation of relative performance, computed as the difference between the absolute return of the relevant fund and the corresponding benchmark return: the dispersion of relative performance is especially high in the classes where the benchmark return is itself more variable. The fourth row gives the breakdown of funds across the six classes.

**[Insert Table 3]**

On average, the performance of the funds in our sample is quite close to that of the TASS fund population. The difference between the mean relative performance of the funds in our sample and that in the TASS database is zero when all fund classes are pooled together, and is small when the comparison is made by asset class, as shown by the top row of Panel B in Table 3. The dispersion of the funds' relative performance in our sample is also comparable to that present in the entire TASS data set, as witnessed by the fact that the ratio between the two (not reported in the table) is very close to 1 (though statistically different from 1). The heterogeneity of funds' relative performance will prove to be important in analyzing the effect of liquidations on individual careers in Section 5, where we examine how the effect varies with the fund's relative performance.

Our sample features a broadly similar breakdown among the six fund classes as the TASS data, although it over-represents security selection funds and under-represents multiprocess funds and funds-of-funds. Importantly, in view of the role of fund liquidations in our empirical analysis, the fraction of liquidated funds in our sample is very close to that in the TASS database, both in the pooled data and within each fund class (except for security selection funds), as shown in the last row of the table.

## 2.6 Fund Liquidations

We identify fund liquidations based on the definition used in the TASS database. Liquidation is the most frequent reason why hedge funds exit the set of "live funds" in TASS and enter its separate "graveyard" database (48.44% of total exits in 1994-2014). The other seven reasons, which are not included in our definition of liquidation, are (i) "fund no longer reporting" (22.33%); (ii) "unable to contact fund" (18.58%), (iii) "fund has merged into another entity" (6.02%); (iv) "fund closed to new investment" (0.96%), (v) "fund dormant" (0.59%), (vi) "programme closed" (0.54%), and (vii) "unknown" (2.54%). [11]

The literature identifies various reasons for hedge fund liquidations, the main

[11]In Section 4.1, we exploit these alternative reasons for fund terminations to conduct robustness tests.

one being the realization of large downside risk in their performance (Liang and Park, 2010 and Brown et al., 2001, among others). However, also successful hedge funds may be liquidated voluntarily. For instance, even if the fund is doing well, its management may liquidate it out of dissatisfaction with the trend performance of the relevant asset class and fear of a future market crash. Another reason for liquidation is the investment company's wish to restructure its fund supply: Liang and Park (2010) cite the example of a fund that produced a cumulative rate of return of 1,139% over its 67-month history, yet was liquidated to be replaced with two new funds with the same strategy but different subscription and redemption policies (p. 213). Finally, hedge fund liquidations may be forced by regulatory interventions in the wake of alleged misconduct. A famous example is S.A.C. Capital Advisors, a hedge fund founded by Steven Cohen, that in 2012 was implicated in an insider trading scandal: in 2013 the hedge fund pleaded guilty to criminal charges in a $1.8 billion settlement that required it to stop handling investments for outsiders.

In line with the literature, we find that the 6,577 funds in the TASS database that were liquidated between 1994 and 2014 typically feature poor performance before the liquidation. As shown in Figure 4, both their rate of return and their performance relative to the relevant benchmark decline in the 4 years before liquidation. Their average rate of return turns negative 6 months before liquidation, and drops below the relevant benchmark as early as 40 months before liquidation. Indeed, 52.1% of liquidated funds feature a negative absolute rate of return in the 6 months before liquidation, and 74.5% perform worse than their benchmark in the 2 preceding years. Figure 4 also shows that in these funds the assets under management on average decline steeply before liquidation, indicating that this typically follow strong net outflows.

**[Insert Figure 4]**

However, a sizable fraction of funds (25.5%) are liquidated despite performing better than their benchmark in the two years before liquidation. Some of these (7.2% of the total) generate negative returns in the 6 months before liquidation: in their case, liquidation may still be triggered by dissatisfaction with performance. For the remaining funds in this group, which put in a positive performance both in relative and absolute terms, liquidation is likely to have been triggered by the other reasons highlighted above: negative trend in the relevant benchmark, reorganization of the fund family or regulatory interventions. In support of the first of these three hypotheses, Figure 5 shows that their absolute monthly returns feature a trend decline from about 1% to 0.4% in the 24 months before liquidation.

[**Insert Figure 5**]

Among the reasons why fund reorganization may lead to their liquidation, there may be the desire to reset a high-watermark clause in incentive fees, by setting up a new fund. However, we find that in our data funds with high watermarks are less likely to be liquidated,[12] and that the effect of a high-watermark clause on the likelihood of liquidation does not vary depending on previous fund performance.[13] Hence, the interaction of poor absolute performance and high watermark does not appear to be a significant trigger of liquidations.

[12] Also Liang and Park, 2010 find that funds with a high watermark are less likely to be liquidated, and suggest that this may be due to the fact that better managers are more likely to accept a high watermark clause than others because they are able to produce a better performance, and thus are liquidated less often.

[13] These results are obtained by estimating a panel probit regression (not reported for brevity) using our entire TASS data set at monthly frequency, where the dependent variable is a fund liquidation dummy, and the explanatory variables are the funds lagged absolute return, a high-watermark clause dummy, and its interaction with the funds absolute return: the coefficients of the funds return and of the high-watermark dummy are both negative and statistically significant, while that of the interaction is small and not statistically different from zero.

# 3 Career Paths in the Hedge Fund Industry

Our data on the career profiles of finance professionals enables us to determine whether the evidence is consistent with the popular belief that being hired by a hedge fund brings enormous career advancement and earnings gains, and to investigate whether such advancement is correlated with managers' talent and funds' performance. In Section 4, we will determine whether professionals who work in the hedge fund industry also face the danger of significant career setbacks.

Figure 6 provides descriptive evidence on career advancement after hiring by a hedge fund company, i.e. the average job level and imputed compensation of 1,379 individuals joining such a company for the first time. Entry into the industry does in fact coincide with a remarkable career leap: the job level jumps by almost a full notch (from an average of 3.8 to 4.6) and then continues to rise gradually by a further half-notch over the subsequent 30 years; similarly, imputed compensation jumps by about $750,000 in the first year and by another $1,000,000 over the next 30 years. Interestingly, entering the hedge fund industry is associated with greater career advancement than switching employers earlier in one's career, which coincides with an average rise of 0.42 notches in job level and $386,000 in imputed compensation.

**[Insert Figure 6]**

In Table 4 we investigate how job levels and imputed compensation upon being hired by a hedge fund company relate to employee and fund characteristics. Column 1 reports the estimates of a regression of the job level upon hiring on education quality (a dummy equal to 1 if the individual has a graduate degree from a top-15 university and 0 otherwise), work experience, experience in asset management and gender. Column 2 adds fund characteristics to the explanatory variables, namely, the average performance of the fund relative to its benchmark in the three years before the hiring, the average return of the fund's benchmark over the same interval, the logarithm of the fund's assets under management, and six dummies capturing the fund's investment style.[14] Columns 3 and 4 replicate the specifications in columns 1 and 2, respectively, using imputed compensation as the dependent variable. All specifications include the individual's previous job level or imputed compensation, as employees starting from higher positions have less room for advancement.

**[Insert Table 4]**

The positive and significant coefficient of the education variable can be read as evidence that talent is rewarded in the hedge fund industry: a graduate degree from a top-15 university is associated with a job level one third of a notch higher and an increase in imputed compensation ranging between \$225,000 and \$315,000 (though not significant in column 4). The career advance upon entering the hedge fund industry is also strongly related to experience, and even more to the time spent working in asset management: each year of asset management experience is associated with a further increase in imputed compensation of \$22,000 to \$29,000, depending on specification. In line with much evidence about the gender gap in finance (Adams and Kirchmaier (2016), Bertrand et al. (2010) and Bertrand and Hallock (2001)), the career progress of women upon entering the hedge fund industry is half a notch lower than that of men, and their rise in imputed compensation is between \$611,000 and \$809,000 lower depending on the specification.

The job level obtained upon entry in hedge fund industry is also positively and significantly correlated with the previous relative performance of the relevant fund. A possible interpretation is that better relative performance enables the investment company to offer higher positions to new hires, because it can attract larger net inflows from investors that allow the company to expand. This does not apply to hedge

[14]Since the job level is an ordinal variable, in Table B.1 we estimate an ordered probit model that includes the explanatory variables in column 2, and obtain results qualitatively similar to those shown in Table 4.

fund classes as such, however: neither the job level nor the imputed compensation are significantly correlated with the benchmark return of the relevant fund. Nor does fund size appear to contribute to the career advancement of new hires.

Career advancement after the hire, instead, is not significantly correlated with the fund's current and past relative performance. This is shown in Table B.2 of Appendix B, where the dependent variable is the change in job level (Panel A) or imputed compensation (Panel B) of employees of hedge fund companies between year $t$ and year $t+k$ (for $k = 1, 2, 3, 4, 5$) and the explanatory variable is the fund's relative performance, averaged over years $t$ and year $t+1$: the estimated coefficients are positive, but invariably small and imprecisely estimated. But, as we shall see in the next section, relative performance has a significant explanatory power for career prospects in the context of fund liquidations.

To summarize, our data corroborate the common opinion that hedge fund managers are very well paid, even when benchmarked against their previous pay in other segments of the finance industry. But the data are also consistent with the idea that they are at least partly rewarded for their skills, as captured by the quality and level of their education, and their experience in asset management. The next section investigates whether the labor market also punishes them for poor performance, reassessing their talent and demoting them accordingly.

# 4 Career Paths after Fund Liquidations

Here we seek to determine whether the career path of asset managers is significantly altered after the liquidation of the funds where they work, by comparison with managers whose funds are not wound up. Hedge funds are particularly well suited to this issue, in that their performance is very volatile and they are liquidated often, especially when performance is unsatisfactory: 31% of the hedge funds in the TASS database between 1994 and 2014 were eventually wound up. Specifically, the question is whether, following the liquidation of a hedge fund, the labor market options of its employees are affected adversely, and in particular whether this effect is more pronounced for high-ranking managers, who have more to lose.

As we shall see, there is evidence of scarring effects, especially for high-ranking managers. Note that our sample is biased against such scarring effects, to the extent that people tend to under-report career setbacks in their profiles on professional websites. In this sense, the effects we estimate should perhaps be seen as a lower bound.

In what follows, we first document that fund liquidations are indeed associated with a subsequent career slowdown (Section 4.1). Next, we investigate whether the post-liquidation career slowdown is greater for high-ranking managers than for low-ranking ones (Section 4.2), and whether the scarring effects of liquidations extend to other aspects of managers' careers, such as the likelihood of exiting the asset management sector or that of founding a company (Section 4.3). We leave the analysis of the possible causes of these scarring effects to Section 5.

## 4.1 Scarring Effect of Liquidations

In order to determine whether fund liquidations adversely affect employees' subsequent job levels and salaries, we use a diff-in-diff framework combined with matching, so as to compare the evolution of the careers of employees that experience liquidation with that of similar employees who do not. This method controls for unobserved talent by including individual fixed effects, and for the differences in individual career paths associated with observable differences in education, experience, gender and initial job level by building a control sample with matching characteristics. Both controls are required to clear the ground of the possible correlation between liquidations and career outcomes induced by assortative matching between funds and managers:

the liquidated funds may have been run by less talented managers, who would have had lackluster careers anyway. Individual fixed effects remove the impact of differences in unobserved talent on job levels and salaries, while the matching procedure filters out the influence of observed characteristics.

In addition, there is substantial variation in the timing of the liquidations (Figure 7). Though there are peaks coinciding with the market turbulence of 2008-09 and 2011, many liquidations also occur in normal times. This strengthens the external validity of our estimates: if funds were wound up only in financial crises, their scarring effects might be compounded by a particularly unfavorable labor market for people seeking new jobs.

[**Insert Figure 7**]

Our event of interest is the first fund liquidation that an employee experiences; in our sample this involves 661 employees, i.e. 34% of the 1,948 professionals in our sample (close to the 31% frequency of liquidations in the TASS database). Each individual who experiences a fund liquidation is paired with a control individual in the calendar year before the liquidation via propensity score matching. The matching algorithm that we use is one-to-one nearest neighbor matching without replacement, and the propensity score is based on education, experience, education quality, gender, job level, change in job level and an indicator for employment in asset management in the year before the liquidation.[15] This provides a counterfactual career development, namely, the time path that the job level, imputed compensation or company switches would have followed in the absence of liquidation. After the matching procedure, we are left with 587 individuals in the sample of liquidated funds and an equal number in the control sample. As a robustness check, we also estimate the same specifications

[15] As a robustness check, we implement another algorithm in which the propensity score is also based on the relevant fund's pre-liquidation performance, and obtain similar estimates.

on the whole sample of 661 individuals that experience a liquidation and 1,287 that do not, without matching: the resulting estimates (shown in Table B.3 of Appendix B) confirm those obtained with the matching methodology.

Our specification controls for individual effects and for time effects:

$$y_{it} = \alpha_i + \lambda_t + \sum_{k=-5}^{5} \delta_k L_{it}^k + \epsilon_{it}, \tag{1}$$

where $y_{it}$ is the variable of interest, namely, the job level, compensation or switch to a new employer, $\alpha_i$ are individual fixed effects, $\lambda_t$ are year effects (relative to the liquidation year, defined as $t = 0$),[16] and $L_{it}^k = L_i \times \mathbf{1}(t = k)$ are a set of 11 dummies, each equals to 1 $k$ periods before or after the liquidation if individual $i$ experiences it ($L_i = 1$), and 0 otherwise.

We normalize the value $\delta_{-1}$ to 0 in order to identify the sequence of $\delta_k$, which can be interpreted as the change in outcome (e.g., job level) from the year before the event to $k$ periods after (or before) by comparison with individuals who did not experience a fund liquidation. Our empirical strategy requires the absence of trend differentials in the outcome variable before the liquidation event. If this assumption holds, then $\delta_k$ should be approximately zero for $k < 0$, and any effects of the liquidation should emerge as estimates of $\delta_k$ significantly different from zero for $k \geq 0$.

We use career data for five years before and after the liquidation event, to make sure that the endpoints of the leads and lags are not a mixture of further leads and lags. Since it has been shown that talented workers tend to leave their companies when these approach bankruptcy (Baghai et al., 2017), we count as affected employees all those who were employed in the relevant fund in a two-year window prior to the event. This avoids the selection bias that could be induced by considering only those

[16]All our results are robust to the inclusion of year fixed effects (in addition to year-from-liquidation effects), intended to control for aggregate shocks equally affecting managers of eventually liquidated funds and those of the control group.

still working at the fund when it is wound up.

The resulting estimates are shown in Figure 8 (job level), Figure 9 (compensation) and Figure 10 (employer switches) for an interval of 11 years centered on the liquidation year. Each figure shows the paths of these three outcomes for the liquidated and control groups (upper panel) and the corresponding differences (i.e., the estimated $\delta_k$) with their 95% confidence intervals (lower panel). None of the three outcome variables shows any significant difference in pre-liquidation trends between the liquidated and control groups, that is, the coefficients $\delta_k$ are not significantly different from zero for $k < 0$, as our empirical strategy requires; but they are significantly different from zero afterwards.

[**Insert Figures 8, 9 and 10**]

In particular, both the job level and imputed compensation decline significantly after the liquidation, without noticeable reversion to their pre-liquidation level. The job level drops by 0.2 notches in the two years after liquidation and remains at this lower level for the next three years. The behavior of imputed compensation is similar: by the second year after liquidation, it drops about $200,000 below the pre-liquidation level, and stays there in the subsequent three years.

