

SKILL, LUCK AND THE MULTIPRODUCT FIRM: EVIDENCE FROM HEDGE FUNDS*

Rui J.P. de Figueiredo, Jr.
University of California Berkeley, Haas School of Business

Evan Rawley
The Wharton School, University of Pennsylvania

August 7, 2009

We propose that higher skilled firms diversify in equilibrium even when agency effects are significant. We formalize this intuition in an equilibrium model and test our predictions using a large panel dataset on the hedge fund industry 1977-2006. The results show that returns fall following new fund launches, but are 11 basis points per month higher in diversified firms compared to a matched sample of focused firms. Consistent with the model, the evidence suggests that managers exploit asymmetric information about their own ability to time diversification decisions, but the discipline of markets ensures that better firms diversify on average.

I. Introduction

Do firms diversify to share unique assets or skills across products or business units (Panzar and Willig 1975, 1981; Teece 1982) or do managers use diversification to appropriate value from investors (Jensen and Meckling 1976; Jensen 1986)? Much of the research on diversification has addressed the question of why multiproduct firms exist by examining the net effect of the costs and benefits of diversification (Lang and Stulz 1994, Berger and Ofek 1995, Campa and Kedia 2002, Villalonga 2004). However, surprisingly little research has been done on how economies of scope and agency costs separately influence firm diversification decisions. This paper builds on the diversification literature by examining returns to diversification in the hedge fund industry 1977-2006, using segment-level (e.g., fund) performance (Villalonga 2004) and controlling for selection on observables using propensity score matching as in Campa and Kedia (2002), and

* We thank Vineet Budhraj, Jacques Chappuis, Paul Gertler, Margaret Kyle, Ryan Meredith, John Morgan, Gabriel Natividad, Santiago Oliveros, Robert Stambaugh, Pablo Spiller, Steve Tadelis, Oliver Williamson and participants at the CRES conference at Washington University, at the 2009 ISNIE conference, the 2009 Econometric Society meeting and seminars at the University of California Berkeley's Haas School of Business, the Harvard Business School, and The Wharton School for helpful suggestions. We acknowledge thoughtful research assistance from Justin Tumlinson and are grateful for financial assistance from the Kauffman Foundation and the Rodney L. White Center for Financial Research.

extends the literature by demonstrating that both economies of scope and agency effects play a role in firm diversification decisions.

The results support a fundamental premise of the economies of scope literature that certain firms' can efficiently expand horizontally because they possess unique capabilities (or skills) in the context of a large sample study that demonstrates a causal connection between firm skill and corporate strategy. In doing so, the paper bridges the gap between intuition and evidence in the firm scope literature by exploiting the behavior of profit maximizing firms to identify skill as a driver of diversification. The paper also contributes to a deeper understanding of the hedge fund industry by examining how hedge funds' product portfolios develop. We build on the burgeoning literature on hedge fund performance measurement¹ and extend this literature to explain how corporate strategy decisions are made in hedge funds as well.

Our empirical tests are derived from a simple model that integrates the predictions of agency theory with the literature on economies of scope. In our model idiosyncratic performance shocks, which we refer to as luck, are the source of asymmetric information underlying potential *ex ante* agency effects, while persistent performance effects reveal a firm's skill *ex post*.² Using the information embedded in hedge funds' fund-level performance before and after new fund launches, we show that firms tend to diversify when they experience idiosyncratic performance shocks but market discipline ensures that higher skilled firms diversify on average.

Because diversified firms replace market mechanisms with managerial fiat, it is reasonable to expect that there may be certain *ex post* inefficiencies associated with diversification, for example influence costs (Rajan, Servaes and Zingales 2000), inefficient internal capital markets (Lamont 1997, Scharfstein and Stein 2002) or managerial distraction costs (Schoar 2002), but in

¹ See for example Fung and Hsieh (2001), Agarwal and Naik (2004), Sadka (2009).

² Our definitions of luck and skill are consistent with Gompers, Kovner, Lerner and Scharfstein (2008).

the absence of strong market frictions, in expectation, these costs should be lower than the benefits of diversification. Liquid capital markets and the public market for corporate control are strong forces for disciplining managers who destroy value through diversification, which should rule out a systematic diversification discount. However, as Campa and Kedia (2002) point out, the absence of a causal diversification discount “does not imply there are no agency costs associated with firms operating in multiple divisions” (p.1732). In this spirit, we acknowledge that agency costs are quite likely to be important in the context of diversification, but do not test for *ex post* agency costs. Rather we propose that the expected benefits of economies of scope should exceed the expected costs of diversification, and test the net effect of these costs and benefits *ex post*. In other words, we demonstrate that higher skilled firms diversify even controlling for *ex post* agency costs.

On the other hand, we do explicitly model and test for *ex ante* agency effects, proposing that, conditional on *ex post* efficiency; managers can exploit asymmetric information for private gain when choosing to launch a new product. The proposition is consistent with the kind of asymmetric information problem that animates Jensen and Meckling’s (1976) seminal work on agency costs, but, in this paper, it is developed in the context of an equilibrium model of product diversification with positive (net) economies of scope *ex post*.

Our theory applies broadly to diversification decisions, but we build the model with the institutional features of the hedge fund industry in mind to develop a tractable theory of related product diversification in financial firms. In particular, we exploit the similarities between product and business unit diversification in the hedge fund industry to refine the theory with respect to the pattern of returns before and after diversification.³ The hedge fund industry

³ For example, we measure product performance in terms of risk adjusted returns to investors net of fees. Our measure is consistent with the idea that investors are consumers of (financial) products, and firms are residual

provides a particularly attractive environment for evaluating our predictions because the two variables of greatest interest—firm performance and new product launches—have naturally observable measures: firm performance is measured by risk adjusted excess returns to investors; diversified or multiproduct firms are those that operate more than one unique fund.

In our model managers are purely self interested and actively seek the opportunity to use asymmetric information to exploit investors. Investors actively seek out managers who are the most likely to deliver the highest future risk-adjusted returns – managers who are the most skilled – while harboring no illusions about managers’ private incentives and information. Given asymmetric information between managers and investors about a firm’s true ability level, investors rationally make inferences about firm skill based on all available information about the firm, particularly the information embedded in each of the firm’s funds past returns. Managers know that investors are rational and will use all observable information about the firm to form beliefs about the firm’s underlying ability, and expect that investors update their beliefs in each period, but managers also know investors are not prescient and can be fooled, at least temporarily, by idiosyncratic performance shocks. Thus, the manager’s problem is whether and when to diversify based on the firm’s performance track record and the firm’s true ability, while the investor’s problem is where to invest.

Based on this simple model, we show the existence of an equilibrium, which helps clarify the nature of firm diversification decisions. In the equilibrium we study, firms are more likely to diversify when their returns are higher independent of their ability, and when their ability is higher independent of their returns. Skilled firms are more likely to diversify into new products—since they are more likely to generate higher future returns—and luckier firms are

claimants. However, investors are also partial residual claimants in the sense that they retain on average 60% of the revenue of the fund. Thus, investors are both consumers and equity investors. We exploit the duality of the investor as consumer and residual claimant to develop sharper predictions in our model.

more likely to diversify—since they have experienced a positive shock to their historical performance record. This result leads us to the first two of three empirically testable predictions. First, because a firm’s ability to raise capital to fund new product launches is increasing in the firm’s performance track record, in expectation diversifiers will out-perform non-diversifiers during pre-diversification periods. This is a straightforward cross-sectional prediction about the expected performance of future diversifiers and non-diversifiers in the pre-diversification period. Second, because the probability that a firm diversifies is increasing in *ex ante* performance—and therefore the luck—of a firm, diversifiers will, in expectation, perform better before they diversify than after they diversify. Thus, we predict there will be (negative) mean reversion in the time-series performance pattern of diversifiers.

The third, and most important, prediction of our model relates to the incentives to diversify conditional on a firm’s track record. Namely, we show that if launching a new line of business is costly, firms will separate probabilistically such that more skillful firms are more likely to diversify than less skillful ones. In other words, firms that achieved a particular track record through being lucky are less likely to diversify than those that are more skillful. The intuition behind this result is that while managers are potentially able to increase their own compensation by diversifying, the attractiveness of diversification depends not only on investors’ current beliefs but also on their expected future beliefs. Since over time, firms reveal their true type through performance – and do so even faster when they diversify – less skillful firms always have weaker incentives to diversify given a particular track record. This logic then provides a final testable prediction: conditional on early performance, diversifiers will out-perform non-diversifiers in future periods.

Our theory predicts a pattern of returns that is broadly consistent with a set of stylized facts reported in other research on diversification. Fund managers' private incentives influence their strategic choices (Chevalier and Ellison 1997). Legacy business unit (fund) returns fall following diversification (Schoar 2002), particularly when preceded by unusually strong reported performance (Teoh, Welch and Wong 1998), yet firms with the best track record tend to launch new funds and their performance tends to persist relative to a valid control group (Kaplan and Schoar 2005). Cabral (2000) develops a related model in which firms extend their existing brands when both quality and returns of earlier products are jointly sufficiently high. Our model explains all of these stylized facts in a simple testable equilibrium framework.⁴ Neither agency costs nor economies of scope alone can explain the full set of results demonstrated.

We test the predictions of the model using a series of empirical tests on a large and rich panel dataset on 1,576 hedge funds. The first hypothesis, predicting better *ex ante* performance for firms that subsequently launch new funds, is tested using a discrete choice model where lagged performance, measured by returns in excess of a multifactor risk-adjusted return benchmark, predicts diversification, conditional on all other observable firm characteristics. The second hypothesis, which predicts that a component of the superior *ex ante* performance of diversifiers is due to positive idiosyncratic performance shocks, is tested by estimating an event study model of changes in legacy (e.g., first) fund returns before and after the launch of a firm's second fund. Consistent with agency theory's prediction that manager's use asymmetric information for private gain, hedge funds launch new funds when they experience positive risk-adjusted excess returns that do not persist after launch.

⁴ MacDonald and Slavinski (1987) provide a general equilibrium model in which equilibria exist in which some firms diversify and others do not, much like our model. Berk and Green (2004) provide a model similar to ours in which firms have heterogeneous abilities to generate gross returns and investors rationally invest, but in equilibrium investment managers' investment and pricing decisions result in little persistence in outperformance.

The pattern of returns evident in the data for diversifiers is striking. Excess returns are well above the sample mean prior to diversifying and fall rapidly almost immediately following the launch of a second fund. To test whether the pattern of falling returns demonstrates that agency costs dominate economies of scope *ex post*, or whether this pattern is consistent with our skill-based explanation, we need to develop a valid counterfactual that allows us to estimate what would have happened to excess returns in diversifying firms had they remained focused. To identify the counterfactual control group we model the selection process by which firms choose to enter into diversification, and control for observable factors influencing selection into diversification by matching diversified firms to firms that remain focused using the propensity scores estimated from the same discrete choice model that predicts diversification.

Our matching model controls for all the observable differences between diversifying and non-diversifying firms so that any *ex post* differences between control and treatment group performance can be ascribed to diversification. In our main specification we go one step further to pinpoint the influence of diversification on the differences in fund returns relative to differences in matched sample returns, by controlling for unobservable time-invariant firm-specific characteristics as well. However, our interpretation of the matched sample results need not rely on diversification *per se* to be the causal mechanism driving the differences in returns. Indeed, our claim is that the evidence assembled points to skill acts as a firm-specific factor, which drives both the decision to diversify and the subsequent performance differences between diversified firms and the matched sample. Although skill cannot be observed directly in the data, our predictions about the patterns of firm performance are consistent with an intuitive notion of skill – diversifying firms outperform firms that remain focused *ex post* when conditioning on historical returns.

Taken together the results are consistent with an agency model where managers time diversification decisions to exploit private information to their own advantage, yet the agency effects exist in an equilibrium context where market effects constrain lower ability firms' horizontal diversification options. Thus, firms launching new funds tend to possess greater investment skill than firms that remain focused, and these firms are able to leverage their investment skill across new funds in a manner consistent with the economies of scope literature.

While we cannot rule out the possibility that diversification has a positive causal impact on performance, the overall pattern of evidence is consistent with the economies of scope literature and with the model we propose where firms choose to diversify when they have private information about their own superior ability. Furthermore, any causal effects of diversification on performance are also consistent with both the economies of scope literature and our selection-based explanation. The interpretation of skill as a selection effect is trivially true if, conditional on luck, skill effects induce firms to launch new funds because they are better at identifying new opportunities. In this case diversification and the resulting economies of scope are simply the result of selection on unobservable skill (to the econometrician), which only serves to shift the selection effect back one step. A second, consistent, interpretation of the matched sample result is that some firms are better able to exploit latent synergies across investment strategies. However, the latent synergies interpretation is just another way of describing economies of scope, and also reduces to a selection effect consistent with the equilibrium we describe. If product diversification enables one firm to capture synergies that other firms cannot capture, the more capable, or skillful, firm will diversify while the other firm remains focused. While it would be ideal to separate selection on skill effects from selection based on latent skills, both interpretations are consistent with economies of scope and our skill-based theory of selection.

Our baseline measures of performance are calculated relative to standard multifactor risk-adjusted investment benchmarks, including adjustments for risks associated with dynamic trading strategies. The results are robust to a wide range of alternative measures of performance, including exposure to option-based risk factors, liquidity risk exposure and exposure to idiosyncratic volatility, and to alternative specifications of the selection and event study models. The results are also robust to self-reporting and survivor biases and weighting matched observations by the inverse probability of treatment. Furthermore we show that skill effects aggregate to the firm level and are not due to cross-subsidization within firm across funds.

In the remainder of the paper we develop this argument in more detail. In the following section, we develop our model of hedge fund diversification, deriving the three testable predictions described above. In Section III, we describe the context for our empirical analysis—the institutional setting, the data, and the variables. In Section IV, we describe our empirical specification and results. In Section V, we offer conclusions.

II. Skill, Luck, Reputation and the Multiproduct Firm

In this section, we develop a formal model of new fund launches by hedge fund firms. In the model, rational mean-variance investors form beliefs about the skill of investment managers based on two observables: the returns generated by managers and whether or not managers choose costly new fund launches. Based on their posterior beliefs about quality, investors allocate funds to managers where the profit of the firm is correlated to their level of assets.

