Between Alpha and Beta: Modeling The Impact of Regulatory Constraints on the Hedge Fund Industry

Anna Ilyina and Roberto Samaniego*

June 2010

Abstract

Decreasing returns to scale and scarcity of manager talent are important determinants of the dynamics of the portfolio management industry. In a calibrated model of the hedge fund industry, we explore the implications of these features for the equilibrium response of the industry to regulatory change. An increase in due diligence costs reduces the number of active hedge funds, while leaving industry capital under management unaffected. By contrast, a leverage limit decreases hedge funds' capital under management significantly – even when small funds are exempt – and may lead certain hedge fund styles to become non-viable.

JEL Codes: G11, G23, L25, L84.
Keywords: Portfolio management, hedge funds, diminishing returns, alpha, manager talent, leverage caps, due diligence costs, financial regulation, industry dynamics.

* Roberto Samaniego (corresponding author): George Washington University, Department of Economics, 2115 G St NW Suite 340, Washington DC, 20052. Email: roberto@gwu.edu. Anna Ilyina: International Monetary Fund, Monetary and Capital Markets, 700 19th St NW, Washington, DC 20431. Email: ailyina@imf.org.

I. INTRODUCTION

The regulation of the financial sector is a topic that has gained prominence in the wake of the subprime crisis and the subsequent global recession. Proposals include the expansion of the "perimeter of regulation" to cover lightly regulated entities such as hedge funds, using measures such as new reporting requirements and limits on leverage. An assessment of the long-run impact of subjecting hedge funds to tighter regulation requires a quantitative model that captures salient features of the industry that would affect its equilibrium response – for example, via changes in industry composition, changes in capital under management and changes in profitability. This paper develops such a model.

Recent work has identified fund size and scarcity of asset manager talent as two important determinants of the returns to actively managed funds. This is in contrast to standard models of asset management, which assume that portfolio returns are driven by the statistical properties of the underlying assets. Berk and Green (2004) argue that differences in the quality of asset managers and decreasing returns to fund size can reconcile a number of empirical regularities in portfolio management with efficient market theory and rational expectations. In addition, several authors find evidence supporting the presence of decreasing returns to scale in the hedge fund industry.[1] Hence, decreasing returns and limited talent are likely to be critical determinants of the response of the hedge fund industry to any changes in regulatory constraints – particularly since proposed changes directly impact the size of hedge fund investments (e.g. caps on leverage) and the composition of the hedge fund industry (e.g. higher fixed costs, such as the cost of due diligence). In spite of work underlining the importance of decreasing returns and limited talent for the behavior of the asset management industry, the implications of these features for the *response of the industry to changes in regulation* have not been explored.

We develop a theoretical model in which the size and composition of the hedge fund industry are endogenous. The model features a set of potential fund managers, but which of them operate hedge funds in equilibrium depends on their profitability. In turn, profitability hinges both on talent and on luck. We estimate the key parameters of the model, and calibrate the model to assess the impact on the hedge fund industry of changes in the regulatory environment, including an increase in the cost of due diligence, an increase in the cost of leverage, and a cap on leverage ratios. These are among the regulatory initiatives that are currently being discussed – see ECB (2006), FSA (2009) and Malcolm et al (2009).

In the model, hedge funds differ in terms of talent, and experience shocks to their returns. At any date they may raise funds and place them in an investment strategy, the returns to which depend on fund size, on talent, and on the shocks (which we will refer to as "luck"). The equilibrium *industry* size is determined by the presence of negative spillovers across funds. This captures the notion that hedge funds may engage in similar strategies, so that increased investments in a given hedge fund lower the returns of *other* funds. For example, to the extent that some hedge funds earn profits from arbitrage, the size of their positions could

[1] See Goetzmann, Ingersoll and Ross (2003), Getmansky (2004), Ammann and Moerth (2005), Jones (2007) and Lo (2008), among others.

affect prices in the mis-priced markets and lead to lower returns (Perold and Salomon (1991)) – and the presence of *other* managers following the same strategy could have similar effect.[2]

Our model builds on the Hopenhayn (1992) industry framework with entry and exit, adapted to match specific features of hedge funds – for example, the presence of cross-fund spillovers, and of leverage. In our paper leverage is capped exogenously, either by best-practice norms or by the regulator, as in the entrepreneurial model of Evans and Jovanovic (1989). Aghion et al (1999) provide a theoretical foundation for fixed leverage ratios, showing that such a borrowing limit can emerge as an equilibrium outcome of a game between borrowers and creditors in an environment with limited commitment in which borrowers may divert funds at a cost.

In order to calibrate the model, we estimate a reduced form panel specification that maps into the model parameters, using data on hedge fund capital under management and returns. The econometric model decomposes hedge fund returns into effects due to size, talent and luck. We identify manager talent using fund-level fixed effects. The identification of managerial talent with a fund-specific fixed effect is consistent with Lo (2008), who argues that the manager essentially *is* the fund, and with Liang and Park (2010), who find that the exit of a hedge fund is often tied to the career decisions of the fund manager. Thus, we can identify the existence and distribution of manager talent though its permanent effect on returns.[3] It should be noted that our specification allows luck to be serially correlated, so our model nests the possibility that there are no fixed effects and only temporary (thought persistent) differences in returns.

Using these estimates, we calibrate the theoretical model and use it to assess the impact on the industry of an increase in entry costs, of an increase in the borrowing cost, and of an imposition of leverage limits. Our simulations show that the interaction of limited talent and decreasing returns are central to the response of the industry to regulatory change. The main results are as follows:

- A significant **increase in entry costs** has a large impact on the number of hedge funds, but little impact on the total industry capital under management and profits.

---

[2] Getmansky (2004), Khandani and Lo (2007) and Chan et al (2007) all mention the possibility of "congestion" of hedge fund positions. An example is the October 28, 2008 spike in the Volkswagen share price as hedge funds closed large short positions that exceeded the value of outstanding Volkswagen shares – leading Volkswagen to be (briefly) the largest company in the world by market value, and generating significant losses for the hedge funds involved.

[3] We do not take a stand on what it is that constitutes manager talent. One determinant of talent is the inherent ability of the fund manager to assess the risk-return trade-offs of different investments. Another might be the rules that govern the hedge fund from its inception: for example, Gompers et al (2003) find that the rules of governance can affect the long-run profitability of firms and, in the case of hedge funds, certain contractual features have been found to be related to hedge fund returns (e.g the existence of a lock-up period, as in Aragon (2007), or the presence of high watermarks, as in Agarwal et al (2009)). We interpret the fixed effect as capturing all these possibilities, but use the term "manager talent" for convenience.

This is because the increase in operating costs raises the bar on the profitability required for hedge funds to enter and survive: however, this would affect mainly the funds with the lowest manager talent, which comprise a small fraction of total industry capital under management.

- By contrast, an increase in the **cost of borrowing** or the imposition of a **leverage limit** at a level below the current industry norms can have a large impact on industry capital under management and profits. This is because a leverage limit lowers the profits that funds can generate with a dollar of capital – the "productivity" of the hedge fund. This does not affect rates of return, because lower profitability is offset by hedge funds optimally reducing their portfolios. Furthermore, exempting funds that are smaller than a certain size threshold from leverage limit does not change this result, but by weakening the negative spillover across the funds, it may encourage the entry of hedge funds that in the absence of such limits would have been unprofitable, and hence, may lead to lower average quality of funds.

The paper has several contributions. First and foremost, the policy implications of talent scarcity and decreasing returns to scale in the asset management industry have not been explored before – in spite of the relevance of these features for the evaluation of the regulation of the industry. Second, the implications of the specific policy changes we contemplate have not been explored in an equilibrium context. There exist studies of the impact of new regulations on hedge funds by regulatory agencies or commissioned by such agencies (e.g. ECB (2006), Malcolm et al (2009) and FSA (2009, 2010)), but these studies do not model the equilibrium response of the industry to changes in regulation.

Third, our calibration procedure can be interpreted as an estimation of a version of the Hopenhayn (1992) framework, for the case of the hedge fund industry. We argue that this framework is appropriate for the asset management industry and, to our knowledge, this is the first application of this framework for policy analysis in the context of financial markets.[4] Fourth, we arguably provide more accurate estimates of the impact of size on returns in the hedge fund industry. We cannot calibrate our model using existing estimates of the impact of size on hedge fund returns because prior studies do not *jointly* estimates the impact of size and talent on hedge fund returns. In a world of non-decreasing returns to scale, heterogeneity of manager talent is of no consequence, since all resources could simply be allocated towards the best manager. Conversely, decreasing returns to fund size need not limit profits if the pool of manager talent is unlimited, as investors could increase returns by spreading their assets more thinly over a larger number of managers. Thus, any attempt to model theoretically or econometrically one feature requires modeling the other. Our quantitative results show that the response to regulation of the asset management industry depends very much on the interaction of size and talent.

[4] However, general equilibrium extensions of the framework have been used to evaluate labor market regulation, e.g. Hopenhayn and Rogerson (1993) and Veracierto (2008).

Section II provides a summary of the related literature. Section III describes the model, and Sections IV calibrates the model parameters, and discusses the empirical relevance of the model framework for the case of hedge funds. Section V assesses the impact of regulatory changes on the hedge fund industry and discusses extensions. Section VI concludes.

II. BACKGROUND ON HEDGE FUNDS

A. The Hedge Fund Industry: some Stylized Facts

We begin with a discussion of some distinguishing features of the hedge fund industry that motivate our modeling approach. Related discussions may be found in Financial Stability Forum (2000), Getmansky (2004), Malkiel and Saha (2005), and CISDM (2006).

Several features of hedge funds distinguish them from more traditional asset managers (such as mutual funds), and are important for modeling hedge fund industry dynamics:

- **Hedge fund strategies may not be "scalable."** Many hedge fund investment styles exploit market imperfections, such as arbitrage opportunities or profitable opportunities in less liquid markets: see Ammann and Moerth (2005) and Lo (2008). If so, sufficiently large positions at a given hedge fund would erode the market conditions that the hedge fund strategy is designed to exploit (e.g. see Perold and Salomon (1991) and Koutsougeras (2003)). The size effect could also be due to administrative costs that increase more than proportionately with capital under management, as in Ammann and Moerth (2005). Lucas (1978) suggests that managers may have limited supervisory resources. The fact that hedge funds tend to close down to new investors whenever they reach certain size is arguably evidence of decreasing returns, with Ackermann et al (1999) and others even arguing that each hedge fund has an "optimal size".

- **There are negative externalities across hedge funds**. To the extent that hedge funds exploit market imperfections such as arbitrage opportunities, their profits may be eroded if the positions of *other funds* following similar investment strategies hare large. There is indeed evidence that hedge fund investment strategies can overlap, and that this reduces profits: see Khandani and Lo (2007) on profit spillovers across "quant" hedge funds in 2007. Getmansky (2004) argues that returns are lower in fund styles with more intense competition, and Chan et al (2007) argue that large inflows into the hedge fund industry were one cause of deteriorating returns in 2004.

- **The fund manager's "talent" is a key determinant of hedge fund returns.** Hedge funds derive a significant part of their return from active portfolio management; see Ackermann et al (1999). Hedge fund performance is commonly linked to "alpha", interpreted as manager talent or as the quality of the manager's investment strategy.[5]

[5] Still, it is important to note that hedge funds are marketed as following a particular "style." This is important because funds within a style may have common risk factors, which matters for the measurement of alpha.

- **Talent is scarce.** Entry costs are far lower than profits at the average hedge fund. Brown et al (2008b) estimate the typical due diligence cost to the investor of contracting a hedge fund to be in the range $50,000-100,000. Strachman (2007) also reports the cost of starting a hedge fund to be about $50,000. By contrast, the mean assets under management at hedge funds is over $100,000,000 and mean annual return is about 9%, so mean annual profits should be over $9,000,000. This suggests that there may be more important constraints on industry growth than entry costs: instead, the size of the hedge fund industry is limited by the availability of *sufficiently talented fund managers*.

- **Exit is common, and often sudden.** Liang and Park (2010) find that about a third of exits can be attributed to low fund profitability, whereas two thirds of exits occur for other reasons, including changes in the career concerns of the fund manager and operational risks (e.g. fraud).[6] Indeed, Lo (2008) argues that in essence the fund manager *is* the fund, so his/her departure for any reason almost certainly marks the end of the hedge fund. Thus, many exits are due to factors unrelated to low profitability. As for the remainder, Getmansky et al (2004) find that profits at hedge funds tend to deteriorate within 12 months before exit, though not obviously before.

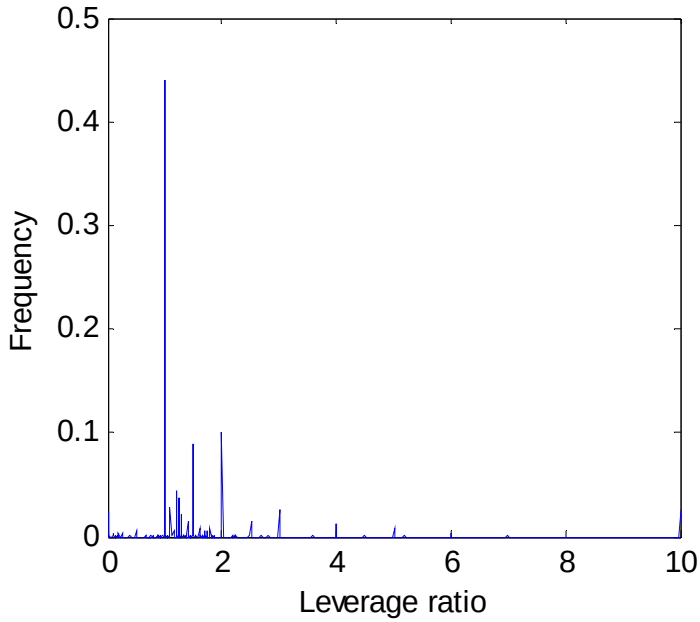
- **Leverage is common, but varies relatively little across funds.** Figure 1 shows reported leverage from the CISDM (2006) database. The distribution is degenerate: about 45 percent of all hedge funds in the database report leverage equal to one – meaning that they typically borrow an amount roughly equal to their capital under management. Independently, the UK Financial Services Authority (2009, 2010) also finds that reported values of leverage cluster around one. In fact, most responses are integers and, if we round all responses to the nearest integer, 65% of hedge funds report leverage of one. Some view differences in leverage as being, in large part, a function of the hedge fund style (e.g., Schneeweis et al (2005) and Managed Funds Association (2009)) and, indeed, a median regression of leverage against style dummies using CISDM (2006) data yields significant coefficients for all styles, (a median regression is appropriate because there are some significant outliers, and because leverage is often reported as an integer: see Figure 1). Thus, the hedge fund's level of leverage is best thought of as a given (possibly style-specific) parameter.

---

[6] Although avoiding fraud is one of the arguments for increasing due diligence costs and other regulations related to transparency, we do not model outright fraud. Feffer and Kundro (2003) find that around half of operational failures are related to fraud which, using the parameters in the paper, imply that fraud brings down about 2% of funds in any given year. The presumption is that greater regulation might catch some of these instances – however, this appears to affect only a small portion of the industry. Furthermore, Feffer and Kundro (2004) argue that fraud is generally due to asset value misrepresentation. It is not clear this will completely remedied by raising entry standards, since mis-pricing can only occur in markets where pricing is inherently difficult, and can only be detected after the fact.

With these stylized facts in mind, we construct a theoretical model of the hedge fund industry. We estimate the parameters of the model using panel regression analysis. We use the estimates to calibrate the theoretical model, and apply the model to quantify the long-run impact on the hedge fund industry of several regulatory restrictions that are currently under consideration.

Figure 1: Distribution of leverage ratios, CISDM database.
The leverage ratio is defined as the ratio of borrowed funds to capital.



B. Regulatory Initiatives for the Hedge Fund Industry

Hedge funds face few investment restrictions, and those they do face are typically determined by their own internal risk management guidelines and "best practice" norms. See, for example, Lo (2008). However, a perceived role of hedge funds in the EM crises of 1997-98, the near collapse of the LTCM, and the subprime crisis, have led policy makers to consider stricter hedge fund regulation – see ECB (2006), FSA (2009) and Malcolm et al (2009).

Policy concerns arise from unease about potential contribution of hedge funds to systemic risk – particularly due to the common practice of boosting returns via leverage and the incidence of crowded trades among hedge funds (i.e., when a significant number of hedge funds that are not necessarily individually systemic take similar positions) – and from a perceived lack of transparency in the industry. Foster and Young (2010), for example, argue that it is difficult to construct an incentive structure that distinguishes between skilled and unskilled hedge fund managers in the absence of investor knowledge about the strategies being pursued. These policy concerns are exacerbated given that it is no longer only wealthy individuals who invest in hedge funds, but also institutional investors (e.g. pension funds, endowments and foundations).

What are the main regulatory changes under consideration and what is their likely impact?