A possible concern about our estimates of the drop in imputed compensation associated with fund liquidation is that our imputation is based on 2015-16 data only, and therefore exploits cross-sectional variation but neglects time-series variation in imputed compensation. This choice is aimed at maximizing our sample size, since we can construct a time-varying measure of imputed compensation only for the 2000-15 interval. However, to test the robustness of our results in this direction, we repeat the estimation using time-varying imputed compensation for this shorter sample: the resulting estimates of the drop in compensation in the first three years after liquidation is very similar to that reported above, i.e. about $144,000, $200,000 and

$160,000 below the pre-liquidation level, respectively.

On the whole, Figures 8 and 9 suggest that individuals working for liquidated funds suffer a significant and durable career slowdown. The slowdown is specifically associated with liquidations, and not to fund terminations due to other reasons. In unreported regressions, we test whether careers feature a significant slowdown when individuals face for the first time a fund termination occurring for other reasons, specifically because, according to TASS, the fund is merged into another entity, is closed to new investment, becomes dormant or has its program closed. We find no significant changes in the career paths of professionals following any of these events. Thus the scarring effects documented here are not merely associated with the fund being dropped from the database of live funds.

The post-liquidation career slowdown is accompanied by increased probability of switching employers. For employees with jobs in more than a single company, a switch occurs when any of the employers changes. However, moving to a different fund managed by the same parent company does not count as a switch (the employment relationship is at company and not fund level). The probability of switching, i.e. job mobility, rises by 10 percentage points in the year after the liquidation, as shown by Figure 10). The figure also shows that, prior to the liquidation date, the managers of the funds that are later liquidated are no more likely to switch employer than those in the control group. This is consistent with the idea that it is the liquidation that triggers mobility, not managerial turnover (due, say, to resignations) that triggers liquidations.[17]

In Figures 8, 9 and 10, the estimate of the effect of liquidation at each date (each $\delta_k$) is based on a different sample, because sample composition changes over time.

[17]This test is possible only because the managers of the liquidated funds include all those who worked for those funds at any time during the two years prior to the event: if we had required them to work for those funds up to the year of the event, then by construction they could not have switched to a new employer beforehand.

For example, asset managers whose funds are liquidated early in their careers are not observed several years prior to the event, and those who experience liquidation at the end of the career are not observed several years after. To allay this concern, as a robustness check, we also estimate equation (1) using a balanced sample of managers of liquidated funds and matched controls, i.e. manager pairs that are observed for all the eleven years surrounding liquidation. The results (not reported for brevity) are very similar to those shown in the above figures.

## 4.2 Scarring Effects for High and Low-Ranking Employees

One may expect scarring effects to vary among professionals depending on their characteristics: for instance, better educated or more experienced individuals may suffer a smaller loss of reputation and find another job more easily. However, we find that post-liquidation career outcomes do not differ significantly by educational quality, work experience or gender.

The only characteristic that does significantly affect the existence and magnitude of scarring effects is the previous job level. Specifically, high-ranking employees are hurt more severely than others following a liquidation, as is shown by repeating the analysis separately for two groups: individuals with high positions (job levels 5 and 6), and those with medium-level jobs (levels 3 and 4) prior to the liquidation. The classification is based on the position held two years before the liquidation in order to test for possible anticipated effects of the liquidation on job levels. Also in this case, we use observations for 11 years centered on the liquidation year, both for the employees of liquidated funds and for the control sample.

The top panel of Figure 11 displays the job level paths for high-ranking employees of liquidated funds and for the respective control group. The two groups advance at the same pace towards top jobs (level 6) before the liquidation, but diverge afterwards: the employees of the liquidated funds gradually lose 0.4 notches over the subsequent five years, the control group less than 0.2. The middle panel, by contrast, shows that mid-level employees keep advancing in their career paths after liquidation, albeit at a slightly slower pace than employees in the control sample. The bottom panel shows that the differences between the post-liquidation career paths of high and mid-level employees relative to their respective controls (i.e. the differences in their estimated $\delta_k$) are significantly different from zero in the first two years after liquidation. While the two top panels show how job levels change differentially for employees starting from a given level, the bottom panel shows the difference between the effect of liquidation for employees starting from top and mid-level jobs, as well as the corresponding 95% confidence intervals.

[**Insert Figure 11**]

The behavior of the imputed compensation of the two groups of employees differs even more markedly (Figure 12). After liquidation, high-ranking employees face a much sharper cut in imputed compensation than their control group, while mid-level employees experience no decline relative to their peers in non-liquidated funds. The difference-in-difference between high-ranking and mid-level employees is about \$500,000 after 5 years, and statistically significant at the 5% level.

[**Insert Figure 12**]

Job mobility also increases substantially after liquidations only for high-ranking employees: for them, the probability of switching to a new employer increases by 10 percent more than for mid-level employees in the year after the liquidation (not shown for brevity).

The fall in the post-liquidation job level implied by our estimates for top-level employees may seem less striking than that documented for executives after bankruptcy by Eckbo et al. (2016): only one third of their sample of executives retain CEO status after bankruptcy, while in our sample 71% of level-6 professionals retain this level in the subsequent 5 years. This difference may be simply because hedge fund liquidations are far less traumatic than firm bankruptcies: investment companies typically manage a family of hedge funds, and therefore generally stay in business even after winding up a fund. Hence top-level professionals working for a liquidated fund can retain their rank within the same company, working for another of its remaining funds. Indeed, the effects of liquidations on top-level professionals differ markedly depending on the number of funds that their investment company operates: five years after liquidation, 84% of level-6 professionals retain their job level if they were employed by an investment company with a number of funds above the median, against 65% at companies with below-median number of funds (the median being 5).

The drop in imputed compensation of high-ranking managers also differs between these two types of investment companies: Figure 13 shows the average compensation for level 5-6 professionals at liquidated funds, separately for companies with above- and below-median numbers of funds. The average post-liquidation loss is about $500,000 less for managers employed by investment companies with more funds, and this difference is statistically significant. These results are consistent with the idea that multi-fund investment companies tend to retain valuable top-level employees, because the liquidation of one of the funds is less likely to be associated with the demise of the company.

**[Insert Figure 13]**

## 4.3 Other Outcomes of Liquidation

In principle, the liquidation of a hedge fund may be associated with even more drastic career outcomes than demotion in the corporate hierarchy or a pay cut. It could mean the exit from asset management or from the finance industry altogether. We investigate whether this is the case in the regressions shown in the first two columns of Table 5, which are based on the sample of individuals that experienced liquidation and their matched controls. For each individual, we use data from 1 year prior to liquidation, the year of liquidation and the 5 years following it (7 years in total). In column 1 the dependent variable is a dummy equal to 1 if the individual works in asset management and 0 otherwise; in column 2, it is a dummy capturing whether the individual works in the finance industry or not. The other regressions in Table 5 investigate two other outcomes of fund liquidations, namely the observed frequency of being a company founder and the number of employment positions held.

**[Insert Table 5]**

All the regressions in Table 5 are estimated separately for top- and medium-level employees, given the foregoing evidence that fund liquidations are associated with different career outcomes for the two groups. And in fact for these other outcomes too there are no statistically significant effects for mid-level employees, whereas for those starting from top-level positions the probability of remaining in asset management in the five years after liquidation is 5 percentage points lower than for their peers not exposed to liquidation (column 1), although their probability of exiting the finance industry altogether is not significantly greater (column 2). Three years after the liquidation, 86% of the employees associated with liquidated funds are still in asset management. Of those leaving asset management, 55% end up outside finance altogether, 27% in commercial banking, 11% in "other finance" (mainly financial advising), 4% in financial conglomerates, and 3% in insurance.

The probability of being the founder of a company drops by about 4 percentage points for top-level employees after a fund liquidation, suggesting that liquidation may depress entrepreneurship, possibly for reputational reasons (column 3). Finally, liquidation does not appear to be significantly associated with change in the number of employment positions, i.e. companies with which an individual is associated.

The main result of this section is that hedge fund liquidations entail significant and persistent scarring effects, mainly on high-ranking managers. In itself this finding does not help us to discriminate between reputational and accidental losses. One could argue that, given their decision-making power, high-ranking employees are subject to the greatest reputation loss. But they also are likely to be those with the most human capital at stake: they may have developed portfolio strategies, client relationships and work habits that cannot be easily transplanted to a new job, possibly outside the hedge fund industry or even the finance industry altogether. Hence, they may stand to lose more than lower-ranking employees. In the next section we use a different approach to distinguish between liquidations that tarnish the managers' reputation and those that do not.

# 5 Possible Causes of Scarring Effects

In principle, the scarring effect of fund liquidations may have two, not necessarily mutually exclusive, causes.

First, liquidation may trigger a reputation loss for the asset managers, with repercussions on their subsequent careers. However, this reputation loss should occur only when liquidation follows underperformance that persists sufficiently long and therefore is not just the reflection of high-frequency noise. In this case, the liquidation of the fund is prompted by dissatisfaction with the perceived skill of its managers. But, since fund performance is publicly observable, the managers also lose reputation with other potential employers, so that after liquidation they cannot find jobs of comparable level.

Second, fund managers may accidentally suffer a career slowdown, simply because the liquidation happens to force them to take new positions where they are less productive, rather than because of a reputation loss. That is, a liquidation can be associated with scarring effects even when the fund has performed broadly in line with its benchmark. For instance, this may occur when the benchmark itself performed poorly; or when liquidation resulted simply from an internal reorganization of the parent investment company or from reaching a planned terminal date. In these cases, the liquidation is due to circumstances outside the manager's control, and therefore should not convey any information about his quality, similarly to workers' dismissals due to plant closures in Gibbons and Katz (1991).[18] It may nevertheless entail a subsequent career slowdown, by inflicting a loss of human capital on the professionals involved. For instance, the corporate reorganization may entail outright exit from the fund class in which the professional is specialized, causing redundancy and forced acceptance of a lower-level position elsewhere.

To discriminate between these two cases, in the Online Appendix we propose a career model featuring moral hazard and adverse selection, where funds' *relative* performance allows the market to gradually learn about managers' skills, and both performance pay and the danger of liquidation play a role in disciplining the choice of effort. In the model, liquidations can be driven either by consistently poor relative performance or by reasons that are not performance-related. Persistently poor performance leads investors to become so pessimistic about the manager's skill that they can no longer profitably incentivize him. At this point, the fund has to be liquidated, after which the manager's poor reputation prevents him from being hired elsewhere.

The model produces two results that are relevant to interpret our empirical findings. First, the scarring effects of liquidations that occur after persistently poor rel-

[18]Gibbons and Katz (1991) develop and test an asymmetric information model of layoffs where individual dismissals lead to reputation loss, wage reduction and long unemployment spells, while such scarring effects are lower for dismissals due to plant closings. In our setting, there is no distinction between individual dismissals and those associated with fund liquidations, but the market can condition on a noisy public signal (fund performance) to update its beliefs regarding the motives of liquidation, so that its scarring effects depend on the realization of this signal.

ative performance reflect reputation losses, unlike those that may arise after normal relative performance. Second, only the scarring effects triggered by these liquidations have a market discipline effect, but this effect is diluted if accidental liquidations are frequent and entail scarring effects: insofar as a manager expects to be terminated almost irrespective of his actions, he has little incentive to shine.

To test whether relative performance before liquidation affects post-liquidation career slowdowns we estimate the following variant of equation (1):

$$y_{it} = \alpha_i + \lambda_{gt} + \gamma L_{it}^{post} + \delta L_{it}^{post} \times P_{it}^{-} + \epsilon_{it}, \tag{2}$$

where $L_{it}^{post}$ is a liquidation dummy equal to 1 in the five years after liquidation and 0 otherwise, and $P_{it}^{-}$ is a "poor performance" indicator, i.e. a dummy equal to 1 if the liquidation follows a period (alternatively, 1 year or 2 years) in which the fund's average monthly return fell short of its benchmark. Equation (2) also includes individual fixed effects, $\alpha_i$, and separate time effects for the two subsamples of control employees, $\lambda_{gt}$, where $g = 1$ for the control individuals matched with the employees of under-performing liquidated funds and $g = 2$ for those matched with employees of well-performing funds.

The coefficient $\gamma$ in equation (2) measures the effect on career outcomes of a liquidation preceded by normal relative performance. A negative estimate of $\gamma$ would be evidence that also accidental liquidations occurring after normal performance have scarring effects, while a zero estimate of $\gamma$ indicates that such liquidations have no scarring effects. The coefficient $\delta$ instead captures the incremental effect of poor performance: a negative estimate of $\delta$ measures the career slowdown due to reputation loss from liquidation.

The resulting estimates are shown in columns 1, 2 and 3 of Table 6 for the job level, imputed compensation and job mobility. We measure pre-liquidation performance over 2 years to filter out high-frequency noise in returns. The estimates of the coefficient $\gamma$ are small and not significantly different from zero for job level and imputed compensation (columns 1 and 2); hence, when there is no prior underperformance, liquidation has no scarring effect. By contrast, the estimates of the coefficient $\delta$ in these two regressions is significantly different from zero. We also estimate these regressions measuring pre-liquidation performance over a single year, and find that the coefficient of the interaction between the liquidation and the poor performance dummies is still negative but is no longer statistically significant. This result is in line with a learning model: the revision of the manager's reputation is more accurate when performance is averaged over 2 years, as time-averaging increases the signal-to-noise ratio in pre-liquidation returns, and hence its informativeness about the manager's talent.

When a liquidation is preceded by underperformance, it triggers a job level drop of 0.32 notches larger than if the liquidation were preceded by normal performance, and an imputed compensation loss over $460,000 larger, which is 26.8% of their imputed compensation in the pre-liquidation year. As a robustness check, we re-estimate the same specifications on the whole sample of individuals, without matching: the resulting estimates (Table B.4 of Appendix B) are in line with those obtained with the matched sample. As a further robustness check, we also estimate equation (2) using time-varying imputed compensation as the outcome variable: as shown in Table B.5 in Appendix B, in this case the imputed compensation loss is about $390,000.

[**Insert Table 6**]

As these estimates condition on poor prior fund performance, one may have concerns about the reliability of imputed total compensation as a measure of the earnings capacity of fund managers around the liquidation date: insofar as their actual compensation is tied to their prior performance, managers of underperforming funds are likely to earn less than the variable compensation typically imputed to their job title, both before and after liquidation of their fund. Hence, to provide a lower bound for the change in compensation associated with the liquidation of underperforming funds, we re-estimate the specification of Table 6 using only the fixed component of imputed compensation. The corresponding results are reported in column 1 of Table B.6: when liquidation is preceded by two years of underperformance, it triggers a \$46,698 drop in the fixed component of imputed compensation, i.e. 15% of their imputed fixed pay in the year before the liquidation (about \$303,000 on average). So the estimated loss is a sizable fraction of pre-liquidation pay even if one neglects the variable component of compensation.

By contrast, the effects of liquidation on job mobility do not appear to vary with pre-liquidation performance: column 3 indicates that liquidation is followed by an increase of 6 percentage points in the probability of switching to a new employer, with no significant difference when liquidation is preceded by underperformance. Even liquidations that imply no information regarding the affected employees presumably induce some employees to switch to other companies for more suitable jobs. By the same token, the employees affected by liquidations preceded by poor performance (and by the associated reputation loss) have an equal probability of switching to a new employer, but suffer a career slowdown. This squares with the idea that the setback does not stem simply from the frictions associated with changing jobs.

To further corroborate the hypothesis that the scarring effects documented above are induced by reputation loss due to fund-specific underperformance rather than by low absolute returns, we estimate equation (2) on the sub-sample of funds with positive absolute returns in the 24 months prior to liquidation. The estimated coefficients, not reported for brevity, are very close to those reported in Table 6: even conditioning on positive absolute returns, liquidations preceded by persistently poor *relative* performance are associated with significant career setbacks. Conversely, liquidations that follow negative absolute returns but positive relative performance are not associated with significant scarring effects. It is relative, not absolute, pre-liquidation performance that triggers scarring effects.