Notably, as the model is primarily designed to provide structure and intuition for our hypotheses and empirical analysis our intention in developing this model is modest. First, the model provides plausible micro-foundations for the informal argument we presented above:

namely, that diversification by hedge fund firms may require both good fortune — above expectation performance, and skill — above average quality. Second, we demonstrate that these results can hold when investors and investment managers are behaving rationally.

A. Model Setup

To understand the basis on which hedge funds will choose to launch new funds, or not, we begin with a model in which there are N investment managers, indexed $j = 1, \dots, N$, and an (representative) investor I .

In each period, the investment managers produce returns according to:

$$r_{jt} = \theta_j + \varepsilon_{jt},$$

where r_{jt} is the period's excess return above the risk-free asset⁵ for investment manager j , θ_j is referred to as the investment skill of the manager, and ε_{jt} is a random shock. Further, we assume for simplicity that $\varepsilon_{jt} \sim$ i.i.d. with $E(\varepsilon_{jt})=0$ and $V(\varepsilon_{jt})=\sigma^2$. In other words, we assume $E(\varepsilon_{jt} \varepsilon_{kt})=0$ for $j \neq k$ and $E(\varepsilon_{jt} \varepsilon_{js})=0$ for $s \neq t$.

Each investment manager has zero cost to operate their first fund.⁶ In addition, as we lay out in more detail later, if the manager decides to launch a second fund, they pay a cost c_j in the period when the second fund is launched. The decision to launch the second fund is tracked by an indicator variable

$$d_{jt} = \begin{cases} 1 & \text{if a second fund launched in current period} \\ 0 & \text{otherwise} \end{cases}$$

⁵ Note, in the foregoing, we will refer to the total return of investment j in period t as R_{jt} , the return of the risk-free assets as R_{ft} , and the excess return of investment j as $r_{jt} = R_{jt} - R_{ft}$.

⁶ We make this assumption for analytic convenience—assuming that an existing firm has already sunk the costs necessary to operate an initial fund. We could modify this assumption—assuming a flow cost for each fund a firm launches. While perhaps more realistic, we eschew this approach for two reasons: first, it complicates the analysis substantially—forcing us to carry extra parameters and to consider the possibility of exits as well as expansion; second, for our purposes, this cost comes at little substantive gain in intuition about diversification.

An investment manager's payoff in period t is simply:

$$u_{jt} = w_{jt}^1 + w_{jt}^2 - d_{jt} c_j$$

where the w_{jt}^k is the weight I assigns to manager j 's fund k in period t . If a second fund does not exist in a particular period, then $w_{jt}^2 = 0$. Further the investment manager's multi-period utility function is simply:

$$v_j = \sum_{t=1}^T \delta^{t-1} u_{jt}$$

In other words, the payoff is increasing linearly in the allocation weight the investor gives to the investment manager's fund less the cost of the fund. This is intended to be a simple version of a profit function for the investment manager where the costs are fixed and the revenues are proportional to assets under management (AUM).

Each investment manager's type is characterized by the pair $\{\theta_j, c_j\}$ where

$$\theta_j = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{otherwise} \end{cases}$$

and where $c_j \sim h(c)$. Further, we assume that the two types are drawn independently so $\text{Corr}(c_j, \theta_j) = 0$. In this set up, θ can be thought of as *investment skill*—as it measures how effectively a manager generates excess returns for investors; and c_j can be thought of as *managerial skill*—as it measures how economically a hedge fund firm can provide its investment skill to investors. As we will see later, these dual sources of uncertainty play a crucial role in the asymmetric information problem between managers and investors.

The investor has a standard Markowitz (1958) mean-variance utility function. In other words, in each period, the investor obtains ex ante utility of:

$$u_{it} = w_t^T \mu_t - \frac{\lambda}{2} w_t^T \Omega_t w_t \quad (1)$$

where w is a vector of allocation weights, μ is a vector of expectations of excess returns, Ω is the variance-covariance of returns the investor faces, and λ is a parameter measuring I 's risk aversion. As with the investment manager, the investor obtains a multi-period utility which is the discounted sum of the ex ante expected utilities, namely

$$v_I = \sum_{t=1}^T \delta^{t-1} u_{it} .$$

In all the foregoing we assume that the investor, in each period, acts myopically with respect to (1). The results of Samuelson (1969) and Merton (1969, 1971) show that this reduced form assumption will hold under various conditions (with rebalancing) that could easily be specified here with no material effect on the analysis. For example, long-term portfolio choice will be myopic if asset returns are drawn i.i.d. and investors have power utility over multi-period wealth (see also Campbell and Viceira 2002). Alternatively, myopic investor portfolio choices will also hold if asset returns are not i.i.d. but the investor has log-normal utility over wealth.⁷

In each period, the investor solves the problem in (1) and allocates their capital, and the investment manager chooses, at the beginning of the second period, whether to launch a new fund. So in the 3-period model, the sequence is as follows:

Period 1:

1-1: Nature draws a type for each investment manager j

⁷ An example of a power utility function would be $U(W_T) = \frac{(W_T^{1-\lambda} - 1)}{1-\lambda}$ where W denotes the investor's wealth, T is the final period of play, and λ is a parameter measuring relative risk aversion. With i.i.d. log-normal returns, this maximization will reproduce simple mean-variance results. An example of log utility would simply be $U(W_T) = \log(W_T)$. In the context of our model, perhaps the latter assumption would be a better fit as returns for the investor are not independent across time given the play of the game (i.e. in equilibrium there may be autocorrelation in returns given the equilibrium choices of the investment managers). See Campbell and Viceira (2002) for a detailed discussion.

1-2: Investor I chooses a vector of weights w_1 to each fund.

1-3: Returns are realized and period payoffs are obtained

Period 2:

2-1: Each investment manager chooses whether to launch a second fund (d_j)

2-2: Investor I chooses a vector of weights w_2 to each fund.

2-3: Returns are realized and period payoffs are obtained

Period 3:

3-1: Investor I chooses a vector of weights w_3 to each fund.

3-2: Returns are realized and period payoffs are obtained

Given this sequence of play, the investor forms beliefs about the characteristics of the funds (and managers) in their opportunity set, and then chooses weights in each period to the funds in their opportunity set based on these beliefs. The strategic choices of managers—whose returns are determined exogenously, are simply whether or not to launch a second fund in period 2, indicated by the dummy variable d_j .⁸

B. Model Results

To solve this game, we use the equilibrium concept of *Perfect Bayesian Equilibrium* (PBE), so equilibrium actions must be sequentially rational and beliefs of the players must be consistent with Bayes' Rule on the equilibrium path of play. Using this solution concept, we derive three primary results which we then evaluate empirically. First, firms which have enjoyed above average performance are more likely to diversify. Second, we show that post-diversification, those that diversify perform worse than they did pre-diversification. Finally, we show that given

⁸ Note, we adopt the notation that when we drop the subscript t from d_{jt} , the indicator variable d_j simply indicates whether a manager has chosen to diversify.

a particular pre-diversification level performance, those with greater investment skill will diversify at a higher rate than those with lesser investment skill; this implies that while diversifiers may revert to the mean, they do not revert as strongly as those with the same pre-diversification performance who do not diversify.

In order to derive these results, we start with an analysis of the behavior of the investor. Consider the investor's problem. Let μ_{jt} denote the investor's expectation, given their beliefs, about the return of manager j in period t , with associated vector of expectations of fund performance in period t denoted $\boldsymbol{\mu}_t$. Note that since a manager may have more than one fund, the vector $\boldsymbol{\mu}_t$ has dimension K_t , where K_t is the cardinality of the funds, not firms, in the investor's opportunity set, i.e. $N + \sum_1^N d_j$. Let $\boldsymbol{\Omega}_t$ be the $K_t \times K_t$ *ex ante* variance-covariance matrix of the return of the funds in the investor's opportunity set, where for convenience we will denote the rows of the matrix jk .

Given these characteristics, in period t , the investor's optimal allocation is:

$$\mathbf{w}_t^* = \frac{\boldsymbol{\Omega}_t^{-1} \boldsymbol{\mu}_t}{\lambda}. \quad (2)$$

In this formulation, a few features of the standard Markowitz optimization solution in (2) are notable. First, if investors have some (posterior) beliefs about a manager's skill represented by q_{jt} , then $E_t(\theta_j) = q_{jt}$ with some associated standard error $\sigma_{j\hat{\theta}}$.

In other words, the *ex ante* uncertainty in a manager's returns are common across all of their funds—since all of the returns are drawn from the same underlying distribution—and is the sum of the error in estimating θ_j and the random error in their return generating process. Further, based on our assumptions, returns across managers are uncorrelated, meaning most of the off-

diagonal elements of Ω_t are zero. Within a manager, however, the returns of funds have a correlated component—due to common estimation error—and an uncorrelated component (the noise from the error in the returns).

As we show in the appendix (proofs of all results also appear in the appendix) this setup has a number of features which substantially simplify characterization of the equilibrium of the game. Perhaps most notable is a result from the standard Capital Asset Pricing Model (Sharpe 1964): that the weights to managers are independent. The result is driven by two features of our model: first, manager returns are drawn independently and second there is no full-investment constraint. Further, although weights to managers are independent, weights within managers—to different funds provided by the same manager—are not independent. Because the error in estimating a manager's skills creates correlated risk across a manager's funds for the investor, the sum of weights to two funds will be (weakly) less than double the weight that would be assigned if there was only one fund.

Having established the behavior of investors, we can now turn to our results concerning diversification. As with many most signaling models, in this model there exists a pooling equilibrium—in which no one ever diversifies. This is a straightforward application of the fact that off path beliefs are unconstrained by PBE. Thus, for example, investors could believe that any diversifier is a low type and that on the equilibrium path the probability that any manager is a high type is p . These beliefs will guarantee that diversification never occurs on the equilibrium path (making the beliefs about diversification consistent with PBE). This result is summarized in

Result 1. *A pooling equilibrium exists for all parameter values of the model.*

As noted earlier, our purpose in developing the model is relatively modest: to provide a more concrete intuition for describing what we believe to be the core mechanisms at work in the

phenomena we study and to show that these mechanisms are logically consistent in the sense they constitute an equilibrium to a reasonable model of behavior. Given these objectives, and the fact that pooling is always an equilibrium, in the foregoing analysis we will examine conditions for the existence of a particular equilibrium, while not claiming uniqueness of the equilibrium or its properties. Specifically, we consider equilibria which we refer to as a **c* cut-off rule equilibrium (CRE)** as defined below.

Definition 1. *A c* cut-off rule equilibrium (CRE) is one in which all players diversify iff $c_j \leq c_k^*(r)$ where $k \in (H, L)$. Otherwise, they remain focused.*

Further, in a CRE, $\frac{\partial c_k^(r)}{\partial r} \geq 0$.*

A CRE as defined above has a few features worth noting. First, it assumes that there is a cost cutoff for each pair of type and first period return that determines whether the player diversifies—in other words players will diversify if costs are sufficiently low. In practice, any equilibrium where there is some diversification will have this feature (i.e. there is some level where no manager, regardless of their investment skill or first period returns will diversify r). Second, and less benign, is the assumption that these cutoffs are increasing in r . This assumption rules out what may be considered pathological cases where, for example, various measures of r alternative between pooling and separation; because each unique “slice” of r may pool, there are equilibria in which at lower levels managers may separate, then at intermediate levels they may pool, and then at higher levels they return to separation. The condition in Definition 1 forces equilibria to have dependence across r .

Before proving existence of a CRE equilibrium, we first establish a result which will hold in any equilibrium in which diversification occurs. In particular, one might think that firms with

identical track records in the first round will make identical decisions about whether or not to launch a new fund. In fact, this intuition is not correct.

To see this, consider the calculus behind launching a new fund for a set of managers with a return history r_1 .⁹ A manager will diversify iff:

$$w_{12}(r_1,0) + \delta E(w_{13}(r_2,0)) \leq w_{12}(r,1) + w_{22}(r,1) + \delta E(w_{13}(r,1)) + w_{23}(r,1) - c_j. \quad (3)$$

The left hand side of (3) is the payoff in the second period and expected payoff in the third period for a manager that chooses not to diversify. The right hand side is the same—for the old and the new fund—less the costs of launching a second fund, for a manager that chooses to diversify. Note that incorporated in (3) are any beliefs the investor may have after first and second period returns conditional on diversification.

Rearranging terms, we have the result that a firm will diversify iff their costs to launch a new fund are below a critical cost level $c_j^*(r_1)$:

$$c_j^*(r_1) \leq w_{12}(r_1,1) + w_{22}(r_1,1) + \delta E(w_{13}(r_2,1)) + w_{23}(r_2,1) - w_{12}(r_1,0) - \delta E(w_{13}(r_2,0)). \quad (4)$$

The inequality in (4) illustrates the tradeoff for the manager. On the one hand, in addition to the sunk costs, there are two other implicit costs to the manager for diversifying. First, as shown in the Appendix, we know that because the returns are *ex ante* correlated, the weight to the original fund in the first period will be unambiguously lower than it would have been in the absence of the launch of a second fund. In other words, there is a *cannibalization effect* that on the margin is costly in terms of a lower weight to fund 1. In addition, there is a potential for either a lower or higher weight to fund 1 in the third period, depending on the expectation of the weight given r_1 . In simple terms, if r_1 is below the manager's type, then in expectation, the weight will be higher, and if it is above the manager's type, in expectation it will be lower. The

⁹ In all the foregoing discussion, we assume that diversification is an equilibrium action, which we will prove later.

reason is that with the launch of the second fund, the manager should expect to be closer to the mean return (their type) than in the case where they do not launch a second fund and allow additional observations on their type. Thus, if r_1 is below average, this will drive down the “costs” and if it is above average, it will drive up the costs. We refer to this as the *track record dilution effect*. Finally, these (potential) costs will then be compared with an unambiguous benefit. Because investors are assumed to be unconstrained in borrowing, investors face no tradeoff in allocating to the second fund—this is simply incremental revenue and therefore will always be better for the firm, conditional on the costs, in both periods following diversification. We refer to this as the *scope extension effect*.