- **Imposing additional reporting requirements**. Brown et al (2008a) study the impact on hedge funds and investor behavior of the (subsequently repealed) requirement that all hedge fund managers register as investment advisors with the United States Securities and Exchange Commission. They find that imposing this requirement did not lead hedge fund managers to provide any substantive information to investors in addition to what was already made available to them. Thus, we focus on quantifying the costs associated with the imposition of additional reporting requirements on hedge funds, in the form of entry and operating costs.

- **Imposing leverage limits**. The justification for leverage limits is that they would reduce the hedge funds' contribution to systemic risk. The FSA (2010), however, concludes that there is no threat from hedge funds to the banking system based on current levels of leverage. In addition, Chan et al (2007) argue that the main systemic threat coming from hedge funds stems from an across-the-board unwinding of positions due to lack of liquidity. While there does not seem to be a clear evidence to suggest that there is any benefit from leverage caps, Malcolm et al (2009), e.g., argue that leverage caps would reduce profits and the number of hedge funds if the limits are much tighter than current best practice. In this paper, we focus on quantifying the potential impact of leverage limits (as well as size-contingent leverage limits) on the number funds and on total capital under management of the hedge fund industry.

- **Increasing the cost of leverage.** Increases in the cost of borrowing might lead to a shrinking of the industry. This could happen, for example, because regulators might require other financial intermediaries to raise the margin requirements for hedge funds. As we have seen during the recent crisis, the sharp 1.2 percent increase in 3-month LIBOR in October 2008 coincided with a significant reduction in the number and size of hedge funds across the board, though clearly not all of the impact could be attributed to a single cause. In what follows, we consider the impact of an increase in the cost of leverage on the number of funds and on total capital under management of the hedge fund industry.

III. THEORETICAL MODEL

A. Basic Structure

The model assumes a single hedge fund style. This enhances tractability, but does not affect the main results of the paper, as discussed in Section VI.

The inflow of *potential* fund managers is exogenous. However, due to the presence of entry costs, not all potential fund managers will be activated.

There is a continuum of risk neutral investors,[7] each of whom invests in hedge funds and decides on the capital q to be allocated to each. At any point in time, the investors may decide to close a hedge fund, if its expected profitability is too low. The investors may also activate hedge funds from the distribution of potential fund managers, at a cost c_e.

B. Hedge Funds

Time is discrete, and there is no aggregate uncertainty. In any period t, each hedge fund i is characterized by a stochastic return factor ε_{it} (luck), and a deterministic factor μ_i (talent). There is a distribution ξ_t over potential fund managers and their current realizations of luck, as well as their incoming assets under management: the distribution may change over time as managers enter, exit, experience changes in luck, or change their capital. Define Θ as the transition function for ξ_t: Θ is *endogenous*, and is determined in equilibrium by the process ε_{it} as well as by flows of potential managers in and out of the industry.

Luck ε_{it} is a random variable that follows a Markov process given by a distribution function $F\left(\varepsilon_{i,t+1} \mid \varepsilon_{it}\right)$. F has an ergodic distribution F^e. When an investor chooses to activate a fund at time t, the hedge fund's initial value of ε_{it} is drawn from a distribution G: before activation we assume $\varepsilon = -\infty$. The range of ε_{it} is assumed to be bounded. Both talent and luck are observable.

Each period a volume ω of potential fund managers becomes available, each one with a value of talent drawn from a distribution ζ. The volume and distribution of entrants is exogenous, capturing the notion that manager talent is a scarce resource (we discuss relaxing this assumption in Section V). Which hedge funds are *active* is determined in equilibrium, however. There is a cost to the investor c_e of activating a fund, representing the cost of due diligence, and which is imposed by regulators. Firms with an expected value below c_e are not activated. Define μ_t^* as the talent level below which fund managers do not receive capital to activate a hedge fund. There is also a per-period cost κ that the investor must pay to keep the fund active. This is the cost of ongoing due diligence.

Liang and Park (2010) distinguish between two different sources of exit. First, funds may close because of exogenous reasons unrelated to firm profitability, in which case they exit the pool of potential fund managers. This occurs in the model with probability δ_e. We interpret this as a change in the manager's career concerns, as the manager's retirement, or as closure due to legal problems. Second, funds may close due to the lack of profitability of their strategy, in which case the managers also leave the industry. We allow this to happen in the model in two ways. In any period the investor may liquidate the position and shut down the

[7] Since investors are risk neutral, the number of investors is not important so long as each one is small relative to the industry (so they cannot internalize externalities), and that together they have enough funds that the industry is not constrained. An interpretation of the model with *risk-averse* investors is that hedge funds make up a small portion of the investors' portfolios, so that the impact of the change in hedge fund returns on their marginal utility of consumption is small.

fund if the fund is unprofitable. In addition, the fund's strategy may cease to be profitable exogenously with probability δ_s. This is interpreted as the *obsolescence of the fund manager's investment strategy or talent value* (for example, due to its revelation and imitation by other types of financial intermediaries, who may engage in similar strategies: see Chan et al (2007)).[8] Thus, fund managers exit exogenously each period with probability $\delta = \delta_e + \delta_s$. Allowing $\delta > 0$ ensures that all hedge funds close in finite time with probability one, and δ represents a lower bound on the exit rate of funds in the industry.

The hedge fund earns revenues for the investor by using investor contributions to open an investment position. The hedge fund can invest funds obtained by raising capital or via leverage. The quantity $m_{i,t-1}$ is the value of the fund's investments. If the hedge fund's capital is $q_{i,t-1}$, and it borrows an additional proportion x of $q_{i,t-1}$, then the fund's position is

$$m_{i,t-1} = q_{i,t-1}(1+x). \tag{1}$$

The revenue from the investment $m_{i,t-1}$ is equal to:

$$f\left(m_{i,t-1}, M_{t-1}, \mu_i, \varepsilon_{it}\right) \geq 0 \tag{2}$$

The revenue f depends on the size of investment position $m_{i,t-1}$, and also on M_{t-1} which is the total size of positions of all funds in a given style. Having observed f, the investor decides whether to allocate funds $m_{i,t} \geq 0$ to the hedge fund for the following period.

Let $p \geq 1$ be the cost of raising funds. We define p in a simple way so as to distinguish between capital and debt, while allowing us to abstract from any particular theory of capital structure. To raise a dollar of capital costs $1+k$ dollars. This represents foregone consumption plus a premium k to open a position. Funds may also use leverage,[9] and the cost of leverage is c, where $c<k$. This last assumption implies that hedge funds would prefer to invest only using borrowed funds. However, we also assume a maximum leverage ratio x, imposed either by "best practice" guidelines or by the regulator (see Section II). We define the leverage ratio x as the ratio of borrowed funds to capital q. This is the definition used by many hedge fund data providers, including CISDM. Thus, the total cost of a position m_{it} is $q_{it}(1+k)+cxq_{it}$. The cost of funding a dollar of capital is $p \equiv (1+k)+xc$. The assumption of an exogenously fixed leverage ratio is a common way of modeling credit constraints, as in Evans and Jovanovic (1989), and Aghion et al (1999) provide a micro-foundation for such a credit constraint based on the borrower being able to divert the profits of the venture, at a cost. Thus, our leverage ratio can be interpreted either as an institutionally imposed value, or as an equilibrium outcome in an environment with limited commitment.

---

[8] As noted, Getmansky et al (2004) find that a link between deteriorating performance and exit appears within 12 months of the exit itself. Later, we identify a period in the model with one year, to avoid having to model a distinct period of several months over which profits deteriorate.

[9] As in practice, we assume that hedge funds borrow using margin accounts, so that the interest is effectively paid up front. This simplifies the notation by ensuring all costs are paid up-front, and abstracts from strategic default.

Recalling Section II, the fact that leverage ratios are so concentrated suggests that the mechanisms of theories that endogenize the cross-sectional variation in capital structure are not appropriate for the case of hedge funds. For example, a motivation for Cooley and Quadrini (2001) is that, in industry, leverage and size are thought to be negatively related, whereas in the case of hedge funds we find that the correlation in CISDM (2006) data is *positive* (9%) and has no statistical significance when conditioning on style dummies.[10] The same is true in a median regression, or with bootstrapped standard errors, procedures which are less sensitive to outliers. This is what motivates our approach to modeling leverage ratios.

At a continuing fund, let distributions to the investor $d_{i,t}$ equal revenues minus costs and capital for the subsequent period, assuming the hedge fund does not close:

$$d_{i,t} = f\left(m_{i,t-1}, M_{t-1}, \mu_i, \varepsilon_{it}\right) - pq_{i,t} - \kappa \qquad (3)$$

If $d_{i,t} > 0$, then the hedge fund is paying out distributions. If $d_{i,t} < 0$, then the hedge fund is raising additional capital from the investor.

There are decreasing returns to scale, so that $f_1 > 0$, $f_{11} < 0$. We also assume that $f\left(0, M_{t-1}, \mu_i, \varepsilon_{it}\right) = 0$. When a manager enters the industry, $q_{i,t-1}=0$, and in order to activate the hedge fund, the manager must raise initial capital.

We assume that $f_2 < 0$, so that higher assets under management in the style lower the returns to all hedge funds in that style. We further assume that $f\left(m_{i,t-1}, 0, \mu_i, \varepsilon_{it}\right) = \infty$ and $f\left(m_{i,t-1}, \infty, \mu_i, \varepsilon_{it}\right) = 0$. These assumptions ensure equilibrium existence.

Finally, returns also depend upon talent μ_i and on luck ε_{it}, so that $f_3 > 0$ and $f_4 > 0$.

The investor maximizes expected discounted distributions $d_{i,t}$ from the hedge fund. We can represent the hedge fund manager's problem recursively (the existence of a unique recursive representation of the hedge fund's problem follows from standard results in dynamic programming: see Stokey et al (1989)). Consider at the beginning of period t a hedge fund with assets under management $m_{i,t-1}$, talent μ_i, and a realization of luck ε_{it}, in an industry with total capital $Q_{t-1} = M_{t-1}/(1+x)$. Define $V\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right)$ as the value of the expected discounted profits of investing in such a hedge fund.

---

[10] In theories of endogenous capital structure, greater leverage is tied to a higher risk of default and to higher interest rates. However, this mechanism does not seem appropriate for hedge funds, who obtain leverage through broker-dealers who essentially only work with clients with very high credit ratings. Whereas theories of endogenous capital structure are developed to explain the cross-sectional distribution of leverage in businesses, in the case of hedge funds, the distribution is almost degenerate.

Furthermore, define $V_c\left(q_{i,t-1}, Q_{,t-1}, \mu_i, \varepsilon_{it}\right)$ to be the value of investing in the fund assuming that it continues in operation, and let $V_e\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right)$ be the value to the investor of investing in a fund assuming it is not going to continue. Then, the value of operating a hedge fund equals the maximum of continuing or closing the hedge fund.

$$V\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right) = \max\left\{V_e\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right), \delta V_e\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right) + (1-\delta) V_c\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right)\right\}. \tag{4}$$

Then, the continuation value of the fund is:

$$\begin{aligned} &V_c\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right) = d_{i,t} + \max_{q_{i,t}}\left\{\frac{1}{1+r} E_\varepsilon V\left(q_{it}, Q_{it}, \mu_i, \varepsilon_{i,t+1}\right)\right\} \\ &s.t. \\ &d_{i,t} + pq_{i,t} + \kappa \le f\left((1+x) q_{i,t-1}, (1+x) Q_{t-1}, \mu_i, \varepsilon_{it}\right) \end{aligned} \tag{5}$$

where the expectation is taken with respect to the distribution of future luck conditional on current luck (distribution F). The solution to this problem $q_{i,t}^*$ is given by:

$$p(1+r) = (1+x)\int f_1\left((1+x) q_{i,t}^*, (1+x) Q_t, \mu_i, \varepsilon_{i,t+1}\right) F\left(\varepsilon_{i,t+1} \mid \varepsilon_{it}\right) d\varepsilon_{i,t+1} \tag{6}$$

so that the optimal fund size depends on the manager's talent, on the current realization of luck, and on capital at other hedge funds.

The value to the investor of closing the fund is:

$$V_e\left(q_{i,t-1}, Q_{i,t-1}, \mu_i, \varepsilon_{it}\right) = f\left((1+x) q_{i,t-1}, (1+x) Q_{i,t-1}, \mu_i, \varepsilon_{it}\right) \tag{7}$$

Thus, the investor allocates $q_{i,t}^*$ to the hedge fund each period, unless the expected return is so low that it is cannot cover the recurring fixed costs. This specification assumes that there is a one-period delay required to open a new hedge fund: this assumption is realistic but not necessary. There is a non-negativity constraint on $q_{i,t}$, but not on $d_{i,t}$.

Equations (4) – (7) should be interpreted as follows. Having made an investment of $q_{i,t-1}$ in the previous period, at the beginning of period t the returns f are realized. Then, the investor decides whether or not to close the fund: if it closes then $d_{i,t} = f$. In addition, with probability δ the fund may close for exogenous reasons. If the fund survives, the investor decides whether or not to liquidate part of the portfolio or raise further capital. This problem can be rewritten by substituting the distributions $d_{i,t}$ using the fund's budget constraint. At each hedge fund, the investor maximizes the following value function:

$$V\left(q_{i,t-1},Q_{i,t-1},\mu_i,\varepsilon_{it}\right)=f\left(\left(1+x\right)q_{i,t-1},\left(1+x\right)Q_{t-1},\mu_i,\varepsilon_{it}\right)$$
$$+\left(1-\delta\right)\max\left\{0,\max_{q_{it}}\left[-pq_{it}-\kappa+\frac{1}{1+r}E_{\varepsilon}V\left(q_{it},Q_t,\mu_i,\varepsilon_{i,t+1}\right)\right]\right\}. \tag{8}$$

C. Equilibrium

The model distinguishes between the distribution of active fund managers and the distribution of potential fund managers. The equilibrium distribution of potential fund managers is exogenous, and can be defined using the results of Hopenhayn and Prescott (1992). The distribution of active fund managers is related, but is truncated. The truncation rule is complex: there is a talent threshold μ_t^* below which firms do not enter, but after entering they may exit as a result of bad luck. The luck threshold below which an agent of a given talent exits is $\varepsilon_t^*(\mu)$.

At the beginning of any period a hedge fund takes as given the vector[11] $x_{it}=\left(q_{it-1},\mu_i,\varepsilon_{it}\right)$. Let $X=\Re^+\times\Re^2$ be the set of possible values of the vector x_{it}. Let $\xi_t : X\rightarrow\Re^+$ be the measure over types of funds at the beginning of date t.[12] Recall that returns (and the economy's state) also depend on Q_{t-1}, which is drawn from the real numbers.

<u>Definition 1:</u> An *equilibrium* is a sequence $\left\{\xi_t,Q_t,\mu_t^*,\varepsilon_t^*\left(\mu\right)\right\}_{t=0}^{\infty}$ and decision rules such that the sequence $\left\{\xi_t,Q_t,\mu_t^*,\varepsilon_t^*\left(\mu\right)\right\}_{t=0}^{\infty}$ results from optimal behavior, and the behavior is optimal at each fund given the sequence $\left\{\xi_t,Q_t,\mu_t^*,\varepsilon_t^*\left(\mu\right)\right\}_{t=0}^{\infty}$. Specifically, $\int V\left(0,Q_t,\mu_t^*,\varepsilon_{it}\right)dG\left(\varepsilon_{it}\right)=c_e$, $\int V\left(0,Q_t,\mu,\varepsilon_{it}\right)dF\left(\varepsilon_{it}\mid\varepsilon_t^*\left(\mu\right)\right)=0$, the hedge fund's optimization problem (8) is solved, and the sequence of measures ξ_t and of industry capital Q_t is consistent with rational behavior as described in the Appendix.

Since there is no aggregate uncertainty in the model, and since the volume of entrants ω is constant over time, the model environment is stationary.

<u>Definition 2:</u> A *stationary equilibrium* is a set $\left\{\xi^*,Q^*,\mu^*,\varepsilon^*\left(\mu\right)\right\}$ such that $\xi_t=\xi^*$, $Q_t=Q^*$, $\mu_t=\mu^*$ and $\varepsilon_t=\varepsilon^*$ *is an equilibrium* for all $t\geq 0$.

---

[11] To account for inactive funds, we will say that $\varepsilon_{it}=-\infty$, unless they enter.

[12] The model requires defining ξ_t and characterizing its evolution over time. The corresponding discussion is somewhat technical and is relegated to the Appendix.

In a stationary equilibrium, individual hedge funds may grow or shrink, enter or exit, but the entire industry is characterized by stable (time invariant) distributions of size and of returns. We focus on such equilibria because we are interested in characterizing the long-run response of the industry to changes in regulation.

To reproduce the stationary features of the hedge fund industry data and to guarantee existence of a stationary equilibrium, we make the following assumptions:

Assumption 1: (Persistence) $F\left(\varepsilon_{i,t+1} \mid \varepsilon_{it}\right)$ is decreasing in ε_{it}.