Interestingly, the labor market appears to penalize more severely the managers of funds that fall short of their benchmark in good times (namely, when the benchmark does well) than those that do so in bad times. A natural interpretation for this finding is that relative underperformance is a stronger signal of low managerial skill when it occurs in booming than in bear markets. We document this pattern by re-estimating equation (2) separately for the subsample where the benchmark features positive returns and for that where it features negative returns. Table 7 reports the coefficient of the liquidation dummy and that of its interaction with the relative prior (2-year) underperformance dummy for each of the two regressions.

**[Insert Table 7]**

When benchmark returns are positive (Panel A), the interaction coefficient is estimated to be negative and significant, and larger in absolute value than in Table 6. In contrast, when benchmark returns are negative (Panel B), the coefficient is not significantly different from zero.[19] This finding contrasts with evidence from other industries that underperforming top executives are less penalized when their industry is doing well: Jenter and Kanaan (2015) document that "better peer group performance substantially reduces the probability that an underperformer is dismissed, which implies that many fewer underperformers are fired in good times than in bad times" (p. 2156). This difference suggests that the labor market for asset managers may be more effective in filtering out aggregate noise when evaluating individual performance than the boards of public companies.

[19] It should be noticed that the coefficients of Panel B are not significantly different from those of Panel A. So the takeaway of Table 7 is that the labor market penalizes the managers of funds liquidated upon underperforming a rising benchmark, but such penalty is not ruled out if liquidation occurs upon underperforming a declining benchmark.

Since the previous subsection shows that only high-ranking managers suffer significant career slowdowns after liquidations, it is worth investigating whether this happens only in the wake of persistent pre-liquidation underperformance. This provides a sharper test of the thesis that the career slowdown arises from reputation loss among top executives. To implement this test, we re-estimate equation (2) separately for high- and mid-ranking employees. The results are reported in Table 8. Panel A reports the estimates for high-ranking employees; Panel B reports those for mid-level employees (level-3 or level-4) two years before the liquidation. Columns 1, 2 and 3 show the results for the job level, imputed compensation and mobility.

**[Insert Table 8]**

In our estimates, only high-ranking employees (those with level-5 or level-6 jobs two years before liquidation) whose funds were liquidated after underperforming their benchmarks for two years suffer a post-liquidation career slowdown. The estimates for low-ranking employees reveal no significant scarring effects, also following underperformance: the relevant coefficients in Panel B are significantly different from those shown in Panel A.

Liquidations after normal performance are not followed by significant change in either the job level or imputed compensation of top employees, but those that come after persistent underperformance do have significant scarring effects. The interaction between liquidation and poor performance has a negative and significant coefficient in both the job level and imputed compensation regressions: the job level drops by 0.47 notches and imputed compensation by $752,000 more than for top employees of funds that are liquidated in the wake of normal performance (i.e., 24.7% of their pre-liquidation imputed compensation).[20] In contrast, the job mobility of top employees

[20]Also in this case, the result is robust to the use of time-varying imputed compensation: as shown in column 2 of Table B.5 of Appendix B, using this variable the estimated loss would be

increases after liquidation regardless of the fund's previous performance: the probability of switching increases by 4 percentage points in the years following liquidations even of well-performing funds (though this coefficient is not precisely estimated).

To sum up, the scarring effects of liquidations preceded by poor performance are very large for high-ranking employees, but no significant effects are observable for mid-level employees. The evidence, then, is consistent with the idea that liquidations cause a career slowdown for managers who can be held responsible for their fund's poor performance. This squares with the thesis that the scarring effects depend mostly on reputation loss, and are not due to accidental liquidations.

Such effects may reveal the presence of "market discipline", providing incentives to fund managers over and above performance-based pay. According to our model, the disciplining role of the managerial labor market crucially depends on the frequency of liquidations not preceded by persistently poor relative performance: if such accidental liquidations are relatively infrequent, fund managers face relatively little risk of career setbacks for reasons outside of their control, and thus have more incentive to exert effort. In our sample, liquidations not preceded by poor relative performance are uncommon, being 21% of total liquidations,[21] and are estimated to have no scarring effects. Hence, the disciplining role of performance-driven liquidations is not diluted by accidental career slowdown arising irrespective of performance.

about \$621,000. The loss is sizable also if the specification of Table 8 is re-estimated using only the fixed component of imputed compensation: as shown in column 2 of Table B.6, liquidation after two years of underperformance triggers approximately a \$76,000 drop in this component of compensation, i.e. 17.6% of their pre-liquidation fixed pay (about \$431,000 on average).

[21]Brown et al. (2001) also find that poor relative performance increases the probability of hedge fund termination.

## 6 Conclusions

We find that, although finance professionals experience a great career acceleration upon entering the hedge fund industry, they also face significant setbacks and are more likely to switch to other employers following the liquidation of their fund.

This "scarring effect" impinges only on high-ranking managers, and only when fund liquidation follows persistent underperformance. Top managers of funds wound up after two years of poor relative performance suffer job demotion and a sizable compensation loss. Instead, when it is preceded by normal performance, fund liquidation is not associated with career slowdown or significant compensation loss.

We interpret these findings as evidence that the scarring effects of fund liquidations are due to reputation losses: funds' relative performance enables investors to gradually learn about managers' skills, so that persistently poor performance tarnishes the managers' reputation in the labor market. Ex ante, this mechanism can act as a discipline device for managers, complementing performance pay, as we show using a model of career concerns featuring moral hazard and adverse selection.

On the whole, our results reveal a new facet of market discipline in asset management, operating via the managerial labor market. This labor market discipline is complementary to contractual incentives within the firm. The job market "stick" may indeed be a corrective to the tendency to motivate asset managers by generous "carrots", i.e. performance-based remuneration that is far more sensitive to upside gain than to downside risk.

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## Table 1: Job Levels and Imputed Compensation

This table illustrates the two dimensions that characterize the employment positions of the individuals in our sample: their job level, i.e. rank within the corporate hierarchy, and the typical compensation associated with that title and sector. Job levels are identified by first matching the job titles reported by individuals in their resumes with the Standard Occupational Classification (SOC) produced by the Bureau of Labor Statistics (BLS), and then grouping the SOC codes into six bins reflecting different degrees of decision-making power. To measure the average annual compensation associated in 2016 with each SOC code, for level 1-4 jobs we use the Occupational Employment Statistics (OES), allowing for differences in salary across the following six sectors: (i) asset management (AM), (ii) commercial banking and other lending institutions (CB); (iii) financial conglomerates, defined as institutions encompassing lending, insurance and/or asset management (CO); (iv) insurance (IN); (v) other finance, which consists mainly in financial consultancies and portfolio advisors (OF); and non-financial firms and institutions, including government, supranational institutions and stock exchanges (NF). For levels 5 and 6, we use data on total compensation (including the variable component) drawn from the 10K forms filed with the SEC in 2015 by companies belonging to the six sectors.

| Job Level | Description | Average Imputed Compensation | Examples of job titles |
|---|---|---|---|
| 6 | CEOs | 3,707,831 | CEO, executive director, founder, managing director, managing partner |
| 5 | Top executives | 1,590,858 | CFO, CIO, COO, CRO, deputy CEO, partner, vicepresident |
| 4 | First/Mid Officers & Managers | 158,150 | director of sales, head of investor relations, investment manager |
| 3 | Professionals | 105,694 | analyst, portfolio manager |
| 2 | Technicians, Sales Workers, Administrative Support Workers | 101,851 | trader, credit officer |
| 1 | Craft Workers, Operatives, Labors & Helpers, Service Workers | 53,845 | assistant, intern |

## Table 2: Descriptive Statistics

The table reports statistics on the characteristics of the individuals in our sample, based on data drawn from individual resumes available on a major professional networking website, together with information available from Bloomberg, Businessweek and companies websites. Education Level variables are indicators for the highest degree held. Subject variables designate the subject of the highest degree. The quality of highest degree is defined on the basis of QS Ranking, with three indicators depending on whether the university of the highest degree ranks in the top 15, 16th to 40th, or below 40th. Cohort dummies are defined by the starting date of the first job reported in the resume. Sector variables are dummies equal to 1 if the job is in that sector, and 0 otherwise. AM stands for asset management, CB for commercial banking and other lending institutions, CO for financial conglomerates, IN for insurance, OF for other financial companies and NF for non-finance companies. The job level reflects different degrees of decision making-power and takes values from 1 (bottom of the hierarchy) to 6 (CEO). For levels 1-4, imputed compensation is the average annual salary associated in 2016 with each SOC code in these sectors; for levels 5-6, it is the total compensation reported in the 10K forms filed with the SEC in 2015 by companies belonging to the same six sectors. Level-6 Position is a dummy variable indicating whether an individual holds a level-6 position (=1) or not (=0). Company Switch is an indicator for whether at time reports working for a different company from the previous year. For some variables, fractional shares do not sum to 1 due to missing observations.

| | Obs. | Mean | Median | St. Dev. |
|---|---|---|---|---|
| *Education Level* | | | | |
| High school | 1948 | 0.00 | 0 | 0.05 |
| College | 1948 | 0.39 | 0 | 0.49 |
| Master | 1948 | 0.41 | 0 | 0.49 |
| JD or PhD | 1948 | 0.03 | 0 | 0.18 |
| *Subject of highest degree* | | | | |
| Econ or Finance | 1948 | 0.59 | 1 | 0.49 |
| Science or Engineering | 1948 | 0.08 | 0 | 0.27 |
| *Quality of highest degree institution* | | | | |
| Ranked top 15 | 1948 | 0.16 | 0 | 0.37 |
| Ranked 16-40 | 1948 | 0.06 | 0 | 0.24 |
| Ranked below 40 | 1948 | 0.44 | 0 | 0.50 |
| *Cohort* | | | | |
| 1962-1979 | 1948 | 0.04 | 0 | 0.20 |
| 1980-1989 | 1948 | 0.22 | 0 | 0.41 |
| 1990-1999 | 1948 | 0.46 | 0 | 0.50 |
| 2000-2013 | 1948 | 0.28 | 0 | 0.45 |
| Male | 1889 | 0.83 | 1 | 0.37 |

**Table 2: continued**

| | Obs. | Mean | Median | St. Dev. |
|---|---|---|---|---|
| *Sector* | | | | |
| AM | 42027 | 0.75 | 1 | 0.43 |
| CB | 42027 | 0.06 | 0 | 0.23 |
| CO | 42027 | 0.01 | 0 | 0.09 |
| IN | 42027 | 0.01 | 0 | 0.10 |
| NF | 42027 | 0.15 | 0 | 0.36 |
| OF | 42027 | 0.02 | 0 | 0.15 |
| *Career variables* | | | | |
| Job Level | 41775 | 4.42 | 4 | 1.41 |
| Imputed Compensation ($ thou) | 40558 | 1,582 | 221 | 1,639 |
| Level-6 Position | 41775 | 0.33 | 0 | 0.47 |
| Level-5 Position | 41775 | 0.15 | 0 | 0.36 |
| Level-4 Position | 41775 | 0.25 | 0 | 0.43 |
| Level-3 Position | 41775 | 0.15 | 0 | 0.35 |
| Level-2 Position | 41775 | 0.11 | 0 | 0.31 |
| Level-1 Position | 41775 | 0.01 | 0 | 0.10 |
| Switch company | 42339 | 0.13 | 0 | 0.34 |

## Table 3: Fund Descriptive Statistics

The table presents summary statistics for the monthly returns of hedge funds in the TASS database and in our sample. All statistics are in percent, and are broken down by fund classes following the TASS classification into six classes by type of strategy (columns 1-6). Panel A refers to the entire sample of 19,367 hedge funds present in the TASS database at any time from 1978 to 2014: the first two rows show the mean and standard deviation of the monthly percentage benchmark returns (i.e. the cross-sectional average of the monthly returns of the funds in each class); the third row shows the standard deviation of funds' relative performance, defined as the difference between the monthly percentage return of a fund and its benchmark; the fourth row reports the percentage of funds in each class. Panel B refers to our own sample of 4,944 hedge funds: the first two rows report the mean and standard deviation of fund relative performances, the third row the percentage of funds in each class. Standard errors clustered at the fund level are shown in parentheses below the respective coefficients: * denotes $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

| | All funds | Relative Value | Security Selection | Multi-process | Direct. Traders | Funds of Funds | Other |
|---|---|---|---|---|---|---|---|
| | | | Panel A: TASS Database | | | | |
| Mean, Benchmark | 1.05 | 0.73 | 1.32 | 1.04 | 1.09 | 0.78 | 1.24 |
| St. Dev., Benchmark | 2.83 | 1.06 | 3.05 | 2.09 | 3.08 | 2.05 | 4.15 |
| St. Dev., Rel. Perf. | 2.97 | 2.21 | 3.62 | 2.24 | 4.37 | 1.73 | 4.23 |
| Fraction of Funds | 100 | 4.80 | 25.61 | 18.23 | 10.77 | 31.77 | 8.76 |
| | | | Panel B: Differences between our sample and TASS | | | | |
| Mean, | 0.00 | 0.01 | 0.03** | -0.13*** | 0.05 | -0.01 | 0.10*** |
| Rel. Perf. | (.01) | (0.03) | (0.02) | (0.02) | (0.03) | (0.01) | (0.03) |
| Fraction | | 0.02*** | 0.08*** | -0.06*** | 0.00 | -0.04*** | 0.00 |
| of Funds | | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) | (0.00) |
| Fraction | -0.01 | 0.05 | -0.04*** | 0.01 | -0.01 | 0.00 | -0.03 |
| of Liq. Funds | (0.01) | (0.03) | (0.01) | (0.02) | (0.02) | (0.01) | (0.03) |

## Table 4: Career Outcomes upon Entering the Hedge Fund Industry

The table shows how career outcomes (job level and imputed compensation) upon being hired by a hedge fund company correlate with individual and hedge fund characteristics. Job Level ranges from 1 (bottom of the hierarchy) to 6 (CEO). Education Quality is a dummy equal to 1 if the individual has a graduate degree from a university ranked in the top 15 and 0 otherwise. Experience (Exp. in AM) is the number of years of work experience (in asset management) at the time of hiring. Female is a dummy equal to 1 for women and 0 for men. Previous job level (compensation) is the job level (imputed compensation) in the year before hiring. Past Performance is the average difference between fund $j$'s monthly percentage return and its benchmark in the three years before hiring, and Past Benchmark is the average percentage return of all the funds in $j$'s class in the three years before hiring. Log(AUM) is the logarithm of lagged average assets under management of fund $j$. Fund Style is a set of six dummies capturing the funds investment style. Robust standard errors are shown in parentheses below the respective coefficients: * denotes $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

| | Job Level | | Imputed Compensation, thousands of USD | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Education quality | 0.320*** | 0.338** | 315.184*** | 225.842 |
| | (0.090) | (0.145) | (118.886) | (199.941) |
| Experience | 0.016*** | 0.022** | 15.285** | 21.356** |
| | (0.006) | (0.009) | (6.869) | (10.235) |
| Exp. in AM | 0.024*** | 0.024** | 22.009** | 29.575** |
| | (0.007) | (0.011) | (9.644) | (13.624) |
| Female | -0.740*** | -0.514*** | -809.212*** | -611.079*** |
| | (0.075) | (0.106) | (77.454) | (109.666) |
| Previous job level | 0.117*** | 0.130*** | | |
| | (0.019) | (0.029) | | |
| Past performance | | 0.063** | | 51.713 |
| | | (0.025) | | (31.525) |
| Past benchmark | | 0.073 | | 103.130 |
| | | (0.079) | | (76.758) |
| log(AUM) | | 0.004 | | 19.568 |
| | | (0.027) | | (30.681) |
| Previous compensation | | | 0.296*** | 0.251*** |
| | | | (0.034) | (0.053) |
| Constant | 4.002*** | 4.242*** | 1294.877*** | 1070.533 |
| | (0.061) | (0.539) | (60.545) | (657.081) |
| Fund style dummies | No | Yes | No | Yes |
| Observations | 1877 | 710 | 1807 | 687 |