These observations mean that, on the one hand, managers with identical histories will be treated symmetrically by the investor in period two. On the other hand, because their expectation of future performance depends on their type, managers with lower investment skill will have less strong incentives, for every level of realized returns in period 1, to launch a second fund—the fact that their second period performance in expectation is lower than for high skilled types means they can expect lower allocations in the third period and therefore will be less willing to launch an additional fund. In other words, $c_H^*(r_1) \geq c_L^*(r_1)$. Notably, this result is irrespective of what the beliefs are conditional on diversification—for *any* beliefs after diversification (or non-diversification) and period 1 returns, in expectation the investment manager who is a low type will have a worse period 2 result than a high type, meaning the manager will expect a lower allocation to funds it owns in the third round. This conclusion is summarized as:

Lemma 1. *Conditional on first period returns r_1 , in any equilibrium in which there is diversification, the probability a high type will diversify is higher than the probability a low type will diversify.*

Lemma 1 says that when managers diversify (for some r_1), it *must* be the case that the high types diversify at higher rates than low types. That said, we still have to show that equilibria exist in which diversification occurs, a task we turn to now.

Lemma 2. *A CRE exists.*

While the proof is in the appendix the basic intuition behind the result is that every r_1 can have a unique equilibrium—we do not need to worry about what happens between different r_1 's: an investment manager cannot change or dissemble about his first period return. This allows us to choose pooling *for any* r_1 by Result 1. Thus, that players pool below the equilibrium cutoff level has to be an equilibrium. Above the cutoff, players may only have an incentive to deviate along their r_1 “slice”. But these players will only diversify if the benefits to diversification are sufficiently high—in other words, if their costs are sufficiently low. But this in turn means that we can choose cost levels such that no one above those costs will have an incentive to deviate. Finally, the beliefs are simply set such that the probability of high types given diversification (non-diversification) is rationalized by the values $\{c_k^*(r_1)\} \quad k = 1,2$.

We now turn to our primary result, Result 2, which summarizes three results from our model.

Result 2. *In a CRE, the following hold:*

(i) *Diversifiers will outperform non-diversifiers in the pre-diversification period.*

In other words, $E_j(r_1 \mid d_j = 1) \geq E_j(r_1 \mid d_j = 0)$.

(ii) *In expectation, the performance of diversifiers will fall after diversification. In*

other words, $E_j(r_1 \mid d_j = 1) \geq E_j(r_{12} \mid d_j = 1)$.

(iii) *Conditional on first period returns, diversifiers will out perform non-*

diversifiers. In other words, $E_j(r_{12} + r_{13} \mid r_{11}, d_j = 1) \geq E_j(r_{12} + r_{13} \mid r_{11}, d_j = 0)$.

At this point, the intuition behind each component of Result 2 follows relatively straightforwardly from the earlier results. The first result that non-diversifiers will under-perform diversifiers, prior to diversification is a result of two facts: cost cutoffs are increasing in first period returns by definition, and that the more skillful managers are more likely to diversify conditional on any r . Given that—as we show in the appendix, the distribution of returns exhibit first order stochastic dominance in the types—it must be the case that diversifiers will outperform non-diversifiers in the pre-diversification period. The second result follows from the same set of facts—namely that the probability of diversifying is increasing in the first period return—which in turn means it is increasing in the random shock to a manager’s return. In expectation, therefore, the post-diversification return must fall. Finally, the last component—that conditional on first period returns, the returns of diversifiers will fall less in expectation than non-diversifiers follows directly from Lemma 1. Since high-skilled types will be more likely to diversify conditional on first-period returns, they will have a higher expected return post-diversification than non-diversifiers. This in turn makes rational investors’ beliefs about the diversifiers.

C. Summary of Results

Our model demonstrates how rational investors and investment managers can create incentives (or disincentives) for the launch of new funds. Broadly, we derived three hypotheses from the model which are empirically testable, which we illustrate in the top panel of Figure 2 and summarize in the bottom panel of the figure. First, we show (Result 2) that managers who have good performance are more likely to launch new funds than those that have poor performance. Second, we show (Result 3) that after diversification, manager performance will slip, in expectation. Thus, the outperformance in the pre-diversification period is partly driven by

“luck”, in the sense of a positive shock to performance. Third, we show (Result 1) that while part of the performance is driven by luck, part is also based on skill. Since skillful firms are more likely to diversify, conditional on track record, the average diversifier is more likely to be a skilled manager relative to a non-diversifier.

III. Data

A. Institutional Background

Hedge funds are investment vehicles that, like mutual funds, pool capital contributed by investors for the purpose of investing in securities and other assets. The hedge fund industry is regulated by the Securities Exchange Commission (SEC), but unlike mutual funds, hedge funds are legally constructed to facilitate extensive short selling, leverage (e.g., debt financing) and non-linear performance-based compensation measures. In order to be exempt from the stricter investment and compensation restrictions that mutual funds face, hedge funds must be open only to accredited investors – individuals with either \$1 million of net worth or an annual income in excess of \$200,000. Hedge funds also face limits on the number of investors, however, in practice this limit is rarely binding as firms may pool individual investors into limited partnerships that count as only a single investor.

The hedge fund industry offers a unique laboratory for studying skill, luck and reputation effects. Hedge funds are owned by the managers that run them, obviating traditional agency costs between investors and managers in operating the firm *ex post*. However, as residual claimants of funds (e.g., products), investors are exposed to managers’ incentives to misrepresent their skill *ex ante* (θ in the notation above). Thus, the hedge fund context allows us to disentangle agency costs associated with asymmetric information about managerial ability from

the broader set of agency costs associated with the separation of ownership and control. Furthermore, firm and performance is readily measurable over relatively long periods of time, which allows us to separate persistent skill effects from idiosyncratic luck.¹⁰

Although our focus is on skill, luck and reputation effects in horizontal diversification decision in general, the hedge fund industry is interesting to study in its own right. As of 2006 the hedge fund industry managed \$1-2 trillion, which is remarkable considering that the industry only managed about \$50 billion as of 1990 (Stulz 2007). While the present financial crisis has clouded the outlook for the industry it appears likely that hedge funds will remain as important financial market intermediaries going forward.

Of course, the hedge fund industry is somewhat unique, and so caution should be applied in generalizing the results of this study to other industrial contexts. Hedge fund firms diversify by launching new funds, which are investment products that deliver a stream of cash flows. Thus, hedge fund customers are also investors. While hedge fund diversification is similar to product diversification in industrial companies, in the sense that the performance of each new product impacts the firm's overall brand reputation (Wernerfelt 1988; Cabral 2000), industrial customers are not typically investors, and industrial investors cannot usually choose which of the firm's products they invest in. The fact that hedge fund customers are also investors has implications for the generalizability of the results in this paper to other product diversification settings. For example, product performance may not be as volatile in industrial markets as in hedge funds, which would imply that agency costs associated with market timing around peak performance may be less important in other product diversification contexts. On the other hand the results generalize easily to other financial firms and to corporate diversification settings, though

¹⁰ Although monthly returns are self-reported, annual returns reported to investors are audited allowing investors to compare audited annual returns to self-reported monthly returns.

managerial skill may be harder (easier) to observe in other settings, and therefore the impact of asymmetric information on diversification decisions will be less (more) important in other contexts.

B. Data and Sample

Hedge funds are closed to the general public and are not required to publicly report their returns. However, a large number of funds do report their returns to one or more private companies that make their data available by subscription to researchers. Our data on hedge funds are from Lipper TASS and Hedge Fund Research (HFR) and were provided to us for research purposes by a major financial institution. Amongst all the datasets used in the hedge fund literature TASS and HFR are considered the most comprehensive (Li, Zhang and Zhao, 2007). The data from both TASS includes “graveyard” funds – funds that stopped reporting to the data providers for any reason including fund failure – dating back to 1994. We use the full dataset for our baseline analysis, and then replicate the analysis using only the survivor bias free sample from TASS 1994-2006. The smaller dataset generates similar, though noisier estimates. Taking TASS and HFR together we have coverage on 3,137 firms over the period 1977-2006 representing approximately 25% of the firms in the industry.¹¹

To make the analysis tractable we examine only the first horizontal expansion decision a firm makes. Our analysis, therefore, focuses on 2,113 firms that enter as focused firms, 1,225 firms that remain focused and 888 firms that subsequently diversify (see Figure 1)¹², and excludes firms that enter as diversified firms, which we define as becoming a diversified firm within the first twelve months of entering the dataset.. After excluding 68 funds that reported less than

¹¹ Where differences arise between TASS and HFR we use data from the provider that captures a longer history of returns on a fund by fund basis.

¹² For legal reasons many firms offer identical funds as onshore (U.S. domiciled) and offshore (non-U.S. domiciled) products. We treat these onshore/offshore twin funds as a single fund..

twelve months of returns or did not report returns continuously the potential data universe contains 2,045 firms including 826 diversified firms. After matching diversified firms to firms that do not diversify (described below), our test sample consists of 86,976 fund-months from 1,576 firms, of which 788 diversified are firms and 788 are matched focused firms.

Getmansky, Lo and Makarov (2004) report that serial correlation can be problematic for measuring excess returns in hedge funds since funds often hold illiquid and hard to value assets. Though we explicitly adjust for liquidity risk exposure in one of our key measures of excess returns we control for serial correlation in the time series of returns using an autoregressive lag one (AR1) correction. The AR1 correction also alleviates concerns that returns may be serially correlated due to self-reporting. A second concern about self-reporting is that firms may wait to report their returns to data vendors (“backfill”) until they do well, while omitting returns for funds that perform poorly. Posthuma and Jelle van der Sluis (2003) drop the first 36 months of self-reported returns to control for backfill bias. We drop the first month of recorded return data as we found that only the first reported monthly return was significantly different from long-run average returns.¹³

We are also concerned that moral hazard may lead firms to manipulate their self-reported returns. Even if external audits forced hedge funds to value assets at their true market values at year end, firms might manipulate monthly returns within a year for strategic reasons in ways our AR1 model cannot pick up, for example by inflating performance just before diversifying and then deflating it several months after diversification. Since we do not know when or if firms manipulate their returns we must rely on our empirical design to control for these effects, or at least to sign the bias associated with return manipulation. Fortunately the most obvious self-

¹³ Although dropping additional months has little effect on estimated coefficients it does lead to noisier estimates as 67% of the firms in the sample diversify for the first time within the first 36 months.

reporting bias is not a problem for our main tests on firm skill, since strategic manipulation in anticipation of diversification would bias the results against our hypothesis (e.g., returns would fall more after diversification than without manipulation). However, inflated *ex post* returns in diversified firms is problematic for skill tests as is *ex ante* manipulation in tests for luck. We address this issue by (1) using multiple years of lagged excess returns as our *ex ante* performance measure, (two years of lagged returns in our baseline model and five years of lagged returns as a robustness check), which firms could only manipulate through multi-year efforts and (2) eliminating firms whose self-reported risk adjusted return profile lies in right tail of the distribution.¹⁴ While we cannot rule out earnings manipulation, given the empirical design it seems unlikely that this effect is driving our results.

C. Dependent Variables

We test our predictions using multiple measures of performance including raw returns, and risk-adjusted excess returns relative to passive and active investment benchmarks. In our theoretical model, relative performance both establishes a hedge fund's reputation and reveals the underlying skill of a firm, but the appropriate empirical measure of performance depends crucially on the risks against which performance is evaluated. The recent financial crisis has raised questions about our understanding of hedge fund risks, and therefore our ability to accurately measure hedge fund performance empirically (Lo 2008). We, therefore, use a range of measures intended to control for systematic and non-systematic risk exposure and show that our results are robust to a wide range of plausible measures of performance. Because there is general agreement in the literature that investors price financial assets controlling for systematic

¹⁴ Specifically we replicated all of the tests below after dropping firms in the top 1%, 5% and 10% of the information ratio distribution, and found that the results were qualitatively unchanged. We also eliminate firms whose *ex ante* characteristics are off the common support of the distribution of propensity scores predicting diversification.

risk exposure, and we assume hedge fund investors benchmark performance against broad market indices or mutual funds as a first approximation of fund performance, we use standard asset pricing models to estimate excess returns in our baseline specification. However, hedge funds may also be exposed to non-systematic risks that are not priced by standard passive market benchmarks. If funds take on significant non-systematic risks, due perhaps to aggressive use of leverage, they may appear to generate large average excess returns that are really an artifact of model mispricing. Similarly funds that hedge against non-systematic risks may appear to be poor performers, when in fact they are really providing value that is not priced by traditional asset pricing models. We account for the non-systematic riskiness of a fund's underlying investments using a dynamic version of the information ratio, the systematic component of excess returns ("alpha") plus the (time-varying) residual, divided by the standard deviation of excess returns. We also control for the average return of other hedge funds in the same strategy class in both the selection equation and as an alternative dependent variable to account for time-varying risk exposures that arise from dynamic trading strategies.

The baseline passive benchmark is developed using the standard Fama-French three-factor model (1996) plus a momentum factor (Carhart, 1997), where excess returns are the sum of a time-invariant fund-specific term a plus a mean zero residual e from the regression:

$$R_{it} = a_i + R_{ft} + \mathbf{X}_i \mathbf{B}_i + e_{it}, \quad (5)$$

where i and t index funds and time (in months) respectively; R_i is a fund's raw return and the vector \mathbf{X} contains the three Fama-French (1996) factors $R_m - R_{ft}$, HML and SMB and Carhart's momentum factor MOM : $R_m - R_{ft}$ is the market equity return less the risk free rate, HML is the return on value relative to growth stocks less the risk-free rate, SMB is the return on small stocks relative to large stocks less the risk-free rate, and MOM is the return on one-year momentum

versus contrarian stocks. The term a_i is the time invariant component of a fund's performance and e is the residual. We take the factors *HML*, *SMB*, *MOM*, R_f , and R_m from Ken French's data library,¹⁵ R_i from TASS and HFR, and compute a , the coefficients on \mathbf{X} and e by running fund-level longitudinal regressions. We call this measure "4-factor excess returns."