Assumption 2: (Mean reversion) There is some ε^* such that, for all $\varepsilon_{it} > \varepsilon^*$,

$$\int_{-\infty}^{\infty} \varepsilon_{i,t+1} dF\left(\varepsilon_{i,t+1} \mid \varepsilon_{it}\right) < \varepsilon_{it}.$$

Proposition 1: *There exists a unique stationary equilibrium.*
Proof: See Appendix. ■

D. Empirical Implementation

In the rest of the paper, we will adopt the following functional form for the investment technology:

$$f\left(m_{i,t-1}, M_{t-1}, \mu_i, \varepsilon_{it}\right) = Ae^{\mu_i + \varepsilon_{it}} m_{i,t-1}^{\phi} M_{t-1}^{\psi} \tag{9}$$

where $\psi < 0$. The return from a given investment is the expression $\Upsilon = f\left(m_{i,t-1},.\right) - pq_{i,t-1}$. Defining the rate of return on assets at a given fund as $R_{it} = \Upsilon / q_{i,t-1}$, we have that:

$$R_{it} \approx C + \mu_i + \left(\phi - 1\right)\log m_{i,t-1} + \varepsilon_{it}, \tag{10}$$

where $C = \log A - \log p + \psi \log M_{t-1}$ is common to all hedge funds. Alternatively, this equation can be expressed as:

$$R_{it} \approx D + \mu_i + \left(\phi - 1\right)\log q_{i,t-1} + \varepsilon_{it}, \tag{11}$$

where $D = \log A + \left(\phi + \psi - 1\right)\log\left(1 + x\right) - \log p + \psi \log Q_{t-1}$. This expression is a fixed effect panel estimation equation, assuming there is no time variation in the factors that have a common impact on hedge fund returns (as in a steady state). In practice, as discussed below, we need to condition on such factors.

Optimal capital satisfies:

$$q_{it}^* = \left(\frac{\phi A\left(1+x\right)^{\phi+\psi}}{p\left(1+r\right)} Q_t^{\psi} \int e^{\mu_i + \varepsilon_{it+1}} dF\left(\varepsilon_{i,t+1} \mid \varepsilon_{it}\right)\right)^{\frac{1}{1-\phi}} \tag{12}$$

Notice that more talented mangers operate larger hedge funds in equilibrium. Also notice that, in the special case in which the shocks ε_{it} are iid (so that $F\left(\varepsilon_{t+1} \mid \varepsilon_t\right) = F\left(\varepsilon_{t+1}\right)$), the optimal fund size depends only on the manager's talent and not on the current realization of luck. Thus, if "luck" is not persistent, the model accounts for the observation that hedge funds often close down to new investment after some point. Indeed, we find that the annual serial correlation of "luck" in that data is low, around 14% or lower.

The realized return at a given hedge fund following the optimal investment rule $q_{i,t}^{*}$ is:

$$R_{i,t} \approx \log\left(1+r\right) - \log\phi + \log\frac{e^{\varepsilon_{it+1}}}{\int e^{\tilde{\varepsilon}_{i,t+1}} dF\left(\tilde{\varepsilon}_{i,t+1} \mid \varepsilon_{it}\right)} \tag{13}$$

where $\varepsilon_{i,t+1}$ is the realization of luck and $\tilde{\varepsilon}_{i,t+1}$ indicates luck as a variable of integration. Interestingly, realized equilibrium returns depend on luck but *not on manager talent*. Moreover, they do not depend on the style capital Q_{t-1} either. The reason is that an increase in talent is offset by an increase in optimal size. The same applies to multiplicative factors such as A and Q_{t-1}^{ψ} as well as talent μ_i.

Evaluating (13), we have that, at a given hedge fund:

$$\begin{aligned} E\left[R_{i,t+1}\right] &\approx \log\left(1+r\right) - \log\phi \\ &+ \int \tilde{\varepsilon}_{i,t+1} dF\left(\tilde{\varepsilon}_{i,t+1} \mid \varepsilon_{it}\right) - \log\int e^{\varepsilon_{i,t+1}} dF\left(\tilde{\varepsilon}_{i,t+1} \mid \varepsilon_{it}\right) \end{aligned} \tag{14}$$

Functional form (11) suggests that equilibrium hedge fund returns depend only on the discount factor, on the decreasing returns parameter ϕ, and – if luck is persistent – on the current realization of luck. However, since luck is transitory, there should be no persistent differences in returns across funds – even if there are significant differences in manager talent.

E. An Alternative Interpretation

The empirical specification (11) that we derive from the model can also be derived independently using a standard hedge fund "style" regression framework. We begin by defining "alpha" as a hedge fund's performance *over and above what can be explained by the fund's "style"*.[13] This follows the definition of Jensen (1968), applied to hedge funds as in Malkiel and Saha (2005). Then, we decompose alpha into three components: a size effect, a fund-specific fixed effect, and a transitory (though possibly persistent) effect. We refer to the

[13] Hedge funds are often marketed as following a particular investment style, and an extensive literature explores the risk factors that are appropriate for different hedge fund styles. See for instance Fung and Hsieh (2001, 2004).

fixed effect as "talent", and to transitory factors as "luck." "Size" is defined as capital under management.

For a given style, the individual fund's "alpha", α_{it}, is defined as hedge fund returns that cannot be accounted for by common factors. Consider the following return equation:

$$R_{it} = \sum_{k=1}^{K} \beta_k x_{kt} + \alpha_{it} \tag{15}$$

The index *i* represents a hedge fund, *t* is the date, and *k* is one of *K* factors that affect hedge fund returns. Then, x_{kt} is the value of risk factor *k* at date *t*, and R_{it} is the return on assets to fund *i* on capital invested at date (*t-1*). Thus, the "alphas" contain everything about the individual funds' returns that is not explained by the influence of the risk factors. Econometrically, identifying alpha amounts to correctly identifying the risk factors, or proxies thereof.

We posit that the value of a fund's "alpha" reflects the manager's own intrinsic ability (as reflected in the quality of his/her investment strategy, their "twist" on the strategy that characterizes their individual fund style), but also may be influenced by the fund's size, as well as transitory elements. Success or failure associated with a manager's intrinsic ability is defined as "talent," and is labeled μ_i. Temporary success or failure is "noise" or "luck." Let $q_{i,t-1}$ be the capital invested in fund *i* at the end of date *t-1*. We decompose α_{it} as follows:

$$\alpha_{it} = \mu_i + \theta \log q_{i,t-1} + \varepsilon_{it} \tag{16}$$

Here, θ is the coefficient on individual fund size and variable ε_{it} is the transient component of returns, which may be serially correlated. Substituting (16) into (15), we obtain the following regression specification:

$$R_{it} = \mu_i + \sum_{k=1}^{K} \beta_k x_{kt} + \theta \log q_{i,t-1} + \varepsilon_{it} \tag{17}$$

Equation (17) has the structure of a dynamic panel regression, with the individual hedge fund as the unit of observation. The regression includes fixed effects for each fund, the capital at each fund, and the style factors. Setting $\theta = \phi - 1$, (17) is similar to equation (11), except that it allows for time-varying "style" factors. Allowing the common multiplicative terms *C* or *D* in equations (10, 11) to vary over time, and setting them equal to $\exp\left(\sum_{k=1}^{K} \beta_k x_{kt}\right)$, the two equations become identical.

IV. Model Calibration

We calibrate the model parameters by using data on hedge fund dynamics drawn from the related literature, and also by estimating equation (11). Equation (11) identifies the critical decreasing returns parameter ϕ, as well as the distributions of talent and of luck. We provide

a broad description of the estimation procedure and outcomes: extensive details may be found in the working version of the paper or in an empirical appendix available from the authors. Estimates are based on hedge fund return data from CISDM (2006).

Figure 2: Manager fixed effects.
Fixed effects are normalized to lie between 0 and 1. The full line reflects the empirical distribution, whereas the dotted line is a fitted Laplace distribution. See the working version of the paper for estimation details.

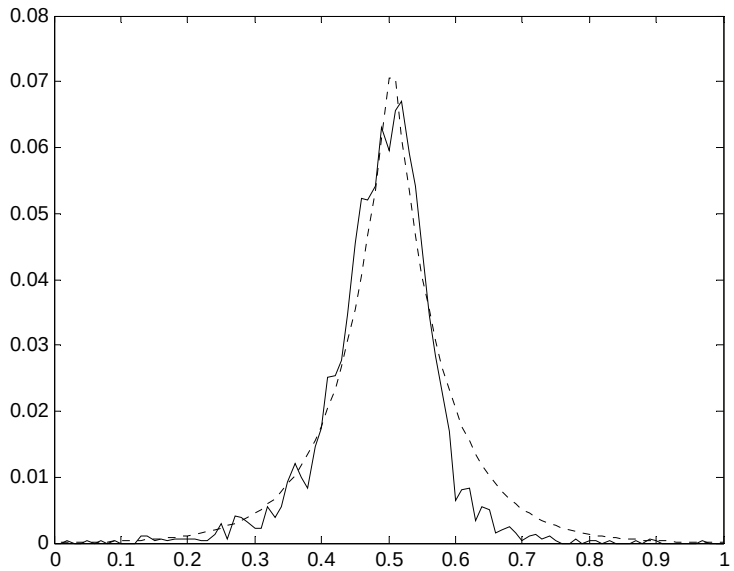
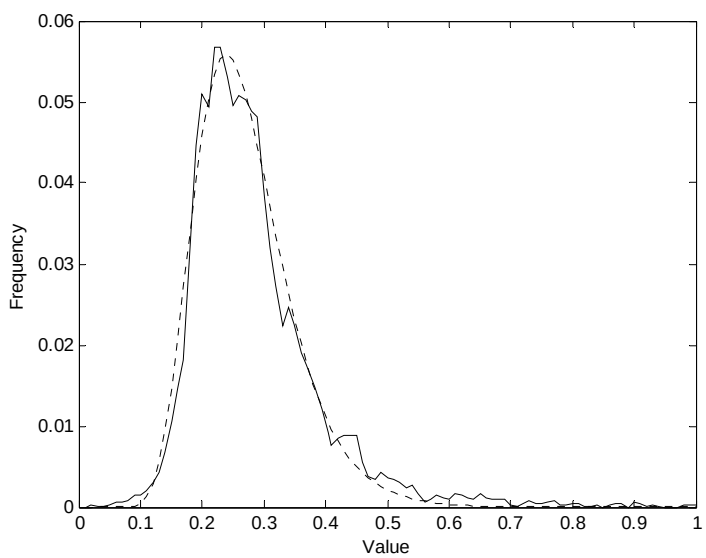


Figure 3: Distribution of Luck.
Luck realizations are normalized to lie between 0 and 1. The full line reflects the empirical distribution, whereas the dotted line is a fitted Frechét distribution. See the working version of the paper for estimation details.



To estimate equation (11), we assume that the return function *f* takes the functional form in equation (9). We also assume that luck displays first order autocorrelation: $\varepsilon_{it} = \rho\varepsilon_{i,t-1} + \upsilon_{it}$, where υ_{it} is an iid random variable with zero mean and finite variance. We allow for serial correlation because Getmansky et al (2004) argue that hedge fund returns are autocorrelated, attributing this to the illiquidity of their investment positions. Thus, equation (11) is a fixed effect unbalanced panel with serially correlated errors. We estimate (11) using the methodology of Baltagi and Hu (1999).

We find that the distribution of talent μ_i (talent) matches well a Laplace distribution – see Figure 2. The Laplace distribution has two parameters: a sample mean $\overline{\mu}$ and a shape parameter σ_μ, and has the following probability distribution function (PDF):

$$\zeta\left(\mu_i\right) = \frac{1}{2\sigma_\mu} e^{\frac{-\left|\mu_i - \overline{\mu}\right|}{\sigma_\mu}}. \tag{18}$$

The distribution of ε_{it} (luck) matches well a Frechét distribution, which has a shape parameter σ and a persistence parameter ρ. See Figure 3. Its PDF is f the form

$$F\left(\varepsilon_{t+1} \mid \varepsilon_t\right) = \frac{1}{\sigma} e^{\frac{-\left(\varepsilon_{t+1} - \rho\varepsilon_t\right)}{\sigma} + e^{\frac{-\left(\varepsilon_{t+1} - \rho\varepsilon_t\right)}{\sigma}}}. \tag{19}$$

We assume that the distribution of entrants' initial luck is drawn from a Frechét distribution with mean equal to the ergodic mean of *F* and standard error σ_ε.

In total, the model has 15 parameters – $A, p, x, \phi, \psi, \overline{\mu}, \rho, \kappa, \delta, \sigma, \sigma_\varepsilon, \sigma_\mu, \omega$, r and c_e. Many of the parameter values can be determined using estimates from the related literature, and by estimating equation (11). We assume that a period equals one year. The calibrated parameter values are reported in Table 1.

1. **Decreasing returns** ϕ: In equation (11), $\phi - 1$ equals the coefficient of a fixed effect regression of hedge fund returns on size. The average value of this coefficient across different specifications is about *-0.073*. Thus, we set $\phi = 0.927$.

2. **Spillover parameter** ψ: In principle we could estimate the spillover parameter ψ using equation (11) by expanding the constant term *D*, given a measure of the capital under management at the competitors of a given hedge fund Q_{t-1}. In practice this is difficult because no hedge fund database is fully comprehensive (reporting is voluntary), and since hedge funds may compete with other types of fund managers. Using total capital at hedge funds in the same style in the CISDM database as a measure of Q_{t-1}, we find that $\psi = -0.035$. However, we prefer to study a range of values. We argue that the extent of decreasing returns to an additional dollar at a given hedge fund is at least as large as the decreasing returns to an additional dollar at *another* hedge fund on the first fund. This implies that ψ likely lies in the range $\left[\phi - 1, 0\right]$. To ensure we examine a sufficiently broad range, we focus on a small spillover of $\psi = -0.001$ and a large spillover $\psi = -0.1$, slightly

outside this range. As we will see, qualitative results are similar. Notice that our estimate of $\psi = -0.035$ lies within these bounds.

3. **Common productivity** A : we use this parameter to match the average fund size, which is $190 million in CISDM (2006) over the period 1994-2005.

4. **Average "talent"** $\bar{\mu}$ is collinear with *log A*, we set it to zero without loss of generality.

5. **Luck persistence** ρ : In equation (11), this parameter is the AR(1) coefficient on the errors in a fixed effect regression of returns on size. We find that $\rho = 0.14$.

6. **Variance of talent** σ_μ : This parameter matches the standard deviation of returns in CISDM (2006).

7. **Variance of luck** σ : This parameter is set so that the ratio $\sigma_\varepsilon / \sigma_\mu$ is as estimated. Across specifications we find that this ratio averages 0.82 across specifications, so that the variance of talent is slightly larger than the variance of luck.

8. **Variance of entrant luck** σ_ε : We set the variance of entrant luck σ_ε equal to σ, so that the environment faced by entrants is similar to that faced by incumbents. Since luck is not very persistent our results are robust to changes in the distribution of entrant luck.

9. **Discount rate** r : Integrating equation (14) over all funds in the industry, we have that average return in the industry equals:

$$\log(1+r) - \log\phi + \frac{\int\int \tilde{\varepsilon}_{i,t+1} dF\left(\tilde{\varepsilon}_{i,t+1} \mid \varepsilon_{it}\right) d\xi^*}{\int d\xi^*} - \frac{\int \log\int e^{\tilde{\varepsilon}_{i,t+1}} dF\left(\tilde{\varepsilon}_{i,t+1} \mid \varepsilon_{it}\right) d\xi^*}{\int d\xi^*}. \quad (20)$$

We use an iterative procedure to calibrate *r*. We assume that the integral expressions equal zero, so this reduces to simply $\log(1+r) - \log\phi$. Then we set the discount rate so that the average return on hedge funds equals 9.6% (as in the CISDM data), and compute the integrals once all the other parameters have been evaluated. Then given this sum, we compute the value of *r* that satisfies (19), and repeat. This implies a discount rate of 1.6%, which is about equal to the real value of 3-month LIBOR over the past 15 years.

10. **Average hazard rate** δ : Getmansky (2004) argues that the average hazard rate of hedge funds is 7.1%. Liang and Park (2010) find that about a third of exits occur for reasons related to profitability, while the rest occur for other exogenous reasons. Thus, we set $\delta_e = 7.1\% \times 0.67 = 4.7\%$, and set probability δ_s so that the overall exit rate equals 7.1%.

11. **Initial cost of due diligence** c_e: We follow Brown et al (2008b) and set it to equal $50,000. Strachman (2007) also reports the cost of starting a hedge fund to be about $50,000.

12. **Continuation cost** κ : We set the cost of continuing a fund equal to an estimate of the cost of ongoing due diligence to the investor. Brown et al (2008b) indicate that, at the Princeton University Investment Company this cost is about 7/40 of the initial due diligence cost.[14] We take it as an indicator of the order of magnitude, suggesting that ongoing costs are considerably lower than startup costs. This implies that the fixed cost c_e and the discounted expected cost of κ affect which funds enter, but that κ has very little impact on fund dynamics beyond entry.