**Table 5: Other Post-Liquidation Career Outcomes**

The table reports estimates of the effects of liquidation on career outcomes. Liquidation is a dummy equal to 1 in the 5 years following liquidation (for funds that are liquidated), and 0 otherwise. Job in Asset Mgmt. is an indicator for working in Asset Management, Job in Non-Finance for working in a non-financial company; Being a Founder designates a company founder, and No. of Jobs is the number of companies employing the professional. Panel A reports the estimated effects of liquidation for professionals that held a level-5 or level-6 position two years prior to liquidation. Panel B reports the effects for professionals that held a level-3 or level-4 position two years prior to liquidation. All specifications include individual and time-to-liquidation fixed effects. The standard errors shown in parentheses are clustered at individual level: * denotes $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

| | Job in Asset Mgmt. (1) | Job in Non-Finance (2) | Being a Founder (3) | No. of Jobs (4) |
|---|---|---|---|---|
| | Panel A: Starting from job levels 5 and 6 | | | |
| Liquidation | -0.049** | 0.023 | -0.044** | 0.028 |
| | (0.021) | (0.020) | (0.020) | (0.040) |
| Observations | 3924 | 3924 | 3924 | 3924 |
| No. professionals | 600 | 600 | 600 | 600 |
| | Panel B: Starting from job levels 3 and 4 | | | |
| Liquidation | -0.049 | 0.040 | -0.003 | 0.035 |
| | (0.032) | (0.028) | (0.013) | (0.034) |
| $N$ | 2994 | 2994 | 2994 | 2994 |
| No. professionals | 463 | 463 | 463 | 463 |

## Table 6: Fund Performance and Careers around Liquidations

The table reports estimates of the career effects of liquidations after poor relative performance. Liquidation is a dummy equal to 1 in the liquidation year and in the 5 subsequent years (for funds that are liquidated), and 0 otherwise. Poor Performance is a dummy equal to 1 for funds with average monthly return below the benchmark return in the 2 years period before liquidation, and 0 otherwise. Columns 1, 2 and 3 show the estimated coefficients of the Liquidation dummy and of its interaction with the Poor Performance dummy. The equation is estimated using data for 5 years before and 5 years after the liquidation date. Job Level ranges from 1 (bottom) to 6 (top). Imputed compensation is the average annual salary associated in 2016 with each SOC code in the six sectors in Table 2 for professionals in job levels 1-4; for levels 5 and 6 it is the average annual total compensation associated in the 2015 10Ks with each job level in the six sectors in Table 2. Switch indicates that in year $t$ an individual is employed by a different company relative to year $t-1$. All specifications include individual and group specific time-to-liquidation fixed effects. The standard errors shown in parentheses are clustered at individual level: $^{*}$ denotes $p < 0.10$, $^{**}$ $p < 0.05$, and $^{***}$ $p < 0.01$.

| | Job Level | Imputed Compensation, thousands of USD | Switch |
|---|---|---|---|
| | (1) | (2) | (3) |
| Liquidation | 0.099 | 216.836 | 0.059$^{**}$ |
| | (0.119) | (148.207) | (0.027) |
| Liquidation×Poor Performance | -0.322$^{**}$ | -464.196$^{***}$ | -0.003 |
| | (0.135) | (167.359) | (0.030) |
| Observations | 12097 | 11863 | 12097 |
| No. professionals | 1174 | 1168 | 1174 |

## Table 7: Fund Performance and Careers around Liquidations, by Benchmark Returns

The table reports estimates of the career effects of liquidations after poor relative performance, when the average benchmark return in the 2 years prior to liquidation is positive (Panel A) or negative (Panel B). Liquidation is a dummy equal to 1 in the liquidation year and in the 5 subsequent years (for funds that are liquidated), and 0 otherwise. Poor Performance is a dummy equal to 1 for funds with average monthly return below the benchmark return in the 2 years before liquidation. Columns 1, 2 and 3 show the estimated coefficients of the Liquidation dummy and of its interaction with the Poor Performance dummy. The equation is estimated using data for 5 years before and 5 years after the liquidation date. Job Level ranges from 1 (bottom) to 6 (top). Imputed compensation is the average annual salary associated in 2016 with each SOC code in the six sectors in Table 2 for professionals in job levels 1-4; for levels 5 and 6 it is the average annual total compensation associated in the 2015 10Ks with each job level in the six sectors in Table 2. Switch indicates that in year $t$ an individual is employed by a different company relative to year $t-1$. All specifications include individual and group specific time-to-liquidation fixed effects. The standard errors shown in parentheses are clustered at individual level: $^{*}$ denotes $p < 0.10$, $^{**}$ $p < 0.05$, and $^{***}$ $p < 0.01$.

| | Job Level | Imputed Compensation, thousands of USD | Switch |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: Positive benchmark | | |
| Liquidation | 0.186 | 255.921 | 0.037 |
| | (0.135) | (162.891) | (0.032) |
| Liquidation× Poor Performance | -0.427$^{***}$ | -515.376$^{***}$ | 0.018 |
| | (0.152) | (182.855) | (0.035) |
| Observations | 10147 | 9938 | 10147 |
| No. professionals | 984 | 979 | 984 |
| | Panel B: Negative benchmark | | |
| Liquidation | -0.122 | 117.603 | 0.114$^{**}$ |
| | (0.238) | (322.379) | (0.052) |
| Liquidation×Poor Performance | 0.017 | -283.578 | -0.046 |
| | (0.293) | (390.368) | (0.065) |
| Observations | 1950 | 1925 | 1950 |
| No. professionals | 190 | 189 | 190 |

## Table 8: Fund Performance and Careers around Liquidations, for High and Low-Ranking Employees

The table reports estimates of the career effects of liquidation after poor relative performance, separately for top-level (Panel A) and mid-level employees (Panel B), respectively defined as employees with pre-liquidation job levels 5 or 6 and 3 or 4. Liquidation is a dummy equal to 1 in the liquidation year and in the 5 subsequent years (for funds that are liquidated), and 0 otherwise. Poor Performance is a dummy equal to 1 for funds with average monthly return below the benchmark return in the two years before liquidation, and 0 otherwise. Columns 1, 2 and 3 show the estimated coefficients of the Liquidation dummy and of its interaction with the Poor Performance dummy. The equation is estimated using data for 5 years before and 5 years after the liquidation date for managers whose funds were liquidated. Job Level ranges from 1 (bottom) to 6 (top). Imputed compensation is the average annual salary associated in 2016 with each SOC code in the six sectors in Table 2 for professionals in job levels 1-4; for levels 5 and 6 it is the average annual total compensation associated in the 2015 10Ks with each job level in the six sectors in Table 2. Switch indicates that in year $t$ an individual is employed by a different company relative to year $t-1$. All specifications include individual and group specific time-to-liquidation fixed effects. The standard errors shown in parentheses are clustered at individual level: $^{*}$ denotes $p < 0.10$, $^{**}$ $p < 0.05$, and $^{***}$ $p < 0.01$.

| | Job Level | Imputed Compensation, thousands of USD | Switch |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: Starting from job levels 5 and 6 | | |
| Liquidation | 0.146 | 262.911 | 0.058 |
| | (0.126) | (174.855) | (0.036) |
| Liquidation× Poor Performance | -0.472*** | -752.389*** | 0.014 |
| | (0.148) | (205.515) | (0.040) |
| Observations | 6268 | 6231 | 6268 |
| No. professionals | 600 | 600 | 600 |
| | Panel B: Starting from job levels 3 and 4 | | |
| Liquidation | -0.057 | 60.930 | 0.084* |
| | (0.190) | (230.771) | (0.043) |
| Liquidation× Poor Performance | 0.044 | 37.619 | -0.049 |
| | (0.213) | (256.892) | (0.049) |
| Observations | 4736 | 4585 | 4736 |
| No. professionals | 463 | 459 | 463 |

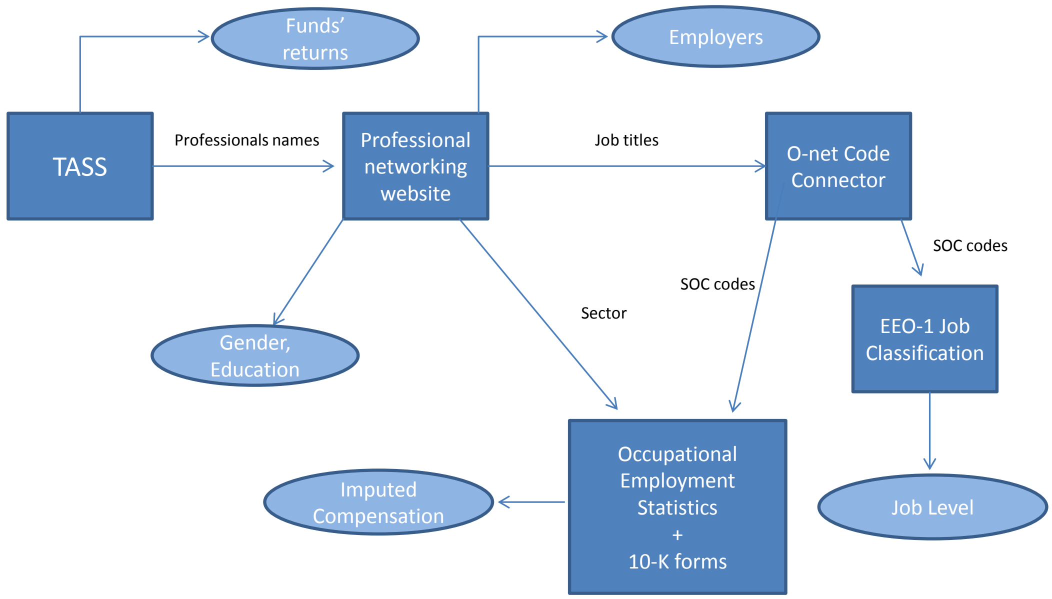


**Figure 1. Construction of the data set.** The figure shows how we combine data sets drawn from different sources in order to construct our sample. We draw the names of hedge fund professionals from the TASS database, the investment companies that employ them, and the funds managed by the company. This information is augmented with previous and subsequent work histories, education, and start dates, end dates, employers and job titles throughout the career, drawn from the individual resumes available on a major professional networking website. Job titles are matched with the Standard Occupational Classification (SOC) produced by the Bureau of Labor Statistics (BLS), via the O*Net code connector platform. To build the job level we group the SOC codes into 6 bins according to the EEO-1 classification system. To impute compensation, we map the SOC codes and the employment sector to average annual compensation statistics drawn from the Occupational Employment Statistics or computed from 10-K and proxy statements.

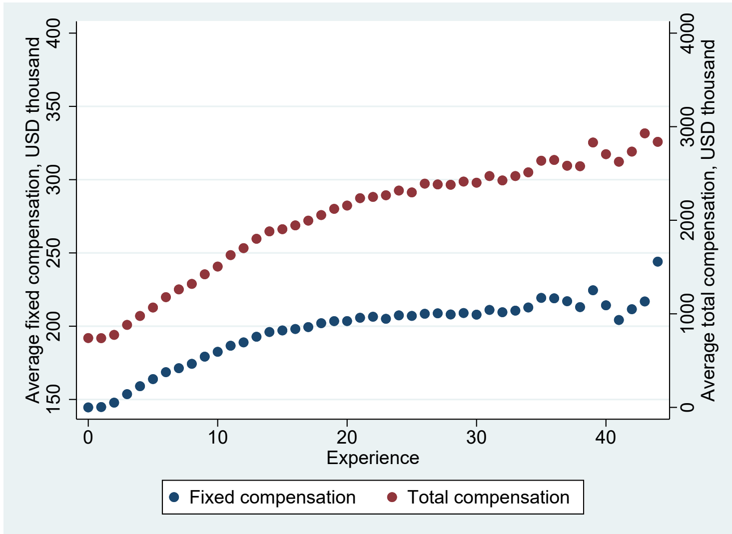


**Figure 2. Career profile.** The figure illustrates career paths by plotting the average imputed fixed compensation (blue) and the average imputed total compensation (red) against work experience for the individuals in the sample. Imputed fixed compensation is the average annual salary in 2016 in each SOC code in the six sectors indicated in Table 2. For top executives imputed total compensation is the average annual total compensation associated in the 2015 10Ks with each job level (5 and 6) in the six sectors of Table 2.

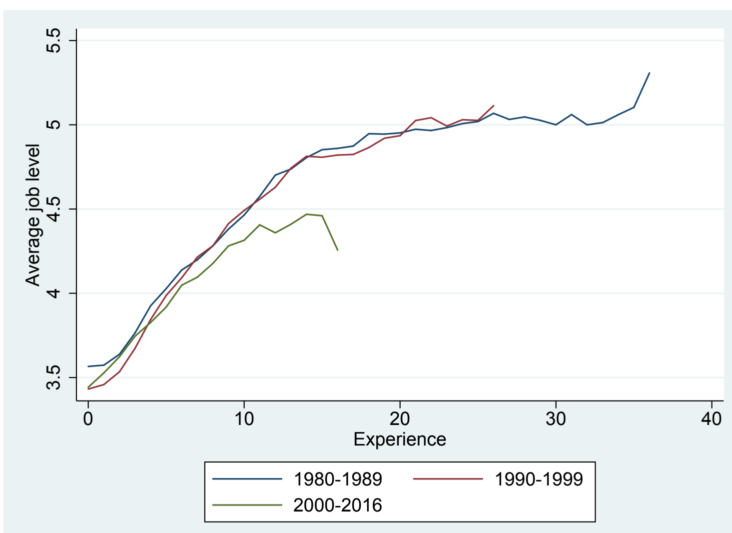


**Figure 3. Career profile by cohort.** The figure plots average job level against work experience by cohort of individuals. The job level reflects different degrees of decision making-power and takes values from 1 (bottom of the hierarchy) to 6 (CEO).

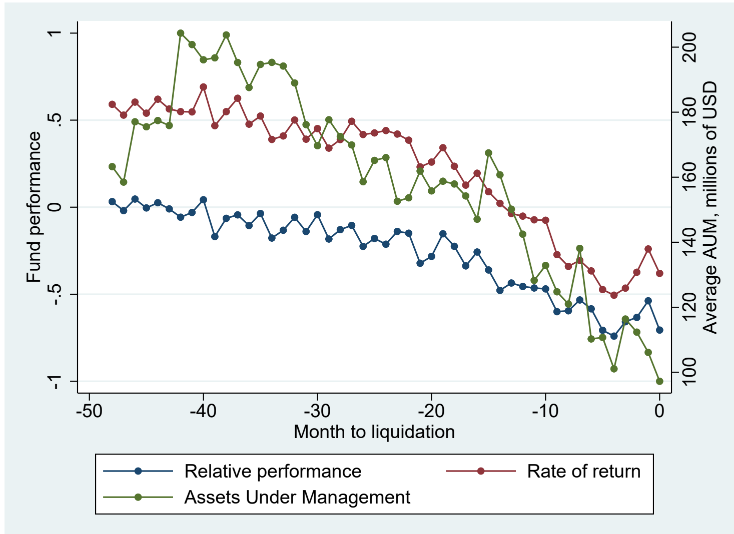


**Figure 4. Fund performance and Assets Under Management approaching liquidation.** The figure shows average fund relative and absolute performance (left axis) and average assets under management (right axis) of liquidated funds in the 48 months preceding liquidations. Fund relative performance is computed as the difference between the monthly fund's absolute return and the monthly return of the relevant benchmark.