Because hedge funds often hold illiquid investments, and liquidity risk can be an important determinant of cross-sectional hedge-fund returns (Sadka 2009), we run an alternative specification of (5) that includes a liquidity factor developed by Pástor and Stambaugh (2003) that controls for investor exposure to illiquidity risk.¹⁶ Including the Pastor-Stambaugh "traded liquidity factor" creates our second passive return benchmark, which we call "5-factor excess returns".¹⁷ There is little agreement in the literature about the appropriate active trading benchmark for hedge funds. To see if the results are robust to a reasonable active benchmark we include the average equal weighted monthly return for all other funds in the same self-identified strategy class as a fifth factor in \mathbf{X} .¹⁸

Excess returns Y in any period t are defined as $Y_i = a_i + e_i$, where excess return captures the combination of a fund's skill and luck relative to a market benchmark. The empirical distribution of excess returns in our sample under all three measures - 4-factor, 5factor and active benchmark - are symmetric and slightly positive on average, though they are more peaked than in a normal distribution. The distribution of the information ratio is approximately normal under

¹⁵ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

¹⁶ Aragon (2007) shows that funds holding assets with higher average liquidity earn higher returns, perhaps due to market frictions associated with heterogeneous investor horizons. We control for systematic differences in average liquidity across funds with a fund fixed effect in our main specification below.

¹⁷ These data are available at http://finance.wharton.upenn.edu/~stambaugh/liq_data_1962_2008.txt.

¹⁸ Alternative asset pricing models are often used in the hedge fund literature including Fung and Hsieh's (2001) 7-factor model and Agarwal and Naik's (2004) multifactor model with controls for exposures to equity, bond, commodity and option-based factors. In practice we found that adding additional terms had little effect our excess return measure (though doing so does reduce the sample size somewhat). All of the tests in this paper were reproduced using Fung and Hsieh's (2001) 7-factor model and the results were qualitatively unchanged. Results are available from the authors upon request.

each specification. Both the information ratio and excess returns are winsorized at the 1% and 99% level to control for extreme values.

We use excess returns as a dependent variable in our OLS regressions and also use excess returns to compute average cumulative abnormal returns (CAR), where $CAR = \sum Y_{it}/n$, the sum of n lagged excess returns divided by the number of months the firm was in operation at time t , a standard measure of a fund's cumulative historical performance, in our probit model predicting the launch of a new fund. We use average two-year CAR as our key performance variable predicting the launch of a new fund as our interviews with hedge fund managers revealed that it generally takes between one and two years from planning a new fund to launching it.¹⁹

Table I shows descriptive statistics for excess returns. On average the funds in our baseline sample generated a thirty-four basis point risk-adjusted return per month with a standard deviation of 4.7% per month.

D. Controls

Table I also shows descriptive statistics for the main right hand side variables drawn from TASS and HFR. Chen, Hong, Huang and Kubik (2003) show fund that size, measured by assets under management (AUM), is negatively correlated with performance in the mutual fund industry, particularly for mutual funds that invest in illiquid assets. It, therefore, seems likely that fund size influences both hedge fund performance and a firm's decision to diversify. The average fund had \$93 million of AUM, while the average firm held \$160 million of AUM. The size distribution of AUM is skewed right with the top 1% of funds growing to \$1.9 billion.²⁰ We take the non-normality of AUM into account by using fund and firm AUM size deciles from the overall distribution of all TASS and HFR funds and firms, although our results are unchanged

¹⁹ The results are not sensitive to the number of months used in the average CAR calculation.

²⁰ Assets under management are reported winsorized at the 1st and 99th percentile, though winsorizing has no effect on the results.

when we use the log of AUM instead of using size deciles. 14% of fund-months had missing AUM, which we control for using a missing AUM dummy variable.

19% of funds reported that they were fund-of-funds that invest in other hedge funds.²¹ 22% were long/short funds – a general type of hedge fund that often has no meaningful restrictions on investment strategy. The other 59% of funds were distributed over 32 additional investment strategy categories with the largest being managed futures (11%), equity hedge (9%), and event driven (8%) strategies. No other strategy category had more than 5% of fund-months. There are two reasons for the fragmented nature of the investment strategy categories. First, in the results reported here we did not attempt to consolidate strategy definitions across TASS and HFR, but rather used the strategy class as reported. As a robustness check we re-ran all of our tests after forcing TASS and HFR to a common, and parsimonious, set of strategies and found that the results were unchanged. Second, many strategies emerged in the late 1990s and so reported relatively few fund-months compared to more traditional hedge funds like long/short funds.

The growth of the hedge fund industry is also reflected in the time weighting of returns, as 49% of reported fund-month returns in our baseline sample came in the last five years of the data set. We report calendar year averages, but we use periodicity in three ways in our analysis: twenty-one year control for hedge-fund specific calendar time effects, market returns for 360 calendar months control for time series variation in market returns in our computation of excess returns, and eighty-four event time categorical variables control for the time path of returns before and after the launch of a new fund (or match date) in our matched tests.

Age effects may also be important in hedge fund diversification decisions as older firms may be less inclined to pursue new strategies once they are well established in their base business.

²¹ Fund of funds take positions in other hedge funds. Since fund of funds are somewhat different from traditional hedge funds we wanted to be sure they were not driving the results in the paper. As a robustness check we replicated all of the results in this paper excluding fund of funds (result omitted).

The average observation in the baseline sample was five years old. We begin tracking firms after their first month of reported returns. Therefore, the youngest fund in our analysis is two months old. We enter age in log months into the probit predicting diversification to control for the long right tail of the distribution.

The hedge fund industry is a global industry, though approximately two-thirds of the firms in our sample are based in the United States. 16% of fund-months come from European firms (8% U.K. and 8% from mainland Europe), 3% from Asia-based firms and the remainder from the rest of the world. To the extent that regional differences influence diversification decisions we also control for the location of the firm's headquarters in the probit.

IV. Empirical specification and results

A. Within-firm changes

One of our key results is evident in a simple time-series plots of excess returns. Figure 2 shows the relationship between fund performance and diversification graphically, plotting first fund average excess returns for 48,410 fund-months from the 788 diversifying firms. The figure shows average monthly 4-factor excess returns from twenty-four months before and sixty months after the launch of a new fund. More formally, we estimate changes in performance using the within firm estimator (6):

$$Y_{it} = \alpha + \lambda_i + \text{DIVERSIFIED}_{it} + T_t + \mathbf{X}_{it}\boldsymbol{\beta}_c + \varepsilon_{it}, \quad (6)$$

where i and t index funds and time (in months) respectively; Y takes on four values: 4-factor and 5-factor excess returns, and the information ratio from 4-factor and 5-factor returns; λ is a fund fixed effect; *DIVERSIFIED* is a dummy variable that is equal to one when a fund is part of a

diversified firm and zero otherwise; T is a vector of twenty-one calendar year dummies; and X_c is a vector of fund size dummies measured by assets under management; and ε is the residual.

Table II shows the results of the within-firm estimator (6). The correlation between diversification and changes in fund performance is clearly negative across all four specifications. Excess returns are 11-12 basis points per month lower following diversification and are reliably different from zero in both 4-factor and 5-factor specifications. Using the information ratio performance is 2-3 basis points per month per unit of risk lower following diversification, though the 5-factor specification is only on the margin of statistical significance.

Excess returns are clearly falling following diversification in Figure 2 and Table II. However, the results also raise questions about the selection process firms undergo when choosing to launch a new fund, as it is clear in the figure that excess returns are quite high prior to the launch of a new fund, suggesting that higher excess returns may cause firms to launch a new fund. To understand if hedge fund returns fall following diversification because diversification causes returns to fall perhaps due to managerial distraction as in Schoar (2002), or because managers exploit lucky streaks to diversify, or whether skilled firms diversify when they are lucky, or some combination of the above, we need to benchmark diversifiers against a control group to establish a valid counterfactual. In particular we need to specify a control group that experienced a similar pattern of *ex ante* returns, which we can use to control for mean reversion from an unusually high baseline around the event window. To develop a valid counterfactual we turn to our matching model.

B. The Propensity to Launch New Funds

Our main objective is to understand how skill and luck influence the firm's decision to launch a new fund. To do so we use both *ex ante* and *ex post* information embedded in returns

and other observable characteristics of firms and funds. Our baseline approach follows the standard event study methodology developed by Fama, Fisher, Jensen and Roll (1969) to measure the relationship between diversification and (legacy) fund returns, and follow Campa and Kedia (2002) in using propensity score matching to develop a valid control group of focused firms against which to measure firm performance after horizontal expansion.

We estimate a probit model to test whether firms tend to launch new funds when they experience unusually strong short-run performance, as predicted by Result 2 (ii). We then expand the probit to include all observable *ex ante* firm and market factors, including interaction and quadratic terms that might plausibly influence firms' decisions to launch new funds for the first time to create a valid control group, as in (7):

$$\text{LAUNCH}_{it}^* = \mathbf{x}_{it}\boldsymbol{\beta} + \xi_{it}, \quad (7)$$

where the unit of observation is the fund-month for fund i in month t . We estimate the latent variable $LAUNCH^*$ using $LAUNCH = 1$ [$LAUNCH^* > 0$] when the firm launches a new fund; \mathbf{x} includes all observable characteristics of firms that might plausibly have an effect on the decision to launch a new fund including all relevant interaction terms and polynomials. The vector \mathbf{x} includes two-year average monthly cumulative abnormal returns (CAR), average CAR for other firms in the same strategy class, ten fund size declines, where size is measured in terms of under management (AUM), log firm age, 21 time (year) dummies, 10 fund investment strategy dummies, four regional geographic location dummies, and ξ - an error term, which is assumed to be normally distributed with mean zero and variance one in a probit specification.

Our objective is to find a set of focused firms are similar to the set of diversifying firms along all observable dimensions just prior to diversification. We, therefore, drop diversifying firms

from (7) following the month in which they launch a new fund, while all fund months are included for firms that remain focused, resulting in 97,713 fund months from 2,045 firms.

We show the result of estimates of the probit model (7) using all 2,045 firms and 97,713 fund months in Table II columns 1-2. Column 1 shows the raw coefficients and standard errors from selected variables from the probit estimation.²² Column 2 shows the marginal effects of each explanatory variable holding all regressors at their mean values. The coefficient on average cumulative abnormal returns (*CAR*) is 0.0005, which means doubling *CAR* from the mean increases the chance that a firm will diversify by 5% in a given month and is strongly statistically significant as predicted by the first hypothesis.

The probit model generates an overall propensity to launch new funds score for each fund-month, which facilitates the creation of a matched control group that we use to understand the implication of information about luck and skill embedded in *ex post* returns. Our propensity score matching approach builds on Rosenbaum and Rubin (1983), who show that matching on propensity scores using all relevant observable characteristics generates a valid control group against which treatment group effects can be compared.

Columns 3-4 in Table II show the mean values for each regressor for focused and diversifying firms, while column 5 shows a t-test on the differences in means between these two values. Inspection of columns 3-5 immediately reveals why propensity score matching is so important in this context as the means of nearly all of the covariates are statistically different between the 826 fund-months where firms launch new funds and the 96,887 months in which focused firms remain focused. Indeed, the comparison between these two groups in columns 3-5 immediately gives rise to fundamental questions about what an appropriate control group is for a firm launching a new fund.

²² For presentation purposes we suppress coefficients for 21 year fixed effects..

We find and exploit a valid control group using standard propensity score matching techniques. First, as in Rosenbaum and Rubin (1983), we calculate the propensity score of the probability of a fund selecting the binary treatment (new fund launch) in any particular month, using the probit model (7). Next, we trim the sample at the 1st and 99th percentile of the propensity score distribution and eliminate firms off the common support of the propensity score of the probability of launching a new fund. Finally, we match diversifiers to controls using nearest neighbor matching without replacement to create a balanced sample of 788 treated (diversified) and 788 control fund-month observations. The interpretation of the control group is that for each fund that did launch a new fund in a particular month we have identified the fund that was most similar in terms of all observable characteristics that did not launch a new fund. Columns 6-8 in Table III replicate columns 3-5 for only the matched and trimmed sub-sample. Overall matching quality is quite strong. Comparing the differences in the means in the full sample (column 5) versus the matched sample (column 8) reveals that matching substantially align the *ex ante* characteristics of the firms in the diversified and focused groups. Figure 4 shows this effect graphically. Figure 4a shows the kernel density plots of the distribution of the propensity scores for diversified and matched focused firms. Whereas the distributions were quite different before matching, after matching (Figure 4b) they are essentially identical.

We construct our event study around the diversification or match date for the 1,576 unique funds identified in our propensity score matching algorithm. We call the period in which these funds launched a second fund or were matched “the event” and refer to the months around the event in terms of event time, with the event taking place at event time zero. To construct our matched test sample we include the twenty-four months before (-24, -23, -22, . . . , -1) and fifty-nine months after the event (1, 2, 3. . . , 59). Altering the window around the event had no

qualitative effect on our results, although the results are generally more precise the wider the window.²³

C. Matched Sample Ex Post Returns

After developing a valid control group, we next estimate the difference in *ex post* returns between diversifying firms and the matched set of focused firms using the OLS model (8):

$$Y_{it} = \alpha + \text{DIVERSIFIED}_{it} + T_t + \mathbf{X}_{it}\boldsymbol{\beta}_c + \varepsilon_{it}, \quad (8)$$

where i indexes 1,576 firms and t indexes calendar time; Y , *DIVERSIFIED* and \mathbf{T} are as above in (6); and \mathbf{X}_c includes fund size dummies. We also include in \mathbf{X} a vector of event time (month) dummies for the sixty months after launching a new fund (or match date for the control group) that controls for the pattern of mean reversion following the event; and ε is the residual. The element of time distinguishes between the matched and the unmatched (within) tests. When the set of diversifying firms is not matched to the control group calendar time dummies are included to control for periodicity. By contrast when diversifying firms are matched to focused firms the matching model precisely defines event time, and the pattern of mean reversion following unusually large *ex ante* excess returns, which we use to compare the *ex post* performance of diversifying firms and firms that will remain focused.

Table IV shows the matched sample *ex post* returns. Excess returns are 11-12 basis points per month higher and the information ratio is 4-5 basis points per month higher per unit of risk in the 4-factor and 5-factor specifications respectively, and the coefficient is reliably different from zero in all four specifications. The interpretation supports our key contention that diversifying firms outperform firms that remain focused *ex post*, conditional on being similar across observable (to the econometrician) dimensions *ex ante*.

²³ We show one such result with a sixty month *ex ante* and sixty month *ex post* event period in the robustness checks (Table VI Panel B) using the matched differences-in-differences specification described below in (9).