13. **Mass of entrants** ω : Set so that the total industry capital in equilibrium equals $1.2 trn.

14. **Leverage ratio** x : CISDM defines the leverage ratio as the ratio of borrowed funds to capital. Recall that leverage ratios in CISDM are largely clustered around one (Figure 1). Malcolm et al (2009) and FSA (2009, 2010) find the same using different data sets. These numbers are based on self-reporting, and are imprecise – indeed, almost all the responses are integer-valued. This suggests there is some noise in the reported leverage – although the order of magnitude should be correct. Hence, we take 1 as the reported value of leverage. However, because hedge funds may also have "implicit" leverage via derivative positions, we use surveys to get an estimate of "effective" leverage. McGuire and Tsatsaronis (2008) find that "effective" leverage that includes synthetic borrowing (through derivatives) is about 10-20% higher than reported leverage. Hence we set x =1.1, and explore other values as well.

15. **Cost of funds** p : Calibrating the cost of funds $p = (1+k) + xc$ requires three inputs: the cost of leverage, the cost of equity, and the leverage ratio. We identify the borrowing cost c with 3-month LIBOR. This implies that $c=0$, recalling that the borrowing cost is paid up-front. We identify the cost of equity k with the equity risk premium,[15] which is about 4%.

Table 1: Parameters used in calibration

Parameters of the model economy are matched to data from different sources and to our econometric estimates. Details may be found in the text or in Appendix D.

A	ψ	ϕ	ρ	σ_μ	σ	σ_ε	β	κ	c_e	δ_e	δ_s	x	p
1.65	-.001, -.01	.927	.14	.175	.143	.143	.984	8750	50000	.047	.024	1.1	1.04

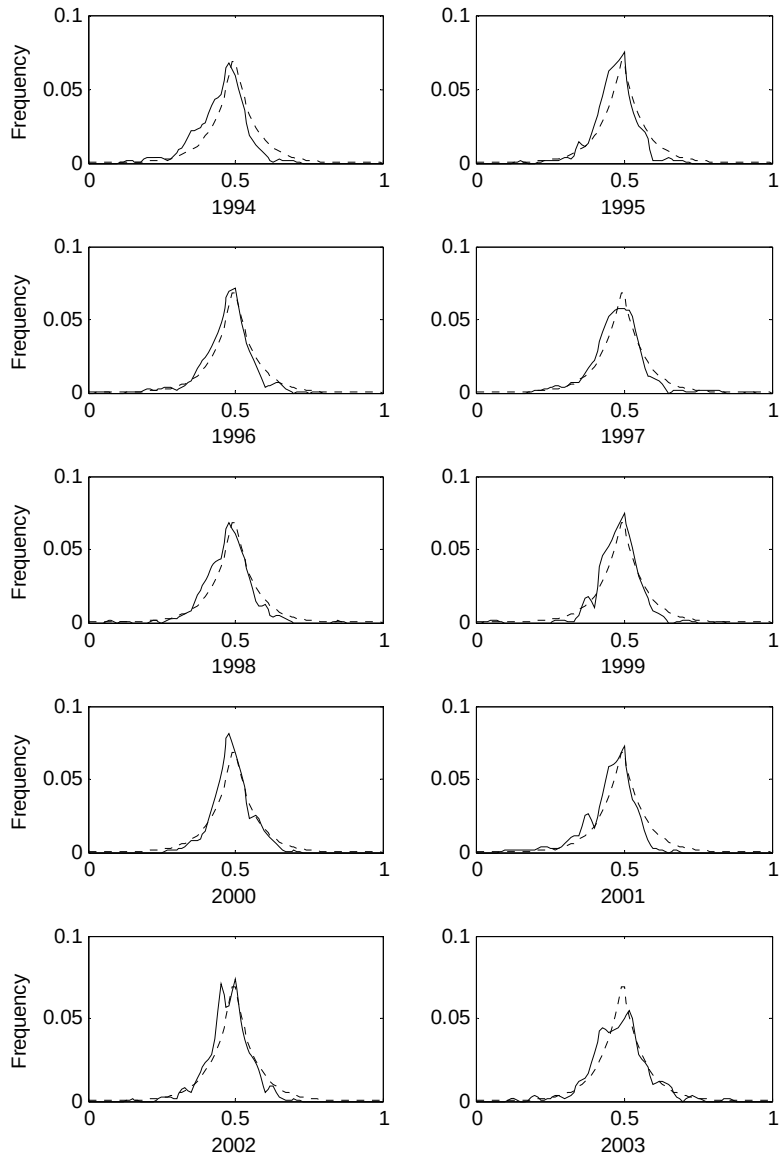
We take the opportunity to discuss the empirical relevance of the model. The model accounts for some well-known features of the hedge fund industry. For example, when the stochastic component of returns is not persistent, the optimal size at any given fund may be constant over time in a world of decreasing returns – see equations (6, 12). This suggests an explanation for the observation that hedge funds close to new investment after reaching a certain size. In addition, Berk and Green (2004) argue that the lack of evidence of persistent

[14] See www.house.gov/apps/list/hearing/financialsvcs_dem/ht031307.shtml.

[15] Essentially, we assume that the investor could invest in equities, and that the return on equity k is foregone if the investor wishes to invest instead in hedge funds.

differences in returns across actively managed funds can coexist with large differences in manager talent because, in a world of decreasing returns, more talented managers optimally operate *larger* funds. We find a strong positive correlation between our measures of manager

Figure 4: Manager fixed effects for entrants by year.
Fixed effects are estimated based on the full panel of hedge funds, and are normalized to lie between 0 and 1. The full line reflects the empirical distribution, whereas the dotted line is the fitted Laplace distribution in Figure 3, which matches the distribution of manager talent in the full sample. It has been rescaled to fit the *number* of HFs in each panel, but the shape is preserved. Since at least two years of data are required to estimate each fund-specific fixed effect, and since return data were not available for all months in 2005, hedge funds born in 2004 and 2005 were not included.



talent and fund size using the hedge fund data. Notably, the correlation between talent and size is positive, equal to 0.693 (s.e. 0.011), as predicted by equation (6). This finding is significant, as it provides evidence that the absence of persistent cross-fund differences in returns can be reconciled with the possibility of significant differences in manager talent if decreasing returns to scale lead more talented managers to optimally manage larger funds.

A stylized fact of the asset management industry is that funds that outperform market benchmarks tend to experience inflows of funds, a fact that has been viewed as a challenge to rational expectations and efficient market theory in light of the fact that persistent differences in performance across funds are difficult to detect – see Berk and Green (2004). In the presence of autocorrelated luck (Assumption 2), the model can account for such a finding because a positive realization of luck is correlated with positive realizations in the near future.

Finally, the model assumes a constant distribution of entrant talent across cohorts. Figure 4 plots the talent distributions for different cohorts in the data along with the Laplace distribution that best fits the distribution of talent for *all* cohorts. While not identical in all years, the match is quite remarkable, underlining the usefulness of a model with the broad features of the Hopenhayn (1992) framework for analyzing hedge fund industry dynamics.

V. POLICY EXPERIMENTS

Having established the empirical relevance of the model, we now consider changes in different regulations, such as the cost of due diligence, the cost of leverage, and leverage limits, to see the impact on the number of the funds, total capital and profits in the model. We focus on regulations that can be interpreted in terms of model parameters, assuming other parameters remain constant. We discuss this assumption further at the end of the section.

A. The cost of due diligence

Suppose that the entry cost c_e doubles from \$50,000 to \$100,000, which also doubles the continuation cost κ. See Table 2. This implies a decline in the returns (including due diligence costs) at the average fund of about 0.73 basis points.[16] The number of funds drops by about 2 percent. However, industry assets under management are almost unchanged. This is because the funds that no longer exist in the stationary equilibrium with new parameters are all very small. Industry profits are unchanged, since the equilibrium rate of return depends on ϕ (which is constant) and industry capital are negligibly affected. As a result, the average hedge fund capital under management rises also by about 2 percent.
Suppose that the entry cost is increased by a factor of five (to \$250,000). Then the number of funds declines by about 10 percent, which leads to a 1.5 percent drop in the industry capital

[16] Malcolm et al (2009) estimate the impact of proposed increases in ongoing hedge fund costs in the EU to amount to 1.2 basis points. Thus the cost increases in our experiments are roughly of the order of magnitude of the reforms contemplated in the AIFM Directive of the EU.

(and total industry profits). Thus, a large change in the cost of due diligence (or other fixed costs of entry or continuation) can have a large effect on the number of funds, but the impact on the size of the industry is an order of magnitude lower, since the affected funds are small.

It is perhaps not surprising that changes in the cost of due diligence have a small effect on the hedge fund industry, since both c_e and κ are too small relative to the returns at most of the hedge funds. To get a sense of this, the average expected cost of due diligence over the lifetime of a hedge fund is about $173,000, whereas the expected return to the average entrant is about $166 million.

Table 2: Experiments – raising the cost of entry

The table reports the impact of an increase in the cost of entry by a factor of 2 or 5.

Spillover parameter ψ	Change in entry costs	# of funds (percent change)	Total capital (percent change)	Average capital (percent change)	Industry profits (percent change)
-0.001	x 2 x 5	-2.32 -10.5	-0.00 -1.52	+2.37 +9.14	-0.00 -1.52
-0.1	x 2 x 5	-1.90 -8.59	-0.08 -0.17	+1.80 +9.25	-0.08 -0.17

It should be noted that the impact of a higher cost of due diligence is smaller when the spillover parameter $|\psi|$ (the sensitivity of the hedge fund returns to the total capital of all funds) is large. As $|\psi| \to 0$, all adjustment to stricter regulation must be carried out by each individual hedge fund. However, when there are significant cross-fund spillovers ($|\psi|$ is large), the fact that *other* funds optimally shrink goes some way towards offsetting the profit loss from the higher due diligence cost at any given hedge fund. Still, the impact of regulation is qualitatively similar for both values of $|\psi|$ we consider. Thus, whatever the hypothetical benefits of increasing the creation and continuation costs of hedge funds might be, the impact on the industry as a whole of higher costs is not likely to be significant.

B. The cost of leverage

How would an increase in the cost of leverage impact equilibrium outcome in the industry?

Suppose that the cost of leverage rises by 1 percentage point (comparable to a spike in 3-month LIBOR in late 2008, which was of magnitude 1.2 percent). An increase in the cost of leverage by 1 percentage point can have a large impact on industry capital (and hence on total profits), especially when the spillover parameter is small, but only a modest impact on the number of funds. See Table 3.

Increasing the cost of leverage has larger impact on industry capital under management for smaller values of spillover parameter $|\psi|$. The reason is that, holding industry capital constant, optimal capital at a given fund depends not just on the cost of capital *p,* but on *p* to the power of $1/(1-\phi)$. Thus, the negative impact from higher *p* is offset somewhat by the fact that other hedge funds are also shrinking in equilibrium, which *caeteris paribus* would

tend to increase optimal capital at any given fund. This offsetting effect is only significant when the spillover parameter $|\psi|$ is large (i.e., when $\psi = -0.1$, the decrease in equilibrium capital is less than half of the decrease when $\psi = -0.001$).

Table 3: Experiments – raising the cost of leverage

The table reports the impact of an increase in the cost of leverage of 1 ppt and 2 ppt.

Spillover parameter ψ	Change in leverage cost	# of funds (percent change)	Total capital (percent change)	Average capital (percent change)	Industry profits (percent change)
-0.001	1 ppt increase 2 ppt increase	-2.1 -4.4	-13.3 -24.6	-11.4 -21.2	-13.3 -24.6
-0.1	1 ppt increase 2 ppt increase	-0.0 -0.0	-5.9 -11.4	-5.9 -11.4	-5.9 -11.4

By contrast, increasing the cost of leverage has a modest impact on the number of funds when $\psi = -0.001$ – and a negligible impact when $\psi = -0.1$. The reason is that even a large decrease in equilibrium capital (and hence in total profits) at a given type of fund is unlikely to drive its value below the cost of entry: the marginal hedge fund (whose value on entry equals the entry cost) is far in the left tail, and the profits of most funds are orders of magnitude larger.

C. Leverage limits

Next, consider the imposition of leverage limits, below the current industry best practice.

There are two channels in the model through which leverage caps might affect the hedge fund industry. The first is by reducing the "productivity" of capital, since under a lower leverage ratio a dollar of capital allows to establish a smaller investment position. Second, leverage caps reduce the effective cost of capital *p* (since the cost of funding a dollar of capital is $p \equiv (1+k) + xc.$) If the cost of leverage is lower than the cost of capital (as in practice), this second channel is likely to be small. Indeed, since the calibrated value of the cost of leverage *c=0*, the second channel is absent from our baseline experiments. However, we later show that introducing this channel does not change the results.

Suppose that the current industry best practice leverage ratio is 1.1 What would be the impact from lowering it to 1 or to 0.9?[17] We find that while industry capital declines very sharply, the decline in the number of funds is fairly modest. See Table 4.

When leverage ratio is reduced from 1.1. to 1, industry capital declines by 21-46 percent, depending on the value of the spillover parameter $|\psi|$. This is because lower leverage limit leads to a dramatic reduction in the "productivity" of capital, which lowers the optimal capital of a hedge fund. Again, there is an offsetting effect from other funds reducing their leverage as well. However, when the spillover parameter $\psi = -0.001$, this effect is negligible.

[17] Malcolm et al (2009) report that the AIFM directive covering EU-domiciled hedge funds is as yet unclear as to the likely leverage limit involved, but also suggest a reduction in leverage to 1 as a benchmark for analysis.

The equilibrium rate of return is not significantly affected by changes in leverage ratios. Thus, the impact on the total profits of the industry is the same as the impact on its size.

Table 4: Experiments – lowering the leverage ratio

The table reports the impact of a decrease in the leverage ratio from 1.1 to 1 and to 0.9

Spillover parameter ψ	Change in leverage	# of funds (percent change)	Total capital (percent change)	Average capital (percent change)	Industry profits (percent change)
-0.001	1.1 to 1 1.1 to 0.9	-6.8 -18.9	-45.7 -71.4	-41.7 -64.8	-45.7 -71.4
-0.1	1.1 to 1 1.1 to 0.9	-1.9 -4.0	-20.8 -38.0	-19.3 -35.5	-20.8 -38.0

When leverage ratio is reduced from 1.1. to 1, the number of active hedge funds declines by 2-7 percent, depending on the value of the spillover parameter $|\psi|$. Why is the number of hedge funds much less sensitive to the imposition of leverage cap than the industry capital? Consider that the productivity of a firm with talent two standard deviations above the mean is almost double the productivity of a firm two standard deviations below the mean. Since decreasing returns due to the parameter ϕ are not steep, a small difference in productivity translates into a significant difference in profits: the expected lifetime profits of a firm with talent two standard deviations above the mean is about $1.37 billion, whereas those of a firm two standard deviations below the mean are about $1.32 million. As a result, even a very large drop in profits across the hedge fund industry has little impact on the number of funds, because the range of the productivity distribution whose expected lifetime profits are driven below c_e by the change is small.

Table 5: Experiments – lowering the leverage ratio when *c=0.01*

The table reports the impact of a decrease in the leverage ratio from 1.1 to 1 and to 0.9 when *c=0.01*.

Spillover parameter ψ	Change in leverage	# of funds (percent change)	Total capital (percent change)	Average capital (percent change)	Industry profits (percent change)
-0.001	1.1 to 1 1.1 to 0.9	-7.6 -17.2	-45.0 -70.7	-40.5 -64.6	-45.0 -70.7
-0.1	1.1 to 1 1.1 to 0.9	-1.9 -6.2	-20.4 -37.3	-18.8 -33.2	-20.4 -37.3

Table 5 repeats these experiments assuming that *c=0.01*. In this way, the "cost of funding" channel is present also. Notice that results are almost identical. The reason is that, for this value of *c*, a reduction in leverage from 1.1 to 1 lowers the cost of funding *p* from 1.051 to 1.05, a 0.1 percent change. If *c=0.02*, then such a change in leverage would still only lower the cost of funding by 0.2 percent. Thus, only an unrealistically high cost of leverage would allow the cost-of-funding channel to significantly impact results.

D. Size-contingent leverage limits

Suppose that leverage limits are imposed *only* on hedge funds above certain size threshold.

In order to analyze possible implications of such restriction, we need to modify our model. This requires rewriting the hedge fund's optimization problem (8) as follows. Let *x* be the

initial leverage ratio, and let $x^{new}<x$ be a newly–imposed leverage limit. Suppose that the regulator chooses to impose the new leverage ratio *only on hedge funds whose capital exceeds a certain size threshold* ς. For example, ς could be selected so as only to affect the largest 25 percent (or the largest 1 percent) of hedge funds. Then, leverage limit x applies if $q_{i,t-1} \leq \varsigma$ and x^{new} applies if $q_{i,t-1} > \varsigma$.