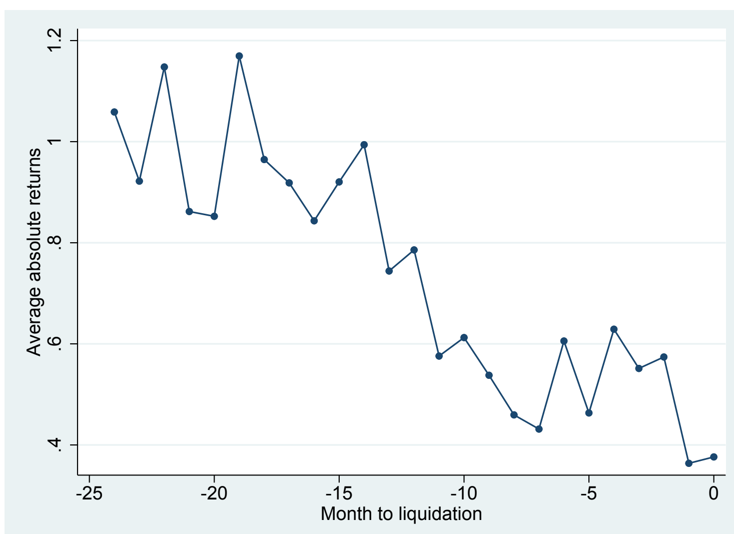


**Figure 5. Absolute returns approaching liquidation: funds with positive relative performance in the 24 months preceding liquidation.** The figure shows the average monthly rate of return of funds that are liquidated irrespective of having positive relative performance in the 24 months before liquidations.

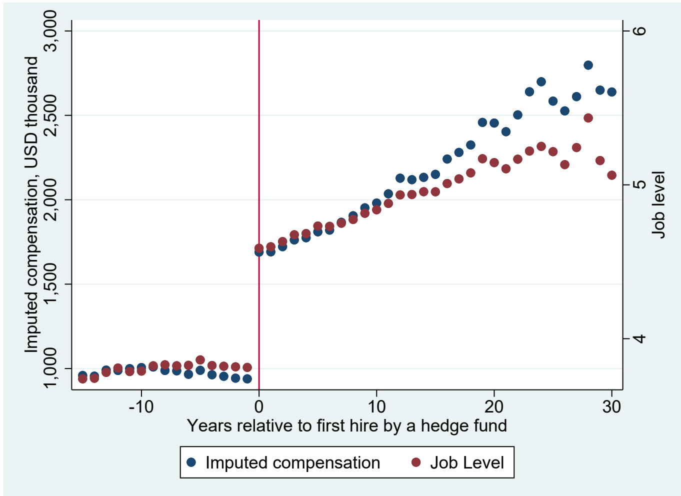


**Figure 6. Entry into the hedge fund industry.** The figure shows average job level (left-hand scale) and average imputed total compensation (right-hand scale) in the fifteen years before an individual is hired by a hedge fund and the thirty years after. The job level reflects different degrees of decision making-power and takes values from 1 (bottom of the hierarchy) to 6 (CEO). For those below level 5, imputed compensation is the average annual salary associated in 2016 with each SOC code in the six sectors listed in Table 2. For top executives (levels 5 and 6) imputed compensation is the average annual total compensation associated in the 2015 10Ks with each job level in the six sectors of Table 2.

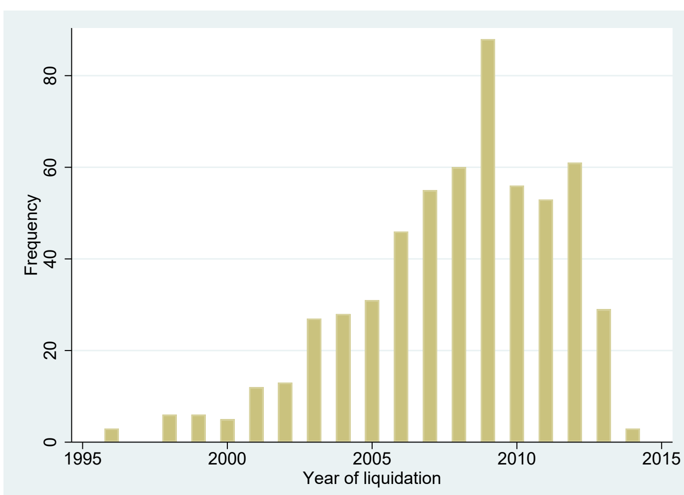


**Figure 7. Histogram of hedge fund liquidations.** The figure plots the histogram of the years in which individuals experience for the first time the liquidation of a hedge fund for which they work.

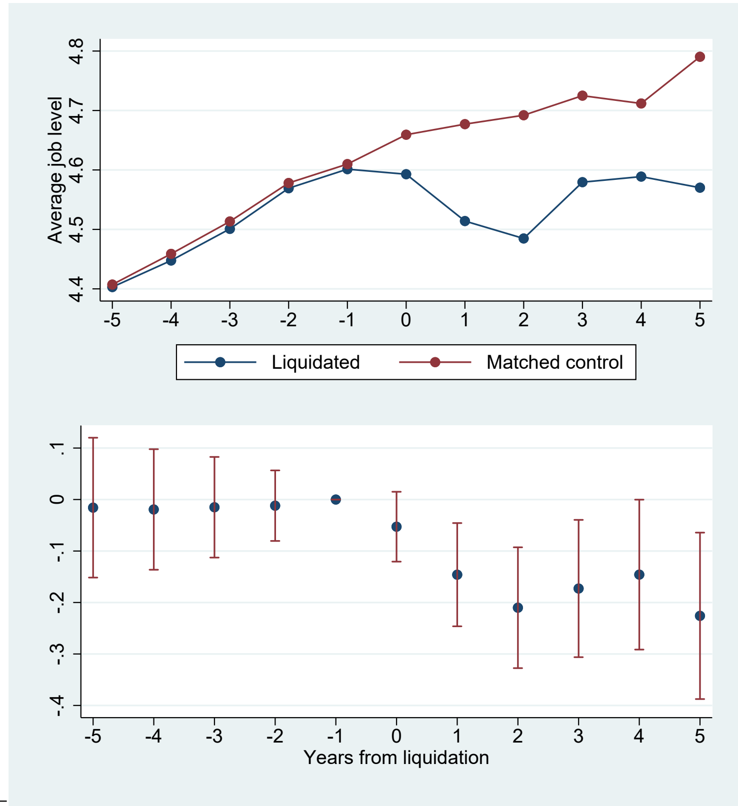


**Figure 8. Job level around liquidations.** The top panel shows the average job level in the five years before and after a hedge fund liquidation, for employees of liquidated funds and for the matched control sample. Job Level reflects different degrees of decision making-power and takes values from 1 (bottom of the hierarchy) to 6 (CEO). The bottom panel of the figure shows the sequence of estimated $\delta_k$ coefficients from equation (1) when the outcome variable is job level (i.e., the coefficients of the interaction terms between having ever experienced a liquidation and indicators for time from liquidation in a model that includes time-from-liquidation and individual fixed effects) and the corresponding 95% confidence intervals.

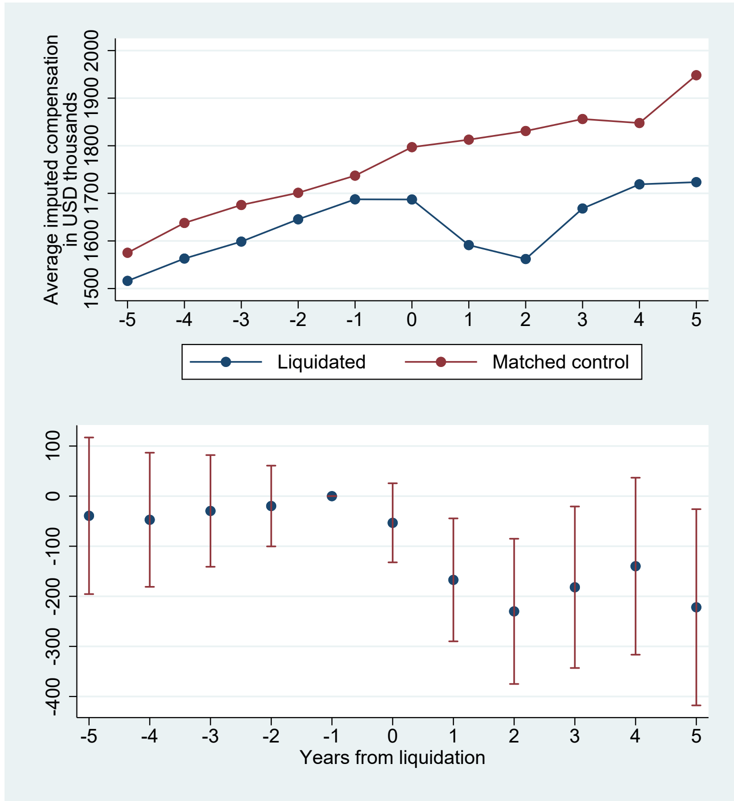


**Figure 9. Imputed compensation around liquidations.** The top panel shows the average imputed compensation in the five years before and after a hedge fund liquidation, for employees of liquidated funds and for the matched control sample. The bottom panel shows the sequence of estimated $\delta_k$ coefficients from equation (1) when the outcome variable is compensation (i.e., the coefficients of the interaction terms between having ever experienced a liquidation and indicators for time from liquidation in a model that includes time-from-liquidation and individual fixed effects) and the corresponding 95% confidence intervals.

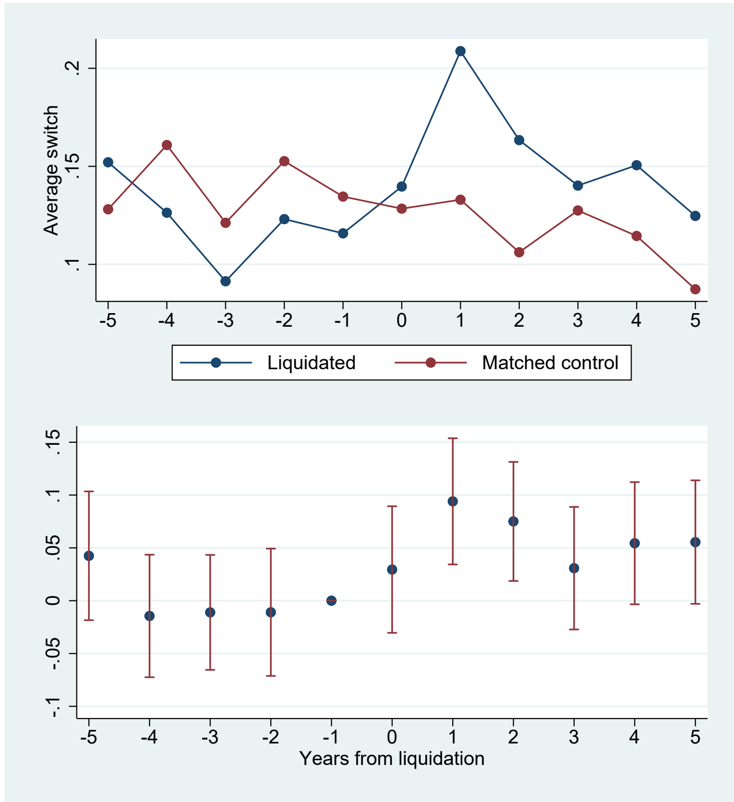


**Figure 10. Mobility around liquidations.** The top panel shows the fraction of individuals switching to a new company in the five years before and after a hedge fund liquidation, for employees of liquidated funds and for the matched control sample. Switch is equal to 1 if the employee switches to a new employer in the current year, and 0 otherwise. The bottom panel shows the sequence of estimated $\delta_k$ coefficients from equation (1) when the outcome variable is switch (i.e., the coefficients of the interaction terms between having ever experienced a liquidation and indicators for time from liquidation in a model that includes time-from-liquidation and individual fixed effects) and the corresponding 95% confidence intervals.

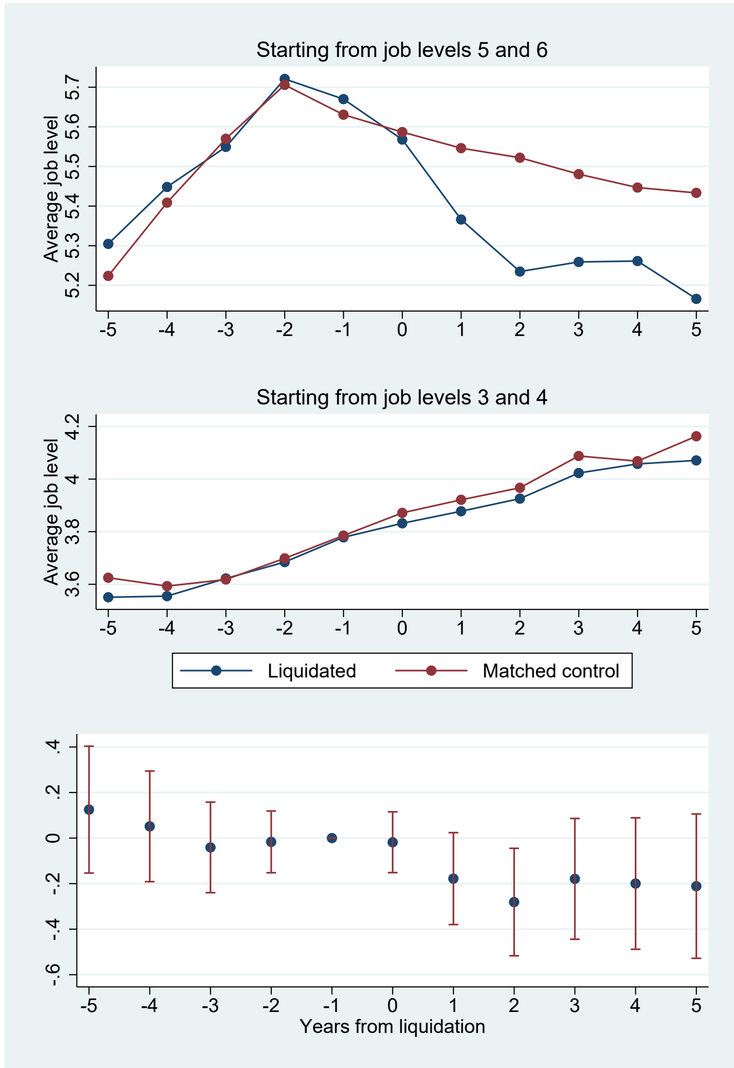


**Figure 11. Job level around liquidations, for high and low-ranking employees.** The top panel shows the average job level in the five years before and after a hedge fund liquidation for employees of liquidated funds and for the matched control sample of individuals who held a top position (job level 5 or 6) two years before liquidation. The middle panel shows the average job level in the five years before and after a liquidation for employees of liquidated funds and for the matched control sample individuals who held a middle position (job level 3 or 4) two years before liquidation. The bottom panel shows the sequence of estimated coefficients of the triple interaction terms between having ever experienced a liquidation, holding a top position two years before liquidation, and indicators for time from liquidation, in a model that includes group-specific time-from-liquidation and individual fixed effects, and the corresponding 95% confidence intervals.