But what if firms in the control and treatment groups differed systematically *ex ante* in ways that are not observable to the econometrician? If any *ex ante* systematic difference are attributable to skill the unobservable factors would support our hypotheses, but if the differences are due to other firm-specific factors like prestige or unique access capital that are unrelated to skill these effects would contaminate the results. Furthermore, we have matched on the propensity to diversify based on all observable *ex ante* characteristics of firms including average cumulative abnormal returns (CAR), but have not forced returns to be identical *ex ante*. Indeed, we know from Table III that diversifiers have higher CAR, though not statistically different, compared to the control group. Thus, the possibility exists that the matched *ex post* returns are higher in diversifiers due to firm specific heterogeneity that is unrelated to skill.

D. Matched Sample Differences-in-Differences

To address identification issues associated with unobserved heterogeneity across firms we go one step further and specify a matched sample differences-in-differences model with firm fixed effects using (9):

$$Y_{it} = \alpha + \lambda_i + \text{DIVERSIFIED}_{it} + T_t + \mathbf{X}_c \boldsymbol{\beta}_c + \varepsilon_{it}, \quad (9)$$

which is identical to (8) but for the inclusion of a firm fixed effect and covers the full sample period from twenty-four months before the event until sixty months after.

By including firm, and calendar time, and event time fixed effects in our (9) we absorb time-invariant firm-specific characteristics, time-varying market characteristics, and control for the precise pattern of mean reversion that may influence the observed returns to horizontal expansion, allowing the coefficient on diversification to capture time varying skill differences embedded in *ex post* returns. Table V shows the relationship between diversification and changes in fund performance, measured by 4-factor and 5-factor excess returns and the

information ratio. The results are consistent with the matched *ex post* results. Changes in excess returns are 12-13 basis points per month higher in diversifying firms relative to changes in firms that remain focused in the 4-factor and 5-factor specifications respectively, and the results are statistically significant at the 5% level. The information ratio results indicate that changes in returns are 3-4 basis points per month higher per unit of risk in diversifying firms relative to changes in firms that remain focused, and are reliably different from zero across both 4-factor and 5-factor specifications. Thus, the positive diversification effect is robust to controls for time-invariant firm-specific heterogeneity suggesting that diversifying firms choose to diversify in the expectation that they have greater ability to generate positive future returns, relative to other firms with the same *ex ante* track record.

We interpret these results, in combination with the probit results, as evidence supporting the first two hypotheses: firms tend to launch new funds when they experience large temporary idiosyncratic performance shocks. Furthermore, consistent with the third hypothesis, diversified firms' legacy funds outperform a control group of firms with similarly strong *ex ante* excess returns who did not launch new funds, even controlling for time-invariant firm-specific heterogeneity. Although the results do not permit us to identify the precise mechanism underlying the skill – advantage diversifiers have over firms that remain focused it is clear that better firms diversify. As we note above, diversifying firms either have greater skill in terms of identifying new opportunities *ex ante* and/or greater skill in the sense that they are able to create value through synergy where similar firms cannot, and both interpretations are consistent with our predictions.

E. Robustness checks

We are concerned about four types of threats to our inferences about the roles of skill and luck in diversification decisions: (1) the results may be sensitive to the measure of performance; (2) firms might launch new funds and use them to subsidize their legacy funds; (3) the results may be influenced by survivor bias; and (4) the results may be sensitive to the matching process. In this section we examine each of these issues in turn.

The results are robust to alternative measures of performance. Including the term *AVGSTRAT*, the average return of other hedge funds in the same strategy class, in our estimates of excess returns controls for systematic risks associated with a fund's active trading strategy relative to other hedge funds pursuing similar trading strategies. As shown in Table VI Panel A we find very similar results using the active measure of excess returns and the information ratio even when including firm fixed effects as in (9). We also found similar results using simple raw returns and Fung and Hsieh's (2001) 7-factor excess return measure (not shown).

If firms launch new funds and use them to subsidize their legacy funds then legacy returns might increase even as overall firm returns remain flat or decline, a result that would be at odds with our skill-based explanation for the results in Table VI. To test whether our results are sensitive to cross-subsidization across funds within a firm we aggregate returns to the firm level and evaluate the relationship between diversification and aggregate performance relative to the matched control group. Table VI Panel A shows the results of firm-level regressions of diversification on 4-factor value weighted and equal weighted firm performance, which are estimated using model (9) with firm-fixed effects.²⁴ 4-factor excess return and information ratio results are even larger than in the fund-level tests, which provides further evidence that

²⁴ In the firm-level regression size is estimated using log assets under management instead of a vector of size categorical.

diversified firms outperform focused firms either because the diversifying firm has better ability to recognize new opportunities or because diversifying firms have the skill to create synergies by operating multiple funds within a single corporate structure, or both. We obtained similar results using alternative performance measures.

Survivorship bias would be problematic for our interpretation that skilled firms diversify, if some firms diversify perform very badly *ex post* and then exit the sample, as this would bias the coefficient on *DIVERSIFIED* upward in the matched sample. To evaluate the impact of survivorship bias on the results we estimate each of the models for only the subsample of the data that is free of survivor bias. We find that all of the results are consistent with the full sample results. Panel B shows the results from the matched differences-in-differences model (9) for the survivor-bias free matched sample. The point estimates on excess returns and the information ratio are larger but noisier than in the baseline model. While the precision is worse, the excess return result is not statistically significant; the results are broadly consistent with the full sample results.²⁵

Matching plays a central role in our empirical design. We, therefore, wish to evaluate whether our results are sensitive to different matching regimes. We are particularly concerned that effect of returns at any point in time might be heterogeneous due to time-varying macroeconomic conditions. Thus, firms with high average cumulative abnormal returns (*CAR*) might not be comparable if matched asynchronously, even with the inclusion of calendar year fixed effects in the test specifications. The precise pattern of *ex ante* returns, as opposed to the smoothed value of *CAR*, might also influence returns. As can be seen in Figure 5 the baseline matched *ex ante* returns dip below diversifiers immediately prior to diversification (or matched

²⁵ Coefficient estimates and standard errors are similar using 5-factor and 7-factor performance measures.

event date) even though the difference in *CAR* is not statistically significant between the diversifiers and the control group.

To address concerns about asynchronous matching and other potential non-linear effects in the selection process we specify a matching model with an expanded set of interactions and higher order polynomials including *CAR* interacted with the full set of calendar year dummies, *CAR* interacted with log age, *CAR* interacted with log size, log size squared, log size interacted with log age, the coefficient values from the asset pricing model (5) and the standard deviation of excess returns, in addition to the matching variables shown in Table III.²⁶ Figure 6 shows the plot of matched excess returns for the expanded matching model. Visually the match on *ex ante* excess returns appears to be an improvement on the more parsimonious baseline matching model, though the match quality on overall propensity score is almost identical. Table VI panel B shows that the coefficient estimates on *DIVERSIFIED* are quite similar in terms of magnitude and precision compared to the baseline model for both excess return and the information ratio specifications. Results are very similar using 5-factor performance measures.

Our empirical strategy rests on the idea that we can identify selection on skill (and luck) into diversification using the information embedded in *ex post* (and *ex ante*) returns. To do so we must correctly identify the relationship between diversification and *ex post* returns. While matching diversifiers to focused firms is a plausible method for identifying the relationship Imbens (2004) shows that identification using matching can be strengthened by weighting observations by the inverse probability of selection. In Table VI Panel A we verify that sample weighting by the inverse probability of selection generates similar coefficient estimates on *DIVERSIFIED* in the matched differences-in-differences specification. Both the point estimates on excess returns and the information ratio are larger and noisier than in the baseline

²⁶ Size, measured in terms of assets under management, enters in logs in the expanded matching model.

specification, but are still statistically significant at the 10% and 5% level respectively. 5-factor and 7-factor performance results are qualitatively the same.

V. Conclusion

We develop an equilibrium model of diversification that is consistent with agency theory and economies of scope, where both skill and luck influence the firm's decision to diversify into a new product. We show that while both skill and luck have a positive impact on a firm's decision to launch a new product, market discipline constrains lucky but low skill firms' horizontal expansion choices. We test our propositions in the context of the global hedge fund industry over a thirty year period 1977-2006. The results show that firms launch new funds when they experience extraordinary short-term positive returns that do not persist, suggesting that firms tend to launch new funds when they are lucky. Comparing firms that experience similar *ex ante* short-term performance reveals that diversified firms outperform firms that remain focused *ex post*. The results are consistent across different measures of performance, different samples and across specifications. Taken together the results support agency theory's prediction that diversification decisions are influenced by private information held by managers with private incentives, yet also suggest that economies of scope dominate agency effects in equilibrium as firms with greater skill are shown to be more likely to engage in product diversification in hedge funds.

APPENDIX

Proofs of Results in Section II

Lemma A1. *The investor's optimal weight to fund manager i has the following properties:*

- (i) *is independent of the weight to fund manager $j \forall i \neq j$;*
- (ii) *is decreasing in μ_{i^*} , and therefore is decreasing in q_{i^*}*
- (iii) *is decreasing in the variance (diagonal element of Ω_t)*
- (iv) *is decreasing in $R_{i^*}^2$ where $R_{i^*}^2$ is from the regression of the returns of manager i on the returns of the other managers*

Proof of Lemma A1. Results (i)-(iv) follow from Sharpe (1964) and (3). ■

Proof of Result 1. Consider for any parameter values an equilibrium in which for any first period return, no player diversifies and in which investors believe

$\Pr(\theta = \theta_H \mid d = 0, r) = \Pr(\theta = \theta_H \mid r)$ and $\Pr(\theta = \theta_H \mid d = 1, r) = 0 \quad \forall r$. To check if this is an equilibrium, consider if a player would want to deviate for some r . Deviations in this case would be for either type to diversify. In the case of non-deviation, a player's expected payoff would be $\Pr(\theta = \theta_H \mid r) + \delta \Pr(\theta = \theta_H \mid (r, \theta_k))$. In the case of diversification, the payoff would be $0 - c_j$ given the investors' beliefs. Since the former is positive and the latter is negative, deviations from the equilibrium are unprofitable. Thus, on the equilibrium path, non-diversification provides no information concerning an investment manager's type, so $\Pr(\theta = \theta_H \mid d = 0, r) = \Pr(\theta = \theta_H \mid r)$. Off the equilibrium path, the investors' belief about the

investment manager are unconstrained in a PBE, meaning $\Pr(\theta = \theta_H \mid d = 1, r) = 0$ is allowable. ■

Proof of Lemma 1. Assume an arbitrary posterior estimate conditional on play of the game to that point that the investor holds about managers with a particular history. Given these beliefs, as in (3), a manager will diversify iff

$$w_{12}(r_1, 0) + \delta E(w_{13}(r_2, 0)) \leq w_{12}(r, 1) + w_{22}(r, 1) + \delta E(w_{13}(r, 1)) + w_{23}(r, 1) - c_j.$$

Rearranging, we have

$$c_j^*(r_1) \leq w_{12}(r_1, 1) + w_{22}(r_1, 1) + \delta E(w_{13}(r_2, 1)) + w_{23}(r_2, 1) - w_{12}(r_1, 0) - \delta E(w_{13}(r_2, 0)).$$

Since $E(w_{13}(r_2, 1)) - E(w_{13}(r_2, 0))$ is lower for a low type than a high type, it must be the case that

$$c_H^*(r_1) \geq c_L^*(r_1). \text{ Since } c_j \sim h(c) \text{ is the same for low and high types, and } \text{Corr}(c_j, \theta_j) = 0, \text{ this}$$

implies that

$$\Pr(d_j = 1 \mid \theta_H, r_1) = \Pr(c_j > c_H^*(r_1)) \geq \Pr(d_j = 1 \mid \theta_L, r_1) = \Pr(c_j > c_L^*(r_1)) \quad (\text{A1})$$

The remainder of the result follows trivially from (A1). ■

Proof of Lemma 2. Consider a CRE (per Definition 1) cutoff functions $\{c_k^*(r_1)\}$. For all r_1 , we must check whether deviations are profitable for type θ_k . Consider θ_L and fix $\{c_k^*(r_1)\}$ $k = 1, 2$.

On the equilibrium path, the investor will believe that $\Pr(d_j = 1 \mid \theta_L, r_1) = \Pr(c_j < c_L^*(r_1))$ and

$$\Pr(d_j = 1 \mid \theta_H, r_1) = \Pr(c_j < c_H^*(r_1)). \text{ Further, from Lemma 1, we know the first term is lower}$$

than the second. Using these expressions, we can then solve for the beliefs of the investor on the

equilibrium path $\Pr(\theta_k | d_j = 1, r_1)$ and $\Pr(\theta_k | d_j = 0, r_1)$. By Bayes Rule and the above results, we have

$$\Pr(\theta_k | d_j = 1, r_1) = \frac{\Pr(r_1 | \theta_k) \Pr(\theta_k) \Pr(c_j < c_k^*(r_1))}{\Pr(r_1 | \theta_k) \Pr(\theta_k) + \Pr(r_1 | \theta_{-k}) \Pr(\theta_{-k})} \quad (\text{A1})$$

and

$$\Pr(\theta_k | d_j = 0, r_1) = \frac{\Pr(r_1 | \theta_k) \Pr(\theta_k) \Pr(c_j > c_k^*(r_1))}{\Pr(r_1 | \theta_k) \Pr(\theta_k) + \Pr(r_1 | \theta_{-k}) \Pr(\theta_{-k})}. \quad (\text{A2})$$

Using these two expressions, the expected utility in equilibrium of each type is

$$EU(\theta_k | d_j = 1, r_1) = \sum_i w_i^* (\Pr(\theta_H | d_j = 1, r_1)) + \delta \sum_i w_i^* (\Pr(\theta_H | d_j = 1, (r_1, E(r_2 | \theta_k)))) - c_j$$

and $EU(\theta_k | d_j = 0, r_1) = w^* (\Pr(\theta_H | d_j = 0, r_1)) + \delta w^* (\Pr(\theta_H | d_j = 0, (r_1, E(r_2 | \theta_k))))$. So a type θ_L

to stay on the equilibrium path is such that she will diversify iff

$$\begin{aligned} \sum_i w_i^* (\Pr(\theta_H | d_j = 1, r_1)) + \sum_i \delta w_i^* (\Pr(\theta_H | d_j = 1, (r_1, E(r_2 | \theta_L)))) - c_{Lj} > \\ w^* (\Pr(\theta_H | d_j = 0, r_1)) + \delta w^* (\Pr(\theta_H | d_j = 0, (r_1, E(r_2 | \theta_L)))) \end{aligned} \quad (\text{A3})$$