Table 6: Experiments – leverage caps with size allowances

The table reports the impact of a decrease in the leverage ratio from 1.1 to 1. Assumes that ψ= -0.001.

Statistic	Size Allowances below which leverage ratios do not apply					
	0	1.2e+7	1e+8	6.9e+9	1e+10	1.82e+10
% of funds originally below	0	73.1	89.7	99.3	99.5	99.9
% of capital at funds originally below	0	1.1	4.2	50.1	62.0	87.9
% of funds at the limit	0	5.9	2.5	0.45	0.38	0.11
% of capital at funds at limit	0	0.7	2.4	20.4	23.1	10.8
% of funds below the limit	0	74.6	90.1	99.3	99.5	99.9
% of capital at funds below	0	1.9	7.2	61.4	70.4	89.2
% change in number of funds	-6.8	0	0	0	0	0
% change in total capital	-45.7	-45.1	-43.5	-18.7	-12.2	-1.3
% change in average capital	-41.7	-45.1	-43.5	-18.7	-12.2	-1.3
% change in ex post returns	-0.51	-0.63	-0.10	-0.09	-0.04	-0.00

Table 7: Experiments – leverage caps with size allowances, assuming that *ψ= -0.1.*

The table reports the impact of a decrease in the leverage ratio from 1.1 to 1. Assumes that ψ= -0.1.

Statistic	Size Allowances below which leverage ratios do not apply					
	0	1.2e+7	1e+8	6.9e+9	1e+10	1.82e+10
% of funds originally below	0	73.1	89.7	99.3	99.5	99.9
% of capital at funds originally below	0	1.1	4.2	50.1	62.0	87.9
% of funds at the limit	0	6.6	2.6	0.4	0.3	0.1
% of capital at funds at limit	0	0.5	1.8	16.3	19.7	11.4
% of funds below the limit	0	69.8	88.5	99.2	99.5	99.9
% of capital at funds below	0	1.4	5.8	58.9	68.7	88.6
% change in number of funds	-1.9	1.2	3.4	2.6	1.8	0
% change in total capital	-20.8	-20.6	-19.8	-8.7	-5.8	-0.6
% change in average capital	-19.3	-23.1	-22.4	-10.3	-7.4	-0.6
% change in ex post returns	-0.81	-0.76	-0.75	-0.31	-0.20	-0.02

An analytical characterization of problem (8) with size-contingent leverage caps is omitted. However, it is straightforward to show that the fund's optimal strategy is to choose between three candidate capital values: one assuming leverage ratio x, another assuming leverage ratio x^{new}, and the size limit itself ς. Since $x^{new}<x$ implies that x is more profitable, the solution for the old leverage ratio x will be adopted unless this involves the hedge fund size exceeding the limit ς. If so, the solution will be the optimum assuming that leverage is x^{new} – unless this turns out to be lower than the optimum under x. If so, then the optimal size is ς itself. See, Veracierto (2008) for a proof of a similar model in the context of evaluating the equilibrium impact of firing costs on employment.

There is no guidance in the literature as to what constitutes a likely size threshold ς, so we explore a variety of values. Tables 6-7 reports the results of the experiments with leverage caps for different size thresholds. While a leverage ratio without a size threshold unambiguously reduces the number of funds, we find that even with a low size threshold this

is no longer the case. Indeed, we find that for relatively large spillover parameter $|\psi|$, it is even possible for leverage limits to *increase* the number of funds. The reason is that, by reducing the size of the largest funds (which make up most of the industry capital), the negative spillover effect is weakened, which turns out to *encourage* entry for certain parameterizations (when $|\psi|$ is large). When the industry capital is low, this enables certain funds that would have otherwise been unprofitable in the absence of leverage restrictions to become profitable. Of course, these new entering funds are among the smallest, so their impact on the industry capital is negligible.

Rather, the main impact of the size-contingent leverage limits is on total capital. Without a size threshold, total capital drops by 46 percent when $\psi = -0.001$ (or by 21 percent when $\psi = -0.1$). A very large size threshold is required for the choice of the size limit itself ς to change the impact of leverage restrictions on industry capital. For example, when ψ =-0.001, a size threshold of $100,000,000 (the 90th percentile for capital under management) implies that leverage restrictions reduce total capital by 43 percent. This is due to the fact that decreasing returns to scale are quite weak, so optimally the vast majority of the capital is managed by hedge funds in the right tail. Leptokurtosis implies an even more disproportionate influence on the industry of the largest funds. For example, in the calibrated benchmark industry, 90 percent of funds are smaller than $100,000,000 in terms of capital, yet these funds manage only 4.2 percent of the industry capital.

E. Extensions

While there are a number of factors from which we have abstracted in this paper, we do not believe that their inclusion is likely to fundamentally change the key conclusions emerging from the policy experiments. Some of these issues are worth mentioning.

- We have assumed that diseconomies of scale do not change in response to policy – i.e ϕ and ψ remain constant. The presumption is that the hedge fund industry does not represent a significant portion of total assets under management in financial markets overall, so that they would not have an impact on this parameter, which is linked to arbitrage, illiquidity and other inefficiencies in asset markets overall. FSA (2010) finds that this is true for fund styles other than Convertible Arbitrage, where hedge funds account for about 10% of the convertible bond market. In any case, a model in which diseconomies of scale in asset management are micro-founded is an extension of independent interest.

- We assume that the flow of potential entrants to the hedge fund industry ω is constant over time. This assumption is consistent with the fact that there are low barriers to entry into the hedge fund industry and that the estimated talent distribution is stable across cohorts, so that the flow of entrants must be determined by other factors: the supply of talent is limited. Relaxing this assumption requires not just a model of the hedge fund industry but of the financial sector as a whole, or of the financial labor market, something that is beyond the scope of this paper. At the same time, endogenizing ω would do little to change the results. The large impact of leverage caps or the cost of leverage on the industry would only be magnified if, in response to lower gross profits, potential managers were to pursue alternatives other than hedge funds. On the other hand, changes in entry costs or continuation

costs would be small compared to profits for most hedge funds, so the likely impact on ω would be small.

- We also abstract from the possibility that agents learn over time about manager talent based on realized returns. This type of learning is an important element in the related Berk and Green (2004) model. Our results would not change significantly if we were to introduce such learning, because differences in profits across hedge funds are so large and luck is sufficiently transitory that learning about talent would be very rapid.

- We have assumed that there is only one hedge fund style. What might change if we consider multiple hedge fund styles in the model industry? If the manager's talent also involves an aptitude for one style over another, then this would be equivalent to having several styles calibrated independently. Since the policy results hinge on broad features of the model and the data, the outcomes of policy experiments are unlikely to change much. The only difference is that some styles tend to rely more heavily on leverage than others, so those are more likely to be hurt by leverage limits. In the working version of the paper, we show that most styles have reported leverage around 1. Out of the fourteen styles considered, four report leverage of around 2 (Convertible Arbitrage, Fixed Income, Equity Market Neutral and Relative Value), and three styles report leverage higher than 2 (Fixed income arbitrage, CTAs and CPOs). Table 8 shows the impact of a leverage cap of 1 on the industry recalibrated to have a baseline level of leverage of 2 or 3, to represent these high-leverage styles. This analysis suggests that lower leverage limits would essentially cause such styles to cease to exist, especially for lower values of the spillover parameter ψ. A more realistic outcome, however, is a relocation of hedge funds to less regulated jurisdictions, unless the same leverage caps are implemented globally.

Table 8: Experiments – lowering the leverage ratio with higher initial values

The table reports the impact of a decrease in the leverage ratio from 2 to 1 and from 3 to 1.

Spillover parameter ψ	Change in leverage	# of funds (percent change)	Total capital (percent change)	Average capital (percent change)
-0.001	2 to 1 3 to 1	-68.8 -84.2	-97.7 -99.5	-92.5 -96.9
-0.1	2 to 1 3 to 1	-23.9 -36.7	-79.9 -89.6	-73.5 -83.6

- We do not model the benefits (or costs) that the proposed regulatory changes might have on returns by alleviating (or exacerbating) the principal-agent problems, or other factors from which the model abstracts. Rather, we focus on the effects of new regulatory burdens on long-run profitability and size of the industry, which are important for weighing against any purported benefits of regulation. What are the benefits from the introduction of regulatory constraints considered in this paper? As noted earlier, the proposed regulatory constraints are motivated by concerns about the hedge funds' contribution to systemic risk. An analysis of systemic risk stemming from hedge funds would require a richer model with aggregate uncertainty and possibly the one in which the hedge fund industry is embedded in the financial sector or the macro-economy, which is beyond the scope of this paper. It is worth noting, however, that our introductory survey finds no clear evidence of benefits from limiting leverage or additional disclosure requirements (and events such as the meltdown of

LTCM, which had a leverage factor of over 100, could be ameliorated via a high leverage cap that would not bind for the vast majority of funds, such as 10).

VI. CONCLUSION

We develop a theoretical model of the hedge fund industry to understand how a combination of decreasing returns to scale and limited fund manager talent might affect the industry response to changes in regulation. Although tractable, the model accounts for a variety of stylized facts that characterize the hedge fund industry, underlining the relevance of these two features for models of asset management.

We find that increasing the fixed costs of regulation does not significantly affect returns in the hedge fund industry, nor its size, although it may affect the *number* of funds. By contrast, leverage limits can have a very large impact on industry capital under management, while having a much smaller impact on the number of funds. Imposing leverage limits only on the largest funds, perversely, may encourage the entry of hedge funds that in the absence of such limits would have been unprofitable, and hence, may lead to lower average quality of funds. At the same time, because diseconomies of scale are weak and the distribution of manager talent is fat-tailed, industry behavior is driven by the activities of the largest players. As a result, exempting smaller funds from leverage limits does not significantly change the industry response to such limits. All of these results highlight the importance of the joint consideration of talent and size as factors of hedge fund industry dynamics.

One of the key conclusions from our analysis is that leverage limits can lead to a significant decline in the capital under management of the hedge fund industry. What are the consequences of a shrinking of the hedge fund industry? While hedge funds often manage investments of high net worth individuals, large institutional investors' allocations to the hedge fund industry have been rising steadily. Thus, a smaller hedge fund industry would mean lower profit and diversification opportunities for a wide range of investors. It is also worth noting that hedge funds tend to provide liquidity to illiquid markets and exploit arbitrage opportunities. As a result, any limitations on hedge funds would also reduce the extent to which they could contribute to market efficiency.

REFERENCES

Ackermann, Carl, Richard McEnally and David Ravenscraft. 1999. The Performance of Hedge Funds: Risk, Return, and Incentives. Journal of Finance 54(3), 833-874.

Agarwal, Vikas, Naveen D. Daniel and Narayan Y. Nail. 2009. Role of Managerial Incentives and Discretion in Hedge Fund Performance. Journal of Finance 64(5), 2221-2256.

Aghion, Philippe, Abhijit Banerjee and Thomas Pikeetty. 1999. Dualism and Macroeconomic Volatility. Quarterly Journal of Economics 114, 1359-1397.

Ammann, Manuel and Patrick Moerth. 2005. Impact of fund size on hedge fund performance. Journal of Asset Management 6 (3), 219-238.

Aragon, George O. 2007. Share Restrictions and Asset Pricing: Evidence from the Hedge Fund Industry. Journal of Financial Economics 83(1), 33-58.

Baltagi, Badi H. & Wu, Ping X. 1999. Unequally Spaced Panel Data Regressions With AR(1) Disturbances. Econometric Theory 15(06), 814-823.

Berk, Jonathan B. and Richard C. Green. 2004. Mutual Fund Flows and Performance in Rational Markets. Journal of Political Economy 112(6), 1269-1295.

Brown, Stephen J., William N. Goetzmann, Bing Liang and Christopher Schwartz. 2008a. Mandatory Disclosure and Operational Risk: Evidence from Hedge Fund Registration. Journal of Finance, 63(6), 2785-2815.

Brown, Stephen J., Thomas L. Fraser and Bing Liang. 2008b. Hedge Fund Due Diligence: A Source of Alpha in a Hedge Fund Portfolio Strategy. Mimeo: Stern School of Business NYU.

Center for International Securities and Derivatives Markets. 2006. Benefits of Hedge Funds 2006. Amherst, MA: Isenberg School of Management, U. of Massachusetts – Amherst.

Chan, Nicholas, Mila Getmansky, and Shane M. Haas and Andrew W. Lo. 2007. Systemic Risk and Hedge Funds. In M. Carey and R. Stulz, eds., The Risks of Financial Institutions and the Financial Sector. Chicago, IL: University of Chicago Press.

Chen, Joseph, Harrison Hong, Ming Huang and Jeffrey D. Kubik. 2004. Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. American Economic Review 94(5), 1276-1302.

Cooley, Thomas F. Vincenzo Quadrini. 2001. Financial Markets and Firm Dynamics. American Economic Review, 91(5), 1286-1310.

European Central Bank. 2006. Financial Stability Review June 2006. Brussels: ECB.

Evans, David S. and Boyan Jovanovic. 1989. An Estimated model of Entrepreneurial Choice under Liquidity Constraints. Journal of Political Economy 97(4), 808-827.

Feffer, Stuart and Christopher Kundro. 2003. Understanding and mitigating operational risk in hedge fund investments. Capco White Paper.

Feffer, Stuart and Christopher Kundro. 2004. Valuation issues and operational risk in hedge funds. Journal of Financial Transformation 10, 41-47.

Financial Services Authority. 2009. The Turner Review: A Regulatory Response to the Global Banking Crisis. London: FSA.

Financial Services Authority. 2010. Assessing possible sources of systemic risk from hedge funds. London: FSA.

Financial Stability Forum. 2000. "Background Information on the Hedge Fund Industry", Annex D, "Report of the Working Group on Highly-Leveraged Institutions". http://www.fsforum.org/publications/Rep_WG_HLI00.pdf

Foster, Dean P. and H. Peyton Young. 2010. Gaming Performance Fees by Portfolio Managers. Quarterly Journal of Economics 125(4), forthcoming.

Fung, Hung-Gay, Xiaoqing Eleanor Xu and Jot Yau. 2004. Do Hedge Fund Managers Display Skill? Journal of Alternative Investments 6(4), 22-31.

Fung, William and David A. Hsieh. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. Review of Financial Studies, 14, 313-341.

Fung, William and David A. Hsieh. 2004. Hedge Fund Benchmarks: A Risk Based Approach. Financial Analyst Journal, 60, 65-80.

Getmansky, Mila. 2004. The Life Cycle of Hedge Funds: Fund Flows, Size and Performance. Working paper, University of Massachusetts – Amherst.

Getmansky, Mila, Andrew W. Lo and Igor Makarov. 2004. An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. Journal of Financial Economics 74(3), 529-610.

Goetzmann, William N., Jonathan E. Ingersoll, Jr. and Stephen A. Ross. 2003. High-Water Marks and Hedge Fund Management Contracts. Journal of Finance 58 (4), 1685-1717.

Gompers, Paul, Joy Ishii and Andrew Metrick. 2003. Corporate Governance and Equity Prices. Quarterly Journal of Economics 118(1), 107-155.

Hopenhayn, Hugo A. 1992. Entry, Exit, and Firm Dynamics in Long Run Equilibrium. Econometrica, 60(5), 1127-50.

Hopenhayn, Hugo A. and Edward C. Prescott. 1992. Stochastic Monotonicity and Stationary Distributions for Dynamic Economies. Econometrica 60(6), 1387-406.

Hopenhayn, Hugo A. and Richard Rogerson. Job Turnover and Policy Evaluation: A General Equilibrium Analysis. Journal of Political Economy 101(5), 915-938.

Jensen, Michel C. 1968. The Performance of Mutual Funds in the Period 1945-1964. Journal of Finance, 23(2), 389-416

Jones, Meredith. 2007. Examination of fund age and size and its impact on hedge fund performance. Derivatives Use, Trading and Regulation 12(4), 342-350.

Khandani, Amir E. and Andrew W. Lo. 2007. What Happened to the Quants in August 2007? Mimeo: MIT.

Koutsougeras, Leonidas C. 2003. Non-Walrasian equilibria and the law of one price. Journal of Economic Theory 108, 169-175.

Liang, Bing and Hyuna Park. 2010. Predicting Hedge Fund Failure: A Comparison of Risk Measures. Journal of Financial and Quantitative Analysis 45(1), 199-222.

Lo, Andrew W. 2008. *Hedge Funds: An Analytic Perspective*. Princeton University Press, Princeton NJ.

Lucas, Robert E. Jr. 1978. On the Size Distribution of Business Firms. Bell Journal of Economics, 9(2), 508-523.

Malcolm, Kyla, Mark Tilden, Tim Wilsdon, Jessica Resch and Charles Xie. 2009. Impact of the proposed AIFM Directive across Europe. Charles River Associates Project No. D14806 (prepared for the Financial Services Authority). London.