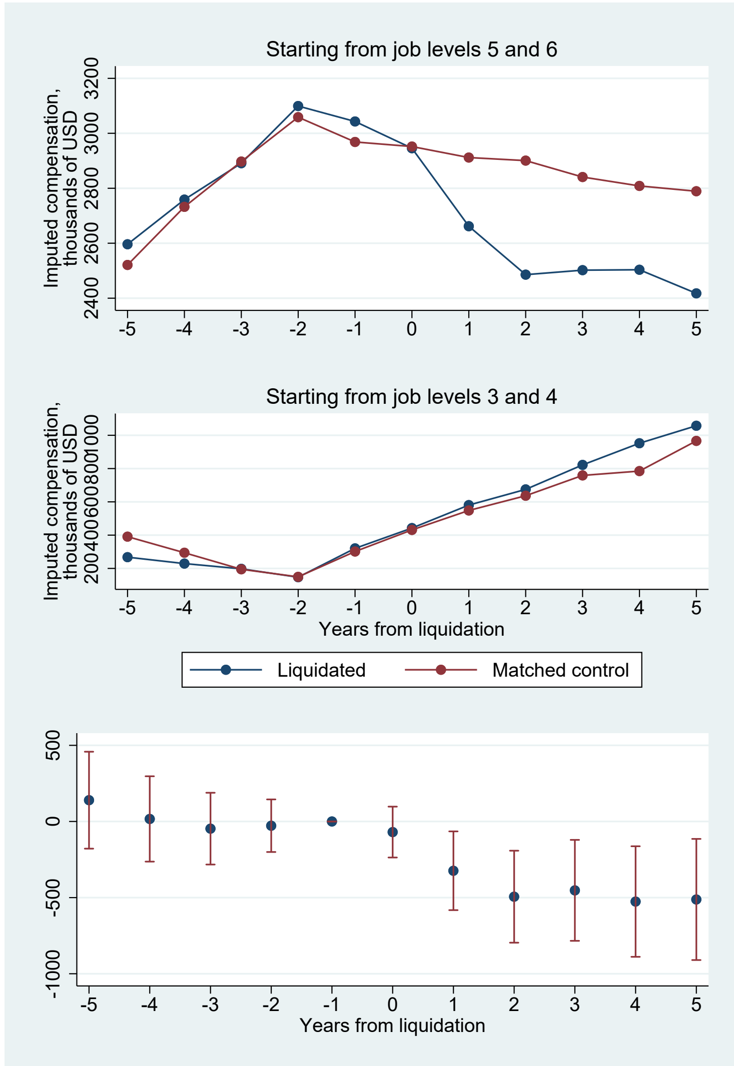


**Figure 12. Imputed compensation around liquidations, for high and low-ranking employees.** The top panel shows the average imputed compensation in the five years before and after a hedge fund liquidation for employees of liquidated funds and for the matched control sample of individuals who held a top position (job level 5 or 6) two years before liquidation. The middle panel shows the average imputed compensation in the five years before and after a hedge fund liquidation for employees of liquidated funds and for the matched control sample of individuals who held a middle position (job level 3 or 4) two years before liquidation. The bottom panel shows the sequence of estimated coefficients of the triple interaction terms between having ever experienced a liquidation, holding a top position two years before liquidation, and indicators for time from liquidation, in a model that includes group-specific time-from-liquidation and individual fixed effects, and the corresponding 95% confidence intervals.

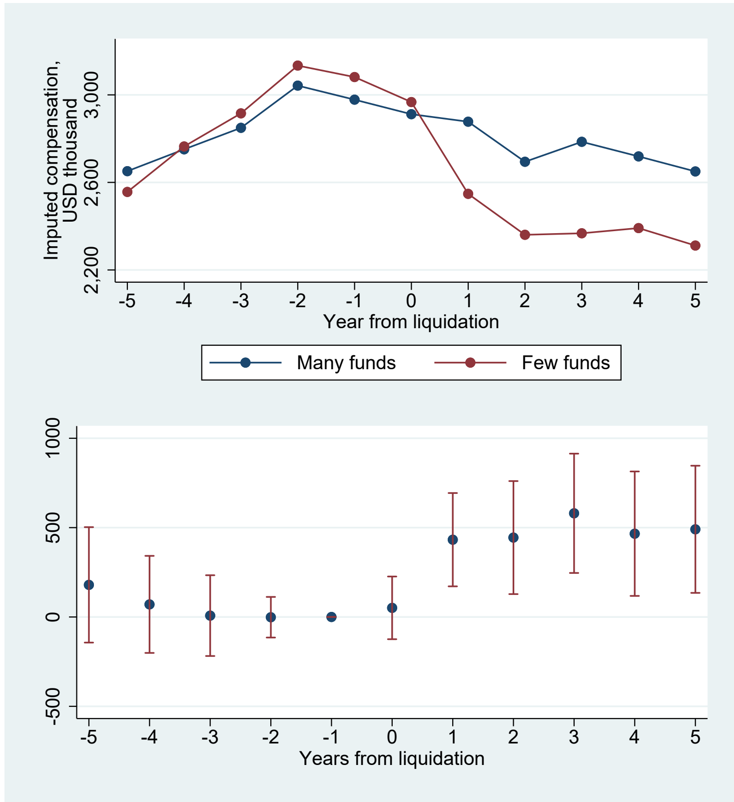


**Figure 13. Imputed compensation around liquidations, by number of funds under management.** The top panel shows the average imputed compensation in the five years before and after a hedge fund liquidation for top executives (job level 5 or 6) of companies that manage more than the median number of hedge funds (5) and those that manage less than 5 funds. The bottom panel shows the sequence of estimated coefficients of the triple interaction between having ever experienced a liquidation, working in a company that manages more than 5 funds, and indicators for time from liquidation, in a model that includes group-specific time-from-liquidation and individual fixed effects, and the corresponding 95% confidence intervals.

# Appendix A: The Sector Imputation Algorithm

As is explained in the text, after manual identification of the sector of 2,129 employers ("classified companies"), we impute the sectors of the remaining 4,642 employers ("unclassified companies") via a machine-learning algorithm. The algorithm exploits the association between job titles and sectors in the subsample of classified companies to assign unclassified companies to their respective sectors: it determines whether an unclassified company's jobs are typical of a certain sector, based on their prevalence in companies already classified as belonging to that sector.

The algorithm must perform three main tasks:

- represent job descriptions in such a way that they can be processed with learning algorithms;
- aggregate the information on job descriptions in order to define broader general tasks;
- associate these broader tasks with sectors and use them to sort the unclassified companies into the sectors.

To overcome these difficulties, we proceed in five steps:

1. **Construct a vocabulary of job descriptions.** To this end, we adopt *term frequency-inverse document frequency* (*tf-idf*) method, a statistic reflecting the importance of a word in a document forming part of a collection of documents. This statistic increases in proportion to the number of times a word appears in the document, with a penalty for the frequency of the word in the collection of documents, so as to adjust for the fact that some words appear more frequently in general.

2. **Express job descriptions as vectors.** The *tf-idf* vectorization results in a matrix in which each row is a vector in $[0,1]^p$ representing a job description ($p$ being the number of words in the vocabulary) and every column is the set of values of the *tf-idf* statistic measuring the prevalence of a given word across all job descriptions. Since this matrix is very large and sparse, in order to reduce its dimensionality without losing relevant information, we use a truncated singular value decomposition of the *tf-idf* matrix, known as *Latent Semantic Analysis*, which is very similar in spirit to *Principal Component Analysis.* The end result is a matrix with 200 columns and a number of rows equal to the number of job descriptions.

3. **Aggregate job descriptions into broader tasks.** The large number of different job descriptions necessitates the aggregation of similar ones into broader tasks, choosing their breadth optimally to learn the type of tasks performed in each sector. We use a clustering algorithm to identify clusters of similar jobs, and represent each job description in the original dataset by its cluster. To cluster the jobs we apply the *k-mean* algorithm to the matrix constructed in step 2. Based on tuning, the number of clusters is set to 200.

4. **Aggregate the information by company.** We use a supervised learning algorithm to associate the broad tasks (clusters) obtained in step 3 with sectors. To do this, the data are reshaped into a matrix where each row is uniquely identified by a company name and each column refers to one of the 200 broader tasks identified in step 3. Each element of the matrix is an integer that counts the number of employees performing a specific task in a given company.

5. **Sort the unclassified companies into their sectors.** This task is performed with a *Neural Network* with one hidden layer of 110 nodes (obtained by tuning). The input is the matrix obtained in step 4 to which a further column is appended, whose elements are the number of employees in each company. We train the *Neural Network* using the classified companies to predict the sector of the unclassified ones.

These five steps form a single iteration of the entire code used to sort the unclassified companies into the six sectors. At each iteration, for each unclassified company the *Neural Network* generates a list of probabilities for the possible sector classification. In each round, we classify within a sector only the companies whose predicted probability of belonging to that sector exceeds some threshold (75% in the first iteration). That is, each round classifies only a portion of the unclassified companies. We use this augmented dataset as the starting point for a new implementation of the entire procedure. Eventually we classify all the companies, with an average cross-validation error of 20%.[22]

[22]The threshold is gradually lowered at successive iterations and is removed in the very last one (where we classify into the sector with the highest probability); cross-validation is computed on 10% of the data at every iteration before the classification; the total number of iterations is 30; all the code is written in Python 3 and uses the *scikit-learn* package (Pedregosa et al., 2011).

# Appendix B: Robustness Checks

### Table B.1: Job level upon hiring: ordered probit estimates

The table shows how the job level upon being hired by a hedge fund company correlates with individual and hedge fund characteristics, estimating an ordered probit. Each column in the table shows the estimates of the marginal effect of the explanatory variables on the probability of being in the respective job level: for instance, the top figure in column 6 (0.08) is the estimated marginal effect of education quality on the probability of being hired at job level 6 (CEO) by a hedge fund company. Education Quality is a dummy equal to 1 if the individual has a graduate degree from a university ranked in the top 15 and 0 otherwise. Experience (Exp. in AM) is the number of years of work experience (in asset management) at the time of hiring. Female is a dummy equal to 1 for women and 0 for men. Previous job level is the job level in the year before hiring. Past Performance is the average difference between fund $j$'s monthly percentage return and its benchmark in the three years before hiring, and Past Benchmark is the average percentage return of all the funds in $j$'s class in the three years before hiring. Log(AUM) is the logarithm of lagged average assets under management of fund $j$. Fund Style is a set of six dummies capturing the funds investment style. Robust standard errors are shown in parentheses below the respective coefficients: $^{*}$ denotes $p < 0.10$, $^{**}$ $p < 0.05$, and $^{***}$ $p < 0.01$.

| | Job Level upon Being Hired | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Education quality | -0.0054 | -0.0408** | -0.0350** | -0.0183** | 0.0195** | 0.0800** |
| | (0.0033) | (0.0201) | (0.0172) | (0.0090) | (0.0097) | (0.0387) |
| Female | 0.0082*** | 0.0617*** | 0.0530*** | 0.0277*** | -0.0295*** | -0.1211*** |
| | (0.0031) | (0.0137) | (0.0119) | (0.0077) | (0.0066) | (0.0259) |
| Experience | -0.0004* | -0.0027** | -0.0023** | -0.0012** | 0.0013** | 0.0053** |
| | (0.0002) | (0.0012) | (0.0010) | (0.0005) | (0.0006) | (0.0022) |
| Exp. in AM | -0.0004* | -0.0033** | -0.0028** | -0.0015** | 0.0016** | 0.0064** |
| | (0.0002) | (0.0015) | (0.0013) | (0.0007) | (0.0007) | (0.0029) |
| Past performance | -0.0011* | -0.0084** | -0.0072** | -0.0037** | 0.0040** | 0.0164** |
| | (0.0006) | (0.0036) | (0.0029) | (0.0016) | (0.0017) | (0.0066) |
| Past benchmark | -0.0012 | -0.0093 | -0.0080 | -0.0042 | 0.0045 | 0.0183 |
| | (0.0014) | (0.0099) | (0.0086) | (0.0046) | (0.0048) | (0.0195) |
| log(AUM) | -0.0001 | -0.0004 | -0.0004 | -0.0002 | 0.0002 | 0.0009 |
| | (0.0005) | (0.0034) | (0.0029) | (0.0015) | (0.0016) | (0.0067) |
| Observations | 710 | 710 | 710 | 710 | 710 | 710 |

## Table B.2: Careers in the Hedge Fund Industry and Fund Relative Performance

The table shows the relationship between changes in the outcome variable $y$ between year $t$ and year $t+k$, for $k = 1, 2, .., 5$, and average relative performance in years $t$ and $t+1$, $\bar{r}_{t,t+1}$. In Panel A, $y$ is the job level; in Panel B, it is the imputed compensation. Relative performance is the yearly average of the difference between the fund's monthly absolute return and the monthly average return of all funds in the relevant category. All specifications include year fixed effects. Standard errors clustered at the individual level are shown in parentheses below the respective coefficients: $^{*}$ denotes $p < 0.10$, $^{**}$ $p < 0.05$, and $^{***}$ $p < 0.01$.

| | $\Delta y_{t+5,t}$ | $\Delta y_{t+4,t}$ | $\Delta y_{t+3,t}$ | $\Delta y_{t+2,t}$ | $\Delta y_{t+1,t}$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Panel A: Job Level Change | | | | |
| $\bar{r}_{t,t+1}$ | 0.038 | 0.044 | 0.027 | 0.004 | -0.003 |
| | (0.037) | (0.038) | (0.027) | (0.014) | (0.006) |
| Constant | -0.012 | -0.014 | -0.009 | -0.001 | 0.001 |
| | (0.012) | (0.013) | (0.009) | (0.005) | (0.002) |
| Observations | 8311 | 8952 | 9546 | 9757 | 9929 |
| No. professionals | 1542 | 1602 | 1639 | 1658 | 1665 |
| | Panel B: Imputed Compensation Change, USD thousands | | | | |
| $\bar{r}_{t,t+1}$ | 40.696 | 49.642 | 22.791 | -7.261 | -5.874 |
| | (44.761) | (44.986) | (28.624) | (17.413) | (8.823) |
| Constant | -13.353 | -16.288 | -7.478 | 2.382 | 1.927 |
| | (14.687) | (14.760) | (9.392) | (5.714) | (2.895) |
| Observations | 8161 | 8801 | 9395 | 9614 | 9798 |
| No. professionals | 1513 | 1574 | 1610 | 1628 | 1639 |

## Table B.3: Diff-in-diff estimates using the whole sample

The table reports estimates for the effects of liquidations on the job level, imputed compensation and employer switches, using the whole sample of 661 individuals that experience a fund liquidation (for the 11 years surrounding the liquidation) and 1,287 individuals that do not (for all the available years), rather than the matched sample used in Figures 8, 9 and 10. The estimates refer to a variant of specification (1) that includes individual fixed effects and calendar year effects instead of time-from-liquidation effects. The parameters $\delta_k$, for $k = -5, ..., 5$ are the coefficients of the 11 dummies $L^k_{it}$, each equal to 1 $k$ periods from the liquidation if individual $i$ experiences it, and 0 otherwise, normalizing the value $\delta_{-1}$ to 0. The standard errors shown in parentheses are clustered at individual level: $^*$ denotes $p < 0.10$, $^{**}$ $p < 0.05$, and $^{***}$ $p < 0.01$.

| | Job Level | Imputed Compensation, thousands of USD | Switch |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\delta_{-5}$ | -0.036 | -2.141 | 0.021 |
| | (0.046) | (54.160) | (0.020) |
| $\delta_{-4}$ | -0.031 | 23.940 | 0.005 |
| | (0.040) | (45.759) | (0.019) |
| $\delta_{-3}$ | -0.009 | 22.281 | -0.020 |
| | (0.034) | (38.900) | (0.019) |
| $\delta_{-2}$ | 0.025 | 26.116 | 0.012 |
| | (0.024) | (27.791) | (0.020) |
| $\delta_0$ | -0.063$^{***}$ | -53.963$^{*}$ | 0.022 |
| | (0.022) | (28.297) | (0.020) |
| $\delta_{+1}$ | -0.153$^{***}$ | -160.983$^{***}$ | 0.103$^{***}$ |
| | (0.037) | (46.862) | (0.021) |
| $\delta_{+2}$ | -0.231$^{***}$ | -251.109$^{***}$ | 0.053$^{***}$ |
| | (0.043) | (55.503) | (0.020) |
| $\delta_{+3}$ | -0.202$^{***}$ | -212.069$^{***}$ | 0.037$^{*}$ |
| | (0.050) | (61.654) | (0.019) |
| $\delta_{+4}$ | -0.224$^{***}$ | -213.951$^{***}$ | 0.050$^{**}$ |
| | (0.054) | (68.110) | (0.021) |
| $\delta_{+5}$ | -0.277$^{***}$ | -237.881$^{***}$ | 0.016 |
| | (0.061) | (74.167) | (0.020) |
| Observations | 34009 | 33137 | 34400 |
| No. professionals | 1948 | 1940 | 1948 |