Similarly, a type θ_H will diversify iff

$$\begin{aligned} \sum_i w_i^* (\Pr(\theta_H | d_j = 1, r_1)) + \delta \sum_i w_i^* (\Pr(\theta_H | d_j = 1, (r_1, E(r_2 | \theta_H)))) - c_{Hj} > \\ w^* (\Pr(\theta_H | d_j = 0, r_1)) + \delta w^* (\Pr(\theta_H | d_j = 0, (r_1, E(r_2 | \theta_H)))) \end{aligned} \quad (\text{A4})$$

To prove the result, we only have to show that there exists a pair $\{c_k^*(r_1)\}$ $k = 1, 2$ such that (A3) and (A4) are satisfied over part of the parameter space and in which the cutoffs are increasing in r . From (A4) we know that the highest possible equilibrium cutoff for a high type takes the form

$$c_{Lj} \leq \sum_i w_i^* (\Pr(\theta_H | d_j = 1, r_1)) - w^* (\Pr(\theta_H | d_j = 0, r_1)) \\ + \sum_i \delta w_i^* (\Pr(\theta_H | d_j = 1, (r_1, E(r_2 | \theta_L)))) - \delta w^* (\Pr(\theta_H | d_j = 0, (r_1, E(r_2 | \theta_L))))$$

Based on (A1), and given the definition equilibrium beliefs, the weights of the investor in the first period must be increasing in r . This in turn implies that the first-period terms ($\sum_i w_i^* (\Pr(\theta_H | d_j = 1, r_1)) - w^* (\Pr(\theta_H | d_j = 0, r_1))$) and the second-period terms ($\sum_i \delta w_i^* (\Pr(\theta_H | d_j = 1, (r_1, E(r_2 | \theta_L)))) - \delta w^* (\Pr(\theta_H | d_j = 0, (r_1, E(r_2 | \theta_L))))$) in the expression above—which measure the difference in the expected weights to the two funds under diversification less the weight in the absence of diversification are increasing. Finally, we know that from the fact that $c_k \geq 0$ and Lemma 1 that in equilibrium the cutoffs are always zero or positive; and positive for at least some high types. Following the same logic concerning low types, we have the existence of an equilibrium in which the cost cutoffs are increasing and diversification takes place for some area of the parameter space.

Proof of Result 2. Part (i). By assumption, $\frac{\partial c_k^*(r^*)}{\partial r} \geq 0$. Since c is independent of r , this

implies that this implies that $\frac{\partial \Pr(d = 1 | r, \theta_k)}{\partial r} \geq 0$. Further, by Lemma 1, we have that

$\Pr(d = 1 | r, \theta_H) \geq \Pr(d = 1 | r, \theta_L)$. Using the fact that $\Pr(r_{i_i} > r | \theta_H) > \Pr(r_{i_i} > r | \theta_L)$ we have

the result. Part (ii) This follows directly from the fact that $\frac{\partial c_k^*(r^*)}{\partial r} \geq 0$. Part (iii) follows directly

from Lemma 1.

References

- Ackerman, Carl, Richard McEnally, and David Ravenscraft, "The Performance of Hedge Funds: Risk, Return, and Incentives," *Journal of Finance* 54 (1999), 833-874.
- Agarwal, Vikas and Narayan Y. Naik, "Risks and Portfolio Decisions Involving Hedge Funds," *Review of Financial Studies* 17 (2004), 63-98.
- Aragon, George O., "Share Restrictions and Asset Pricing: Evidence from the Hedge Fund Industry," *Journal of Financial Economics* 83 (2007), 33-58.
- Berger, Philip G., and Eli Ofek, "Diversification's Effect on Firm Value," *Journal of Financial Economics* 37 (1995), 39-65.
- Berk, Jonathan B., and Robert C. Green, "Mutual Fund Flows and Performance in Rational Markets," *Journal of Political Economy* 112 (2004), 1269-1295
- Cabral, Luís M.B., "Stretching firm and brand reputation," *RAND Journal of Economics* 31 (2000), 658-673.
- Campa, José Manuel, and Simi Kedia, "Explaining the Diversification Discount," *Journal of Finance* 57 (2002), 1731-1762.
- Campbell, John Y. and Luis Vicera, *Strategic Asset Allocation for Long-term Investors*. (Oxford University Press, 2002.)
- Carhart, Mark, "On Persistence in Mutual Fund Performance," *Journal of Finance* 52 (1997), 57-82.
- Chevalier, Judith and Glenn Ellison, "Risk Taking by Mutual Funds as a Response to Incentives," *The Journal of Political Economy* 105 (1997), 1167-1200.
- Chen, Joseph, Harrison Hong, Ming Huang and Jeffrey D. Kubik, "Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization," *American Economic Review* 94 (2003), 1276-1302.
- Fama, Eugene F., Lawrence Fisher, Michael C. Jensen and Richard Roll, "The Adjustment of Stock Prices to New Information," *International Economic Review* 10 (1969), 1-21.
- Fama Eugene F., and Ken French, "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance* 51 (1996), 55-84.
- Fung, William and David A. Hsieh, "The Risk in Hedge Fund Strategies, Theory and Evidence from Trend Followers," *Review of Financial Studies*, 14 (2001), 313-341.

Getmansky, Mila, Andrew W. Lo, and Igor Makarov, "An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns," *Journal of Financial Economics* 74 (2004), 529-609.

Gompers, Paul, Anna Kovner, Josh Lerner and David Scharfstein, "Skill vs. Luck in Entrepreneurship and Venture Capital: Evidence from Serial Entrepreneurs," *SSRN Working Paper*, 2008.

Imbens, Guido, "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review," *The Review of Economics and Statistics* 86 (2004), 4-29.

Jensen, Michael C. and William H. Meckling, "Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure," *Journal of Financial Economics* 34 (1976), 305-360.

Jensen, Michael C., "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers," *American Economic Review* 76 (1986), 323-329.

Kaplan, Steven N., and Antoinette Schoar, "Private Equity Performance: Returns, Persistence, and Capital Flows," *Journal of Finance*, 60 (2005), 1791-1823.

Lang, Larry H.P. and Rene M. Stulz, "Tobin's q, Corporate Diversification and Firm Performance," *Journal of Political Economy*, 102 (1994), 1248-1280.

Lamont, Owen, "Cash Flow and Investment: Evidence from Internal Capital Markets," *Journal of Finance*, 52 (1997) 83-109.

Lo, Andrew W., "Hedge Funds, Systemic Risk and the Financial Crisis of 2007-2008: Written Testimony for the House Oversight Committee Hearing on Hedge Funds" (2008), *SSRN Working Paper*.

Li, Haitao, Rui Zhao and Xiaoyan Zhang, "Investing in Talents: Managers Characteristics and Hedge Fund Performances," *SSRN Working Paper*, 2007.

MacDonald, Glenn M., and Alan Slivinski, "The Simple Analytics of Competitive Equilibrium with Multi-Product Firms," *American Economic Review*, 77 (1987), 941-953.

Markowitz, Harry, *Portfolio Selection: Efficient Diversification of Investment*. (New Haven, Conn: Yale University Press, 1958).

Merton, Robert C., "Lifetime Portfolio Selection Under Uncertainty: The Continuous Time Case," *Review of Economics and Statistics*, 51 (1969), 247-257.

Merton, Robert C., "Optimum Consumption and Portfolio Rules in a Continuous-time Model," *Journal of Economic Theory*, 3 (1971), 373-413.

- Panzar, John C., and Robert D. Willig, "Economies of Scale and Economies of Scope in Multi-output Production," *Working Paper #33 Bell Laboratories*, 1975.
- Panzar, John C., and Robert D. Willig, "Economies of Scope," *The American Economic Review* 71 (1981), 268-272.
- Pástor, Lubos and Robert F. Stambaugh, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111 (2003), 642-685.
- Posthuma, Nolke, and Pieter Jelle van der Sluis, "A Reality Check on Hedge Funds Returns," *SSRN Working Paper*, 1993.
- Rajan, Raghuram, Henri Servaes, and Luigi Zingales, "The Cost of Diversity: The Diversification Discount and Inefficient Investment," *Journal of Finance*, 55 (2000), 35-80.
- Rosenbaum, Paul R., and Rubin Donald B., 1983, The central role of the propensity score in observational studies for causal effects, *Biometrika* 70, 41-55.
- Sadka, Ronnie, "Liquidity Risk and the Cross-Section of Expected Hedge-Fund Returns," *SSRN Working Paper*, 2009.
- Samuelson, Paul, "Lifetime Portfolio Selection by Dynamic Stochastic Programming," *Review of Economics and Statistics* 51 (1969), 239-246.
- Scharfstein, David, and Jeremy Stein, "The Dark Side of Internal Capital Markets: Divisional Rent-seeking and Inefficient Investment," *Journal of Finance*, 45 (2002), 2537-2564.
- Schoar, Antoinette, "Effects of Corporate Diversification on Productivity," *The Journal of Finance*, 57 (2002), 2379-2403.
- Sharpe, William, "Capital Asset Prices: A theory of Market Equilibrium Under Conditions of Risk," *Journal of Finance*, 19 (1964), 425-442.
- Stulz, Renee, "Hedge Funds: Past Present and Future," *Journal of Economic Perspectives*, 21 (2007), 175-194.
- Teece, David J., "Towards an Economic Theory of the Multiproduct Firm," *Journal of Economic Behavior and Organization*, 3 (1982), 39-63.
- Teoh, Siew Hong, Ivo Welch and T.J. Wong, "Earnings Management and the Long-run Market Performance of Initial Public Offerings," *Journal of Finance*, 53 (1998), 1935-1974.
- Villalonga, Belén, "Diversification Discount or Premium? New Evidence from the Business Information Tracking Series," *The Journal of Finance* 59 (2004), 479-506.

Wernerfelt, Birger, “Umbrella Branding as a Signal of New Product Quality: An Example of Signaling by Posting a Bond,” *RAND Journal of Economics*, 19 (1988), 458-466.

Table I
Descriptive Statistics: Main Sample

N=86,976 fund-months from 1,576 firms				
	Mean	Std dev	Min	Max
Raw returns (%)	0.92	4.70	-94.83	88.11
4-factor monthly excess returns (%)	0.34	4.05	-11.54	13.77
5-factor monthly excess returns (%)	0.35	4.02	-11.44	13.66
4-factor information ratio	0.13	0.96	-2.44	2.91
5-factor information ratio	0.13	0.97	-2.43	2.91
Diversified firms (fraction)	0.39	0.49	0	1
Fund assets under management (\$M)	93	230	0.3	1,890
Firm assets under management (\$M)	160	367	0.3	8,310
Missing AUM (fraction)	0.14	0.35	0	1
Age (months from founding)	61	52	2	356
Calendar year	1999	4.4 yrs	1977	2006
Strategy 1: Fund of funds	0.18	0.39	0	1
Strategy 2: Long/short fund	0.22	0.41	0	1
Strategy 3: Equity hedge	0.09	0.28	0	1
Strategy 4: Managed futures	0.11	0.32	0	1
Strategy 5: Equity market neutral	0.05	0.21	0	1
Strategy 6: Event driven	0.08	0.27	0	1
Strategy 7: Emerging markets	0.05	0.21	0	1
Strategy 8: Global macro	0.04	0.19	0	1
Strategy 9: Convertible arbitrage	0.02	0.14	0	1
Strategy 10: Fixed income arbitrage	0.03	0.16	0	1
All other strategies	0.13	n/a	0	1
Headquarters in USA	0.67	0.47	0	1

The main sample includes the fund-months from twenty-four months before diversification (or match date) until sixty months after diversification (or match date) for 788 diversifiers and 788 matched focused firms.

Table II
Diversifiers: Within-Firm Changes

	4-factor excess returns		5-factor excess returns	
	Returns (1)	Inf. ratio (2)	Returns (3)	Inf. ratio (4)
<i>DIVERSIFIED</i>	-0.12 ** (0.05)	-0.03 ** (0.01)	-0.11 ** (0.05)	-0.02 * (0.01)
Size decile 2	-0.04 (0.15)	-0.04 (0.03)	-0.06 (0.15)	-0.04 (0.03)
Size decile 3	-0.08 (0.14)	-0.04 (0.03)	-0.09 (0.14)	-0.03 (0.03)
Size decile 4	-0.22 (0.14)	-0.08 ** (0.03)	-0.24 * (0.15)	-0.08 ** (0.03)
Size decile 5	-0.21 (0.16)	-0.10 *** (0.03)	-0.23 (0.16)	-0.10 *** (0.03)
Size decile 6	-0.43 *** (0.15)	-0.14 *** (0.03)	-0.45 *** (0.15)	-0.14 *** (0.03)
Size decile 7	-0.46 *** (0.16)	-0.15 *** (0.03)	-0.48 *** (0.16)	-0.15 *** (0.03)
Size decile 8	-0.63 *** (0.17)	-0.20 *** (0.04)	-0.63 *** (0.17)	-0.20 *** (0.04)
Size decile 9	-0.60 *** (0.17)	-0.24 *** (0.04)	-0.61 *** (0.17)	-0.23 *** (0.04)
Size decile 10	-0.56 *** (0.19)	-0.23 *** (0.05)	-0.58 *** (0.19)	-0.23 *** (0.05)
Missing size	-0.14 (0.17)	-0.09 ** (0.04)	-0.16 (0.17)	-0.09 ** (0.04)
Constant	Y	Y	Y	Y
Year fixed effects	21	21	21	21
Fund fixed effects	788	788	788	788
N	48,410	48,410	48,410	48,410
Adjusted R ²	0.03	0.05	0.03	0.05

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Standard errors are clustered by fund

Table includes 788 diversifiers from twenty-four months before diversifying until sixty months after.