Malkiel, Burton and Atanu Saha. 2005. Hedge Funds: Risk and Return. Financial Analysts Journal, 61(6), 80-88.

Managed Funds Association. 2009. Sound Practices for Hedge Fund Managers. Wash., DC.

McGuire, Patrick and Kostas Tsatsaronis. 2008. Estimating Hedge Fund Leverage. Bank for International Settlements Working Paper 260.

Perold, André F. and Robert S. Salomon, Jr. 1991. The Right Amount of Assets under Management. Financial Analysts Journal 47(3), 31-39.

Pozen, Robert C. *The Mutual Fund Business*. Cambridge: MIT Press, 1998.

Schneeweis, Thomas, George A Martin , Hossein B Kazemi , and Vassilis Karavas. 2005. The Impact of Leverage on Hedge Fund Risk and Return. Journal of Alternative Investments 7(4), 10-21.

Stokey, Nancy L., Robert E. Lucas Jr. and Edward C. Prescott. 1989. *Recursive Methods in Economic Dynamics*. Cambridge, MA: Harvard University Press.

Strachman, Daniel A. 2007. *The fundamentals of hedge fund management : how to successfully launch and operate a hedge fund*. Hoboken, NJ: Wiley.

Veracierto, Marcelo. 2008. Firing Costs and Business Cycle Fluctuations. International Economic Review 49(1), 1-39.

A. Appendix: Auxiliary results

In this section, we provide some auxiliary results for the discussion in the text.

Definition and evolution of the measure of hedge fund types

The following discussion follows Hopenhayn (1992) and Hopenhayn and Prescott (1992).

Recall that at the beginning of any period a hedge fund takes as given the vector $x_{it} = \left(q_{it-1}, \mu_i, \varepsilon_{it}\right)$. Let $X = \Re^+ \times \Re^2$ be the set of possible values of the vector x_{it}. Let the bounded positive function $\xi_t : X \to \Re^+$ be the measure over types of active fund managers. Thus, ξ_t is a measure over possible values of x_{it}, which is determined in equilibrium based on the investor's choice of managers and the history of the economy. At date t, it is taken as given.

Let Ξ be the space of integrable distributions over X, so that $\xi_t \in \Xi$. The distribution ξ_t changes over time according to a transition function $\Theta : \Xi \to \Xi$, which satisfies:

$$\begin{aligned} \xi_{t+1}(\chi) = (1-\delta) & \int_{\left(q^*(\mu_i,\varepsilon_t),\mu_i,\varepsilon_{t+1}\right)\in\chi} \int_{\varepsilon_t \geq \varepsilon(\mu_i)} dF\left(\varepsilon_{t+1} \mid \varepsilon_t\right) d\xi_t \\ +\omega & \int_{\left(q^*(\mu_i,\varepsilon_t),\mu_i,\varepsilon_{t+1}\right)\in\chi} \int_{\mu_i \geq \mu^*} dG\left(\varepsilon_{t+1}\right) d\zeta(\mu) \end{aligned} \tag{A}$$

where χ is any Borel subset of X, the set of active hedge funds, $\varepsilon(\mu_i)$ is a cut-off value of luck below which a fund with a given level of talent μ_i closes, and $q^*\left(\mu_i, \varepsilon_{it}\right)$ is the optimal choice of capital at a fund with talent μ_i and luck ε_{it}. Equation (A), together with Assumptions 1 and 2, implies that the functional Θ satisfies the premises of Theorems 1 and 2 from Hopenhayn and Prescott (1992), so ξ^* exists and is unique given the decision rules.

Proof of Proposition 1

Consider an industry with total capital equal to Q. For any given fund, this yields an optimal investment $q_{it}=q(Q,x)$ where x is the fund's type. Notice that the function q is decreasing in Q. Now define the function $\tilde{Q}(Q) = \int q(Q,x)\, d\xi^*$. The distribution ξ^* exists and is unique as a result of standard recursive methods, as described above. The function $\tilde{Q}$ is monotonic for a given value of ω, because a higher Q leads funds to shrink and also shrinks the distribution of active fund managers. To see this, using a value of Q, we can compute the value of entry $V^*(\mu;Q) \equiv \int V(0,Q,\mu,\varepsilon) dG(\varepsilon)$. Active funds will be those such that $V^*(\mu;Q) \geq c_e$. Since shrinking Q increases fund size and also fund value (so it increases the set of active funds), and since it is straightforward to show that $\lim_{x\to 0} \tilde{Q}(x) = \infty$ and $\lim_{x\to\infty} \tilde{Q}(x) = 0$, there exists a unique fixed point $Q^* = \tilde{Q}\left(Q^*\right)$. Hence the equilibrium exists.

Between Alpha and Beta: Modeling Size and Regulation in the Hedge Fund Industry. Empirical Appendix

Anna Ilyina and Roberto Samaniego

June 2010

Abstract

We describe in detail the procedure used to estimate the extent of decreasing returns in the hedge fund industry, as well as the distributions of "talent" and of "luck." We also perform several robustness checks to identify the underlying causes of decreasing returns and heterogeneity of manager talent. Decreasing returns appear related to a sensitivity to liquidity risk, and manager talent appears to be a comparative advantage in risk-taking.

JEL Codes: G11, G23, L25, L84.
Keywords: Portfolio management, hedge funds, diminishing returns, alpha, manager talent, leverage caps, due diligence costs, financial regulation.

I. DATA AND METHODOLOGY

We estimate equations (10) and (11), as defined in the paper, as well as the distributions of talent and luck. We focus on (11) because data on capital q are more accurate than data on overall positions m. Thus, the equation to be estimated is:

$$R_{it} = \mu_i + \sum_{k=1}^{K} \beta_k x_{kt} + \theta \log q_{i,t-1} + \varepsilon_{it} .$$

This is equivalent to equation (11), but allowing for K time-varying return factors that are either common to the hedge fund industry or common to funds within a given style, as in (17). Broadly, we are estimating a fixed effect panel regression of hedge fund returns on a list of factors x_{kt}, and on hedge fund size $q_{i,t-1}$.

A. Data description

As a benchmark specification, we choose the estimation using annual data. This is because (i) the monthly horizon may not be an appropriate investment horizon for some of the HF strategies and (ii) realized monthly returns are not likely to lead to exit except in very extreme cases (for example, Getmansky et al (2004) find that a link between deteriorating performance and exit appears within 12 months of the exit itself). Nonetheless, we do repeat our estimation using monthly data for robustness.

Sample

Hedge fund data are drawn from the Center for International Securities and Derivatives Markets (CISDM) database. All funds with reported assets in currency other than $ are removed, including funds that do not report a currency. All funds without a reported style are also removed. Coverage is erratic until the early 1990s: hence we do not use data before 1994.[1] Our final data set contains 6186 hedge funds. In 2005 this includes 3406 funds, compared to about 6700 for the industry as a whole, according to CISDM (2006). Thus, for 2005, our data set covers about half the funds in the industry with the aggregate capital of about $1 trillion, i.e., accounting for about two thirds of the estimated $1.4 trillion of capital under managemente in the hedge fund industry in that year.

CISDM provides 32 style codes. We aggregate them up to 14 styles, as some of these 32 style bins are very close to each other and contain very few funds. See Table 1 for some summary statistics and a list of funds styles. When we pool all the hedge funds together we exclude *funds of funds*: however, we do analyze funds of funds when we look at styles independently.

[1] We found that before 1994 it was not unusual for any given style in CISDM to experience an increase in total capital of over 100 percent, whereas after 1994 there were no such instances. We interpret this as evidence that data coverage stabilized after 1994. We do not use data after 2005, as it was not available at the time of writing.

Returns

In our benchmark specification, we use returns R_{it} reported by CISDM defined as net of compensation and expenses. We also check whether our results are robust to defining R_{it} as net return (return net of the cost of capital), where the cost of capital is equal to the 3-month LIBOR rate. We also re-estimate equation (11) replacing R_{it} with the Sharpe ratio, to see whether *risk-adjusted* returns are affected by size, talent and luck in the same way as unadjusted returns.[2]

Finally, we estimate a regression specification, where R_{it} is replaced with the standard deviation of monthly returns over a 12 month period.[3] We use this specification to determine whether larger funds are also more risky, whether funds with high fixed effects in a return regression also have high fixed effects in a "risk" regression, and whether funds with good luck in terms of returns tend to have high return volatility.

Size

As a benchmark, we measure the fund size in terms of capital under management and estimate equation (11).[4] An alternative is to use the total value of the fund's investment positions, $m_{i,t-1}$, as a measure of size, as per equation (10), which requires information on leverage. CISDM contains data on reported leverage for a fraction of funds in the database, though the quality of this data is questionable. However, when we multiplied capital by reported leverage ratios and used the resulting numbers as a proxy for the size of the fund's total investment position, we obtained very similar results to those with capital as a measure of fund size.

Returns are regressed on *lagged* rather than *contemporaneous* capital under management, consistent with the model. When using monthly data, we annualize the monthly returns (so that monthly and annual coefficients are comparable) by multiplying the monthly returns by 12.When using annual data, we measure capital as the capital under management in January of the corresponding year, and measure annual returns as the returns between February and the following January. An additional advantage of looking at annual returns is that we can

---

[2] Some authors ask whether Sharpe ratios are appropriate for hedge funds given that their returns are known not to be normally distributed and given that hedge fund strategies are closer to options than to directional strategies (Fung and Hsieh (2001)). For example, FSF (2000) notes that Sharpe ratios at the style level are sensitive to the time period over which they are measured. Still, Fung and Hsieh (1999) find that the Sharpe ratio is useful for *ranking* the performance of hedge funds on a risk-adjusted basis for standard utility functions. As a result, we interpret Sharpe ratios as indicators of *relative* performance

[3] We also examine monthly data for robustness of our results.

[4] In what follows, the terms "capital under management" and "assets under management (AUM) will be used interchangeably. Capital under management refers to the sum of contributions by the fund's investors and all subsequent capital gains and losses. The terms 'total assets under management' or 'total dollars under management' are also used by data providers to refer to the same concept.

also compute Sharpe ratios over the corresponding 12 month period using the monthly data,[5] as discussed below, which allows us to see whether our results are robust to risk-adjusting the returns. We use the GDP deflator to ensure that size and returns are measured in real terms: the base year is 2000.

Table 1: Hedge Fund Styles

This table presents the list of hedge fund styles used in this paper, along with the number of funds of each type and the average annual percentage return, as well as the monthly Sharpe ratio. We also indicate the measure of style opportunity we use later in order to scale capital relative to investment opportunities. Hedge fund data are from CISDM (1994-2005). Monthly Sharpe ratios are similar to those reported for hedge funds in FSF (2000).

	Style	Opportunity index	Funds	Average return	Sharpe ratio	Industry share	Median Leverage
1	Short bias	Equity	44	3.0	.01	0.7%	1
2	Convertible Arbitrage	All	183	8.7	.12	3.0	2
3	Fixed income	Bond	117	9.9	.11	1.9	2
4	Emerging Markets	EM	316	12.7	.19	5.1	1
5	Equity Market Neutral	Equity	179	7.6	.08	2.9	2
6	Event Driven	All	367	10.6	.13	5.9	1
7	Fixed income arbitrage	Bond	134	4.9	.08	2.2	3
8	Global Macro	All	234	8.7	.12	3.8	1.5
9	Long/short equity	Equity	1278	12.4	.17	20.7	1.1
10	CTA	All	935	9.7	.11	15.1	2.7
11	Funds of funds	Total HF capital	1224	6.8	.10	19.8	1
12	Relative value	All	98	8.7	.11	1.6	2
13	Long bias	Equity	47	11.5	.18	0.8	1.3
14	CPO	All	1030	6.6	.08	16.7	2.7
	TOTAL	-	6186	9.1	.12	100	1.1
	TOTAL (excl. FoFs)	-	4962	9.6	.12	80.2	1.25

[5] The Sharpe ratio is measured as the mean monthly net return divided by the standard deviation of the monthly net return over the year of interest, annualized by being multiplied by the square root of 12.

One of the reasons we would expect to find a negative effect of size on the returns of individual funds is because the funds may become large relative to available profit/investment opportunities available in markets in which they operate. Or in other words, what matters is not whether the fund is "too large" in absolute terms, but rather whether it is "too large" relative to the scope of available investment opportunities. To account for this possibility, we measure q_{it} as the fund's capital *divided by a measure of investment opportunities*. We adopt four approaches to measuring opportunities. First, we allow the measures to depend on the style (total global market capitalization may be appropriate for some styles, while for others, emerging market cap may be more suitable, see Table 1 for details). Second, we rescaled all funds using global market capitalization. Third, we rescaled using total capital in each style. Fourth, we used the capital data without rescaling. Results were similar for either approach.

The hedge fund "style" factors

We adopt two approaches to accounting for factors that have a common impact on the returns of hedge fund following the same strategy. As a benchmark, we adopt an agnostic approach, using dummy variables, i.e., for each style-date combination we introduce a dummy variable to capture any time-varying style factors that affect returns. Each dummy variable equals one for a particular style-date combination, and zero otherwise. Some authors have argued that hedge funds are not wedded to any particular style, and can in principle invest in any market, so we also repeat our estimates with time dummies that do not vary across styles. Second, we adopt a traditional approach using the risk factors that the literature has identified as being the main determinants of hedge fund returns (see Appendix A below for a list of the Fung and Hsieh (2001, 2004) factors used in the estimation).

As mentioned earlier, one of the style factors x_{kt} could be *the total capital of all funds that follow this style*, as congestion within styles may also affect returns. In our theoretical section, we require a style-level size effect (even if it is very small) for there to be an industry equilibrium. As a matter of empirics, we do not have a direct measure of this variable from the data, because (i) CISDM data do not cover the entire universe of hedge funds; (ii) certain financial intermediaries compete in the same markets (and with the same strategies) as hedge funds, for example private equity or the trading arms of investment banks (see Chan et al (2007)); and (iii) even if we did have a good measure of the total style-level capital, there would be too few data points for identification, at least in annual data.[6] Nonetheless, our two approaches to accounting for style factors are adequate for identifying the parameters of

[6] A rough measure of style size is of course the total capital in each style as reported in CISDM. This should proxy for true style size as long as coverage does not change significantly over time. We do not have a way to assess this, and hedge funds may compete in the same markets and with the same strategies as other intermediaries, so we are not confident of using this variable to estimate ψ. However, we did include the observed style size in our regressions in one specification, conditioning on time dummies. We found a negative style size effect as conjectured, but statistical significance depended on using monthly data. The coefficient was -0.035*** (0.004), about half the fund-level fixed effect, and in the middle of the range of values we explore in our policy experiments. It is worth noting that our *fund-level* size effects are not sensitive to the inclusion of the style-size variable.

equation (3). In the case of the approach using style-date dummies, the dummies will account for all style-level factors (observed or otherwise), including style size. The approach using Fung and Hsieh (2001, 2004) factors may capture style capital implicitly: style capital is likely collinear with the factors themselves, since any persistence in the factors will imply that a positive innovation in any one of them will likely be linked to increased capital.

Method

Entry and exit of hedge funds from the database creates an unbalanced panel. In addition, Getmansky et al (2004) find that hedge fund returns are autocorrelated, and Jagannathan et al (2010) find that alphas are persistent. To deal with these econometric issues, we adopt the Baltagi and Wu (1999) generalized least squared method for estimating fixed-effect dynamic panels with missing observations and serially correlated errors. The procedure assumes that errors display first order autocorrelation $\varepsilon_{it} = \rho\varepsilon_{i,t-1} + \upsilon_{it}$, where υ_{it} is a random variable with zero mean and finite variance drawn iid from some probability distribution.

The possibility of autocorrelated errors raises an additional concern. If current shocks have information regarding future shocks, then they may lead to higher capital investments. Thus, variable $q_{i,t-1}$ may be correlated with ε_{it}. However, as it turns out, estimates of ρ turn out to be very small, suggesting endogeneity is not a serious concern.[7] In addition, we find that hedge fund age predicts hedge fund size, but not returns. The dependence on age is non-linear and wears off after 2-3 years. Thus, in another of our specifications, we use fund age as an instrument for size. We measure age using dummy variables for 0, 1, 2 and >2 years of age. We do not measure age more finely, as reported fund births are bunched at the end of the calendar year.[8] We also report results with bootstrapped standard errors.

As discussed in Ackermann et al (1999), Brown et al (2001), Malkiel and Saha (2005) and elsewhere, there are several sources of selection bias in the hedge fund data. Because reporting is voluntary, hedge funds that perform badly may exit the data set before shutting down, whereas funds that do very well may cease reporting because they are no longer looking for new investors. However, Getmansky et al (2004) and Liang and Park (2010) both find that a significant portion of exits are not predictable a year in advance. This suggests that selection bias is less of a concern, because exit is not correlated with the variables of interest (size, talent, luck and returns) nor with other observables. In addition, ongoing administrative costs of hedge funds are much smaller than startup costs so that, once born, a hedge fund is unlikely to close simply due to a low realization of ε_{it} unless ε_{it} is extremely persistent (which it turns out not to be). Thus, selection bias is unlikely to be a severe problem in annual hedge fund data – another reason why we use annual data in our benchmark regression specification. Even at higher frequency Ackermann et al (1999) argue that selection does not bias estimates using hedge fund data.