**Table B.4: Liquidation and performance: estimates obtained using the whole sample**

The table reports estimates for the career effects of liquidations after poor relative performances, using the whole sample of 661 individuals that experience a fund liquidation (for the 11 years surrounding the liquidation) and 1,287 individuals that do not (for all the available years), rather than the matched sample used in Table 6. Liquidation is a dummy equal to 1 in the liquidation year and in the 5 subsequent years (for funds that are liquidated), and 0 otherwise. Poor Performance is a dummy equal to 1 for funds with average monthly return below the benchmark return in the 2 years before liquidation, and 0 otherwise. Columns 1, 2 and 3 show the estimated coefficients of the Liquidation dummy and of its interaction with the Poor Performance dummy. All specifications include individual and year fixed effects. The standard errors shown in parentheses are clustered at individual level: * denotes $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

| | Job Level | Imputed Compensation, thousands of USD | Switch |
|---|---|---|---|
| | (1) | (2) | (3) |
| Liquidation | 0.018 | 140.288 | 0.058*** |
| | (0.088) | (103.233) | (0.019) |
| Liquidation×Poor Performance | -0.262*** | -438.848*** | -0.012 |
| | (0.097) | (115.827) | (0.021) |
| Observations | 34009 | 33137 | 34400 |
| No. professionals | 1948 | 1940 | 1948 |

## Table B.5: Fund Performance and Liquidations: Time-Varying Imputed Compensation

The table reports estimates for the effects of liquidations after poor relative performance. Liquidation is a dummy equal to 1 in the liquidation year and in the 5 subsequent years (for funds that are liquidated), and 0 otherwise. Poor Performance is a dummy equal to 1 for funds with average monthly return below the benchmark return in the 2 years before liquidation, and 0 otherwise. Columns 1 and 2 show the estimated coefficients of the Liquidation dummy and of its interaction with the Poor Performance dummy respectively, for all professionals and for those holding top-executive positions (job levels 5 and 6) 2 years before liquidation. The equation is estimated using data for 5 years before and 5 years after the liquidation date. All specifications include individual and group specific time-to-liquidation fixed effects. Imputed compensation is the average annual salary associated in each year (from 2000 to 2015) with each SOC code in the six sectors in Table 2 for professionals in job levels 1-4; for levels 5 and 6 it is the average annual compensation associated in each year (from 2000 to 2015) in the 10Ks with each job level in the six sectors in Table 2. The standard errors shown in parentheses are clustered at individual level: $^{*}$ denotes $p < 0.10$, $^{**}$ $p < 0.05$ , and $^{***}$ $p < 0.01$.

| Dependent variable: Time-varying Imputed Compensation | | |
|---|---|---|
| | All professionals | Top executives |
| | (1) | (2) |
| Liquidation | 159.798 | 214.543 |
| | (130.094) | (152.413) |
| Liquidation×Poor performance | -390.890$^{***}$ | -620.792$^{***}$ |
| | (146.151) | (174.645) |
| Observations | 10481 | 5762 |
| No. professionals | 1160 | 600 |

## Table B.6: Fund Performance and Liquidations: Fixed Compensation

The table reports estimates for the effects of liquidations on imputed fixed compensation after poor relative performance. Liquidation is a dummy equal to 1 in the liquidation year and in the 5 subsequent years (for funds that are liquidated), and 0 otherwise. Poor Performance is a dummy equal to 1 for funds with average monthly return below the benchmark return in the 2 years before liquidation, and 0 otherwise. Columns 1 and 2 show the estimated coefficients of the Liquidation dummy and of its interaction with the Poor Performance dummy respectively, for all professionals and for those holding top-executive positions (job levels 5 and 6) 2 years before liquidation. The equation is estimated using data for 5 years before and 5 years after the liquidation date. All specifications include individual and group specific time-to-liquidation fixed effects. Imputed fixed compensation is the average annual salary associated in 2016 with each SOC code in the six sectors in Table 2 for professionals in job levels 1-4; for levels 5 and 6 it is the average annual fixed compensation associated in the 2015 10Ks with each job level in the six sectors in Table 2. The standard errors shown in parentheses are clustered at individual level: $^{*}$ denotes $p < 0.10$, $^{**}$ $p < 0.05$ , and $^{***}$ $p < 0.01$.

| Dependent variable: Imputed Fixed Compensation, in thousands of USD | | |
|---|---|---|
| | All professionals | Top executives |
| | (1) | (2) |
| Liquidation | 24.056 | 29.410$^{*}$ |
| | (14.686) | (16.188) |
| Liquidation×Poor Performance | -46.698$^{***}$ | -76.545$^{***}$ |
| | (16.751) | (19.395) |
| Observations | 11863 | 6231 |
| No. professionals | 1168 | 600 |

# Online Appendix A: Theoretical Framework

We construct a model of asset managers' careers where fund relative performance is affected both by moral hazard and adverse selection, and the market gradually infers managers' skills from performance. As we shall see, some of the key parameters of the model can be directly estimated from our data, allowing us to determine the strength of the market discipline exerted by liquidations in our hedge fund sample.

The model considers an infinite-horizon economy with a continuum of funds and managers, each fund being run by a single manager. Managers are scarce relative to the number of potential funds, so that competition leads managerial compensation to absorb all of the surplus generated by the fund in excess of the minimum target acceptable to investors. Both investors and managers are risk neutral, and have time discount factor $\rho$.

The return of fund $i$ at time $t$ is the sum of its benchmark return and its return relative to the benchmark, i.e. its relative performance $R_{it}$. Both the fund's return and its benchmark are publicly observable. Hence so is its relative performance, defined $R_{it} \equiv \Delta_{it} - w_{it}$, where $\Delta_{it}$ is the gross return generated by manager $i$ and $w_{it}$ is his compensation at time $t$. The gross return $\Delta_{it}$ is determined by idiosyncratic forces, namely the talent and effort of the fund manager, as explained below.

A fund can be liquidated for either of two reasons. First, investors liquidate funds that are not expected to meet their target relative performance $\alpha$, i.e. violate investors' participation constraint:

$$\mathbb{E}(R_{it} \mid \Omega_{t-1}) \geq \alpha, \tag{3}$$

where $\Omega_{t-1}$ denotes public information at time $t-1$, including past values of the fund's relative performance $R_{it-s}$, for $s > 0$. As we shall see, such performance-related liquidations make the respective fund managers effectively unemployable in the asset management industry, as also other investors will regard them as incapable of delivering a satisfactory performance.

Second, a fund may be liquidated irrespective of its expected relative performance: even if the fund satisfies condition (3), at any time $t$ it is liquidated with probability $p$ due to adverse events affecting its whole class or the entire market, such as permanent shifts in policy or in risk appetite. In principle, also these liquidations may damage the subsequent career of the affected managers, by forcing them to take new jobs where their productivity drops by a fraction $\phi$ of its initial level: if $\phi = 1$, these liquidations have the same scarring effects as performance-related ones; at the other extreme, if $\phi = 0$ they have no scarring effects. Hence, even if fund $i$'s expected performance is satisfactory, its manager's future compensation is expected to decline by a fraction $p\phi$. Accordingly, the manager's effective discount factor is $\beta \equiv \rho(1-p\phi)$: future compensation is discounted more heavily the greater the probability $p$ of the fund being fortuitously liquidated, and the greater the associated income loss $\phi$.

Managers differ in skill level: a fraction $\lambda$ of them are good ($G$), and $1 - \lambda$ bad ($B$). A fund's relative performance depends both on the manager's quality and on his effort level. If run by a good manager, fund $i$'s gross relative performance $\Delta_{it}$ is a Bernoulli random variable that equals $e \cdot \Delta$ with probability $\pi$, and 0 otherwise, where $e = \{0, 1\}$ is the manager's effort, chosen at the private cost $C = e \cdot c$. If run by a bad manager, instead, fund $i$ invariably produces zero relative performance, even if the manager chooses $e = 1$.[23] While managers know their skill level, investors do not, nor can they observe managers' effort. Hence, asset management features both adverse selection and moral hazard.

Effort is assumed to be efficient, covering both its cost to the manager and the target return required by investors:

$$\pi\Delta > c + \alpha, \tag{4}$$

so that under perfect information the fund is viable. Poor performance by managers cannot be penalized by negative earnings: the best that investors can do to attenuate moral hazard is to give them performance-based compensation, by which they receive a fee $w_{it} = w$ if $\Delta_{it} = \Delta$, and $w_{it} = 0$ if $\Delta_{it} = 0$.[24] Hence, fund $i$'s relative performance is $R_{it} = \Delta - w$ in case of "success", and 0 otherwise. In a one-period setting, incentive compatibility requires that $\pi w \geq c$: the manager's fee given "success" cannot be less than $c/\pi$, to compensate him for the cost of effort.

[23] The results would be qualitatively unchanged if the assumption that bad managers always produce zero return were relaxed: in this case, observing the payoff $\Delta$ would not *per se* imply that the manager's type is good, so that the market's updating about the manager's quality would be more complex and gradual than under our starker assumptions. Our results would be substantially unaffected also if low relative performance (produced by bad managers and by good but "unlucky" ones) were assumed to be negative rather than zero, as in our model.

[24] In practice the performance fee of hedge fund managers is based on absolute returns, which are partly determined by the performance of the benchmark. The results of the model would be qualitatively unaffected by positing such a compensation scheme. In fact, such a scheme would make incentive pay less effective in alleviating moral hazard and would therefore make the disciplinary role of liquidations all the more important.

Since the managerial labor market is competitive, however, the investors' participation constraint (3) is binding. Denoting investors' belief (at time $t$) that manager $i$ is good by the conditional probability $\theta_{it} \equiv \Pr(G \mid \Omega_{t-1})$, compensation is determined by the condition $\mathbb{E}(R_{it} \mid \Omega_{t-1}) = \theta_t \pi(\Delta - w) = \alpha$. Hence, the competitive fee pledged to the manager in case of "success" at time $t$ is

$$w_{it} = \Delta - \frac{\alpha}{\theta_{it}\pi}. \tag{5}$$

Note that in a one-period setting incentive compatibility would require $\pi w_{it} \geq c$, which together with the investors' participation constraint (5) implies

$$\pi\Delta \geq c + \frac{\alpha}{\theta_{it}}. \tag{6}$$

This condition is stronger than assumption (4), and is bound to be violated if the investors' perception of the manager's quality, $\theta_{it}$, is sufficiently low. Since initially the belief about the manager's quality is the unconditional probability of him being good ($\theta_{i0} = \lambda$), in the extreme case where $\pi\Delta \leq c + \alpha/\lambda$ the fund will not even be able to get initial funding. However, as we shall see, this is not necessarily the case when managers allow for the danger of liquidation, which creates further "market discipline" in addition to that produced by performance pay.

## 1. Two useful benchmarks

To frame our ideas, let us consider two useful benchmark cases: (i) investors know the manager's skill level, and (ii) investors never liquidate the fund for poor relative performance.

If the manager's type is public information, so that there is moral hazard but no adverse selection, then bad managers will not get funding (they fail to meet condition (3)), while good managers will be funded and earn the competitive fee

$$w = \Delta - \frac{\alpha}{\pi} \equiv \overline{w} \tag{7}$$

in case of "success", and zero otherwise, as can be seen by setting $\theta_{it} = 1$ in (5). This compensation is incentive-compatible on a period-by-period basis (since $\pi\overline{w} > c$ by assumption (4)) and makes expected relative performance just equal to the investors' target: $\mathbb{E}(R_{it}) = \alpha$, for all $t$.

Next, consider what happens if investors do not know the manager's skill level, yet never liquidate the fund, being satisfied with the benchmark return ($\alpha = 0$). In this case, investors learn the manager's quality over time, but this does not trigger any incentive effect. This learning is very simple, as by assumption only good managers succeed. Thus, as soon as the fund reports a "success" (i.e. $\Delta_{it} = \Delta$), the manager is recognized as good ($\theta_{it} = 1$) and from then on always receives the fee $\overline{w} = \Delta$ in case of "success" (obtained by setting $\alpha = 0$ in (7)), and zero otherwise. Instead, whenever the manager's type is unknown, i.e. in the initial period 0 and in any period $t$ after an uninterrupted sequence of "failures" ($\Delta_{it-s} = 0$, for $s = \{1, 2, ..., t\}$), the investors' belief is

$$\theta_{it} = \frac{\lambda(1-\pi)^t}{1-\lambda+\lambda(1-\pi)^t}, \tag{8}$$

so that $\theta_{i0} = \lambda$. Clearly, this belief is increasing in the quality of the manager pool, $\lambda$, and decreasing in good managers' probability of "success", $\pi$, and in the number of previous uninterrupted "failures", $t$. Hence, the longer the string of "failures", the more pessimistic investors become about the manager's quality. Nevertheless, if $\alpha = 0$, investors are willing to pay the fee $\overline{w} = \Delta$ upon "success" and earn $\mathbb{E}(R_{it} \mid \Omega_t) = 0$, without liquidating the fund even if their belief $\theta_{it}$ drops close to zero. The manager's compensation is incentive-compatible on a period-by-period basis, as $\pi\Delta \geq c$ holds by assumption (4). Hence, in this case, even though investors gradually learn about the manager's type, their compensation policy is unaffected: absent liquidation, learning does not translate into "market discipline".

The question is whether it is appropriate, given that the problem is dynamic, to verify incentive compatibility on a period-by-period basis. It turns out that in the two cases just analyzed it is appropriate, because the expected value of the future payoffs is not affected by the current choice of effort. To see this, consider that from the standpoint of a good manager who exerts effort in each future period, the payoff (compensation net of effort cost) can be described by an infinite binomial tree where the node at each time $t$ leads with probability $\pi$ to a payoff $\beta^t(\overline{w} - c)$ and with probability $1 - \pi$ to a payoff $-\beta^t c$. As the tree is the same starting from any node, its expected value is the same at each date $t$:

$$V_t = \frac{\pi\overline{w} - c}{1-\beta}. \tag{9}$$

Since the manager expects the same continuation value $V_t$ irrespective of current "failure" or"success" (and investors' belief $\theta_t$), the incentive compatibility constraint is the same as in the one-period case.

## 2. Enter liquidation

If investors have a positive target for expected relative performance ($\alpha > 0$), they will want to liquidate the fund when their belief about the manager's skill becomes sufficiently pessimistic, following a long enough sequence of "failures". The intuitive reason for this is that, in order to obtain their expected target return, they have to reduce the compensation promised to the manager for "success"; but if "failures" persist long enough, this reduction becomes so great as to thwart the manager's incentives. At that point, the investors' participation constraint (3) is violated, and the fund must be liquidated. Interestingly, the manager of a fund liquidated after persistent "failures" will not be taken on by other fund investors as a fund manager, since he does not satisfy their participation constraint either: his post-liquidation compensation is zero, i.e. liquidation after continuing poor relative performance produces scarring effects. By contrast, it does not if the fund is liquidated after a "success", as in this case the liquidation does not affect investors' beliefs about the manager's skill.

If liquidation occurs at time $t^*$, a good manager's binomial payoff tree is no longer symmetric, as in the benchmark cases described in Section . Rather, the branch associated with the first $t^*$ "failures" leads with probability $(1-\pi)^{t^*}$ to the liquidation node, which yields a payoff of zero forever after (see Figure 1, where $t^* = 2$).