Table III
Matching

Dependent variable = firm launches a second fund at time t; all RHS variables are lagged one month to t-1

			Full sample means			Matched sample means		
	(1) Coef.	(2) $\partial y/\partial u$ at \bar{u}	(3) Focused	(4) Divers.	(5) t on Δ	(6) Focused	(7) Divers.	(8) t on Δ
Avg. CAR	0.03 (0.01)	0.0005* (0.0002)	0.49 (0.00)	0.71 (0.05)	-4.5	0.57 (0.06)	0.68 (0.05)	-1.5
Size decile 1	-0.23 (0.08)	-0.0038* (0.0011)	0.14 (0.00)	0.09 (0.01)	4.4	0.11 (0.01)	0.08 (0.01)	1.6
Size decile 2	-0.13 (0.08)	-0.0024 (0.012)	0.12 (0.00)	0.09 (0.01)	2.6	0.11 (0.01)	0.09 (0.01)	1.2
Size decile 3	0.02 (0.08)	0.0004 (0.0016)	0.11 (0.00)	0.11 (0.01)	-0.6	0.14 (0.01)	0.12 (0.01)	1.4
Size decile 4	0.06 (0.08)	0.0013 (0.0018)	0.09 (0.00)	0.11 (0.01)	-1.0	0.09 (0.01)	0.10 (0.01)	-0.5
Size decile 5	0.07 (0.08)	0.0016 (0.0018)	0.09 (0.00)	0.09 (0.01)	-0.8	0.10 (0.01)	0.10 (0.01)	-0.1
Size decile 6	0.08 (0.08)	0.0017 (0.0019)	0.08 (0.00)	0.08 (0.01)	-0.8	0.09 (0.01)	0.08 (0.01)	0.2
Size decile 7	0.16 (0.08)	0.0039 (0.0023)	0.06 (0.00)	0.08 (0.01)	-2.0	0.08 (0.01)	0.08 (0.01)	0.0
Size decile 8	0.18 (0.08)	0.0029 (0.0022)	0.05 (0.00)	0.07 (0.01)	-1.8	0.04 (0.01)	0.06 (0.01)	-2.0
Size decile 9	0.12 (0.08)	0.0029 (0.0022)	0.05 (0.00)	0.06 (0.01)	-0.7	0.04 (0.01)	0.06 (0.01)	-1.5
Size decile 10	Excluded	Excluded	0.05 (0.00)	0.04 (0.01)	1.8	0.04 (0.01)	0.04 (0.01)	0.3
Missing AUM	0.06 (0.07)	-0.0011 (0.0012)	0.16 (0.00)	0.19 (0.01)	-2.1	0.17 (0.01)	0.19 (0.01)	-1.2
Log age	-0.13 (0.01)	-0.0027* (0.0003)	3.42 (0.00)	3.10 (0.03)	9.4	2.95 (0.03)	3.14 (0.03)	-4.2
Avg. CAR Strategy	0.04 (0.03)	0.0008 (0.0005)	0.40 (0.00)	0.45 (0.02)	-2.2	0.39 (0.02)	0.43 (0.02)	-1.4
Fund of funds (1)	0.04 (0.04)	0.0009 (0.0011)	0.18 (0.00)	0.19 (0.01)	-0.9	0.16 (0.01)	0.19 (0.01)	-1.3
Long/short (2)	-0.13 (0.05)	-0.0025* (0.0008)	0.26 (0.00)	0.19 (0.01)	4.6	0.23 (0.01)	0.19 (0.01)	1.8

Table III
Matching (continued)

			Full sample means			Matched sample means		
	(1) Coef.	(2) $\partial y/\partial \mathbf{u}$ at $\bar{\mathbf{u}}$	(3) Focus.	(4) Div.	(5) t on Δ	(6) Focus	(7) Div.	(8) t on Δ
Equity hedge (3)	0.01 (0.06)	0.0002 (0.0011)	0.08 (0.00)	0.08 (0.01)	-0.5	0.08 (0.01)	0.09 (0.01)	-0.3
Managed futures (4)	0.13 (0.05)	0.0030* (0.0014)	0.10 (0.00)	0.12 (0.01)	-2.0	0.11 (0.01)	0.12 (0.01)	-0.8
Equity driven neutral (5)	0.01 (0.07)	0.0002 (0.0015)	0.04 (0.00)	0.05 (0.01)	-0.4	0.04 (0.01)	0.05 (0.01)	-0.5
Event driven (6)	0.01 (0.06)	0.0001 (0.0012)	0.07 (0.00)	0.08 (0.00)	-0.5	0.06 (0.01)	0.08 (0.01)	-1.1
Emerging markets (7)	0.06 (0.07)	0.0014 (0.0016)	0.04 (0.00)	0.05 (0.01)	-1.3	0.05 (0.01)	0.05 (0.01)	-0.5
Global macro macro (8)	0.06 (0.08)	0.0012 (0.0018)	0.03 (0.00)	0.04 (0.01)	-0.7	0.04 (0.01)	0.04 (0.01)	0.6
Convertible arbitrage (9)	0.10 (0.09)	0.0023 (0.0023)	0.02 (0.00)	0.03 (0.01)	-1.9	0.02 (0.00)	0.03 (0.01)	-1.2
Fixed income arbitrage (10)	0.05 (0.09)	0.0011 (0.002)	0.02 (0.00)	0.03 (0.01)	-1.6	0.04 (0.01)	0.02 (0.01)	1.9
HQ USA	excluded	excluded	0.69 (0.00)	0.66 (0.02)	1.7	0.65 (0.02)	0.66 (0.02)	-0.5
HQ UK	0.05 (0.05)	0.0012 (0.0011)	0.07 (0.00)	0.09 (0.01)	-2.2	0.08 (0.01)	0.09 (0.01)	-0.5
HQ Europe (non-UK)	0.02 (0.05)	0.0005 (0.0011)	0.07 (0.00)	0.09 (0.01)	-1.6	0.08 (0.01)	0.09 (0.01)	-0.5
HQ Asia	-0.07 (0.09)	-0.0014 (0.0015)	0.03 (0.00)	0.02 (0.01)	0.6	0.03 (0.01)	0.03 (0.01)	0.6
Yr. fixed effects	(a)	(a)	(a)	(a)		(a)	(a)	
Pseudo R ²	0.03							
Unique funds	2,045		1,219	826		788	788	
N	97,713		96,887	826		788	788	

*Significant at the 5% level

(a) 21 year fixed effects included, 1985-2006. The excluded category is pre-1985. Effects are statistically significant at the 5% level in 1994 and 1995. Unmatched year means are statistically different in 1995, 1996 and 2006. After matching year means are statistically different in 1987, 1989, 2004 and 2005. Table shows coefficient values for variables used to match diversified funds to non-diversified funds, and t-statistics on the differences in the means of those variables in the unmatched and matched samples. Observations are included as potential matches when average cumulative abnormal returns (Avg. CAR) contains at least 12 months of returns. Diversified funds are only included in the month in which they diversify.

Table IV
Matched Sample: *Ex Post* Returns

	4-factor excess returns		5-factor excess returns	
	Returns (1)	Inf. ratio (2)	Returns (3)	Inf. ratio (4)
<i>DIVERSIFIED</i>	0.11 ** (0.04)	0.04 *** (0.01)	0.12 *** (0.04)	0.05 *** (0.01)
Size decile 2	0.10 (0.12)	0.01 (0.03)	0.10 (0.12)	0.01 (0.03)
Size decile 3	0.17 (0.11)	0.03 (0.02)	0.17 (0.11)	0.03 (0.02)
Size decile 4	0.24 ** (0.11)	0.06 ** (0.03)	0.22 ** (0.11)	0.06 ** (0.03)
Size decile 5	0.22 ** (0.11)	0.06 ** (0.03)	0.21 * (0.11)	0.06 ** (0.03)
Size decile 6	0.17 (0.11)	0.07 *** (0.03)	0.16 (0.11)	0.07 ** (0.03)
Size decile 7	0.20 * (0.11)	0.08 *** (0.03)	0.19 * (0.11)	0.08 *** (0.03)
Size decile 8	0.25 ** (0.11)	0.08 *** (0.03)	0.24 ** (0.11)	0.08 *** (0.03)
Size decile 9	0.30 *** (0.11)	0.12 *** (0.03)	0.28 ** (0.11)	0.12 *** (0.03)
Size decile 10	0.33 *** (0.11)	0.13 *** (0.03)	0.31 *** (0.11)	0.13 *** (0.03)
Missing size	0.29 *** (0.11)	0.09 *** (0.03)	0.27 ** (0.11)	0.09 *** (0.03)
Constant	0.39 (0.33)	0.00 (0.07)	0.39 (0.33)	0.01 (0.07)
Year fixed effects	21	21	21	21
Event time fixed effects	60	60	60	60
Fund fixed effects	N	N	N	N
N	61,072	61,072	61,072	61,072
R ²	0.01	0.01	0.01	0.01

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Standard errors are clustered by fund

Table includes 788 diversifiers and 788 matched focused firms for sixty months after diversification (or match date).

Table V
Matched Sample: Differences-in-Differences

	4-factor excess returns				5-factor excess returns			
	Returns		Inf. ratio		Returns		Inf. ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
<i>DIVERSIFIED</i>	0.12 **	0.03 **	0.13 **	0.04 **				
	(0.06)	(0.01)	(0.06)	(0.01)				
Size decile 2	-0.02	-0.03	-0.01	-0.03				
	(0.11)	(0.02)	(0.11)	(0.02)				
Size decile 3	-0.05	-0.04	-0.04	-0.04	*	*		
	(0.10)	(0.02)	(0.10)	(0.02)				
Size decile 4	-0.12	-0.06	-0.12	-0.06	**	**		
	(0.11)	(0.02)	(0.11)	(0.02)				
Size decile 5	-0.22	-0.10	-0.22	-0.10	*	**	***	
	(0.11)	(0.03)	(0.11)	(0.03)				
Size decile 6	-0.37	-0.14	-0.37	-0.13	***	***	***	
	(0.11)	(0.03)	(0.11)	(0.03)				
Size decile 7	-0.36	-0.14	-0.35	-0.13	***	***	***	
	(0.12)	(0.03)	(0.11)	(0.03)				
Size decile 8	-0.49	-0.17	-0.48	-0.17	**	***	***	
	(0.12)	(0.03)	(0.12)	(0.03)				
Size decile 9	-0.42	-0.20	-0.41	-0.19	***	***	***	
	(0.13)	(0.03)	(0.13)	(0.03)				
Size decile 10	-0.46	-0.22	-0.45	-0.22	***	***	***	
	(0.14)	(0.03)	(0.14)	(0.03)				
Missing size	-0.20	-0.10	-0.20	-0.10	*	*	***	
	(0.12)	(0.03)	(0.12)	(0.03)				
Constant	Y	Y	Y	Y				
Year fixed effects	21	21	21	21				
Event time fixed effects	84	84	84	84				
Fund fixed effects	1,576	1,576	1,576	1,576				
N	86,976	86,976	86,976	86,976				
Adjusted R ²	0.03	0.07	0.03	0.05				

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level
Standard errors are clustered by fund

Table includes 788 diversifiers and 788 matched focused firms for twenty-four months before diversification (or match date) until sixty months after.

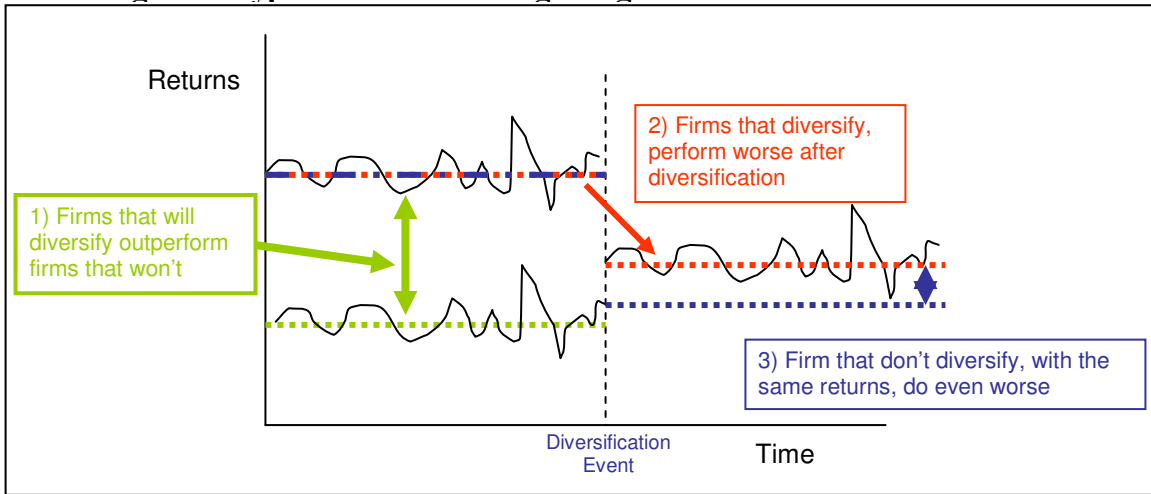
Table VI
Robustness Checks: Differences-in-Differences

Panel A: Baseline matched sample					
	N	(1) Returns		(2) Inf. ratio	
Active benchmark	86,976	0.13 (0.06)	**	0.03 (0.01)	**
4-factor firm returns equal weighted	86,976	0.22 (0.06)	***	0.09 (0.02)	**
4-factor firm returns value weighted	86,976	0.22 (0.07)	***	0.07 (0.02)	***
4-factor excess returns sample weighted	86,976	0.12 (0.07)	*	0.05 (0.02)	**
Panel B: Alternative matched samples					
	N	(1) Returns		(2) Inf. ratio	
4-factor excess returns survivor-bias free sample	44,330	0.13 (0.08)		0.04 (0.02)	**
4-factor excess returns alternative matching regime	88,782	0.14 (0.06)	**	0.03 (0.02)	**
4-factor excess returns 120 event months	100,554	0.12 (0.06)	**	0.04 (0.01)	***

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level
Standard errors are clustered by fund or firm.

Only coefficient values for *DIVERSIFIED* are reported, though all regressions contain the same controls as in Table V. In panel A, the “active benchmark” regression uses an alternative dependent variable, which includes the 4-factors used in the baseline tests plus a hedge-fund strategy specific risk factor. The “sample weighted” regression observations are weighed by the inverse probability of diversifying. In Panel B, the “survivor-bias free sample” regression uses only the subset of returns that is free of survivor bias. The “alternative matching regime” regression relies on an expanded matching model to generate the matched sample, while the “120 event months” regression extends the pre-diversification period back to sixty months.