---

[7] The correlation between changes in capital and lagged errors is not statistically significant.

[8] Including age dummies in our regressions did not affect results, nor was age statistically significant.

Even so, we adopt an econometric method that is suitable for data with the presence of entry and exit, and with possible selection. The Baltagi and Wu (1999) method allows fixed-effect estimation of dynamic panel data with missing observations. Thus, the fact that hedge funds may enter and exit the database is of itself not a concern: our estimates of the fixed effects and of the size effects remain consistent. Since we are estimating fixed effects for each fund, rather than relying on the representativeness of our sample, selection bias should not be a serious concern so long as we adequately control for the risk factors. As mentioned, we do so in two ways: using the Fung and Hsieh (2001, 2004) factors, and also using time-style dummies. We also intentionally exacerbated selection and reporting bias by excluding the least-talented 20 percent of funds according to our baseline estimation, and by removing all observations with a negative realization of luck in the baseline estimation. Estimates of the size coefficient were similar in all these cases (and are available upon request).

II. EMPIRICAL RESULTS

A. Fund size and returns

Pooling the data for all hedge funds (excluding Funds of Funds), we find strong evidence of negative fund size effects (θ). See Tables 2-3. The value of coefficient θ is between -0.06 and -0.08, depending on the specification. This means that an increase in capital of 10 percent lowers the expected return by about 25 basis points. These values are economically large and statistically significant.

We conduct a variety of robustness tests. We measure size using capital under management, but also capital plus leverage, as well as different ways of scaling capital by investment opportunities. We also use several different return metrics, including gross return, net return, and the risk-adjusted return (or the Sharpe ratio). We use monthly, in addition to the annual, data. We repeat the estimation with bootstrapped standard errors, and we also exacerbate problems of selection bias to explore their role. Results for size effect θ are similar regardless of the approach. By contrast, when we do not allow for fixed effects, the estimate of θ is an order of magnitude smaller and not always statistically significant. This supports our hypothesis that size effects and talent must be jointly estimated. See Table 2.

Table 2: Hedge fund returns, pooled results

This table presents the results of estimating equation (11). Funds of funds are omitted. Specification A has different factor coefficients by style and allows for serial correlation. B has common factors for all styles. C has different factors by style, and excludes funds under 2 years. D adjusts for opportunities using style capital. E does not allow for serial correlation and uses bootstrapped standard errors. F instruments capital using fund age. In G there are no fixed effects: the data are treated as multiple time series using the Prais-Winsten procedure. In H the dependent variable is excess returns (returns minus LIBOR). In I we estimate equation (10), which measures size using capital plus leverage. In J we use monthly instead of annual data. In K we estimate the baseline specification conditioning on FH factors instead of dummies. In L we again use FH factors but restrict their effects to be the same across styles. In M the dependent variable is the monthly standard deviation of returns over LIBOR. In N the dependent variable is the Sharpe ratio.

	Specification	Decreasing returns θ	ρ	Obs	Groups	R^2
A	Baseline	-.075*** (.003)	.14	17709	4227	.760
B	Common Factors	-.077*** (.003)	.11	17709	4227	.725
C	Excluding the young	-.080*** (.004)	.14	11878	2922	.759
D	Divide by style capital	-.074*** (.003)	.14	17709	4227	.760
E	ρ=0, bootstrap	-.057*** (.004)	–	22671	4962	.717
F	Instrumental variables	-0.055*** (.006)	–	22671	4962	.717
G	No fixed Effects	.000 (.001)	.08	28133	–	.655
H	Dependent variable = = net returns	-.070*** (.003)	.16	17709	4227	.795
I	With leverage	-0.080*** (.005)	.12	9061	2151	.773
J	Monthly Data	-0.069*** (.002)	.07	333397	5804	.946
K	Baseline, FH Factors	-.073*** (.003)	.10	17709	4227	.763
L	Common Factors, FH	-.076*** (.003)	.07	17709	4227	.732
M	Dependent variable = =s.d. of returns	.015*** (.001)	.25	17629	4227	.760
N	Dependent variable = = Sharpe ratio	-0.069*** (.003)	.04	13543	3500	.352

Previous work has presented some evidence of a negative size-return relationship among hedge funds. However, these findings could be sensitive to certain econometric concerns. For example, Ammann and Moerth (2005) and Jones (2007) sort funds into size bins, without conditioning on style factors. Consequently, their results could potentially be capturing differences in returns across styles with different typical fund sizes rather than a size effect per se. Furthermore, if size and manager talent are correlated, then studies that do not account for talent may suffer from omitted variable bias. An additional concern is the existence of serial correlation in fund returns, which could lead to inconsistent estimates in the absence of appropriate corrections. Using panel econometric methods, we find evidence of a size effect even accounting for all of these considerations.

Another issue is that, in case size for any reason is correlated with risk, we need to check whether the size effect remains negative and statistically significant when returns are measured on a risk-adjusted basis. We re-run the regressions using the standard deviation of monthly returns, and the Sharpe ratio, as dependent variables. Interestingly, there is a *positive* impact of size on the standard deviation. Larger hedge funds are not just less profitable, but their returns also appear riskier. As a result, on a risk-adjusted basis we would expect to see a significant negative coefficient when the Sharpe ratio is the dependent variable. This is indeed what we find: see Table 2. Thus, regardless of the return metric, large funds yield lower returns.

We also estimate equation (11) separately for each style, to allow θ to vary across industries. We obtain a significant, negative estimate of θ for almost all styles. Emerging Market funds exhibit the largest size effect (θ is about -0.15). Long bias, short bias, Long/short equity and fixed income all have coefficients of θ around -0.09 or -0.10, whereas other styles have smaller size effects. See Table 3.

Recalling our model notice that, if we consider the existence of many styles, equation (14) predicts a *negative* correlation across styles between the style rate of return and θ. Using Table 3 to compute style level values of this parameter and using Table 1 to measure style-level returns, we find a rank correlation of -0.56 when we condition on Fung-Hsieh factors, or of -0.70 if we remove an outlier (Short Bias). This is independent evidence supporting the model feature of decreasing returns to scale.

What might be behind *decreasing returns to size*? Interestingly, we find that larger hedge funds have both lower returns *and higher risk*. See Table 2. Consistent with this, the fund size coefficient is negative when the dependent variable is the Sharpe ratio.

Comparing across styles yields further insight into the possible mechanisms of diseconomies of scale. In particular, we examined whether differences across styles in the sensitivity to fund size θ are related to differences in the styles' sensitivity to any of the ten Fung-Hsieh risk factors – as measured by the β_k coefficients in equation (11) when we condition on those factors. We found that only one of the factor coefficients was statistically significantly related to the style-specific measures of θ: the *equity risk factor*. See Figure 3. The equity risk factor is the return on a stock index look-back straddle, as defined in Fung and Hsieh

(2001). Noting that straddles generate returns based on *volatility*, rather than the direction of the market per-se, this implies that strategies that display greater diseconomies of scale are those the returns on which are *positively related to equity market volatility*.

Table 3: Hedge fund returns, style-specific results

This table presents the results of estimating the size coefficient θ by the panel regression estimation of equation (11), with fixed effects and allowing for serial correlation. Estimates condition on time-style dummies, and on fund fixed-effects.

	Dependent variable	
Style	Gross return	Sharpe ratio
Emerging Markets	-.160*** (.017)	-.107*** (.021)
Fixed income	-.111*** (.020)	-.101*** (.021)
Long bias	-.107** (.046)	-.163*** (.052)
Long/short equity	-.097*** (.007)	-.087*** (.007)
Short bias	-.089*** (.027)	-.094*** (.035)
CTA	-.072*** (.006)	-.080*** (.007)
Global Macro	-.065*** (.015)	-.035** (.017)
CPO	-.051*** (.006)	-.045*** (.007)
Event Driven	-.050*** (.009)	-.038*** (.010)
Funds of funds	-.046*** (.005)	-.045*** (.004)
Equity Market Neutral	-.042*** (.015)	-.055*** (.014)
Fixed income arbitrage	-.041 (.026)	-.062*** (.017)
Convertible Arbitrage	-.022 (.014)	-.031** (.014)
Relative value	.014 (.012)	-.001 (.014)

Pástor and Stambaugh (2003) have linked the equity risk factor to an exposure to aggregate liquidity, and Acharya and Pedersen (2005) find evidence linking the level of liquidity in a particular asset market to its sensitivity to aggregate liquidity. Thus, our results suggest that diseconomies of scale are related to exposure to *liquidity risk*. This result echoes that of Chen et al (2004), who find that actively managed mutual funds display diseconomies of scale when they invest in less liquid stocks/markets – indeed our finding is a generalization of theirs in the sense that hedge funds cover a broader spectrum of asset markets and strategies with their investments than do mutual funds.

Figure 1: Decreasing returns and sensitivity to equity risk across hedge fund styles.
The vertical axis represents the coefficient of hedge fund returns on the equity risk risk factor in equation (3). The factor is defined in Fung and Hsieh (2001).

B. Distribution of "talent"

The distribution of fund-specific fixed effects ("talent") appears symmetrical, and has fat tails – see Figure 4 and Table 4. The talent distribution matches well a Laplace distribution – a distribution with much fatter tails than the normal distribution. Skewness of talent is negative but minor. If we believe that funds that have very strong or very weak talent are less likely to report to the database, then the distribution of talent in the industry as a whole (including funds omitted from the database) will also have fat tails. The fact that our estimates have tails that are "at least as fat" as those in the true distribution is important for our results.

We estimated equation (11) without fund size as a dependent variable, to see whether the distribution of talent (measured using fixed effects) was very different from the distribution obtained when conditioning on size. We found that, conditioning on time-style dummies, the standard deviation of talent was 0.194 when size is omitted, compared to 0.284 when it is not omitted. Thus, the contribution of talent to hedge fund returns is underestimated when we do not condition on size.

Figure 5 displays the distribution of "talent" among *entrants* in each cohort 1994-2003 in the database. Each subplot also displays the parameterized Laplace distribution that most closely matches the pooled talent distribution for all hedge funds in Figure 1, to see whether the talent distribution of entrants differs from the talent distribution across all funds in the database. The fact that the entrant talent distribution and the industry talent distribution are similar indicates that the probability of exiting the database is unrelated to hedge fund talent,

Table 4: Moments of the distributions of talent and luck

Second, third and fourth moments computed from the empirical distributions of talent (μ) and luck (ε). Talent is the fund-specific fixed effect and luck is the regression residual, computed using the Baltagi and Wu (1999) estimator for fixed-effect dynamic panels with serially correlated disturbances and missing observations.

Variable	Factors	St. Dev.	Skewness	Kurtosis
Talent	Time-style indicators	0.2839	-0.504	6.69
	Fung and Hsieh (2001, 2004)	0.2378	-0.501	6.45
Luck	Time-style indicators	0.2201	1.93	9.51
	Fung and Hsieh (2001, 2004)	0.2139	2.11	10.95

Figure 2: Manager fixed effects.

Fixed effects are normalized to lie between zero and one. Style returns are controlled for using the dummy factors. The full line reflects the empirical distribution, whereas the dotted line is a fitted Laplace distribution.

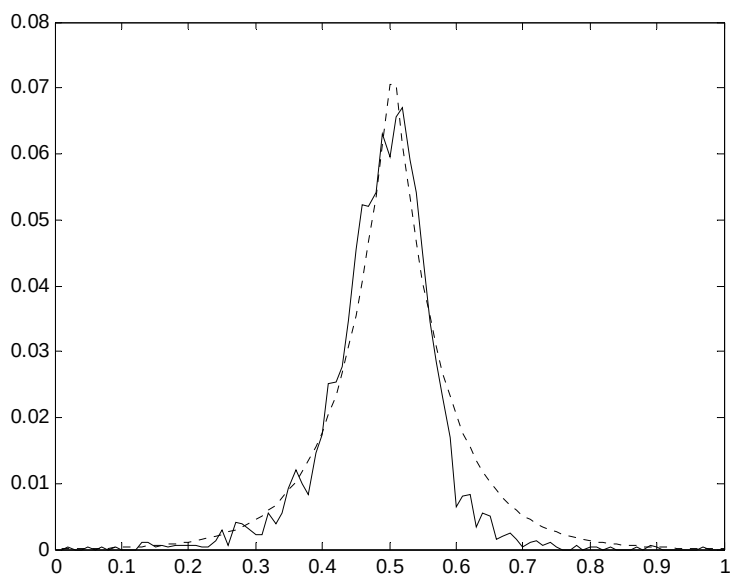
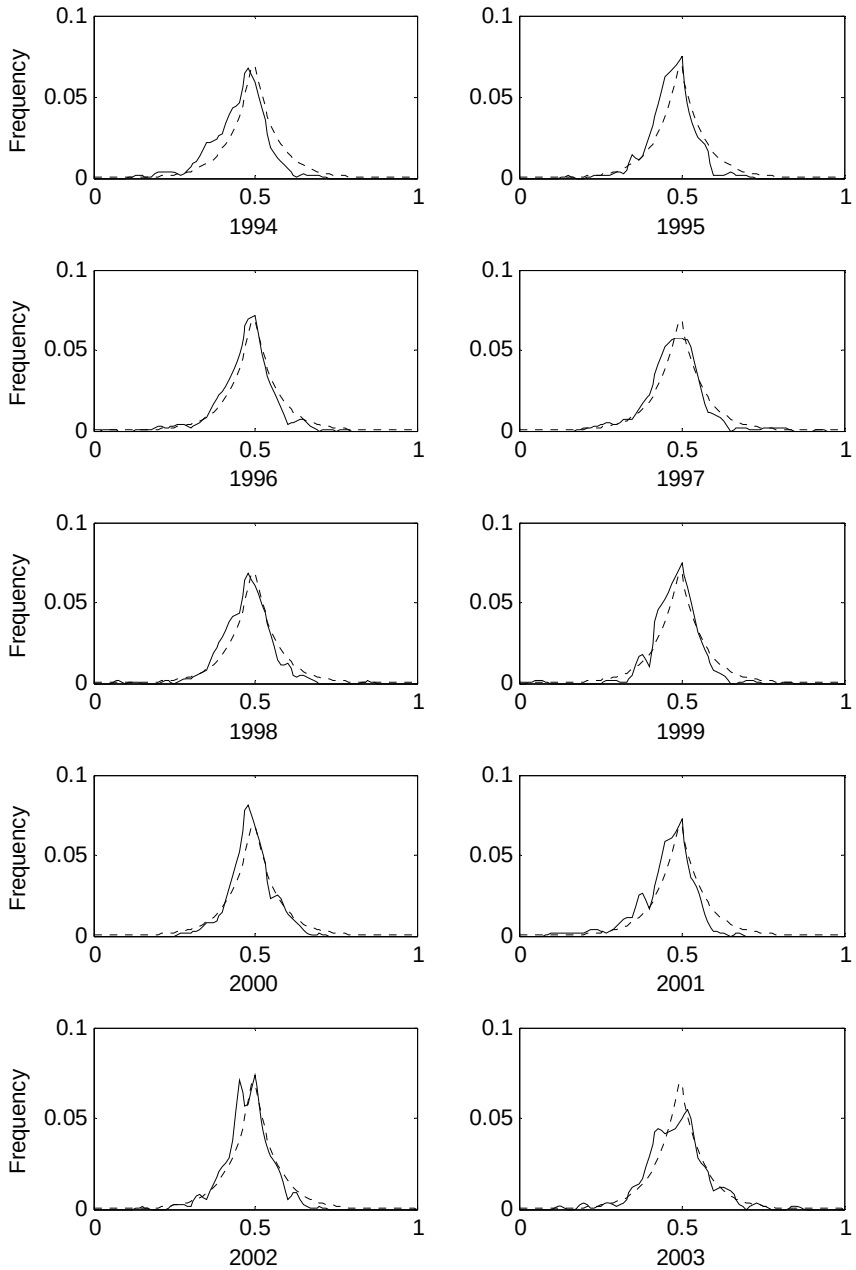


Figure 3: Manager fixed effects for entrants by year.

Fixed effects are estimated based on the full panel of hedge funds, and are normalized to lie between 0 and 1. The full line reflects the empirical distribution, whereas the dotted line is the fitted Laplace distribution in Figure 3, which matches the distribution of manager talent in the full sample. It has been rescaled to fit the *number* of HFs in each panel, but the shape is preserved. Since at least two years of data are required to estimate each fund-specific fixed effect, and since return data were not available for all months in 2005, hedge funds born in 2004 and 2005 were not included.



as argued earlier. Interestingly, the talent distribution among entrants appears stable across cohorts, suggesting a stable pool of manager talent. This is consistent with the entry process in our theoretical model. The finding is also consistent with Géhin and Vaissié (2006), who argue that there is no evidence of "alpha" declining over time.