**[Insert Figure 1]**

To derive the incentive compatibility constraint in the period prior to possible liquidation, consider the two possible situations that may arise at $t = 1$:

1. After "success" at $t = 0$ (the upper node in the figure), the manager is recognized as good ($\theta_t = 1$) and from then on always receives the fee $\overline{w}$ in (7) in case of further "successes" and zero otherwise, which as we know is incentive-compatible and satisfies investors' participation constraint. The continuation value $V_1$ of the manager's expected subsequent payoffs is given by (9) regardless of future "success" or "failure", so it does not affect the manager's incentives, as in the benchmark cases of Section . Importantly, this applies to all nodes with a "success".

2. Instead, "failure" at $t = 0$ (the lower node) leaves the manager's type uncertain, and in fact by (8) the investors' belief about the manager's skill drops below

its unconditional value $\theta_{i0} = \lambda$:

$$\theta_{i1} = \frac{\lambda(1-\pi)}{(1-\lambda\pi)} < \lambda,$$

and by (5) the fee pledged to the manager upon success at $t = 1$ is

$$w_1 = \Delta - \frac{\alpha}{\theta_{i1}\pi} < w_0 = \Delta - \frac{\alpha}{\lambda\pi}.$$

However, the manager's incentives are affected not only by the fee $w_1$ that he expects for "success" at $t = 1$ but also by the threat of liquidation at $t = 2$ if he were to fail again at $t = 1$. Indeed, in this case, the manager's expected continuation payoff differs depending on whether he succeeds or fails at $t = 1$: in case of "success", $V_1(\Delta_{i1} = \Delta)$ is given by (9), while in case of "failure" $V_1(\Delta_{i1} = 0) = 0$. Hence, after "failure" at $t = 0$ the manager's incentive constraint is

$$\pi\left[w_1 + \beta V_1(\Delta_{i1} = \Delta)\right] = \pi\left[\Delta - \frac{\alpha}{\theta_{i1}\pi} + \beta\frac{\pi\overline{w} - c}{1-\beta}\right] \geq c, \tag{10}$$

where the term $\beta V_1(\Delta_{i1} = \Delta)$ is the "market discipline" effect of liquidation at $t = 2$, which supplements compensation $w_1$ as an incentive to the manager's performance at $t = 1$. It is easy to show that it also supplements the effect of compensation $w_0$ in raising his incentive to perform at $t = 0$.[25]

For liquidation to occur in case of "failure" at $t = 1$, the analogue of condition

[25] Suppose initially that $\pi\Delta - \alpha/\lambda > c$, so that at $t = 0$ compensation would be the sole incentive. The incentive-compatibility constraint at $t = 0$,

$$\pi\left\{\left[w_0 + \beta V_0(\Delta_{i0} = \Delta)\right] - \pi\beta\left[(w_1 - c) + \beta V_1(\Delta_{i1} = \Delta)\right]\right\} > c,$$

can be rewritten as

$$\pi\left\{\left[\Delta - \frac{\alpha}{\lambda\pi} + \beta\frac{\pi\overline{w} - c}{1-\beta}\right] - \beta\pi\left[\left(\Delta - \frac{\alpha}{\theta_1\pi} - c\right) + \beta\frac{\pi\overline{w} - c}{1-\beta}\right]\right\} > c.$$

Given that $\pi\Delta - \alpha/\lambda > c$, and recalling that $\Delta - \frac{\alpha}{\theta_{i1}\pi} - c < \pi\overline{w} - c$, a sufficient condition for the previous inequality is

$$(1-\pi\beta)\frac{\pi\overline{w} - c}{1-\beta} > 0,$$

which is true. Since this is just a sufficient condition, the incentive-compatibility constraint at $t = 0$ can hold even if $\pi\Delta - \alpha/\lambda < c$.

(10) at $t = 2$ must be violated, namely:

$$\pi\left[w_2 + \beta V_2(\Delta_{i2} = \Delta)\right] = \pi\left[\Delta - \frac{\alpha}{\theta_{i2}\pi} + \beta\frac{\pi\overline{w} - c}{1-\beta}\right] < c. \tag{11}$$

Inequalities (10) and (11), together with expressions (7) and (8), yield the following conditions for liquidation to occur at $t = 2$:

$$\frac{1}{1-\pi} \leq \frac{\lambda(\pi\Delta - \alpha - c)}{(1-\lambda)\alpha}\left(1 + \frac{\beta\pi}{1-\beta}\right) < \frac{1}{(1-\pi)^2}.$$

More generally, the liquidation date is $t^* = \lceil\tau\rceil$, i.e. the smallest integer larger than the real number $\tau$ that solves

$$\left(\frac{1}{1-\pi}\right)^{\tau} = \frac{\lambda(\pi\Delta - \alpha - c)}{(1-\lambda)\alpha}\left(1 + \frac{\beta\pi}{1-\beta}\right), \tag{12}$$

where the left-hand side is increasing in $\tau$, and therefore in $t^*$, since $\pi < 1$.

Expression (12) yields two results that are relevant for the empirical analysis of the causes of scarring effects:

First, if a fund continuously produces poor performance relative to its benchmark for more than a critical number of periods $t^*$, it will be liquidated: its manager can no longer be incentivized to perform while meeting investors' required rate of return. But, since fund performance is public, all investors will perform the same updating of the manager's skill, implying post-liquidation scarring effects.

Second, expression (12) shows that the optimal liquidation time $t^*$ is increasing in the parameter $\beta$, namely the manager's effective discount factor. Recalling that $\beta \equiv \rho(1 - p\phi)$, expression (12) implies that the time $t^*$ to liquidation is decreasing in the probability $p$ that the fund is fortuitously liquidated and in the resulting fractional income loss $\phi$. Intuitively, if these two parameters are high (close to 1), so that $\beta$ is low (close to 0), the fund is likely to be liquidated regardless of its relative performance and such fortuitous liquidation would result in large scarring effects for the manager. This dilutes the incentive effect of liquidation, and thus brings forward the date at which the fund must be liquidated. Conversely, if the probability $p$ of fortuitous liquidation and/or the severity of its scarring effects $\phi$ are low (close to 0), then $\beta$ is high (close to the time discount factor $\rho$), and the "market discipline" effect of liquidation is commensurately large: being confident that the liquidation will occur only if the fund performs worse than its benchmark, the manager will have strong incentive to shine, and this will induce investors to tolerate a longer period of underperformance before triggering liquidation. This is not only because they gradually learn about the manager's skill, but also because the discipline from liquidation itself gives the manager credibility in the eyes of investors. Our data enable us to estimate the parameters $p$ and $\phi$, and thus measure the strength of the "market discipline" from liquidation.[26]

[26]Expression (12) also implies other intuitive comparative statics results regarding the optimal liquidation time $t^*$. The more severe the information asymmetry, the less tolerant investors are of persistently poor relative performance: the time to liquidation is decreasing in the severity of moral hazard (low productivity $\Delta$ and high private cost $c$ of managerial effort) or adverse selection (low quality of the manager pool $\lambda$). Intuitively, when information problems are worse, underperformance results in a sharper fall in the manager's reputation, inducing investors to cut in the manager's fees more deeply, and thus bringing forward the moment when he is no longer willing to exert effort. Liquidation is also hastened if investors set a more demanding target rate $\alpha$.

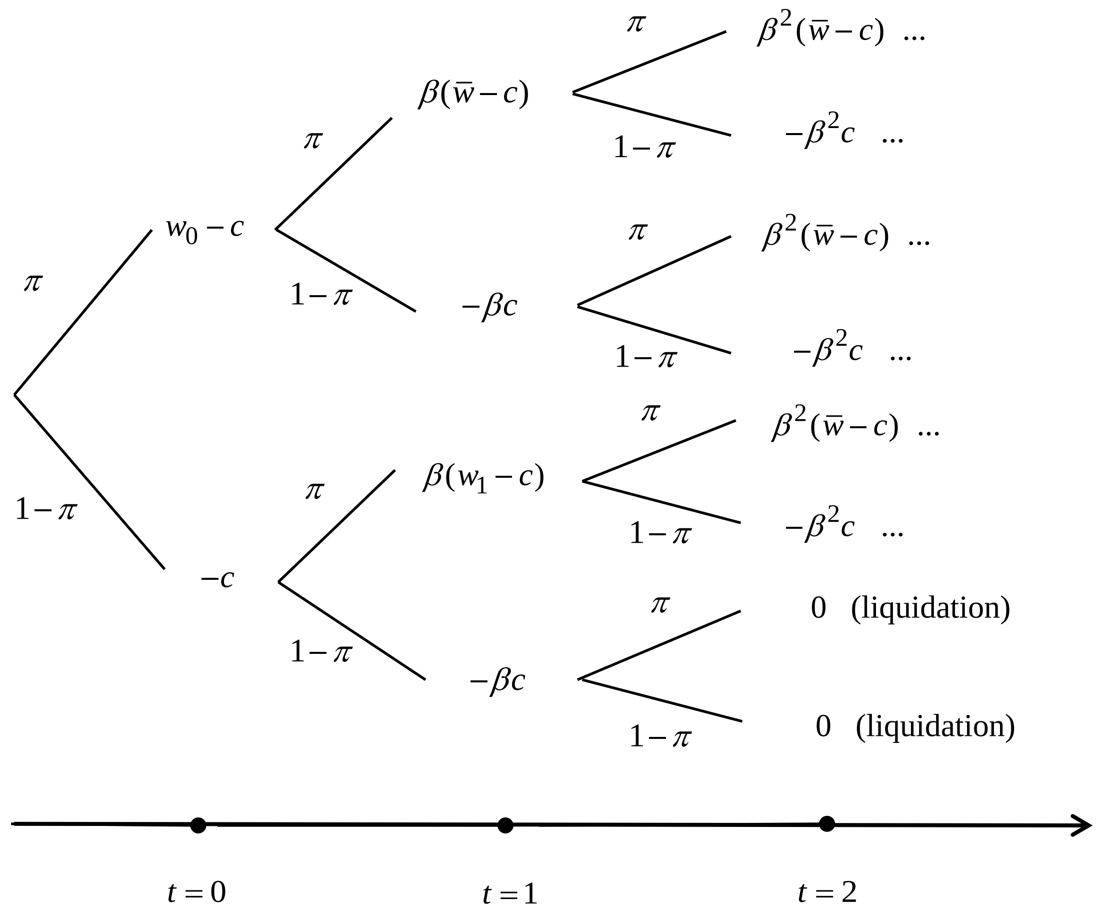


**Figure 1. Managers' payoff tree with liquidation at t=2.** The figure shows the payoff obtained in the first three periods by a manager who exerts effort at the private cost $c$. In each period, the fund's relative performance is positive with probability $\pi$ and zero with probability $1-\pi$. Accordingly, the manager receives a positive fee with probability $\pi$ and zero with probability $1-\pi$, except in case of the fund's liquidation. The assumption is that, given the model's parameters, upon low performance at $t=0$ and $t=1$ investors choose to liquidate the fund at $t=2$.

# Online Appendix B: Data Construction Roadmap

This appendix explains in detail all the steps followed in the construction of the data regarding the careers of the individuals in our sample.

## 1. Building the sample of professionals

We draw the names of 13,056 hedge fund professionals present in the 2007-2014 vintages of the Lipper Hedge Fund Database (TASS) and the names of the investment companies that employ them in each year in which they appear in TASS. We draw the names of the professionals relying on information reported both in the "live funds" and the "graveyard" TASS databases. We then complement the information provided by TASS with resume data drawn from a major professional networking website. To make sure that we match individuals in TASS with their respective resumes, we search them on the networking website not only by first and last name, but also by the name of the company that employs them in a specific year (as reported in TASS). Due to limits imposed by the online platform, for each search we can only access the first ten pages of results. The final sample consists of 1,948 individuals, for which we have data on education (degrees and dates, subject and school for each degree), year of the first job, and start dates, end dates, employers and job titles for all the positions held throughout their career. On average, the observed career of the individuals in our sample spans about 21.7346 years. Hence, the total number of person-year observations is $1{,}948 \times 21.7346 = 42{,}339$, which is the maximum number of observations reported in Table 2.

## 2. Mapping job titles to Standard Occupation Classification (SOC) codes

Job titles are matched with the Standard Occupation Classification (SOC) codes produced by the Bureau of Labor Statistics (BLS), via the O*NET code connector platform (https://www.onetcodeconnector.org). In the resumes of the 1,948 individuals in our sample there are 4,196 unique job titles. For each of these job titles the O*NET code connector lists a set of possible O*NET-SOC codes ranked according to how well they match the given job title. To each job title we associate the O*NET-SOC code with the highest score and map it to the corresponding SOC code. Then, in order to create a measure of the position of an employee in the company's job ladder, we group the SOC codes into six bins, designed to capture different degrees of decision-making power. These job bins are based on the EEO-1 Job Classification system (available at https://www.eeoc.gov/employers/eeo1survey/jobclassguide.cfm), except for top executives, which are grouped in a separate bin.

## 3. Merging resume data with OES and 10-K statements data

The total number of companies that employ the 1,948 professionals in our sample is 6,771. We sort these companies into the following 6 sectors:

1. asset management: firms with SIC 67 and NAICS 5251 or 5231;
2. commercial banking and other lending institutions: firms with SIC 60 or 61 and NAICS 5211, 5221, 5222 or 5223;
3. financial conglomerates, i.e. institutions encompassing lending, insurance and/or asset management, namely: Chase Manhattan Bank, Barclays de Zoete Wedd, CIBC World Markets, Citi, Merrill Lynch, Anand Rathi Financial Services Ltd, Calyon Financial, Charles Schwab, EF Hutton, EFG Eurobank Securities, Fimat, Julius Baer, Macquarie Bank, Mizuho Bank, Morningstar, Susquehanna International Group, Commonwealth Bank of Australia;
4. insurance: firms with SIC 63 or 64 and NAICS 5241 or 5242;
5. other finance: firms with SIC 62 and NAICS 5232 or 5239;
6. non-financial firms, government entities, supranational institutions and stock exchanges: firms with remaining SIC and NAICS.

We sort 2,129 companies that employ individuals in our sample into these 6 sectors based on information available in their websites, LinkedIn webpages and online financial press. To determine the sectors of the remaining 4,642 companies, we use the machine learning algorithm described in Appendix A of the paper.

Once all employers are sorted into sectors, for job levels 1 to 4, we impute compensation based on the average salary corresponding to each SOC code and sector, from the 2016 Occupational Employment Statistics (OES). For job levels 5 and 6, we impute compensation from data drawn from 10-K forms available through the Edgar system, which report both the fixed and variable components of top management pay.

More precisely, to impute the compensation of occupations in job levels 1 to 4, we draw the average annual salary from the 2016 OES for each SOC code and each 4-digit NAICS. Then, since we must aggregate the OES salary data to the level of the above-listed 6 sectors, for each combination of SOC code and sector we impute the employment-share-weighted average of the annual salaries computed across the relevant 4-digit NAICS. For conglomerates, we impute the highest annual salary corresponding to each occupation across all other sectors.

To impute the compensation of occupations in job levels 5 and 6, we hand-collect data from the annual 10-K and proxy statements filed by firms with the SEC on total compensation and its components (salary, bonus, stock options and stock-based remuneration) awarded in 2015 to the top five executives by the boards of the listed firms in the financial industry. We collect data for firms in each of the 6 above-listed sectors (based on the relevant SIC codes), with the following breakdown: (i) 114 firms in asset management, (ii) 388 in commercial banking and other lending institutions, (iii) 22 financial conglomerates, (iv) 109 insurance firms, and (v) 244 firms defined as "other finance". To impute the executive compensation awarded by non-financial firms we randomly choose 400 firms in the service sector. 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. Chairmen and CEOs are classified as job level 6, all the others as level 5.

The end result is an imputed compensation for each job title and sector. For individuals employed by more than one company at a time, we keep track of all their positions, defining their job level as the highest one held at any moment and their imputed compensation as that associated with the corresponding SOC code and sector.