Figure 1 Hypotheses Concerning Hedge Fund Firm Diversification



**Figure 2
Number of firms by entry and diversification status**

	Enter	Subsequently	
Focused	2,113	Stay focused	1,225
		Diversify	888
Diversified	1,024	Stay diversified	909
		Switch to focused	115

Source: Hedge Fund Research and Lipper TASS.

Figure 3
Diversifiers: Time Path of Excess Returns

This figure shows average 4-factor excess returns on the vertical axis versus event-time on the horizontal axis for diversifiers. Event time is measured in months around the event (e.g., new fund launch) at event time 0. The chart shows the time path of returns from twenty-four months before launching to sixty months after launching a new fund. n=788 firms representing 48,410 fund-months.

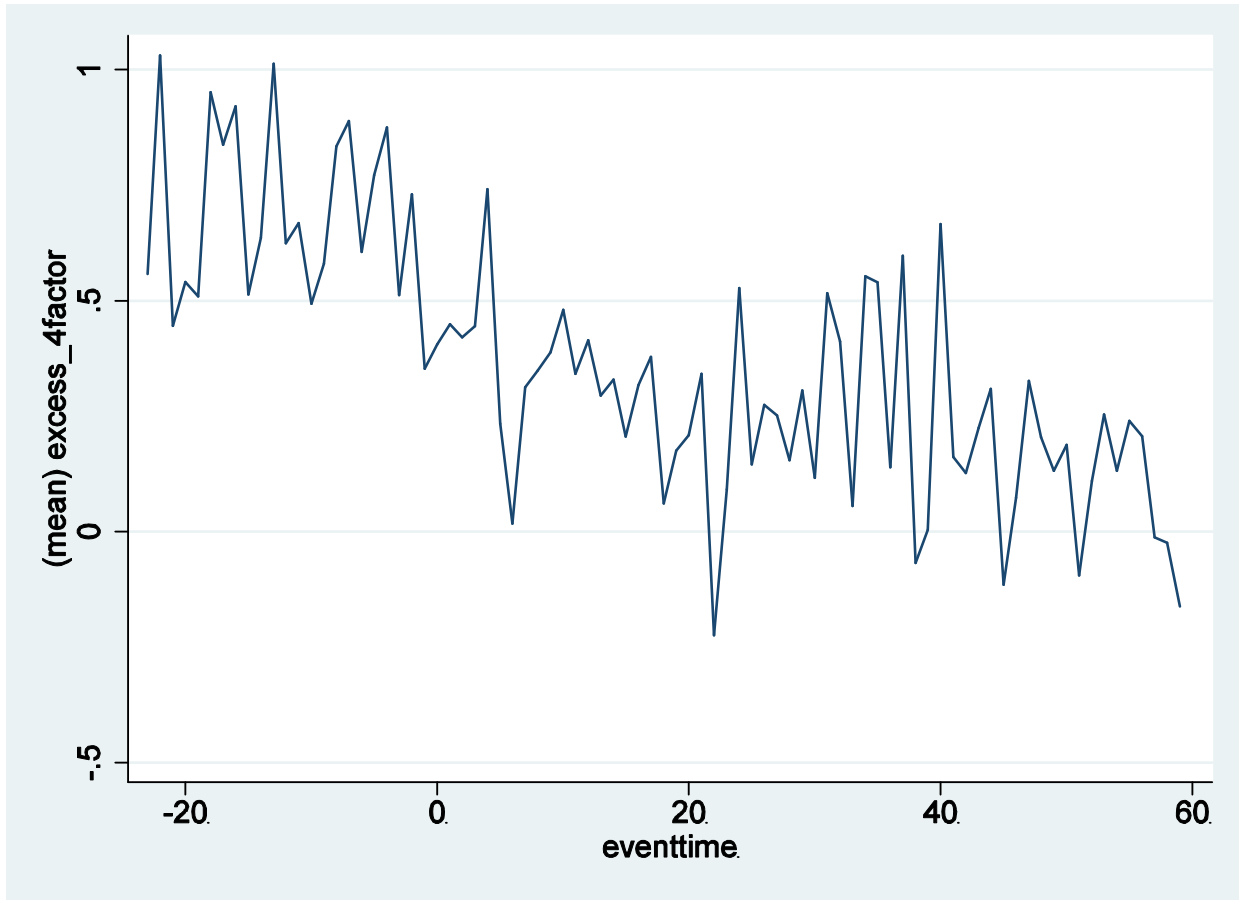


Figure 4
Propensity Score Predicting Diversification Before and After Matching

Figure 4a Propensity Scores before Matching

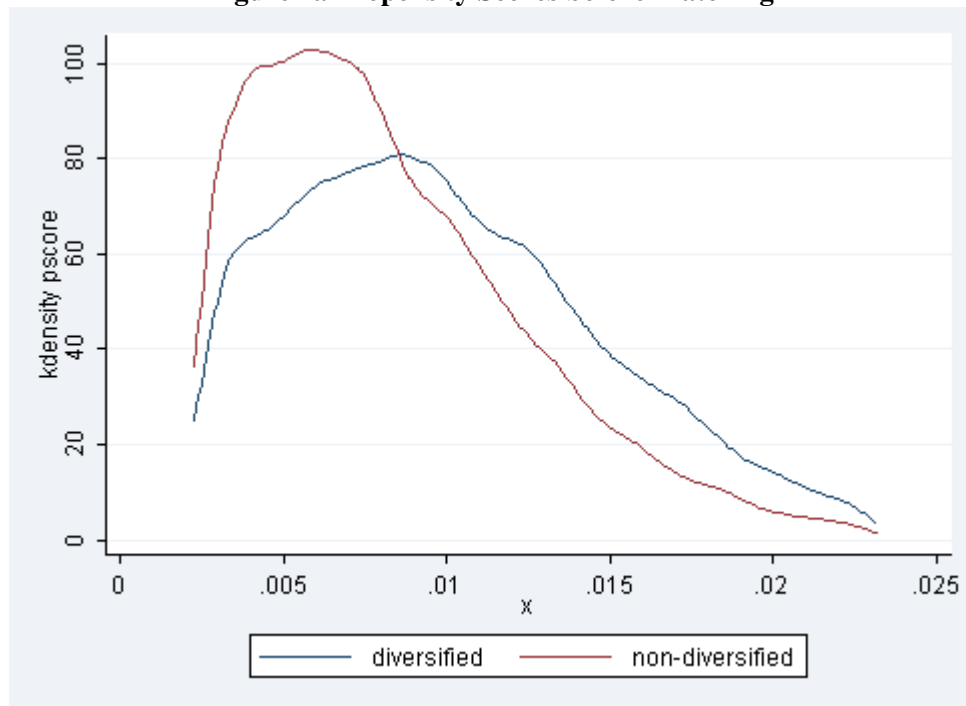


Figure 4b Propensity Scores after Matching

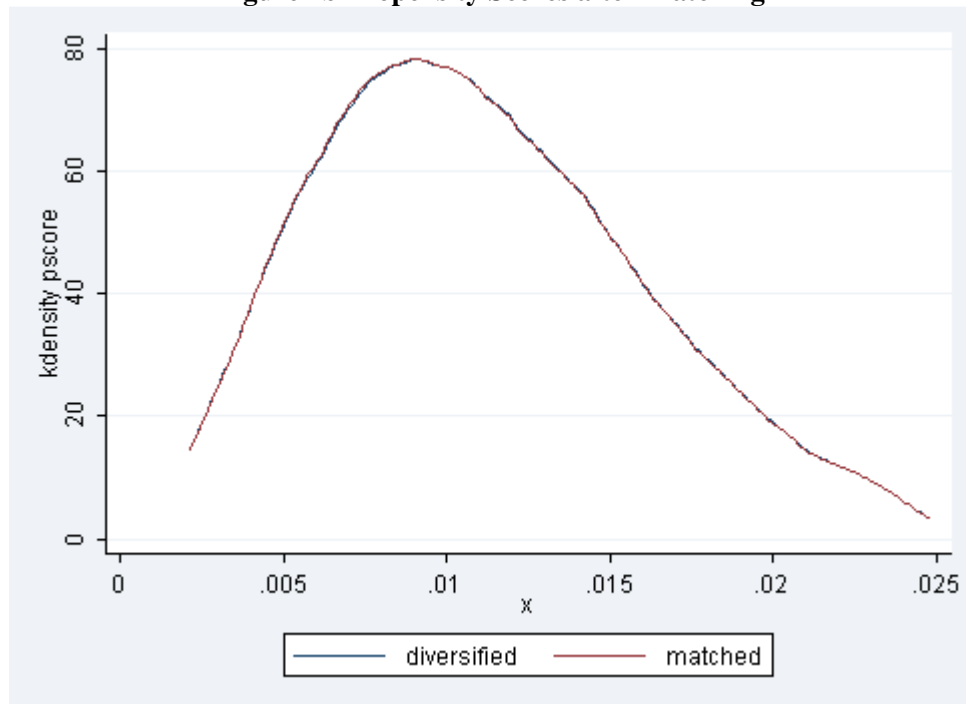


Figure 5
Baseline Matched Sample: 4-factor Excess Returns

This figure shows average excess returns on the vertical axis versus event-time on the horizontal axis for diversifiers (blue) versus matched firms that did not launch a new fund (red). Event time is measured in months around the event (e.g., new fund launch) at time 0. The control group is matched to the treatment group based on the *ex ante* characteristics of the treatment group at time 0 described in Table III. The chart shows the time path of returns from twenty-four months before launching a new fund, (or match date) to sixty months after launching a new fund, (or match date). n=1,576 firms, 788 diversifiers and 788 matched focused firms, representing 86,976 fund-months.

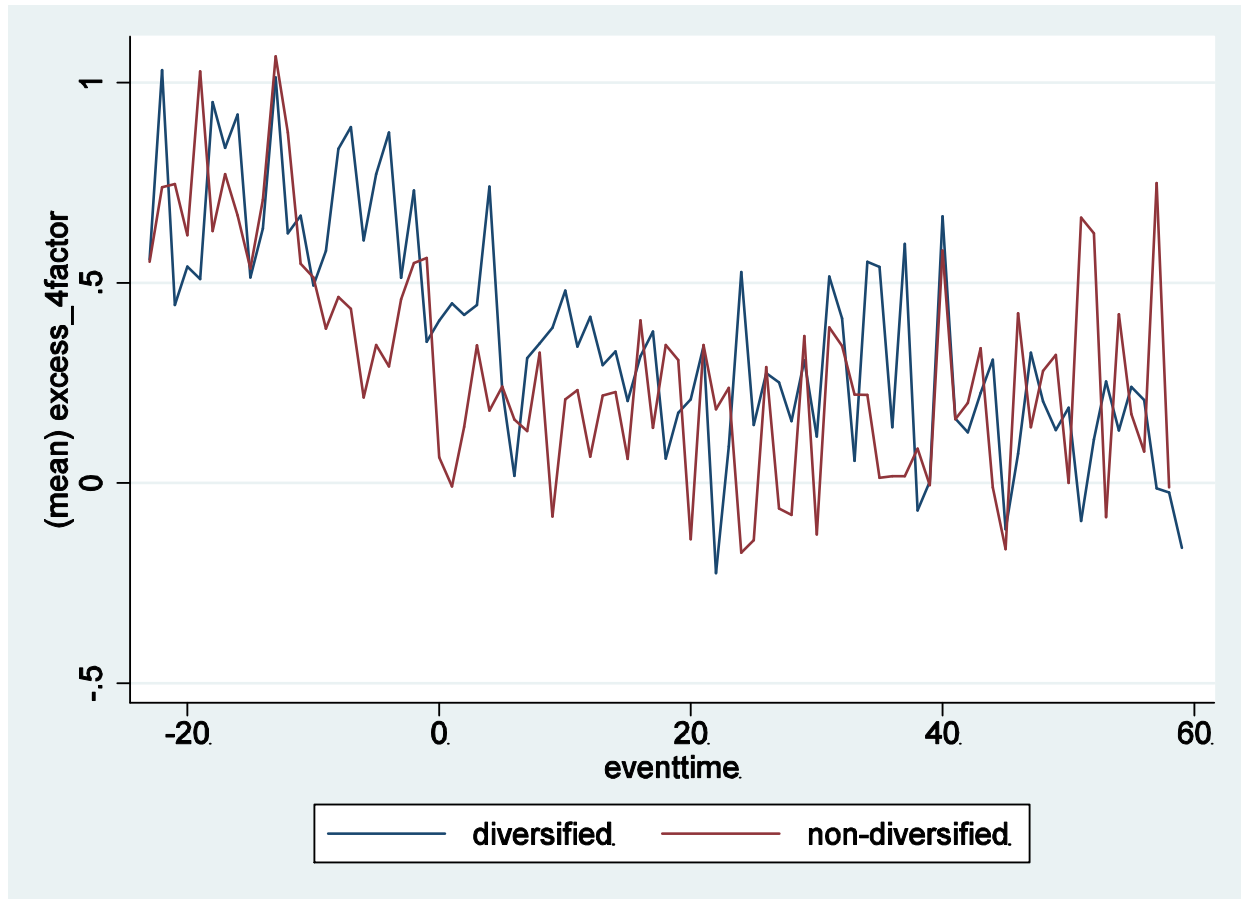


Figure 6
Alternative Matching: 4-factor Excess Returns

This figure shows average excess returns on the vertical axis versus event-time on the horizontal axis for diversifiers (blue) versus matched firms that did not launch a new fund (red). Event time is measured in months around the event (e.g., new fund launch) at time 0. The control group is matched to the treatment group based on the *ex ante* characteristics of the treatment group at time 0 described in Table III plus additional terms, interactions, and polynomials including: the interaction between average cumulative abnormal returns (CAR) and calendar year, CAR and firm age, CAR and firm size, firm size and firm age, size squared, number of competitors, size of competitors, time invariant firm-specific factors from the 4-factor asset pricing model, as well as the standard deviation of firm excess returns. The chart shows the time path of returns from twenty-four months before launching a new fund, (or match date) to sixty months after launching a new fund, (or match date). n=1,576 firms, 788 diversifiers and 788 matched focused firms, representing 86,976 fund-months.