Notably, the correlation between talent and size is positive, equal to 0.693 (s.e. 0.011), as predicted by equation (6). This finding is significant as it provides evidence that the absence of persistent cross-fund differences in returns can be reconciled with the possibility of significant differences in manager talent if decreasing returns to scale lead more talented managers to optimally manage larger funds.

What factors underlie differences in *talent*? To answer this question, we compare the fixed effects obtained from estimating three different specifications, i.e., where the dependent variable is the return, the Sharpe ratio, and the standard deviation of monthly returns. In the first two cases, the fixed effects reflect different measures of talent. In the third case, the fixed effect measures the degree of variability in monthly returns.

It turns out that managers, who have a "talent" for generating higher returns, also have a "talent" for delivering higher risk adjusted returns (Sharpe ratios). The correlation between fixed effects with returns as the dependent variable and fixed effects as measured when the dependent variable is the Sharpe ratio is 0.404*** (s.d. 0.018).[9] It is worth noting that the correlation between fixed effects for returns and fixed effects when the *standard deviation* of monthly returns is used as a dependent variable is also positive, at 0.131*** (s.d. 0.016). This suggests that, to some extent, the more talented fund managers are also taking on more risk. At the same time, the correlation between fixed effects for the Sharpe ratio and for the standard deviation of returns is negative, at -0.140*** (s.d. 0.015). Thus, more talented managers deliver higher risk-adjusted returns. This is consistent with the theory of "prediction ability" developed by Takii (2003), who shows that, if better managers have a comparative advantage in risky activities, they rationally take on more risk.

C. Distribution of "luck"

The distribution of luck also has fat tails, but has positive-skew. The presence of fat tails in both talent and luck is consistent with leptokurtosis in returns found by Ackermann et al (1999). The distribution of luck matches a Frechét distribution. See Figure 6.

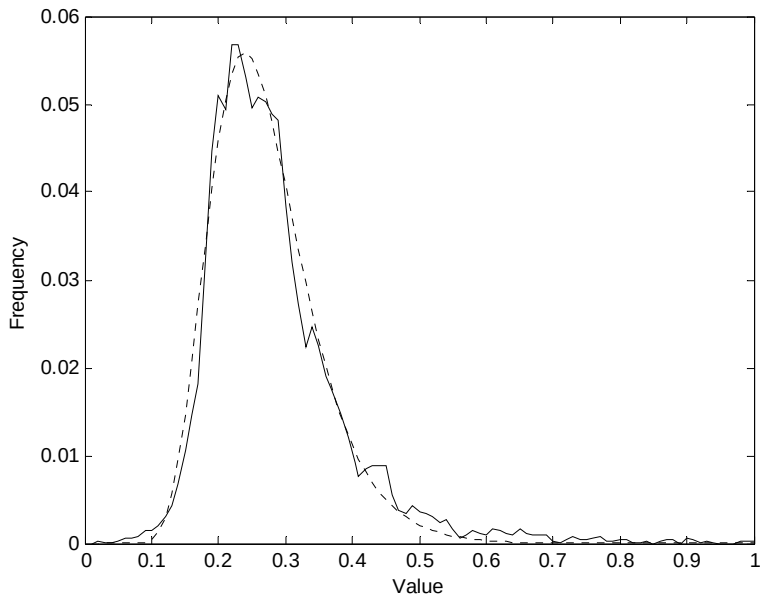
It is worth asking whether there is any evidence that investors learn about manager talent over time. It turns out that the correlation between capital and lagged errors is -0.007 (s.d. 0.034), which is not statistically significant. The correlation between changes in capital under

[9] We report results for regressions conditioning on the time-style dummies rather than the Fung-Hsieh factors as we do not know what are the right factors when the dependent variable is the standard deviation of returns or the Sharpe ratio rather than returns. However, results are similar using the Fung-Hsieh factors. We also estimated equation (11) with Sharpe ratios as the dependent variable but using the fixed effects estimated when the dependent variable is returns, finding similar size coefficients to when we use Sharpe ratios to estimate size and talent effects jointly.

management and lagged errors is -0.003 (s.d. 0.008). A positive correlation would be expected if agents were learning about a fund's talent on the basis of realized returns. Thus, it appears that any learning about hedge fund manager talent must occur within the first year of the hedge fund's birth, or even before the fund goes "live" (i.e., appears in the database).

Figure 4: Distribution of Luck.

Fixed effects are normalized to lie between zero and one. Style returns are controlled for using the dummy factors. The full line reflects the empirical distribution, whereas the dotted line is a fitted Frechét distribution.



Interestingly, in cross-section, the standard deviations of talent and of luck are of comparable magnitude (see Table 4), so that luck and talent are of similar importance in accounting for the cross-sectional variation of returns. On the other hand, luck is not very persistent, with the annual autocorrelation coefficient in the range of 5 to 14 percent (see Table 2).[10] Hence, while luck leads to significant variation in returns over time, the lack of persistence in luck means that talent should be the dominant factor of success in the hedge fund industry.

What factors might determine *luck*? Funds that appear to have better "luck" in terms of returns also tend to have better "luck" in terms of Sharpe ratios. The correlation between luck with returns as the dependent variable and luck as measured when the dependent variable is the Sharpe ratio is 0.663*** (s.d. 0.013). At the same time, it is worth noting that the correlation between luck for returns and the errors when the dependent variable is the *standard deviation of returns* is positive, at 0.161*** (s.d. 0.014). Consider that the error when the dependent variable is the s.d. of returns represents unexpected *changes* in the

[10] Recall that Getmansky et al (2004) find that hedge fund returns are serially correlated, which they interpret as an indicator of illiquidity. Our much lower value is attributable to the fact that, in our specification, part of the autocorrelation is due to hedge fund fixed effects. Also we use annual data: any serial correlation left after accounting for fund fixed effects would be higher in high frequency data.

standard deviation. Thus, "good luck" in returns is related to large unexpected changes in the volatility of returns.

III. REFERENCES

Acharya, Viral V. and Lasse H. Pedersen. 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77(2), 375-410.

Ackermann, Carl, Richard McEnally and David Ravenscraft. 1999. The Performance of Hedge Funds: Risk, Return, and Incentives. Journal of Finance 54(3), 833-874.

Agarwal, Vikas, Naveen D. Daniel and Narayan Y. Nail. 2009. Role of Managerial Incentives and Discretion in Hedge Fund Performance. Journal of Finance 64(5), 2221-2256.

Aghion, Philippe, Abhijit Banerjee and Thomas Pikeetty. 1999. Dualism and Macroeconomic Volatility. Quarterly Journal of Economics 114, 1359-1397.

Ammann, Manuel and Patrick Moerth. 2005. Impact of fund size on hedge fund performance. Journal of Asset Management 6 (3), 219-238.

Aragon, George O. 2007. Share Restrictions and Asset Pricing: Evidence from the Hedge Fund Industry. Journal of Financial Economics 83(1), 33-58.

Baltagi, Badi H. & Wu, Ping X. 1999. Unequally Spaced Panel Data Regressions With AR(1) Disturbances. Econometric Theory 15(06), 814-823.

Berk, Jonathan B. and Richard C. Green. 2004. Mutual Fund Flows and Performance in Rational Markets. Journal of Political Economy 112(6), 1269-1295.

Brown, Stephen J., William N. Goetzmann, Bing Liang and Christopher Schwartz. 2008a. Mandatory Disclosure and Operational Risk: Evidence from Hedge Fund Registration. Journal of Finance, 63(6), 2785-2815.

Brown, Stephen J., Thomas L. Fraser and Bing Liang. 2008. Hedge Fund Due Diligence: A Source of Alpha in a Hedge Fund Portfolio Strategy. Mimeo: Stern School of Business NYU.

Brown, Stephen J., William N. Goetzmann & Robert Ibbotson. 1999. Offshore hedge Funds: Survival and Performance 1989-1995. Journal of Business, 72, 91-118.

Brown, Stephen J., William N. Goetzmann & James Park. 2001. Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry. Journal of Finance, 56(5), 1869-1886.

Center for International Securities and Derivatives Markets. 2006. Benefits of Hedge Funds 2006. Amherst, MA: Isenberg School of Management, University of Massachusetts – Amherst.

Chan, Nicholas, Mila Getmansky, and Shane M. Haas and Andrew W. Lo. 2007. Systemic Risk and Hedge Funds. In M. Carey and R. Stulz, eds., The Risks of Financial Institutions and the Financial Sector. Chicago, IL: University of Chicago Press.

Chen, Joseph, Harrison Hong, Ming Huang and Jeffrey D. Kubik. 2004. Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. American Economic Review 94(5), 1276-1302.

Cooley, Thomas F. Vincenzo Quadrini. 2001. Financial Markets and Firm Dynamics. American Economic Review, 91(5), 1286-1310.

European Central Bank. 2006. Financial Stability Review June 2006. Brussels: ECB.

Evans, David S. and Boyan Jovanovic. 1989. An Estimated model of Entrepreneurial Choice under Liquidity Constraints. Journal of Political Economy 97(4), 808-827.

Feffer, Stuart and Christopher Kundro. 2003. Understanding and mitigating operational risk in hedge fund investments. Capco White Paper.

Feffer, Stuart and Christopher Kundro. 2004. Valuation issues and operational risk in hedge funds. Journal of Financial Transformation 10, 41-47.

Financial Services Authority. 2009. The Turner Review: A Regulatory Response to the Global Banking Crisis. London: FSA.

Financial Services Authority. 2010. Assessing possible sources of systemic risk from hedge funds. London: FSA.

Foster, Dean P. and H. Peyton Young. 2010. Gaming Performance Fees by Portfolio Managers. Quarterly Journal of Economics 125(4), forthcoming.

Fung, Hung-Gay, Xiaoqing Eleanor Xu and Jot Yau. 2004. Do Hedge Fund Managers Display Skill? Journal of Alternative Investments 6(4), 22-31.

Fung, William and David A. Hsieh. 1999. Is mean-variance analysis applicable to hedge funds? Economics Letters 62, 53-58.

Fung, William and David A. Hsieh. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. Review of Financial Studies, 14, 313-341.

Fung, William and David A. Hsieh. 2004. Hedge Fund Benchmarks: A Risk Based Approach. Financial Analyst Journal, 60, 65-80.

Géhin, Walter and Mathieu Vaissié. 2006. The Right Place for Alternative Betas in Hedge Fund Performance: an Answer to the Capacity Effect Fantasy, Journal of Alternative Investments, 9(1), 9-18.

Getmansky, Mila. 2004. The Life Cycle of Hedge Funds: Fund Flows, Size and Performance. Working paper, University of Massachusetts – Amherst.

Getmansky, Mila, Andrew W. Lo and Igor Makarov. 2004. An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. Journal of Financial Economics 74(3), 529-610.

Gnedenko, Boris. 1943. Sur La Distribution Limite Du Terme Maximum D'Une Serie Aleatoire. Annals of Mathematics, Second Series, 44(3), 423-453.

Goetzmann, William N., Jonathan E. Ingersoll, Jr. and Stephen A. Ross. 2003. High-Water Marks and Hedge Fund Management Contracts. Journal of Finance 58 (4), 1685-1717.

Gompers, Paul, Joy Ishii and Andrew Metrick. 2003. Corporate Governance and Equity Prices. Quarterly Journal of Economics 118(1), 107-155.

Hopenhayn, Hugo A. 1992. Entry, Exit, and Firm Dynamics in Long Run Equilibrium. Econometrica, 60(5), 1127-50.

Hopenhayn, Hugo A. and Edward C. Prescott. 1992. Stochastic Monotonicity and Stationary Distributions for Dynamic Economies. Econometrica 60(6), 1387-406.

Financial Stability Forum. 2000. "Background Information on the Hedge Fund Industry", Annex D, "Report of the Working Group on Highly-Leveraged Institutions". http://www.fsforum.org/publications/Rep_WG_HLI00.pdf

Jagannathan, Ravi, Alexey Malakhov and Dmitry Novikov. 2010. Do Hot Hands Exist Among Hedge Fund Managers? An Empirical Evaluation. Journal of Finance 65(1), 217-255

Jensen, Michel C. 1968. The Performance of Mutual Funds in the Period 1945-1964. Journal of Finance, 23(2), 389-416

Jones, Meredith. 2007. Examination of fund age and size and its impact on hedge fund performance. Derivatives Use, Trading and Regulation 12(4), 342-350.

Khandani, Amir E. and Andrew W. Lo. 2007. What Happened to the Quants in August 2007? Mimeo: MIT.

Koutsougeras, Leonidas C. 2003. Non-Walrasian equilibria and the law of one price. Journal of Economic Theory 108, 169-175.

Liang, Bing and Hyuna Park. 2010. Predicting Hedge Fund Failure: A Comparison of Risk Measures. Journal of Financial and Quantitative Analysis 45(1), 199-222.

Lo, Andrew W. 2008. *Hedge Funds: An Analytic Perspective*. Princeton University Press, Princeton NJ.

Lucas, Robert E. Jr. 1978. On the Size Distribution of Business Firms. Bell Journal of Economics, 9(2), 508-523.

Malcolm, Kyla, Mark Tilden, Tim Wilsdon, Jessica Resch and Charles Xie. 2009. Impact of the proposed AIFM Directive across Europe. Charles River Associates Project No. D14806 (prepared for the Financial Services Authority). London.

Malkiel, Burton and Atanu Saha. 2005. Hedge Funds: Risk and Return. Financial Analysts Journal, 61(6), 80-88.

Managed Funds Association. 2009. Sound Practices for Hedge Fund Managers. Washington, DC.

Merton, Robert C, 1981. On Market Timing and Investment Performance. I. An Equilibrium Theory of Value for Market Forecasts. Journal of Business 54(3), 363-406.

Pástor, Luboš and Robert F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111(3), 642-685.

Perold, André F. and Robert S. Salomon, Jr. 1991. The Right Amount of Assets under Management. Financial Analysts Journal 47(3), 31-39.

Pozen, Robert C. *The Mutual Fund Business*. Cambridge: MIT Press, 1998.

Schneeweis, Thomas, George A Martin , Hossein B Kazemi , and Vassilis Karavas. 2005. The Impact of Leverage on Hedge Fund Risk and Return. Journal of Alternative Investments 7(4), 10-21.

Stokey, Nancy L., Robert E. Lucas Jr. and Edward C. Prescott. 1989. *Recursive Methods in Economic Dynamics*. Cambridge, MA: Harvard University Press.

Strachman, Daniel A. 2007. *The fundamentals of hedge fund management : how to successfully launch and operate a hedge fund*. Hoboken, NJ: Wiley.

Takii, Katsuya. 2003. Prediction Ability. Review of Economic Dynamics 6(1), 80-98.

Veracierto, Marcelo. 2008. Firing Costs and Business Cycle Fluctuations. International Economic Review 49(1), 1-39.

A. Appendix: Fung and Hsieh (2001, 2004) factors

In this section, we provide some auxiliary results for the discussion in the text.

We use ten different style factors to account for style-wide or industry-wide returns. Fung and Hsieh (2004) suggest the following:

- The S&P 500 monthly return.
- The spread between the Russell 2000 and the S&P 500.
- The monthly change in the 10 year treasury yield.
- The monthly change in the Moody's Baa yield minus the 10 year treasury yield.
- The IFC (or MSCI) emerging market index.[11]

They arrive at this list by considering risk factors that affect the returns of traditional fund managers who may trade in the same markets as hedge funds. There are also five *risk-based* factors developed in Fung and Hsieh (2001). They define a "primitive trend-following strategy" (PTFS) and compute the values of the following options.[12]

- The return on a PTFS Bond look-back straddle (an interest-rate risk factor)
- The return on a PTFS Currency look-back straddle (a currency risk factor)
- The return on a PTFS Commodity look-back straddle (a commodity risk factor)
- The return on a PTFS Short Term Interest Rate look-back straddle (a macro risk factor)
- The return on a PTFS Stock Index look-back straddle (an equity risk factor)

In our benchmark estimation results we pool the data for all styles except funds of funds, although we allow the impact of each risk factor to vary across styles. Since hedge funds are not actually constrained to stay with any particular style, however (see Fung and Hsieh 1997), we also estimate (11) restricting the style factors to be the same.

---

[11] They recommend this factor but omit it from the paper. See http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

[12] They argue that (a) a generic asset manager's strategy can be thought of in terms of market-timing, see Merton (1981) (b) the payoffs to a successful market timer are similar to option payoffs, (c) by not being short-sale constrained, the direction of the market is irrelevant, hence a "straddle" (d) by actively trading and timing the market, the HFs payoffs are similar to those on a "look-back" option (Fung and Hsieh do not find that the look-back aspect is quantitatively important, but support it on theoretical grounds). Since in principle any HF can hold any kind of asset, regardless of style, we use *all* factors for each style, allowing coefficients to vary across styles.